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LOCALIZED TECHNOLOGICAL CHANGE AND EFFICIENCY WAGES: THE EVIDENCE ACROSS EUROPEAN REGIONS

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THE LOCALIZED INTRODUCTION OF BIASED TECHNOLOGICAL CHANGE AND PRODUCTIVITY GROWTH. THE EMPIRICAL EVIDENCE IN THE ITALIAN MANUFACTURING INDUSTRY[1]

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ABSTRACT
The features of the industrial system within which innovation processes take place affect the pace and the characteristics of the innovation processes and influence their evolution. The analysis of the industrial structure and of the innovation strategies of firms cannot be separated. The introduction of general technological changes that concern mainly the position rather than the slope of the maps of isoquants characterize the innovation process of large corporations. Small manufacturing firms instead rely upon technological knowledge implemented by means of learning processes and introduce technological changes typically characterized by a bias finalized to make the most efficient use of locally abundant production factors. Their contribution to economic growth in terms of total factor productivity is important and can be grasped only when the role of output elasticity of production factors in growth accounting is properly appreciated. The empirical evidence for a sample of 6000 Italian firms in the years 1997-2005 confirms that localized technological changes were mainly introduced by small firms with low levels of profitability and high wages and had significant positive effects on their economic efficiency.

KEYWORDS: BIASED TECHNOLOGICAL CHANGE; LOCALIZED INNOVATIONS; GROWTH ACCOUNTING.

JEL Code: O30

1. INTRODUCTION

The traditional apparatus of the standard production theory can be stretched so as to accommodate the analysis of the characteristics and effects of the introduction of localized technological innovations that can be represented mainly as changes in the shape of the existing isoquants. Localized technological changes are the result of innovation efforts that take place in the close surroundings of the techniques in use and are finalized to make the most efficient use of locally abundant production factors. Their effects in terms of total factor productivity can be grasped when the role of output elasticity of production factors in growth accounting is properly appreciated. The rest of the paper is structured as follows. Section 2 explores the characteristics of the introduction of localized technological changes. It explores the role of the innovation activities carried out by small firms active in skill intensive manufacturing industries and contrast them with the typical innovation process carried out by large corporations and young science-based firms. The analytical frame work enables to articulate the basic hypotheses: the localized introduction of new technologies is the result of the typical innovation activity carried out by small firms in skill intensive industries and can be represented as a biased technological change. In order to appreciate the actual contribution of such small firms to the pace of technological change it seems necessary to rely upon output indicators of innovation activities, such as total factor productivity indicators, that specifically take into account the role of biased technologies that are able to match the local abundance of production factors. Section 3 elaborates the procedure to extract from traditional growth accounting methodology an approach that enables to appreciate the effects of the technological innovations consisting in a bias, i.e. in changes of the output elasticity of production factors on total factor productivity growth, as distinct from the effects of technological changes consisting in the shift of the production function. Section 4 presents the dataset of the Italian firms considered. The econometric evidence is discussed in section 5. The conclusions summarize the main findings and put them in perspective.

2. THE ANALYTICAL FRAMEWORK

Recent advances in the economics of innovation and knowledge have renewed the understanding of the analytical complementarity between market structure, the size of firms and the type of innovation process.

Innovation processes are characterized by the features of the industrial system within which they take place and of course influence their evolution. The analysis of the industrial structure and of the innovation strategies of firms cannot be separated. As a matter of fact such an approach had been implemented by the first generation of Schumpeterian economics, but faded in a second wave of investigations more concerned with the analysis of the specific characteristics of technology. The growing interest in the economics of knowledge has brought it back to the center stage (Scherer, 1984; Malerba, 2004).

Within the manufacturing industry two aggregates can be identified. The classical high-industries such as electronics, telecommunications, farmaceuticals and chemicals are characterized the role of large and diversified corporations at one extreme and small and young science based firms. High levels of concentration shape their industrial structure and competition is based upon fierce oligopolistic rivalry. The second aggregate is represented by skill intensive industries such as mechanics and the array of fashion industries. Industrial concentration is lower and monopolistic competition is pervasive. Such industries exhibit high levels of heterogeneity both with respect to product and process specificities and to factor markets. Within skill intensive manufacturing industries there is a great variety of product and factor niches, with substantial barriers to mobility. Product differentiation is very high and firms specializing in a narrow spectrum of highly complementary products are based in industrial districts that are rooted in well defined regional spaces. Entry and exit is limited and firms exhibit high levels of variance in terms of performances. The very notion of industry, as a matter of fact, is put under question. The inter-industrial heterogeneity of basic indicators such as rates of growth and profitability, wage levels and capital intensity is often lower than intra-industrial one.

The divide between high tech industries and skill intensive ones concerns the innovation process as well. By now a large evidence has shown that the traditional assumption according to which technological change was relevant only in the first aggregate should be rejected. The pace of technological change in skill intensive industries is relevant and relies primarily upon the flow of innovations introduced by small manufacturing firms (Rothwell and Dodgson, 1994).

A wide literature has explored and assessed the characteristics of the innovation process at the firm level. The evidence gathered confirms that there is not a single way to innovation, but rather a variety of innovation processes. Innovation processes of new science-based firms differ from the innovation processes of large incumbent corporations but both have little in common with the innovation process of small and medium sized firms active in skill intensive manufacturing industries (Malerba and Brusoni, 2007).

The innovation processes practiced by small and medium size firms, active in skill intensive industries have distinctive features and characteristics that deserve to be identified and assessed (Acs, Audretsch, 1988 and 1990).

Much attention has been paid to the distinctive features of the innovation process practiced by large corporations and recently young science based firms. Much less attention has been paid to small, skill intensive firms. Yet their role within the manufacturing industry is quite relevant not only in terms of employment and sales, but also in terms of contribution to the pace of technological change (Piva et al., 2005 and 2006; Vaona and Pianta, 2008).

The notion of localized technological change integrates in a single framework and articulates the main issues of this specific kind of innovation process (Atkinson and Stiglitz, 1969; Antonelli, 2003).

Localized technological changes can be represented as the result of a local search for new technologies that are in the proximity of existing ones. The localization stems from the characteristics of the exploration, generation and exploitation of new technologies within a limited distance from existing techniques (Antonelli, 2003). Let us consider the three aspects.

Localized technological change builds mainly upon the tacit knowledge acquired by means of learning by doing, learning by using and learning by interacting. The origins of such knowledge limit the ray of possible innovations. As Atkinson and Stiglitz (1969) note "knowledge acquired through learning by doing will be located at the point where the firm (or economy) is now operating (p. 574). In order to introduce technological innovations such firms rely mainly if not exclusively upon a form of localized technological knowledge based upon the skills of the workforce active at the plant level and implemented in the interactions with customers and clients. Localized technological knowledge has been built out of learning activities. It is the result of bottom-up processes of induction based upon tacit knowledge that is eventually implemented and codified. Firms can improve the technologies they have been able to practice and upon which they have acquired a distinctive competence that is characterized by an idiosyncratic and narrow scope of application. Localized technological knowledge cannot be easily stretched and applied far away from its original locus of accumulation. These firms are not able to command a broad and codified base of scientific knowledge and to extract out of it, with the typical top-down deductive procedure, a wide range of new possible applications that can characterize all the range of production techniques represented on the full isoquant.

Localized technological knowledge contrasts general technological knowledge. The latter is to a large extent if not exclusively, the product of formal research and development activities performed intra-muros, and clearly identified with explicit procedures and protocols. Research activities are conducted by highly qualified personnel with formal doctoral training, are fed by systematic relations with the academic community and generate a flow of discoveries and original applications that can be easily protected by patents. General technological knowledge has a wide scope of application and can feed the introduction of such a wide array of technological innovations that it often leads to the diversification of firms and creation of new industries (Ruttan, 1997).

Localized knowledge enables mainly the introduction of incremental product and process innovations while large corporations and more recently science based young firms are able, occasionally, to introduce radical innovations. The latter can be represented with the basic tools of production theory in substantial changes of the map of isoquants with significant effects both on the shape and the position of the representative isoquant: the effects in terms of shift are larger than in terms of bias.

Table 1 provides a synthesis of the main issues and contrasts the characteristics of the innovation process based upon scientific knowledge with those of innovation processes based upon localized skills.

The innovation process practiced by small and medium size firms active in skill-intensive industries relies primarily upon tacit knowledge acquired by means of repeated learning activities that are highly idiosyncratic with respect to the limited range of techniques that each firm has been able to practice in the past. Research activities are rarely identified and rarely formal R&D laboratories with clear assignment of scientific tasks can be found. New technological knowledge is the product of informal activities although it relies upon the wide and deep participation of a variety of functional activities implemented within the firm ranging from production to procurement and especially marketing.

The access to external knowledge available within industrial clusters is a major source of technological knowledge and provides substantial inputs to the innovation process (Rogers, 2004; Beaudry and Swann, 2009).

TABLE 1. TYPES OF INNOVATION PROCESSES: GENERAL VERSUS LOCALIZED

TYPES OF INNOVATION PROCESSES/MAIN FEATURES	GENERAL	LOCALIZED
MAIN SOURCE OF KNOWLEDGE	SCIENTIFIC DISCOVERIES	COMPETENCE
KNOWLEDGE GENERATION	RESEARCH AND DEVELOPMENT	LEARNING BY DOING AND BY USING
FORM OF KNOWLEDGE	MAINLY CODIFIED	MAINLY TACIT
SCOPE OF APPLICATION	LARGE	NARROW
TYPES OF INNOVATION	RADICAL	INCREMENTAL & CREATIVE ADOPTION
APPROPRIATION	PATENTS	SECRECY AND TIME LAGS
EXPLORATION	GLOBAL SOURCING ON THE INTERNATIONAL SCIENTIFIC FRONTIER	LOCAL KNOWLEDGE SOURCING WITHIN CLUSTERS
EXPLOITATION	GLOBAL PRODUCT MARKETS	LOCAL FACTOR MARKETS
FIRMS	CORPORATIONS&SCIENCE BASED YOUNG FIRMS	SMALL AND MEDIUM SIZE
INDUSTRIES	HIGH TECH	SKILL INTENSIVE
REPRESENTATION IN PRODUCTION THEORY	MAINLY SHIFT EFFECTS	MAINLY BIAS EFFECTS

These characteristics of the knowledge base limit the ray of exploration in the space of new technological knowledge within a substantial proximity to its source. Firms command a form of technological knowledge that enables them to change the shape of the existing isoquants and alter portions of it, rather than the position of the full isoquant (Atkinson and Stiglitz, 1969).

Financial factors add on to explain the distinctive features of the localized exploration in the surroundings of existing techniques. The access to financial resources is constrained by low levels of cash flow and high levels of the ratio of debt to equity. Typically these firms rarely enjoy the financial reputation of large corporations, have not entered the stock markets and rely exclusively on local credit for the provision of finance. The local banks are characterized by low levels of specialization and competence hence high levels of risk aversion and are reluctant to provide long-term financial resources to fund risky technological adventures with extended time horizons and outcomes characterized by high levels of uncertainty. The covenants are very strict and push towards short-term, high yield investments with low levels of uncertainty (Scellato, 2007; Scellato and Ughetto, 2009). As a result these firms are often characterized by credit rationing especially for risky undertakings that cannot be backed by tangible assets. These financial factors direct the exploration and generation of technological knowledge towards innovative undertakings that are more likely to be met in the short-term and with low levels of technological risk.

The characteristics of the production process and of the appropriation strategies explain the substantial bounds to exploitation. Let us consider them in turn. Quasi-irreversibility of both tangible and intangible inputs limits the exploitation of technological knowledge within a limited scope of application from the factor intensity viewpoint: firms prefer to remain near by the techniques in use because this enhances the chances to keep using the existing production factors. Typically these firms are active in capital-intensive industries within product niches and are not young. The combination of high levels of capital intensity and age explains why the effects of the quasi-irreversibility of existing production factors characterize their innovation process. The existing stock of both tangible and intangible capital goods cannot be changed easily and hence limits the ray of efficient exploitation of new and more efficient techniques. Firms must take into account the effects of sunk costs and the related switching costs that increase with the distance of the new techniques from the original ones.

Bounded exploitation strategies are also explained by appropriability conditions. Large corporations and new, science-based firms can rely upon the credible enforcement of intellectual property rights and specifically upon patents to increase the appropriability of the rents stemming from the introduction of their technological innovations because of their strong content in terms of originality and priority. To increase the a appropriability of the rent stemming from the localized introduction of new technologies based upon tacit knowledge small firms active in skill intensive industries can take much less advantage of intellectual property rights. The application to patent offices is quite expensive and the screening process, based upon the search for originality and priority of the technological content, does not favor them. Hence small firms rely more systematically upon secrecy and especially upon time-lags. In turn the selection of biased technologies that are characterized by a strong intensity of inputs that are locally abundant becomes an effective source of barriers to entry and to imitation for other firms based in regions with different factor markets. Appropriation strategies hence clearly favor the exploitation of new technologies in the proximity of existing techniques.

Localized technological changes are typically combined with systematic processes of creative adoption of new technologies introduced by larger corporations. Small firms constrained by both bounded exploitation and exploration for new technologies are fast and creative imitators that adopt timely the new technologies and change them so as to adapt them to their specific product and factor markets.

The incentives to try and change the shape of isoquants and to direct technological change towards the more intensive use of locally abundant factors is stronger when:

A) the local factor markets are characterized by strong asymmetries in the relative abundance of either inputs. The larger is the differences in terms of endowments and hence in the relative costs of production inputs and the farther away is the slope of the isocost from unity. The larger is the difference of slope, in absolute terms, of the isocost from unity and the stronger are the incentives to reshape the isoquants so as to make possible the most intensive the use of the most abundant and hence cheaper factor.

All changes in the asymmetric costs of the inputs increase the incentives to direct the technology;

B) the technology being adopted would favor the intensive usage of locally scarce factors. The wider the mismatch between the output elasticity of the production factors of the new superior technology introduced elsewhere and adopted and the local endowments, and the stronger are the incentives to adapt it to the local factor markets. Here the dynamics is exogenous to the local system. Localized technological changes are a convenient technological strategy when the direction of new technologies originally introduced elsewhere differs from the local endowments.

Localized technological changes can be portrayed as the result of the effort to adapt the existing technologies to the specific conditions of each firm, not only in terms of competence, but also in terms of the internal endowments that are the result of past decision of investments and the external endowments that are determined by the conditions of factor markets.

The introduction of localized technological innovations enables more efficient production processes because they are able to adapt existing technologies to the specific conditions of the local factor markets, while they are the result of the specific historic path of growth of each firm in terms of their acquired competence and the stock of quasi-irreversible tangible and intangible production factors. Localized technological changes consist mainly in incremental innovations that improve the cost efficiency of existing techniques.

Localized technological changes can twist the form of isoquants rather than move them in the space of techniques. Localized technological changes consist much more in modifications of the shape of existing isoquants than in their shift.

In Figure 1 firms in equilibrium in region A explore the surroundings techniques within the limits of the ray R. Firms try and move from region A, in the attempt to produce the same quantity with a lower amount of inputs and hence to increase their efficiency by means of new technologies (Farrell, 1957). The farther they move away from A and the more expensive is both the generation of the necessary technological knowledge and the introduction of technological innovations respectively because of missing competence and switching costs. The new techniques that allow for the most intensive use of cheaper inputs are likely to engender the most effective results in term of output.

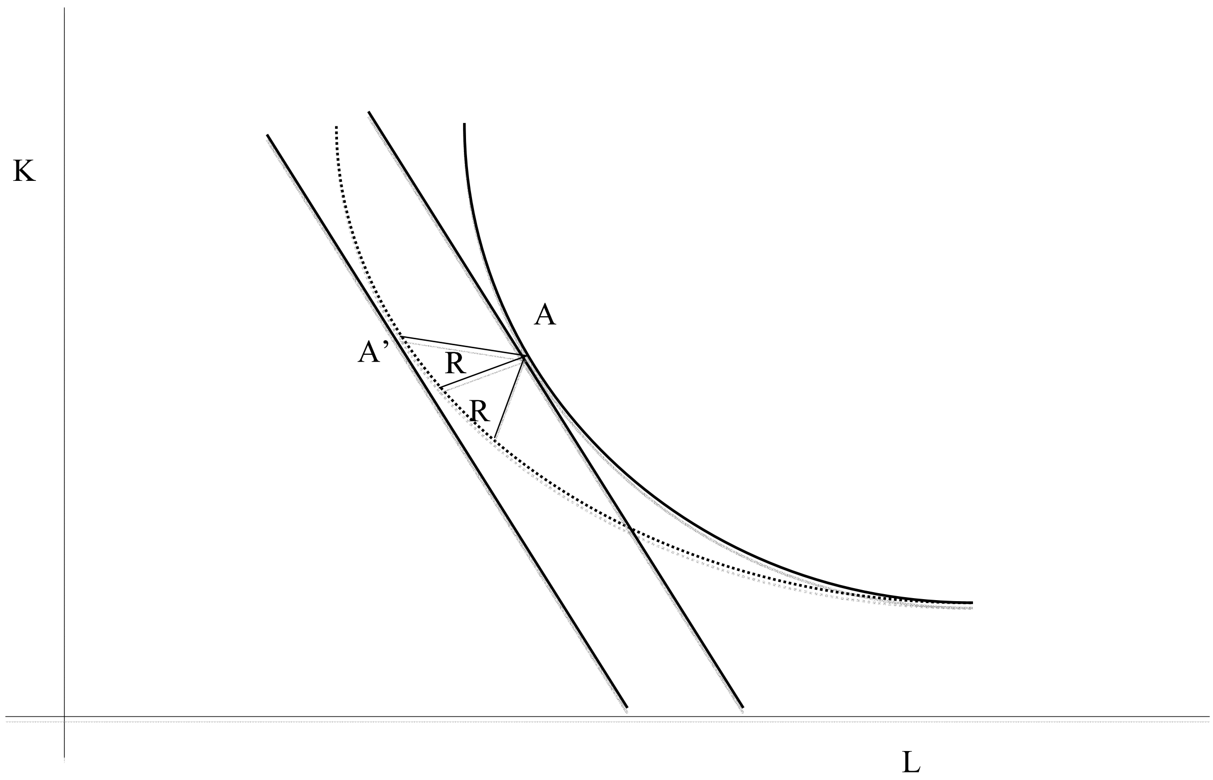
To make an example, it is clear that firms active in capital abundant regions, with a given amount of resources available to try and innovate, have not the competence, the technological knowledge and the incentives to introduce new labor intensive technologies. Moreover they have much stronger incentives to try and introduce capital-intensive superior technologies, than labor-intensive ones. The bias in technological change is both the result of the circumscribed competences of the firms and of the structure of incentives determined by the local structure of factor markets.

Large corporations able to impinge upon scientific advances as a major source for technological knowledge, share the same incentives in terms of factor intensity, but face a much wider spectrum of new possible technologies. For them the introduction of a neutral and superior technology may then be taken into account, especially if the shift the science-based knowledge enables to implement is so important that the incentives exerted by factor costs account for a small fraction of the overall positive effects of the new technologies.

Smaller firms able to command a localized, skill-based technological knowledge, able to generate just a minor shift and hence a small change in the position of the isoquant, will find it more convenient to introduce new and superior techniques that make a more intensive use of capital. The search for new techniques will be localized in the upper portion of the technical region identified by the ray R, in the proximity of the region A where the skill-intensive firms operate and have acquired their distinctive competence.

Their new technology will be shaped by such efforts. The tools of the traditional theory of production can be used to represent the equivalent isoquant that belongs to new technology: as the dotted line in Figure 1 shows, the slope of the new isoquant will change and became more flat. The new equilibrium A’ will be found on a much lower isocost with evident advantages in terms of reduction of unit costs, and a strong increase in output for a given budget cost.

FIGURE 1. THE LOCALIZED INTRODUCTION OF BIASED TECHNOLOGICAL CHANGE



For the sake of clarity let us consider a simple numerical example to grasping the basic point. Let us assume that a firm uses a labor-intensive technology in a capital abundant region:

$$Y_t = K^a \; L^{1-a} \text{ where a= 0.5} \quad (1)$$
$$C = rK + wL \text{ where r=1 ; w=10 ; C = 100} \quad (2)$$

Standard optimization tells us that the firm will be able to produce at best Y=16.

If the firm is able to change the technology at time t+1, so as to adapt it to the local conditions of the factor markets, the new production function will be:

$$Y_{t+1} = K^a \; L^{1-a} \text{, where a= 0.75} \quad (3)$$
$$C = rK + wL \text{ , where r=1 ; w=10 ; C = 100} \quad (4)$$

It is obvious that the firm, after the localized introduction of a new biased technology, characterized by a much larger output elasticity of capital and hence, assuming constant returns to scale, a much lower output elasticity of labor, with the same budget and the same factor costs will now be able to increase its output to 32.

The new technology is twice as productive as the old one and yet it consists just of a bias. The traditional methodology to measure total factor productivity would completely miss this important residual. Only when the output elasticities are kept constant, so as to appreciate their change as a specific form of technological change, the ratio of the expected output to the actual one can grasp the effects of the changing shape of the isoquants. In our example in fact, the position of the isoquant has not changed. Its shape instead is clearly different and specifically it is now much flatter.

The change in the output elasticity of the production factors is by all means the result of the introduction of a specific technological innovation. The standard theory of production in fact tells us that all changes in the production function are the product of the change in technology and *viceversa* all changes in technology do change the specification of the production function. The introduction of a new and biased technological change in turn engenders, for the given amount of total costs, with no changes in the unit costs of production factors, a clear increase of the output.

The new biased technology can be considered as the result of a localized process of exploration of new superior techniques shaped by the internal constraints in terms of competence and sunk costs and directed towards the more efficient use of the production factors that are locally more abundant. The bias in the new technology is the result of a specific type of constrained exploration.

Localized technological change is clearly biased and it can be considered as the result of the typical innovation process that characterizes firms:

i) with small size that limits the access to managerial skills and hence the foresight of broader technological opportunities;
ii) with low profitability that limits the possibility for the internal funding of research and development activities that may extend the ray of technological exploration;
iii) with high levels of debt that limit the possibility to access financial markets to fund extended research activities;
iv) with high levels of sunk costs that engender switching costs and hence increase the opportunity cost for new business lines characterized by different kinds of quasi-irreversible stocks of tangible and intangible inputs;
v) with high levels of human capital and hence average wages that valorize dedicated manpower and long-term industrial relations;
vi) with high levels of internal competence based upon learning processes implemented by dedicated workforce;
vii) active in skill intensive manufacturing industries;
viii) active in factor markets with a strong difference in the endowments of inputs;
ix) adopting new superior technologies characterized by a mismatch between the structure of the endowments and the ratio of output elasticities.

The identification of the characteristics of the innovation process of small firms active in skill intensive manufacturing industry enables to elaborate proper empirical methodologies to better appreciate, and actually grasp their actual contribution to the pace of technological change.

As the analysis has shown the firms that rely mainly upon the localized introduction of bias technological change are not likely to contribute patent and R&D statistics. Actually their innovation efforts are likely to be systematically underestimated by such statistical surveys and indicators that are based upon the quantity of patents applications and the actual performance of formal research and development activities within intramuros laboratories. The evidence based upon the measure of the formal inputs to technological change risks to miss the considerable amount of technological innovations carried out by smaller firms in skill-intensive manufacturing industries (Arvanitis, 1997).

In such a context the analysis of an indicator of the output of the innovation process such as the increase of the total factor productivity increases might enable to better grasp the actual amount of technological change generated by smaller firms. Such a procedure would be even more relevant if a dedicated indicator of the specific effects of the localized introduction of new biased technologies might be implemented.

3. IMPLICATIONS FOR TFP MEASURES: METHODOLOGY

In order to single out an index of biased technological we elaborate upon the standard procedures of calculation of total factor productivity (TFP) and apply a new index based upon the assumption that only a constant-share of inputs on income can measure properly all the changes in output that are not engendered by changes in inputs. The basic methodology is elaborated in Antonelli (2002, 2003 and 2006).

As it is well known the measure of total factor productivity is given by the difference between the actual output and the theoretical one, i.e. the output that should have been produced taking into account only the changes in input (Ruttan, 2001).

The methods to measure the theoretical output differ widely with respect to the timing of the variables considered and the source of empirical evidence. A huge literature has addressed the problems raised by the correct measure of inputs. Much less attention has been paid to the timing of the output elasticities and to their methods of measurement, identification and approximation.

According to our theoretical framework, the levels of the output elasticities of capital and labor of course reflect directly the technology: a two-way relationship exists between the production function and the state of technology. All changes in one imply a change in the other and viceversa. Hence their changes should be considered as the effect of a specific form of technological change.

Yet the founders of the very notion of total factor productivity did not take into account other forms of technological change but the classic Hicks-neutral. Robert Solow (1957) did not consider the effects on the theoretical output of the changes in the output elasticities. He allowed them to change over time. Following the Euler's theorem he assumed that the factor shares on income were a correct measure for the output elasticities and computed the theoretical output as the result of the production function changing every year the value of the share of property on income as the measure of the output elasticity of capital. In so doing Solow did not pay any attention to the effects on TFP of a possible bias in the direction of technological change.

Yet his evidence on the one hand confirms that in the US the share of property on income did not exhibit significant variations when the starting year is confronted with the end one: in 1909 it was 0.335 and 0.326 in 1949 with a negligible change that might warrant the assumptions about the Hicks neutrality. On the other hand however Solow's data exhibit significant changes through the period considered: the share of property in income decreased from 0.335 in 1909 to a minimum of 0.322 in 1927 and fetched a maximum of 0.397 in 1932.

At a closer examination it seems clear that Solow's methodology is able to grasp the effects of a neutral technological change, but not the effects of a biased one. Yet it seems clear that technological change in the US in the years 1909-1949 has not been neutral. Hence we can claim that Solow's methodology enables to grasp the effects of the shift of technological change, but not the effects of the bias.

Even since, a variety of approaches have been considered in the literature (Van Biesebroeck, 2007). Traditional growth accounting actually keeps fixed the output elasticities at a given level assuming typically a 0.30 and 0.70 for respectively capital and labor output elasticity. Translog production functions instead use data for wages and capital service costs that change yearly (Jorgenson and Griliches, 1967).

In other approaches the output elasticities of capital and labor are not measured by means of income's shares, but directly and actually measured by means of econometric estimates of inter-temporal production functions so that the output elasticity is given a single estimated value that reflects the full set of actual values of each year (Diliberto, Pigliaru, Mura, 2008).

Microeconomic investigations of the evolution of TFP at the firm level apply the same methodology and rely on econometric estimates at the sectoral level to measure the output elasticity of inputs. They apply such sectoral levels to each firm, assuming that such common levels solve noise and adjustment problems at the firm level (Olley and Pakes, 1996).

Our approach appreciates the changes of output elasticities as the clue to assess the effects of a specific form of technological change, that is the localized introduction of biased technological changes, and explores the individual changes of output elasticities, at the firm level, as vectors of reliable information about the actual features of the technological innovations being introduced, rather than a source of noise and adjustment problems.

When the intra-industrial variety of firms in terms of such basic indicators as capital intensity, wages, profitability and labor productivity is very high, the attention and ensuing estimation of industry-wide indicators seems to wipe out and miss completely the determinants of the intrinsic economic heterogeneity that characterizes the context. Firms differ because they are localized in different contexts and operate within different product and factor niches. The variance with respect to common average values at the industrial level does not clear for white noise: it risks to under-estimate the role of a specific and idiosyncratic feature of the system under investigation (Crepon, Duguet, Mairesse, 1998).

The analysis of the changes of the output elasticity of capital and labor as measured by their respective shares on income at the individual firm level can yield an effective measure for the productivity-enhancing effects of the localized introduction of biased technological changes (See Antonelli, 2002, 2003 and 2006; more recently Bailey, Irz, Balcombe, 2004 applied the same methodology).

Let us recall here the main passages. The output *Y* of each firm *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 shape:

$$Y_{i,t} = A\,(K_{i,t}, L_{i,t}) \tag{5}$$

Whose standard Cobb-Douglas takes the following specification:

Following Solow, we can measure the total factor productivity (TFP) as follows:

$$Y = A\,(K^{a(t+n)}\,L^{b(t+n)}) \qquad (6)$$

$$AS = Y^* / K^{a(t+n)}\,L^{b(t+n)} \qquad (7)$$

Where Y* is the actual output at time t+n, K and L respectively are the inputs of capital services and labor services at time t+n, and $a_{i,t}$ and $b_{i,t}$ are their output elasticities, with the standard assumption of constant returns to scale: a + b = 1. AS measures the TFP as Solow did, i.e. allowing the yearly change of output elasticities.

Such a measure accounts for "any kind of shift in the production function" (Solow, 1957: 312), and it can be considered a rough proxy of technical change. By means of it Solow meant to propose a way to "segregating shifts of the production function from movements along it". But the change in the technology of the production function is made up of two elements. Besides the shift effect one should account for the bias effect, i.e. the direction of technological change.

Once we get the TFP accounting for the shift in the production, we can investigate the impact of the bias effect with a few passages. First of all we get a measure of the TFP that accounts for both effects (for this reason we call it *total-TFP*), by assuming output elasticities unchanged with respect to the first year observed:

$$ATOT = Y^* / K^{a(t)}\,L^{b(t)} \qquad (8)$$

Here clearly the output elasticity of each production factor does not change every year, as in Solow (1957), but remains fixed at the value of the first year of observation. Now it is clear that the theoretical output is actually measured as if no changes in the technology had been made. Neither the position, nor the slope of the isoquants has changed. Hence the difference between the real, historic output Y* and the theoretical one now accounts for both forms of technological change, as represented in the production theory. The position and the slope of the new map of isoquants are now allowed to exert their effects.

Next we get the measure for the bias effect as the difference between the two indexes we introduced above, i.e.:

$$BIAS = ATOT - AS \quad (9)$$

This amounts to measure BIAS as the difference between a theoretical output calculated with the output elasticities kept fixed at time t and a theoretical output calculated with changes in the output elasticities:

$$BIAS = Y^* / K^{a(t)} L^{b(t)} - Y^* / K^{a(t+n)} L^{b(t+n)} \quad (10)$$

The output elasticities have been calculated by assuming constant returns to scale, and focusing on labour's elasticity, which is computed as the factor share in total output of total wages.

4. EMPIRICAL ANALYSIS

4.1 THE EMPIRICAL EVIDENCE AND THE DATA

In this section we introduce our empirical methodology to assess the relationship between firm level productivity and the introduction of localized and biased technological innovations, using an original dataset containing balance sheet accounting data for a large sample of Italian manufacturing companies.

The Italian evidence seems to be especially appropriate to assess empirically the theoretical framework elaborated so far and to test the hypotheses that have been laid down in the previous sections. The Italian manufacturing industry, at large, in fact seems to be characterized by the strong role of a skill intensive form of technological change mainly introduced by small and medium firms able to adopt and adapt new technological innovations timely and to base their strong competitive advantage on the consequent positive effects in terms of total factor productivity.

Large empirical evidence at the industrial and sectoral levels suggests that the strength of the Italian economy resides in the persistent flow of creative adoptions of new technological innovations, introduced by a core of large corporations, by small firms. These small firms are typically active in medium-tech sectors and specialize in the filieres that lead to the supply of consumer products (See table A in the Appendix). They implement a systematic effort to adopt and change the new technologies introduced by large corporations in Italy and abroad, so as to adapt them to their local conditions both with respect to the local factor markets and to their specific and idiosyncratic production characteristics as shaped by the vintages of existing capital stocks of both tangible and intangible production factors characterized by substantial levels of quasi-irreversibility. This innovative process is not characterized by a strong science base, but rather build on a qualified body of competence and skills acquired by means of learning processes by dedicated and committed workforce that is associated to the performances of the company by strong family ties and a variety of participative forms to the gross margins that stem from the introduction of innovations. Industrial relations based upon trust and long terms relationship favor the accumulation of competence and its direct participation in a bottom-up process of localized introduction of new technologies strongly biased towards the intensive use of locally abundant production factors.

The dataset includes financial accounting data for a large sample of manufacturing companies, observed along years 1996-2005. The data have been extracted from the AIDA database provided by Bureau Van Dick, which reports accounting information for public and private Italian firms with a turnover larger than 0.5 millions of Euros. The companies included in the analysis have been founded before year 1996, they are registered in a manufacturing sector according to the Italian ATECO classification, and they are still active by the end of year 2005.

We have included all the companies with at least 15 employees at the end of fiscal year 1996. In order to drop outliers due to possible errors in the data source, we computed a set of financial ratios and yearly growth rates of employees, sales and fixed capital stock. The final dataset is composed of 6212 firms. All financial data have been deflated according to a sectoral two-digit deflator using year 2000 basic prices.

4.2 VARIABLES AND METHODOLOGY

In this section we show the methodology used to estimate the determinants of the bias component of total factor productivity as defined in the previous section 3.

For each firm included in the sample, fixed capital stock has been computed using a perpetual inventory technique according to which the first year accounting data, i.e. year 1996 in our case, are used as actual replacement values. The subsequent yearly values of fixed capital are computed using a depreciation parameter δ, assumed equal to 6.5%, and adding deflated yearly investments. The investment parameter ($I_{i,t,}$) has been computed as the yearly variation in net fixed capital in companies' balance sheets plus yearly amortizations. Hence, the time series of fixed capital is defined as follows:

$$K_{i,t} = (1-\delta)K_{i,t-1} + I_{i,t} / p_t \tag{11}$$

Firm level factor shares of labour and capital have been computed yearly respectively as the ratio of total labour costs to valued added and - under the standard assumption of constant returns to scale - as the complement to one[3]. In the following table we show the summary statistics of the variables used in the econometric analysis.

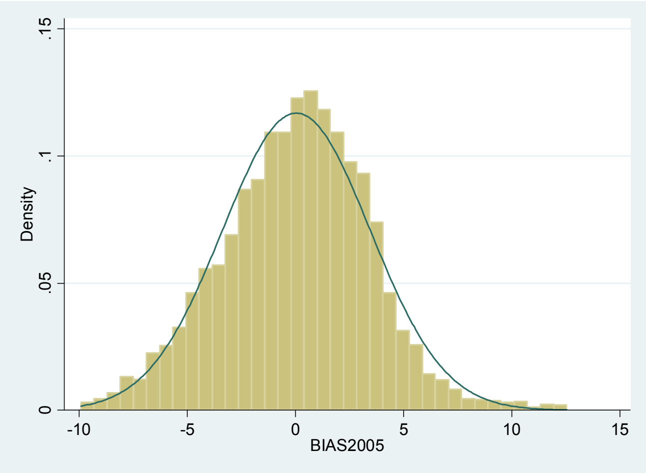
Table 1 Summary statistics

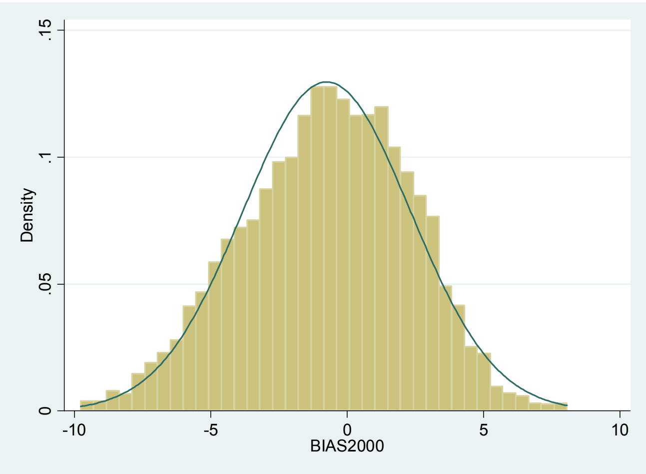
Definition	Year 1997				
	mean	Std dv	5%	median	95%
ln (Fixed capital stock)	14.03	1.31	11.80	14.05	16.16
Labour costs/employees (Euros)	30249	8065	19702	29191	43999
Ebitda/revenues (%)	7.6	8.0	-0.3	5.7	21.7
Liquidity ratio (current assets /current liabilities)	1.05	0.60	0.44	0.91	2.14
intagible assets/tangible assets	0.230	4.282	0.000	0.029	0.654
Labour costs / value added	0.649	0.158	0.386	0.651	0.891
	Year 2000				
	mean	Std dv	5%	median	95%
ln (Fixed capital stock)	14.11	1.37	11.76	14.15	16.28
Labour costs/employees ('000 Euros)	30393	8853	20284	28569	44000
Ebitda/revenues (%)	6.1	5.9	-0.5	4.9	17.1
Liquidity ratio (current assets /current liabilities)	1.05	0.66	0.44	0.89	2.17
intagible assets/tangible assets	0.255	2.338	0.000	0.030	0.752
Labour costs / value added	0.628	0.164	0.360	0.633	0.875

[3] The standard procedure to measuring TFP at the firm level that relies upon sectoral estimates of the relevant output elasticities seems inappropriate because of our emphasis upon the intraindustrial variance stemming from the localized introduction of idiosyncratic and biased innovations.

The BIAS variable for year t is computed for each firm in logarithmic form, according to specification reported in eq. 10. In the remaining of the paper we have adopted a time lag of three years (n=3 in eq. 10) to estimate the value of the BIAS. The two subsequent graphs show the distribution of the bias indicator for years 2000 and 2005. The shape of the frequency distribution is centered around zero, the value obtained when a firms does not show a change in the factor shares between time t and t-3, and show the presence of a significant number of firms with either a positive or a negative value of the BIAS parameter for the time lags considered.

Graph 1 – Distribution of the BIAS indicator for years 2000 and 2005, using year 1997 and 2000 factor shares.





We started the econometric analysis by implementing a set of simple OLS models for two different time windows. The model specification reflects the different hypotheses on the expected determinants of the BIAS, as illustrated in section 2. More specifically, we test whether and to what extent the firm level variance in the level of BIAS is explained by factors related to the dimension of the company, to its capability to generate internally financial resources required for investing in formal innovation projects, to the level of human capital present within the company.

The first set of models are based on the following specification:

$$BIAS_{i,t} = \beta_1 SIZE_{i,t-2} + \beta_2 PROF_{i,t-2} + \beta_3 WAGE_{i,t-2} + \beta_4 LR_{i,t-2} + \beta_5 INTG_{i,t-3} + \varepsilon_{i,t} \quad (13)$$

Where SIZE is the log of total assets, PROF is the ratio of earnings before interests and taxes to revenues, LR is the liquidity ratio test (a measure of the capability of the firm to cover current liabilities through current assets, one of the most simple and straightforward indicator used by financial intermediaries to assess firms' creditworthiness), WAGE is the average salary per employee, INTG is the ratio between the book value of intangible assets and fixed assets. The equation includes a full set of sectoral dummies (20 sectors defined at 2 digit level ATECO codes) and regional dummies (20 Italian regions). The two sets of dummies are expected to capture sector specific dynamics in the bias component of TFP levels as well as the impact of heterogeneity across Italian regions in the local development of labour markets and in the local availability of relevant inputs for the innovation process. In order to avoid possible spurious correlations we have inserted independent variables specified with a two years time-lag while the BIAS in year t is computed using three years lagged factor shares. We adopted as first reference year for the computation of firm-level factor shares year 1997. The above equation (13) has been estimated for years 2000 and 2005.

Table 2 OLS models, dependent variable BIAS.

	Year 2000				**Year 2005**			
	model I		**model II***		**model I**		**model II***	
	Coeff.	***Std err***	***Coeff.***	***Std err***	***Coeff.***	***Std err***	***Coeff.***	
SIZEt-2	-1.203	0.024	-1.297	0.024	-1.191	0.025	-1.240	0.026
WAGEt-2	0.894	0.150	1.187	0.142	0.803	0.244	1.055	0.249
PROFt-2	-0.205	0.013	-0.192	0.015	-0.251	0.009	-0.241	0.009
LRt-2			-0.133	0.077			-0.293	0.048
INTGt-2			-0.044	0.027			-0.142	0.030
REGD	yes	yes	Yes	yes	yes	yes	yes	Yes
SECTD	yes	yes	Yes	yes	yes	yes	yes	Yes
Const	7.895	1.820	8.864	2.862	8.571	2.493	8.864	2.862
Observations	6212		5959		6212		6204	
R^2	0.459		0.429		0.486		0.493	

* The smaller number of observation for models II is due to the presence of missing values in the original data sources for the computation of the LR and INTG covariates.

The first results show a negative and significant association between firms' size and the BIAS indicator, suggesting how the biased component of TFP level is more pronounced for relatively smaller firms. The negative sign estimated for the two variables capturing the profitability and the financial conditions of firms (PROF and LR) is in line with our theoretical expectations: on the one hand, low profitability limits the possibility for the internal funding of research and development activities that may extend the ray of technological exploration, on the other hand, previous higher levels of debt and related interest payments reduce to possibilities to access financial markets to fund additional research and development activities. The positive sign of the variables WAGE, which is expected to approximate the average level of skill intensity within a company, seem to suggest how a major source of the biased component of the TFP is indeed related to the adoption and adaptation of new incremental technologies performed by a internal skilled personnel.

The joint interpretation of the results on firms' size, profitability and financial conditions is consistent with a scenario in which the bias in the new technology is actually the result of a specific type of constrained exploration in the technological space.

The evidence obtained for the variable capturing the intensity of intangible assets (INTG) suggests that a higher incidence of intangible assets (patents, licensees, capitalized R&D expenditures) is a associated to a relatively lower level of bias. According to our view of the BIAS indicator, this is a reasonable result: companies endowed with a higher proportion of intangible assets have been able in the past to introduce new technologies performing formal R&D activities so that the change in their levels of TFP is mostly determined by Hicks-neutral types of technological change represented by a homogeneous shift of the isoquants.

In order to provide further evidence we have also implemented a panel analysis, using a fixed effect OLS model. The structure of the data is based on three temporal observations: year 2000, 2003 and 2005.

Table 3 Panel fixed effects model, dependent variable BIAS.

	Model I		Model II	
	Coeff.	Std err	Coeff.	Std err
SIZEt-2	-0.494	0.031	-0.507	0.032
WAGEt-2	0.323	0.097	0.328	0.099
PROFt-2	-0.117	0.007	-0.119	0.007
LRt-2			-0.188	0.046
INTGt-2			-0.018	0.010
Const	3.910	1.085	4.242	1.120
Observations	18636		18356	
F test	178^{***}		127.15^{***}	
R-sq overall	0.4396		0.449	

Heteroskedaticity robust standard errors. The smaller number of observation for models II is due to the presence of missing values in the original data source for the computation of the LR and INTG covariates.

The results from the latter analysis fully confirm our previous findings, suggesting the presence of a significant persistence along time of a bias component in total factor productivity.

6. CONCLUSIONS

Small firms active in skill intensive manufacturing industries carry out major innovation activities that are characterized by strong idiosyncratic features. Their typical innovation process consists in the localized introduction of biased technological changes that are in the proximity of existing ones. Localized technological changes consist mainly in changes in the shape of isoquants, as opposed to general technological change that affects primarily the position of the isoquants.

The localization stems from the twin limitations to both the exploration and the exploitation of new technologies within a limited distance from existing techniques.

Exploration is limited by the source of technological knowledge based upon learning processes implemented by dedicated workforce high levels of human capital and hence average wages that valorize dedicated manpower and long-term industrial relations. Technological exploration is also limited by the constrained access to managerial skills and hence by bounded foresight of broader technological opportunities; high levels of debt that limit the possibility to access financial markets to fund extended research activities; high levels of sunk costs that engender switching costs and hence increase the opportunity cost for new business lines characterized by different kinds of quasi-irreversible stocks of tangible and intangible inputs.

Technological exploitation takes place in the proximity of existing techniques and it leads to the systematic introduction of a bias in favor of the intensive use of locally abundant inputs because of the switching costs arising from the quasi-irreversibility of tangible and intangible inputs, the higher levels of production efficiency and because of the larger opportunities to better appropriate the benefits stemming from their introduction in terms of increased appropriability.

Small firms active in skill intensive sectors excel in the localized introduction of biased technologies that can be found and exploited within the proximity of existing techniques. In order to appreciate the idiosyncratic characters of their innovation process and their contribution to the pace of technological change traditional indicators of technological advance based upon input indicators such as patent and R&D statistics are inappropriate.

The implementation of a measure of total factor productivity that identify the specific contribution of the introduction of biased technological changes, as distinct from the effects of the introduction of neutral technological changes has enabled to appreciate their distinctive role.

The empirical evidence of a large sample of Italian manufacturing firms has confirmed the advantages of the methodology implemented and has tested the hypotheses outlined about the distinctive features of the localized introduction of biased technological change as a typical aspect of a widespread form of innovation process.

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ANNEX

Table A - Sectoral composition of the sample

Food and beverages	491	7.9%
Textile	518	8.3%
Textile product industry	169	2.7%
Leather and leather products manufacturing	227	3.7%
Wood and wood products manufacturing	145	2.3%
Pulp, paper and paper products manufacturing	156	2.5%
Printing	168	2.7%
Chemical industry	338	5.4%
Plastics and rubber manufacturing	383	6.2%
Non-metallic mineral product manufacturing	350	5.6%
Metallurgy	244	3.9%
Metal products manufacturing	913	14.7%
Mechanical machinery and equipment manufacturing	957	15.4%
Electrical machinery and equipment manufacturing	248	4.0%
Telecommunication machinery and equipment	77	1.2%
Medical, optical and precision equipment	132	2.1%
Transportation equipment manufacturing	112	1.8%
Other transport equipment manufacturing	55	0.9%
Furniture	436	7.0%
Software	93	1.5%
TOT	6212	100.0%

Table A - Sectoral composition of the sample and summary statistic for the BIAS indicator in year 2000

			BIAS for year 2000		
	Firms		mean	std	median
Food and beverages	491	7.9%	-2.030	3.075	-1.955
Textile	518	8.3%	-1.186	3.026	-1.015
Textile product industry	169	2.7%	-0.116	3.134	0.335
Leather and leather products manufacturing	227	3.7%	-0.124	2.781	0.026
Wood and wood products manufacturing	145	2.3%	-0.874	2.809	-0.901
Pulp, paper and paper products manufacturing	156	2.5%	-1.812	3.293	-1.569
Printing	168	2.7%	-0.135	3.102	0.217
Chemical industry	338	5.4%	-1.986	3.304	-1.723
Plastics and rubber manufacturing	383	6.2%	-1.383	2.817	-1.215
Non-metallic mineral product manufacturing	350	5.6%	-1.082	2.915	-0.883
Metallurgy	244	3.9%	-1.752	2.874	-1.792
Metal products manufacturing	913	14.7%	-0.498	3.082	-0.297
Mechanical machinery and equipment manufacturing	957	15.4%	-0.051	2.872	0.178
Electrical machinery and equipment manufacturing	248	4.0%	-0.292	3.176	0.313
Telecommunication machinery and equipment	77	1.2%	-0.113	3.198	0.232
Medical, optical and precision equipment	132	2.1%	0.371	2.994	0.588
Transportation equipment manufacturing	112	1.8%	-0.565	3.333	-0.282
Other transport equipment manufacturing	55	0.9%	-0.618	2.764	-0.245
Furniture	436	7.0%	-0.471	2.645	-0.440
Software	93	1.5%	1.893	2.491	2.393
TOT	6212	100.0%			