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Total Factor Productivity Growth and the Spillover Hypothesis: an Empirical Analysis for the Italian Manufacturing using Non Parametric Frontiers, 1989-1994

by

Vania Sena

Department of Economics and Related Studies
University of York
Heslington
York, YO10 5DD

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Vania Sena
Department of Economics
University of York *

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Abstract

The purpose of this paper is to propose a new test of the spillover hypothesis of the endogenous growth literature and to apply it to a panel of firms from the Italian manufacturing over the period 1989-1994. I depart from previous literature into two respects: first, I measure total factor productivity growth by the Malmquist index computed with Data Envelopment Analysis; second, I use as a measure of the knowledge spillover the actual technical change registered by firms with a high proportion of R&D expenditure and I test whether it can explain the total factor productivity change of firms with a low proportion R&D spending where productivity change is measured by DEA.

1 Introduction

The purpose of this paper is to propose a new test of the spillover hypothesis of the endogenous growth literature and to apply it to a panel of firms from the Italian manufacturing over the period 1989-1994.

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Theoretical models of endogenous growth emphasize that innovative activities of individual firms contribute to sustained long-run growth of an economy through their industry-wide spillover effect (Romer, 1986; Grossmann and Helpman, 1990). According to them, firms invest in R&D to acquire private knowledge that enhances their productivity and profits; then their private knowledge spills over to the rest of the economy and becomes social knowledge, acting as an external effect in enhancing the productivity of all firms. In contrast, Cohen and Levinthal (1989), among others, argue that a firm must invest in private R&D to acquire the technical capability needed to make use of the public domain knowledge to enhance its productivity.

These theoretical debates have originated several empirical studies aimed at testing the spillover hypothesis. Among others, Jaffe (1986) provided empirical evidence on the spillover effect by using patent applications to construct a measure of similarity of research activities among firms. He calculated the external R&D pool available to a firm by taking the weighted aggregated R&D expenditures and found that both external pooled R&D and in-house R&D efforts significantly influenced the quantity of patent applications and the market value of the firm. Bernstein and Nadiri (1988) constructed a measure of the external R&D pool of a firm and found the spillover effect to be statistically significant in all industries. Raut (1995) estimated the productivity effects of a firm's own R&D and industry-wide R&D expenditures as well as physical capital and labour inputs for a sample of Indian firms. His estimates support the spillover hypothesis in all sectors.

These works on the impact and size of the spillover effect share a common structure. They usually try to establish an empirical relationship between technical change in the form of R&D (usually external) and the growth rate of added value of a single firm, used as a measure of productivity growth. However, this specification raises several problems. As pointed out in Griliches (1979), there are all sorts of problems associated with R&D statistics as indicators of innovative activities. These are of two types. First, it is not clear to what extent R&D expenditure is an adequate proxy of the firm's innovative efforts: there may exist a difference in ability of firms to extract innovations from a given expenditure in research and development as internal inefficiencies can interfere with the firm's innovative effort. Second, the R&D spending (both internal and external) is likely to be correlated with the commonly used measures of productivity growth (i.e. rate of added value growth) as they are subject to the same stochastic shocks; therefore the introduction of this variable in a general equation linking the change in added value and R&D expenditure can create simultaneity problems.

This paper proposes a new approach to test the spillover hypothesis; I depart from previous works in this fields in two respects: first, I measure total factor productivity growth by the Malmquist index computed with Data Envelopment Analysis; second, I use as a measure of the knowledge spillover the actual technical change registered by firms with a high proportion of R&D expenditure (defined henceforth as high-tech firms) and I test whether it can explain the total factor productivity change of firms with a low proportion R&D spending (defined therefore non high-tech firms), where productivity change is measured by linear programming techniques (namely DEA) . Therefore, the empirical strategy I adopt is articulated into two stages: first I measure the total factor productivity growth registered by the two subsamples of firms computing the Malmquist index, proposed by Caves et at. (1982) with DEA. I decompose it into technical change and technical efficiency change. Then I test whether the technical change registered by high-tech firms can explain the total factor productivity growth of non high-tech firms, after controlling for factors which can potentially affect productivity growth.

The advantages of this approach are two. First, technical change is a measure of the actual output of the R&D spending, and therefore it is a better measure of firms' innovative effort than just R&D. Second, the two-stage procedure and the use of linear programming techniques allows the avoidance of the simultaneity problem: indeed the chosen measure productivity growth is not simultaneously determined with the measure of technical change. This new approach is then implemented to test whether there has been a knowledge spillover from high-tech to non-high-tech firms in the Italian manufacturing, using a panel of firms drawn from the Italian manufacturing over the period 1989 - 1994.

The structure of the paper is the following. In Section 2, I provide a brief summary of the literature (both theoretical and empirical) concerning the spillover hypothesis. In Section 3, I show in detail the two-stage empirical strategy to test for the spillover hypothesis: to this purpose, I will show first how to derive the Malmquist index using Data envelopment analysis (DEA) and then I will describe the approach used in the second-stage estimation. Section 4 reports data sources, summary statistics and also outlines the procedure used to construct the variables; the main results are shown and commented in Section 5. Finally some concluding remarks are offered in Section 6.

2 The spillover hypothesis of endogenous growth literature and its empirical tests: a brief survey

Theoretical models of endogenous growth emphasize that innovative activities of individual firms contribute to sustained long-run growth of an economy through their industry-wide spillover effect (Romer, 1986; Grossmann and Helpman, 1990). According to this view, individual firms invest in R&D to acquire private knowledge that enhances their productivity and profit. Private knowledge of individual firms then spills over to the rest of the economy and becomes social knowledge which acts as an external effect in enhancing the productivity of all firms. According to this view, the output of R&D investment, namely technological knowledge, is regarded as a public good: once it is generated by a firm, it can be copied almost without cost by any number of firms. With the spillover effect of R&D, an aggregate production function with either constant or decreasing returns to scale may exhibit increasing returns to scale and thus may lead to sustained long-run growth (Romer, 1986; Raut and Srinivasan, 1993). Implications of this view would be that a firm with low R&D expenditure can draw from the high-tech technology firm at zero cost and therefore the high-tech firms' innovative efforts may explain other firm's productivity growth.

As mentioned briefly in the Introduction, Cohen and Levinthal, among others, have argued against this view. They wrote (p. 570):

> "...economists have assumed that technological knowledge which is in the public domain is a public good. Like a radio signal or smoke pollution, its efforts are thought to be costlessly realized by all firms located within the neighborhood of the emission."

They suggest that the cost of utilizing public domain knowledge fruitfully is minimal for those firms which have accumulated technological capability or the stock of technological knowledge capital through considerable investments in R&D in the past. Thus, an implication of this view is that the effect of R&D capital on productivity would be permeated mainly through the effect of own R&D capital. Therefore firms with a high percentage of R&D expenditure will not contribute to private productivity gains unless firms do not invest themselves in R&D.

Following the theoretical debates, the issue of how measuring and evaluating the R&D spillovers empirically has gained relevance. Griliches (1991) and Nadiri (1993) have provided overview on the issue of measuring and evaluating R&D spillovers. Three different methodologies to assess the empirical impact of R&D spillovers emerge from their surveys. First, there is the case-study approach where detailed data are used to measure spillovers in particular cases such as agriculture[1]. Second, spillovers might be embodied in intermediate-input flows or patent-flows between sectors (Nadiri, 1993). Lastly, there is the econometric approach where cost or production functions are estimated using R&D by other firms or sectors as an input alongside own R&D. In this short survey, I concentrate on this last methodology, which is the most widespread.

Following Griliches (1979), Jaffe (1986) provided some empirical evidence on spillover effects of R&D by using patent applications to construct a measure of similarity of research activities among firms. He calculated the external R&D pool available to a firm by taking the weighted aggregate R&D expenditures of all other firms using the measure of research similarities as weights. He found that both external R&D and in-house R&D efforts significantly influence the quantity of patent applications and the market value of the firm. Bernstein and Nadiri (1988) constructed a measure of the external R&D pool of a firm by taking unweighted aggregate R&D expenditures of other firms in the industry and found the spillover effect to be statistically significant in all industries. Park (1995) has quantified the cross-national effects of private and public investment in R&D using a panel data set of 10 OECD countries. The results show that domestic private research is a significant determinant of both domestic and foreign productivity growth. Raut (1995) estimates the effects of individual R&D expenditures and industry-wide R&D spillovers on the individual firm's productivity growth. Indeed, according to the author, an alternative channel through which R&D spillovers can have positive effect on productivity of individual firms is in situations where a firm might benefit from firms research findings within the industry. In such a situation, firm will benefit not only from its own R&D efforts but also from the total R&D efforts in the industry. Therefore, he considers an extended Cobb-Douglas production function, including in-house R&D capital and two-digit industry level R&D capital as inputs. The estimates give general support to the spillover hypothesis in all industries; more specifically, he finds that firms gain significantly from the aggregate industry level R&D capital spillover. Van Heijl (1997) has measured the effect of in-house R&D spending on productivity growth using a database of manufacturing firms for France covering the period 1978-1992. He finds out that this variable has a positive impact on firms' productivity growth. Vueri (1997) has examined the importance of inter-industry spillovers in Finnish manufacturing in the

[1] See Griliches (1991) for a detailed survey of these case-studies.

1980s and early 1990s. He measures the spillovers effect using measures of technological distance based on the industry-specific distributions of R&D expenditures. The results show that domestic spillovers (among other) are the most important technology source of total factor productivity.

The studies identified above which work on the impact and size of the spillover effect share a common structure. They usually try to establish an empirical relationship between technical change (proxied by external R&D spending) and the growth rate of added value. Griliches (1979) has outlined the main problems when trying to measure the contribution of technical change (both internal and external) using the R&D indicator. He distinguishes among:
a) problems associated with the use of R&D spending as a proxy of the technical change;
b) econometrics problems associated with the introduction among R&D spending on the right-hand side.

Let us analyze these two points in more detail. As for the point (a), R&D spending cannot be regarded as a good proxy of the innovations of firms as firms differ in their ability to extract innovations in the productive process from a given Research and Development spending. Indeed, lack of managerial abilities and forms of x-inefficiency can prevent firms from getting the most out of their investment in R&D and therefore this measure can overestimate the innovation of firms and its impact on productivity growth of firms. Moreover, the value of knowledge is likely to be realized (and therefore subject to appropriability by other firms) a considerable time after the R&D effort has been made. The lags involved relate to time lapsing between the time the R&D spending is made and the time it turns into actual innovation.

Regarding point (b), the introduction of R&D spending as right-hand side variables creates simultaneity problems with measures of productivity growth; these are likely to be correlated as they are subject to the same stochastic shocks.

This brief survey shows that so far it is not clear how much the spillover effect can be regarded as important in explaining the productivity growth of firms in the economy. Therefore the spillover effect, its existence and its quantification, is still an open issue. As written at the outset, in this paper I propose a new test of the spillover hypothesis. Unlike previous works in the field, I use the actual technical change registered by firms with a high proportion of R&D expenditure (defined henceforth as high-tech firms) as a measure of the knowledge spillover of the actual technical change and I test whether it can explain the total factor productivity change of those firms with a low proportion R&D spending (defined therefore non high-tech firms), where productivity factor productivity change is measured by linear programming techniques (namely DEA). Therefore, the empirical strategy I adopt is articulated into two stages. First, I measure the total factor productivity growth registered by two subsamples of firms (high-tech and low-tech firms) computing the Malmquist index, proposed by Caves et at. (1982) with the DEA. I decompose it into technical change and technical efficiency change. Then I test whether the technical change registered by high-tech firms can explain the total factor productivity growth of non high-tech firms, after controlling for factors which can potentially affect productivity growth.

This approach has two distinctive advantages. First, unlike previous work, I use a different measure of technical change; more precisely, I use the technical change by high-tech firms as this is supposed to measure the actual result of the innovative effort at a time when it can be observed by other firms and therefore it can be adopted. Furthermore, the simultaneity problem is solved by using the two-stage approach. Indeed, the measure of productivity growth is derived at the first stage using DEA and therefore it is a measure which should not be affected by spurious correlation with variables used in the second stage. Therefore, in the second stage there should not be correlation between the right-hand side and left-hand side variables. The empirical approach is explained in more detail in the next section.

3 The empirical model

As I wrote in the Introduction to this paper, this paragraph is devoted to the explanation of the empirical strategy used to test for the spillover effect. This is articulated into two stages: first I measure the total factor productivity growth registered by the two subsamples of firms computing the Malmquist index, proposed by Caves et at. (1982) with the DEA. I decompose it into technical change and technical efficiency change. Then I test whether the technical change registered by high-tech firms can explain the total factor productivity growth of non high-tech firms, after controlling for factors which can potentially affect productivity growth.

Consequently, the section is composed into two parts; in the first one, I explain how to compute total factor productivity growth and its components (i.e. technical efficiency change and technical change) by using DEA. In the second paragraph, I will detail the second stage procedure aimed at testing to what extent technical change experienced by high-tech firms can have a positive impact on productivity growth of non high-tech firms.

3.1 Malmquist index and its components using Data Envelopment Analysis

In this paragraph, I introduce the Malmquist index and its relationship with total factor productivity

Following Fare et al (1994), total factor productivity growth can be identified with the following Malmquist index at time t:

$$M = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}} \tag{1}$$

as the geometric average of two distance functions computed at time t and $t+1$. Expression (1) can be reformulated in such a way to highlight the roles of technical progress and of the change in technical efficiency:

$$M = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)} \right]^{1/2} \tag{2}$$

The ratio outside square brackets is the relative variation of (output-oriented) technical efficiency whereas the ratio within square brackets is a measure (in relative terms) of technical progress. Indeed, this term equals the geometric mean of the vertical distances between the frontiers of the production sets, evaluated respectively in x^t and in x^{t+1}.

It turns out that the term between square brackets corresponds to the geometric mean of the distances between the points located on the production functions in correspondence with x^t and x^{t+1}. Of course, a Malmquist index greater than one indicates a growth of TFP and viceversa; the same is true for its components. It should be noted, however, that there can be an improvement (deterioration) of TFP even in presence of a deterioration (improvement) of the technical efficiency or of technical regress (progress) in case the variation of the other variable has an opposite sign and is greater in absolute value. It is evident that in practice the computation of (2) is based on obtaining the distance functions that compose this formula.

3.2 Second stage estimation

In this subsection, I will detail the empirical approach used to estimate the spillover effect; in this second stage estimation, I regress the Malmquist index for non high-tech firms on the measure of technical change registered by high-tech firms, after controlling for some variables which can have a potential impact on total factor productivity growth. In the equation to estimate, the dependent variable is the Malmquist index; as already detailed before, a value greater than 1 indicates a positive growth in total factor productivity while a value smaller than 1 indicates the opposite. This is regressed on the technical change, registered by non-high tech firms, computed in the previous stage, the investment rate of the non-high tech firms and the squared investment rate to identify eventual increasing returns to scale in the relationship between productivity growth and investment ratio.

The technical change is introduced as a measure of the actual innovations in the productive process experienced by high-tech firms. It is intended to substitute the measure of R&D spending used in previous studies. The investment rate is included to control for the impact of capital accumulation (of non high-tech firms) on the variation of total factor productivity over time. In this sense, I follow the suggestion by Scott (1991) and Hay and Liu (1997) that the appropriate contribution of capital accumulation to a firm's productivity growth should be measured by gross investment. Indeed gross investment incorporates new techniques and therefore does more for output than merely replacing old capital. Indeed old capital stock may be scrapped not because it is "worn out" but because it is technically obsolete.

This relationship is estimated empirically using three different estimators. First, it is estimated by using Ordinary Least Squares (OLS). In this sense, the panel structure of the available data-set is not exploited. Usually, OLS estimates assume a common intercept for all firms. It implies that firms react in the same way to the business cycle. However, the assumption of a common intercept for all firms is hard to maintain; to understand why, consider the following[2]. In the short run, the stock of physical capital is fixed. During booms, a firm utilizes extra labour and the maximum possible use of installed capacity, whereas during recessions these inputs remain idle. Thus a combination of capital stock and employment level will produce higher levels of production (and therefore a higher productivity growth) during booms and lower levels of production during recession. Therefore, not controlling for the effect of capacity utilization will bias the parameter estimates. To this purpose, I assume that all firms face common business cycles and adjust capacity utilization in response to business cycles in a similar manner. This amounts to defining the constant of the model as being the sum of a time trend capturing the response in terms of capacity utilization to the business cycle impact as well as a firm-specific constant capturing the effect of firm-specific characteristics, such as managerial ability and input quality. These factors are usually observable to the manager of the firm, but not observable to the econometrician. There are no reasons why these omitted factors should take the same value for all firms. However, these can have characteristics that

[2]In this respect, I follow the approach used by Raut (1995).

make them vary across firms but remain constant over time.

To estimate these models, the estimators from the panel data literature are of help. The estimates of the parameters will depend crucially upon whether we assume the constant to be fixed effect or random effect. In the first case, the best linear unbiased estimator (BLUE) is OLS applied on the differences from the time average; the estimator is also called the *Within estimator*. The random effect model, on the contrary, assumes that the firm-specific factors which affect the firm's productivity, but are not included explicitly as regressors, can have the characteristics of a random variable similar in nature to the Normal Law of Errors. In this case the BLUE estimator is the Generalized Least Squares (GLS) estimator. To choose between these models, a useful statistics result from the Hausmann test (1978). It is based on the idea that under the hypothesis of no correlation, both OLS in the Fixed Effect model and GLS are consistent but OLS is inefficient, while under the alternative OLS is consistent but GLS is not. Therefore, under the null hypothesis, the two estimates should not differ systematically and a test can be based on the difference.

The proposed empirical specification can encounter two additional problems: first, the technical change measure may not be exogenous. Indeed, it may happen that, unlike what is postulated in my model, it is the productivity growth (in non high-tech firms) which causes the technical change in high-tech firms and not viceversa. Therefore, it is important to test whether the assumed causality between the dependent and the independent variables is correct. Next, I need to run some additional tests to check whether there is eventual correlation between the error term and regressors. This is important in this context as measures of productivity and technical change might be affected by the same shocks and therefore the parameter estimates might be biased and inconsistent and the standard distributions to conduct significance tests of parameter estimates might be invalid.

Therefore, I conduct the Wu-test to test for both the absence of correlation between regressors and the error term and the correct causality direction between the dependent and the independent variables . Wu (1973, 1974) proposed a series of tests in cases where instrumental variables exist for regressors which are correlated with the error term. The approach suggested is therefore the following: the first step is to obtain the predicted values of the set of right-hand side variables which are presumably correlated with the error term by regressing them on a set of instrumental variables that includes regressors which are uncorrelated with the errors. The next step is to run a regression of the original regression equation augmenting the right-hand variables with these predicted values of the regressors. The Wu-test is equivalent to conducting the F-test of the null hypothesis that the regression coefficients of the predicted values are zero.

4 The data and the variables

The empirical analysis has been conducted on a panel of 206 firms from the Italian manufacturing in the period 1989-1994; they were drawn from the Mediocredito Central database. The sample has been divided into two groups: the high-tech and the low-tech firms. There is no standard definition of high-tech firm. Conceptually, a high-tech firm is one in which knowledge is a prime source of competitive advantage for producers, therefore making large investment in knowledge creation. Thus high-tech firms are characterized by a greater proportion of modern capital equipment and intensity of R&D activity, that is by a continuous effort to develop new products and to find ways to produce them efficiently. Using these criteria, the sample has been divided into 103 firms which can be defined high-tech and 103 firms definable as low-tech as they are characterized by low investment rate and R&D expenditure share.

Afterwards, I have derived the measures of inputs and output. The output of manufacturing firms is measured by the monetary added value. However, this figure has been deflated properly where deflators have been derived by dividing the added value at constant prices by the added value at constant prices (at prices 1990, namely)[3].

The capital has been measured by the gross fixed capital stock. As this measure is available at market prices, it has been deflated by the deflator of the gross fixed investment for each sector as provided by ISTAT (Italian Central Institute for Statistics). This has been computed by dividing the gross fixed investment at current prices with the gross fixed investment at constant prices. Finally, the labour input has been measured by average number of employees per firm[4].

Table 5.1 presents the average value of the deflated monetary added value, of deflated gross fixed capital and of number of employees divided by groups of firms and years.

Table 1: Average values of monetary added value, gross capital and employees for high-tech firms

[3]These two figures have been taken from the database of the National Contability, prepared by Golinelli and Monterastrelli (1990).

[4]Data from the balance sheets do not allow to distinguish among categories of workers.

	Added value	Gross capital	Number of employees
1989	37085.14	39783.88	491.17
1990	61352.37	46559	672.4712
1991	61326.95	47949.86	625.3301
1992	36894.42	40176.94	446.1538
1993	43703.71	37776.48	479.7692
1994	42038.18	37477.91	475.1154

For high-tech firms, there has been an average increase of the added value from 1989 to 1990 in contrast with the general trend in the manufacturing sector. In 1992, there has been a slowdown in production as also high-tech firms are hit by the recession of that year. After 1992, the output has increased, even if it has not reached the level of 1990-1991. Again, the added value increases in 1993 and in 1994. The capital has been pretty stable across years: there has been a slight increase from 1989 to 1990, followed by a slight decrease after 1991. The labour force has shared the output behaviour: indeed, it has sharply increased from 1989 to 1991, while it has decreased in 1992 and then increased again in 1993 and in 1994.

Table 5.2 introduces the average values of added value, gross capital and employees for non high-tech firms.

Table 2: Average values of monetary added value, gross capital and employees for non high-tech firms

	Added value	Gross capital	Number of employees
1989	13943.76	21667.27	187.5243
1990	8158.181	14552.12	131.2885
1991	16896.77	25621.32	235.8846
1992	16848.91	22293.41	232.9327
1993	13955.29	11795.11	187.5769
1994	18645.69	19778.19	243.0707

Added value decreases from 1989 to 1990 as sharply as the rest of manufacturing, while it increases as fast as it decreased from 1990 to 1991 and 1992. In 1993, there is another dip while a new increase is registered in 1994. The labour force follows the same pattern across years, while capital behaviour along years is more difficult to associate to that of the output: indeed, it decreases sharply in 1990 and increases again in 1991 and 1992; in 1993 a disinvesting process is in action while in 1994 it increases very fast.

4.1 The empirical results

Table 5.3 presents the computed Malmquist index and its decomposition in technical change and efficiency change for both high-tech and non high-tech firms. As written before, the usual interpretation of the Malmquist index is that a value greater than 1 implies an improvement in total factor productivity, while a value lower than 1 implies a worsening total factor productivity. The same is true for the components of the total factor productivity.

Table 3: The Malmquist index and its decomposition for non high tech firms

Year	Efficiency change	Technical change	Malmquist index
1989	-	-	-
1990	1.213	0.801	0.972
1991	1.021	1.003	1.024
1992	1.495	0.742	1.110
1993	0.760	1.183	0.899
1994	1.000	1.000	1.000

In general non high-tech firms have a positive efficiency change over years except from 1992 to 1993, while from 1993 to 1994 there has been no efficiency growth. As for the technical change, it has a more random pattern: indeed it is generally negative from 1989 to 1990, while constant from 1990 to 1992. Then it increases from 1992 to 1993, being again constant from 1993 to 1994. The Malmquist index shows that total factor productivity decreases from 1989 to 1990, while it is more or less constant from 1990 to 1991; it improves from 1991 to 1992 while it has again a dip from 1992 to 1993 and remains constant from 1993 to 1994. In general, technical change is negative as capital decreases, while efficiency improves as output remains the same. Interestingly, recession creates room for inefficiency while technical change is positive in spite of the disinvesting process.

Table 5.4 presents the Malmquist index and it decomposition for high-tech firms.

Table 4: The Malmquist index and its decomposition for high tech firms

Year	Efficiency change	Technical change	Malmquist index
1989	-	-	-
1990	1.589	0.618	0.981
1991	0.863	1.143	0.987
1992	1.207	0.874	1.056
1993	0.445	2.755	1.226
1994	1.985	0.468	0.929

For high-tech firms, the efficiency has improved from 1989 to 1990 and therefore the boost in production has to be attributed to an improvement in efficiency. The following year there is a decrease in efficiency; however, it has again increased from 1991 to 1992. This might be interpreted as a better use of capital after its increase. Afterwards, there is a serious slowdown from 1992 to 1993 and remains constant from 1993 to 1994. The technical change shows an opposite pattern: it decreases from 1989 to 1990 and increases in the following year. It has an outburst from 1992 to 1993 due to the renewal of the machinery, followed by a deep decrease from 1993 to 1994. The Malmquist index follows the same random pattern: it decreases from 1989 to 1991, registering a slight increase from 1991 to 1992. The growth of productivity is more important from 1992 to 1993 and is constant from 1993 to 1994.

4.2 The spillover hypothesis and the productivity growth of non high-tech firms: the empirical results from the second stage estimation

In this subsection, I will explore the impact of high-tech technical change on total factor productivity change in non high-tech firms. The empirical approach reported in this section is an application of the idea that technical change registered in high-tech firms spills over to other firms in the economy and therefore affects positively these firms' productivity growth. The dependent variable is the Malmquist index computed in the previous section. A value greater than 1 indicates that the firm's productivity is increasing over time; a value smaller than 1 implies that the firm is allowing its productivity to slip over time. Note that the Malmquist index is implicitly a ratio between technical efficiency scores at successive times; it is therefore appropriate to express all regressors as changes over time. The explanatory variables used in this stage are of two types. The first type consists of the technical change registered by the high-tech firms. As already written before, this variable is introduced as measure of the knowledge spillover from firms with a higher proportion of expenditure in R&D to firms whose investment in R&D is lower. I expect the coefficient of this variables to be positive. This means that technical change in high-tech firms affects the productivity growth of non high-tech firms and therefore a knowledge spillover from a group of firms to another is verified. The second kind of regressors reflects the fact that the productivity growth of non high-tech firms is affected by their own average gross investment rate over time. In this sense, I follow the suggestion by Scott (1991) and Hay and Liu (1997) that the contribution of capital accumulation to the firm's productivity change should be controlled by inserting the gross investment rate among regressors. Indeed this incorporates new techniques and therefore does more than merely replacing old capital. Indeed old capital stock may be scrapped not because it is "worn out" but because it is technically obsolete. In the equation to estimate, the gross investment rate is also squared to control for the return to scale in the relationship between the investment ratio and the productivity growth. Finally, the empirical equation is completed by introducing firm and year fixed effects. I would not expect the firm fixed effect to be significant since the variables are variation of variables in level. Year dummies should pick up any cyclical effects. The regression results are given in Table 5.5.

Table 5: The impact of technical change on productivity growth in non high-tech firms: the second stage estimation

Variables	OLS	Fixed Effect	Random Effect
Technical change	1.27	1.28	1.27
	(3.89)	(3.64)	(3.67)
Investment ratio	0.02	0.03	0.02
	(1.98)	(1.98)	(1.99)
Squared Inv. ratio	0.04	0.06	0.04
	(0.71)	(1.02)	(0.75)
Constant	0.10	-	0.09
	(0.31)	-	(0.7)
	Hausmann Test	0.28	$\chi^2 = 9.35$
	Wu Test	0.326	$F = 3.84$

Note: Between parentheses, the t-ratios are reported. The Hausmann test is the test to choose between the fixed and random effect model and it has been constructed as detailed in the text. The Wu test is to test for exogeneity of the technical change and it has been constructed as detailed in the text.

The tables show the empirical results from the estimation of the empirical models using the three different estimators, namely the Ordinary Least Squares (OLS), the Fixed Effect estimator (FE) and the Random Effect estimator (RE)[5]. The coefficient of the time fixed effects are not shown but they are generally significant. In addition, the results from the Hausmann test and the Wu test are reported with the degrees of freedom for each estimated equation. Notice that the estimates are more or less the same across the three estimation methods. The Hausmann statistics show that the preferred estimator to take into account the firms' heterogeneity is the Random Effect Estimator. The Wu statistics shows that the technical change has to be regarded as exogenous and therefore the causation relationship assumed in the model (that is, from the high-tech technical change to the non high-tech productivity growth) is correct.

Regression results are much as expected for technical change. It is a positively significant variable and therefore, a positive technical change in high-tech firms has a positive impact on other firm's productivity growth. Productivity growth is positively influenced by the change in their investment rate and, as indicated by the positive coefficient on the quadratic term, this relationship is subject to increasing returns. To sum up, these estimates give support for the spillover hypothesis within the Italian manufacturing sector over the period 1989-1994.

[5]The equation have also been estimated by Two stage least squares by introducing lagged values of the finance constraints have been introduced. However, the new coefficient are not significant and therefore they have not been shown.

5 Concluding remarks

The purpose of this paper was to propose a new test of the spillover hypothesis of the endogenous growth literature and to apply it to a panel of firms from the Italian manufacturing over the period 1989-1994.

Theoretical models of endogenous growth emphasize that innovative activity of individual firms contribute to sustained long-run growth of an economy through their industry-wide spillover effect (Grossmann and Helpman, 1990; Romer, 1986). According to them, firms invest in R&D to acquire private knowledge that enhances their productivity and profits; then their private knowledge spills over to the rest of the economy and becomes social knowledge acting as an external effects in enhancing the productivity of all firms. In contrast, Cohen and Levinthal (1989), among others, argue that a firm must invest in private R&D to acquire the technical capability needed to make use of the public domain knowledge to enhance its productivity.

These theoretical debates have originated several empirical studies aimed at testing the spillover hypothesis. Among others, Jaffe (1986) provided empirical evidence on spillover effect by using patent applications to construct a measure of similarity of research activities among firms. He calculated the external R&D pool available to a firm by taking the weighted aggregated R&D expenditures and found that both external pooled R&D and in-house R&D efforts significantly influenced the quantity of patent applications and the market value of the firm. Bernstein and Nadiri (1988) constructed a measure of the external R&D pool of a firm and found the spillover effect to be statistically significant in all industries. Raut (1995) estimates the productivity effects of a firm's own R&D industry-wide R&D expenditures as well as physical capital and labour inputs. The estimates support the spillover hypothesis in all sectors.

These works on the impact and size of the spillover effect share a common structure. They usually try to establish an empirical relationship between technical change in the form of R&D (both in-house and external) and the growth rate of added value, used as a measure of productivity growth. However, this specification raises several problems (Griliches, 1979). These are of two types. First, it is not clear to what extent R&D expenditure is an adequate proxy of the firm's innovative efforts: there may exist a difference in ability of firms to extract innovations from a given expenditure in research and development as internal inefficiencies can interfere with the firm's innovative effort. Second, the R&D spending is likely to be correlated with the commonly used measure of productivity growth and therefore the introduction of this variable can create simultaneity problems.

This paper has proposed a new approach to test the spillover hypothesis to overcome the problems related with the use of the R&D spending variable as a measure of firms' innovative efforts. It has departed from previous works in this field in two respects; first, I have measured total factor productivity growth by the Malmquist index derived using DEA and not by the growth of added value. Second, I have used the actual technical change registered by firms with a high proportion of R&D expenditure (defined henceforth as high-tech firms) as a measure of their firms' innovative effort, and I test whether it can explain the total factor productivity change of firms with a low proportion R&D spending (defined therefore as non high-tech firms).

Therefore, the empirical strategy to test for the spillover hypothesis has been articulated into two stages: first I have measured the total factor productivity growth registered by the two subsamples of firms computing the Malmquist index, proposed by Caves et at. (1982) with the DEA. I have decomposed it into technical change and technical efficiency change. Then I have tested whether the technical change registered by high-tech firms can explain the total factor productivity growth of non high-tech firms, after controlling for factors which can potentially affect productivity growth.

The advantages of this approach are two. First, technical change is a measure of the the actual output of the R&D spending and therefore it is a better measure of the firm's innovative effort than just R&D. Second, the use of the Malmquist index as a measure of total factor productivity growth, jointly with the two-stage procedure allows to avoid the simultaneity problem: indeed productivity growth is derived using DEA and therefore it is not simultaneously determined within a unique equation system with measure of technical change. This new approach has been implemented to test whether there has been a knowledge spillover from high-tech to non-high-tech firms in Italian manufacturing, using a panel of firms over the period 1989 - 1994. The empirical results support the hypothesis of a knowledge spillover from high-tech to non high-tech firms in Italian manufacturing, and confirm the validity of the new suggested approach based on the non-parametric frontier techniques to test for eventual knowledge spillovers.

References

Afriat, S., (1972), Efficiency Estimation of Production Functions, *International Economic Review*, 13:3, October, 568-598;

Aghion, P. , Howitt, P., (1998), *Endogenous Growth Theory* , MIT Press;

Aigner, D.J., Chu, S.F., (1968), On Estimating the Industry Production Function, *American Economic Review*, 58, 4, 826-839;

Aigner, D.J., Lovell, C.A.K., Schmidt, P.J., (1977), Formulation and Estimation of Stochastic Frontier Production Function Models, *Journal of Econometrics*, 6, 1, 21-37;

Amemiya, T.- Macurdy, T.E., (1986), Instrumental Variable of an Error Component Model*Econometrica*, 54, 869-881;

Banker, R.D., Charnes, A., Cooper, W.W., (1984), Some Models for Estimating Technical and Scale Efficiency in Data Envelopments Analysis, *Management Science*, v. 30, 9, 1078-1092;

Beenstock, M, (1997), Business Sector Production in the Short and Long Run in Israel, *Journal of Productivity Analysis*, 8(1), 53-69;

Bernstein, J.I and Nadiri, M.I., (1988), Research and Development and Intra-Industry Spillovers: An Empirical Application of Dynamic Duality, *Working Paper, NYU*;

Bhargava, A., (1991), Identification and Panel Data Models with Endogenous Regressors, *Review of Economic Studies*, 58, 129-140;

Caves, D., Christensen, L. and Diewert, W.E., (1982), The Economic Theory of Index Numbers and the Measurement of Input, Output and

Productivity, *Econometrica*, 50(6), 1393-1414;

Charnes, A., Cooper, W.W., Rhodes, E., (1978), Measuring the Efficiency of Decision-making Units, *European Journal of Operation Research*, 2(6), 429-444;

Chamberlain, G., (1982), Multivariate Regression Models for Panel Data, *Journal of Econometrics*, 19, 5-46;

Cohen, W.M. and Levinthal, D.A., (1989), Innovation and Learning: Two Faces of R&D, *Economic Journal*, 99, 569-596;

Fare, R., Grosskopf, S., Lovell, C.A. K., (1994), *Production Frontiers*, 1994;

Fare, R., Grosskopf, S., Lindgren, B. and Roos, P., (1992), Productivity in Swedish Pharmacies: A Malmquist Input Index Approach, *Journal of Productivity Analysis*,3(1/2), 270-285;

Fare, R., Grosskopf, S., Lindgren, B. and Roos, P., (1995), Productivity Developments in Swedish Hospitals: A Malmquist Output Index Approach, in A. Charnes, W.W. Cooper, A.Y. Lewin and L.M. Seiford, (eds) *Data Envelopment Analysis: Theory, Methodology and Applications*, Boston, Kluwer, 253-272;

Fried, H., Lovell, C.A.K., Schmidt, S., (eds.), (1993), *The Measurement of Productivity Efficiency: Techniques and Applications*, London, OUP;

Gerosky, P. A., Small, I., Walters, C.F., (1975), *Agglomeration Economies, Technology Spillovers and Company Productivity Growth*, Discussion Paper, 1867, CEPR, London;

Golinelli R. - Monterastelli M., (1990), Un metodo per la ricostruzione di serie storiche compatibili con la nuova Contabilita' Nazionale, *Nota di lavoro*, n. 9001, Prometeia, Bologna;

Greene, W.H., (1993), *Econometric Analysis*, MacMillan;

Griliches, Z., (1979), Issues in Assessing the Contribution of Research and Development to Productivity Growth, *Bell Journal of Economics*, 10, 1;

Griliches, Z., (1991), The Search for R&D Spillover, *NBER Working Paper N. 3768*;

Grosskopf, S., (1993), Efficiency and Productivity, in *The Measurement of Productive Efficiency, eds. Fried, H., Lovell, C.A.K. and Schmidt, P.*, OUP;

Grossman, G. and Helpman, E., (1990), Trade, Innovation and Growth, in *American Economic Review*, 80-2, 86-91;

Hausman, J.A., (1978), Specification Tests in Econometrics, *Econometrica*, 46, 1215-1271;

Jaffe, A., (1986), Technological Opportunity and Spillovers of R&D: Evidence from Firm's Patents, Profits and Market Value, *American Economic Review*, 76, 984-1001;

Hay, D.A. - Liu, G.S., (1997), The Efficiency of Firms: What Difference Does Competition Make, *Economic Journal*, 107, 597-617;

Mediocredito Centrale, (1997), Indagine sulle Imprese Manifatturiere. Sesto Rapporto sull'Industria Italiana e sulla Politica Industriale, Roma.

van Meijl, H., (1997), Measuring Intersectoral Spillovers: French Evidence, *Economic Systems Research* , 9(1), 25-46;

Nadiri, I.M., (1993), Innovations and Technological Spillovers, *NBER Working Paper N. 4423*;

Nakamura, A. and Nakamura, M., (1981), On The Relationships Among Several Specification Error Tests presented by Durbin, Wu and Hausman, *Econometrica*, 49(6), 1583-1588;

Park, W.G., (1995), International R&D Spillovers and OECD Economic Growth, *Economic Inquiry*, 33(4), 571-591;

Raut, L.K., (1995), R&D Spillover and Productivity Growth: Evidence from Indian Private Firms, *Journal of Development Economics*, 48, 1-23;

Raut, L.K. and Srinivasan, T.N., (1993), Theories of Economic Growth: Old and New, in *Capital Investment and Development, Basu et al. eds*, Basil Blackwell;

Romer, P.M., (1986), Increasing Returns and Long-Run Growth, *Journal of Public Economics*, 94, 1002-1037;

Scott, M. FG., (1991), *A New Theory of Economic Growth*, OUP, Oxford;

Siegel, D., (1995), Errors of Measurement and the Recent Acceleration in Manufacturing Productivity Growth, *Journal of Productivity Analysis*, 6(4), 297-320;

Vuori, S., (1997), Interindustry Technology Flows and Productivity in Finnish Manufacturing, *Economic Systems Research*, 9(1), 67-80;

Wu, D.., (1973), Alternative Tests of Independence between Stochastic Regressors and Disturbances, *Econometrica*, 41, 733-750;