TECHNOLOGY DIFFUSION AND HUMAN CAPITAL: AN ANALYSIS ON ITALIAN FIRM DATA

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Abstract

In this paper, we test the extent to which human capital can be considered among the factors facilitating spillovers and the diffusion of new technologies. This is highly relevant for the debate on recent trends in the competitiveness of the Italian economy, as the low educational attainment of the latter has often been quoted as one of its main weaknesses. More specifically, we test whether the impact of spillovers on productivity is higher in firms where the stock of human capital is higher. The results so far are mixed as in some sectors of the manufacturing, the role of human capital in enhancing the impact of spillovers on productivity seems limited.

Keywords: productivity, spillover effects, human capital.

JEL Classification System: D24, J24, O33.

1. Introduction

The hypothesis that technological knowledge acquired by a firm can spillover to other firms and enhance the latter group's total factor productivity[1] was first suggested by Arrow (1962) in his work on the effects of learning embodied in new capital equipment. Since then, there has been a considerable theoretical debate on the extent to which a firm can benefit from spillovers and also how much of its productivity growth such spillovers can explain (Romer, 1986; Grossmann and Helpman, 1990; Cohen and Levinthal, 1989).

These debates have sparkled a wealth of empirical studies searching for evidence in favour of the spillover hypothesis (Jaffe, 1986; Bernstein and Nadiri, 1988; Raut, 1995). Several channels through which spillovers can diffuse have been identified. They may take the form of intra- and inter-industry relationships (where firms can imitate patented innovations produced by technologically similar leading firms), supplier and purchaser connections (where spillovers are embodied in intermediate-inputs flows between sectors) and geographical location (where geographical proximity may facilitate informal contacts among firms and therefore knowledge spillovers). In these studies, the role of human capital in facilitating the assimilation of knowledge spillover is somehow neglected. The only exception to this is the contribution by Benhabib and Spiegel (1994) who present empirical evidence showing the importance of human capital in enhancing the effect of knowledge spillovers on firms' productivity.

This paper belongs to this literature in its attempt to quantify the importance of human capital to assimilate knowledge spillovers in Italian manufacturing. To this purpose, we estimate a productivity equation on a panel of firms from twelve sectors from the Italian manufacturing over the period 1989-2003 where both knowledge spillovers and measures of human capital appear among the regressors. A good spillover measure should be able to capture the actual improvement in the productive capability of a firm following the innovative effort of other firms. In this respect, a measure of the technical change experienced by either the innovating firm or the innovating sector is a good candidate as explanatory variable, while usually the change in total factor productivity is taken as response variable. In this paper, we concentrate on a particular

[1] In this paper, total factor productivity growth and productivity growth will be used as synonymous.

response variable: the change in technical efficiency, that is the change in a firm's ability to use the available technology optimally. Our explanatory variable is the index of technical change of innovating firms computed by estimating a technology frontier by the Free Disposal Hull (FDH) for each sector, while the response variable is the change in technical efficiency computed through the same technique.

The structure of the paper is the following. In Section 2, we provide a brief overview of some of the themes and outcomes of the empirical literature on the spillover hypothesis highlighting the methodological problems encountered when trying to measure the influence of the spillovers on productivity growth. We conclude by pointing out to some gaps in the existing literature and thus set out the main lines along which our empirical work will be developed. In Section 3, we present an empirical strategy to test for the spillover hypothesis. Section 4 reports the data source and the summary statistics; it also outlines the procedure used to construct the spillover measures. The main results are presented and discussed in Section 5. Finally, some concluding remarks are offered in Section 6.

2. The spillover hypothesis and the role of human capital

Theoretical models in the endogenous growth literature emphasise that innovative activities of individual firms contribute to sustained long-run economic growth through industry-wide spillover effects (Romer, 1986; Grossmann and Helpman, 1990). According to this view, individual firms produce technological knowledge. At first, this is private to the firm; afterwards, it spills over to the rest of the economy as it can be copied immediately and at almost no cost by any number of firms, becoming social knowledge acting as an external effect in enhancing the productivity of all firms. With the spillover effect, an aggregate production function which would otherwise have either constant or decreasing returns to scale may exhibit increasing returns to scale allowing sustained long-run growth (Romer, 1986; Raut and Srinivasan, 1993). An implication of this view is that a firm, not able to innovate on its own, can benefit from the research findings of firms working along similar lines. Cohen and Levinthal (1989), among othhers, 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 realised by all firms located within the neighbourhood of the emission...we suggest that if these costs are relatively small, it is by virtue of the considerable R&D already conducted by the firms in the vicinity of the "emission".

Cohen and Levinthal suggest that the cost of utilising public domain knowledge fruitfully is minimal only for firms which have accumulated sufficient technological capability to absorb external knowledge (so-called absorption view). Hence, the importance of spillovers in enhancing productivity is limited only to these firms.

These theoretical debates have been followed by a quite large literature searching for empirical evidence in support of the joint hypothesis that knowledge spillovers exist and that they can also enhance a firm's productivity (see Sena, 2004). In its simplest form, the empirical strategy employed involves estimating a relationship between the productivity (or productivity growth) of firm (or industry) j and a measure of the innovative activity of some other firm (or industry) i, linked to firm (or industry) j by some type of relationship. If a positive and significant relationship is found, then this is interpreted as evidence in favour of knowledge spillovers. Studies, though, differ in two main points: the assumed transmission mechanism (i.e. the spillover's carrier) allowing knowledge produced in one firm to be transported to another firm and the type of relationship the two firms are linked by.

A first group of studies assumes that spillovers might be embodied in either intermediate-input flows or patent-flows between firms (or industries) (Nadiri, 1993). Suppose firm j uses as inputs for its production process goods produced by firm i. In this case, the two firms are involved in the same vertical relationship and therefore the innovative efforts of firm i will provide firm j with higher quality inputs allowing it to increase productivity. To test the relevance of transmission mechanism, researchers have used either input-output (I-O) coefficients or technology flow matrices based on patent data. Typically, they distinguish between firms of origin and firms users of innovation and between process innovations geared toward improving efficiency in production and product innovations aimed at improved output quality. Only the latter, though, are considered potential carriers of spillovers from the standpoint of the purchasing firm. Two hypotheses are tested. First, innovative activity performed in a firm may affect the technology of both customers (i.e. forward linkages) and suppliers (i.e. backward linkages). Second, innovative activity carried out in one firm may affect the linkage structure with other firms in other sectors in the economy.

A second group of studies assumes that knowledge will spillover from firm i to firm j through the former's investment in R&D. Indeed it is a well-known feature of R&D investment that firms are unable to capture all the benefits of their investment (Nordhaus, 1962). Innovations can be readily imitated by other firms as patents stop imitators from appropriating part of the benefits of innovations only for a limited time period. There is evidence that within the same industry, some firms devote resources to either the improvement of current products and processes or the discovery of new products, while the remaining firms are devoted to copying the success of the innovative firms, as reproducing knowledge is cheaper than producing it. For instance, this type of mechanism is at work in Bernstein and Nadiri (1988) who 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 US industries. In the case of intra-industry spillovers, knowledge spillovers mediated through R&D expenditure are possible as both the innovator and the imitator share the same technology. However, inter-industry R&D spillovers are also possible as long as firms in the different sectors are similar technologically or share a common technology base. Indeed, in several papers, Jaffe (1986, 1989) provided empirical evidence on the inter-industry spillover effect in the US manufacturing.

Finally a third group of studies suggests knowledge spillovers may be facilitated by geographic proximity. In this case, technological knowledge can spillover through a set of informal contacts, such as industry conferences, talks and seminars, made possible because firms (and more importantly, individuals working for them) share the same location, something which decreases the cost of participation to these activities. On these occasions, potential adopters of innovations (who have limited information about costs and benefits of the innovations) come in contact with existing users, so the diffusion of intangible technological capabilities is promoted. The implicit assumption is that there is a specific type of knowledge, so called tacit knowledge, which cannot be patented and that therefore can only be transmitted through direct contacts between the source and the recipient. This is typically true for basic research that generates new fundamental ideas. In spite of the fact that the core work can be made available through normal public codified channels (e.g. scientific journals), there is still a considerable portion of the research that can only be conveyed via direct interaction and discussions with scientists (Poyago-Theotoky et al., 2002).

In this research on knowledge spillovers and productivity, the role of human capital in helping to assimilate knowledge spillovers is somehow neglected. The existing studies that consider the interaction between spillovers and human capital concentrate on cross-country comparisons and focus their attention on how human capital can facilitate international spillovers across countries. For instance, Engelbrecht (1997) finds that human capital affects total factor productivity both directly as a production factor and indirectly by enhancing the effect of international spillovers. Only a couple of studies look at the interaction between knowledge spillovers and human capital at either firm- or sector-specific level. Among these, Jacobs et al. (2002) estimate a productivity equation for eleven sectors of the Dutch manufacturing over the period 1973-1992 where both human capital and measures of spillovers appear as regressors. They find that human capital does not seem to have an impact on productivity and cannot find evidence that human capital can enhance the effect of knowledge spillovers.

To summarise, there are still doubts on the relationship between human capital and knowledge spillover; while at a cross-country level, human capital is important to enhance spillovers, this seems to lose its importance when studies focus on industry-level data.

3. The empirical specification

The empirical strategy we adopt is based on the following general specification of the link between efficiency growth and spillover effect:

$$EFFCH_j = f(SPILL_i, HC_j, SPILL*HC, Othvar_j) + u_j \qquad (1)$$

where we regress firm's j technical efficiency change (EFFCH) on both a measure of the spillover effect from firm i (SPILL), firm’s j human capital (HC), an interaction term between spillover and human capital (SPILL*HC) and a set of variables (Othvar) controlling for other factors known to be affecting firm’s j productivity growth.

Before moving to the empirical implementation of (1), it is necessary to specify the following:

1) the measure of spillover to be used (allowing to identify also the carrier of the spillover);

2) how we measure firm's j efficiency change;

3) how firm i and firm j are related;

4) what are the additional variables introduced in the specification.

Let us start from the spillover measure. Valid measures of the spillover effect should capture the overall output of a firm's innovation productive process. However, it is a well-known fact that measuring the output of this very specific productive process is not obvious, as defining the very same concept of innovation output is difficult. It has been suggested by Griliches (1979), though, that the output of the innovation productive process is made by all those innovations improving a firm's technology. In more technical jargon, this implies that, once innovations are put into use, a firm's boundary of the technology production possibilities set will shift outwards (i.e. the firm experiences positive technical change) and this will allow the firm to increase its output for given level of inputs. If so, a good measure of the innovative output (and of the spillover effect as well) must be an index of firm-specific technical change. In our empirical exercise we use the measure of technical change computed using a Malmquist index from a Free Disposal Hull (FDH) frontier. The advantage of FDH over other parametric techniques is that it does not require restrictive assumptions on the functional form of the production function and its convexity.

As mentioned in the Introduction, the empirical exercise will be carried out on a data-set of firms belonging to twelve sectors of the Italian manufacturing. So, what we are really testing for is the presence of intra-industry spillovers in these sectors. This obliges to define the source of the spillovers. There is a large body of evidence suggesting that within one sector, there will be a group of firms playing the role of the innovators, while the remaining firms will prefer to imitate and follow behind. Typically, innovators make large investments in knowledge creation and therefore spend more on R&D than imitators, as this is the prime source of competitive advantage for them. Therefore we assume knowledge-spillover producers are characterised by a greater proportion of modern capital equipment and higher intensity of R&D activity than the imitators. More specifically, firms whose investment rate and R&D expenditure are both higher than the whole sample mean are considered to be the source of knowledge spillovers; we define them as high-tech firms, as opposed to non high-tech firms, which are the recipients of the knowledge spillovers. Once the firms have been sorted into the high-tech and non high-tech groups, they are matched according to a geographic criterion, i.e. each high-tech firm is associated with the closest non high-tech firm. As our data do not allow me to trace whether the firms in our sample are linked by some input-output flow, we will consider geographical proximity as the mechanism allowing technological knowledge to spillover. However, this does not imply that our analysis is restrictive because it only considers a specific type of transmission mechanism. On the contrary, it is a well-known fact that tacit knowledge is an important output of the innovation productive process, whose diffusion can only be possible thanks to geographical proximity (Nadiri, 1993).

In our empirical specification, the index of technical change is not lagged; this is consistent with both the previous empirical literature (see Jaffe, 1986; Nadiri, 1988; Bernstein and Nadiri, 1991) and the notion from the theoretical literature that technological knowledge can be immediately and costlessly absorbed by the recipient firm. Among the additional regressors of (1), we introduce the investment rate of the non high-tech firms. Indeed, it is plausible that the efficiency growth of non high-tech firms is affected by their own average gross investment rate over time. In this sense, we 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. We also control on whether the firms have received tax or financial subsidies to test the extent to which these may have a direct impact on efficiency.

The empirical strategy we adopt can be summarised as follows: in the first stage, we am going to sort the firms into two groups, high-tech and non high-tech. For each group, we compute the index technical change and technical efficiency for each sector. Next, we regress the index of efficiency growth of non high-tech firms on the technical change of high-tech firms, human capital, the interaction between technical change index and human capital and other control variables.

4. The data and the variables

The empirical analysis has been carried out on twelve sectors of the Italian manufacturing (see the Appendix for a full list). The sample covers the period 1989-2003. The source of the data is the Mediocredito Centrale (now Capitalia) database. According to the criteria specified in Section 3, the firms in each sector have been divided into firms which can be defined as high-tech firms and non high-tech firms. The output of manufacturing firms is measured by value added value, deflated at 1995 prices by a value added deflator, extracted from the Istat National Accounts. The capital stock has been measured by the gross fixed capital stock at book value. As this measure is available at current prices, it has also been deflated by the deflator of the gross fixed capital provided by Istat. Finally, the labour input has been measured by *two* variables: the number of white and blue collars in the company. This is well in agreement with the empirical literature on Italian firm data.

We provide below some descriptive statistics for the efficiency scores obtained from this production set for the twelve sectors.

Table 1. The efficiency scores: some descriptive statistics

Sector	**Mean**	**Median**
Apparel and Leather	0.60	0.83
Food	0.61	0.86
Paper and Printing	0.74	0.95
Chemicals and Rubber	0.59	0.77
Fabricated Metal Products	0.64	0.81
Non-electrical Machinery	0.58	0.81
Non-met. Mineral Products	0.67	0.92
Metal Products	0.71	0.97
Means of Transport	0.75	0.94
Textiles	0.60	0.83
Electrical machinery	0.63	0.90
Other Industries	0.79	0.98

The efficiency scores are reasonably high, which is favourable evidence for the appropriateness of the production set. The discrepancy between mean and median suggests however the presence of outliers among the observation. Subsequently, before to calculate technical and efficiency change through the Malmquist index, we trim the lower 2.5% of the scores.

5. The results

Table 2 presents the results of the estimation of (1). The estimates have been carried out by using GMM. Human capital, which is possibly endogenous, has been instrumented by age of the firm and age squared.

Table 2. The impact of technical change and human capital on efficiency growth

Sector	**Variables**	**Coefficient**	**T-ratio**
Apparel and Leather	Technical change	1.07	2.49
	Human Capital	0.00	1.68
	Human Capital*Technical change	0.01	1.36
	Investment ratio	0.01	0.71
Food	Technical change	0.25	1.12
	Human Capital	0.11	0.36
	Human Capital*Technical change	0.12	0.79
	Investment ratio	0.03	0.41
Paper and Printing	Technical change	1.37	2.56
	Human Capital	0.49	1.99
	Human Capital*Technical change	0.03	0.02
	Investment ratio	0.18	0.58
Chemicals and Rubber	Technical change	2.05	2.79
	Human Capital	1.18	1.28
	Human Capital*Technical change	1.99	0.02
	Investment ratio	0.00	0.00
Fabricated Metal Products	Technical change	1.11	2.47
	Human Capital	0.26	0.01
	Human Capital*Technical change	0.03	1.39
	Investment ratio	0.69	0.49
Non-electrical Machinery	Technical change	1.46	2.01
	Human Capital	1.08	0.79
	Human Capital*Technical change	0.14	0.60
	Investment ratio	0.00	0.00
Non-met. Mineral Products	Technical change	2.17	1.56
	Human Capital	1.19	1.98
	Human Capital*Technical change	0.006	0.80
	Investment ratio	0.01	0.05
Metal Products	Technical change	1.67	1.79
	Human Capital	0.56	2.46
	Human Capital*Technical change	0.01	1.43
	Investment ratio	0.01	0.04
Means of Transport	Technical change	2.16	2.79
	Human Capital	0.27	2.11
	Human Capital*Technical change	0.56	0.79
	Investment ratio	0.01	1.21

Textiles	Technical change	2.29	2.47
	Human Capital	0.45	2.11
	Human Capital*Technical change	1.49	1.94
	Investment ratio	0.05	0.002
Electrical machinery	Technical change	1.67	2.96
	Human Capital	0.02	0.81
	Human Capital*Technical change	0.16	1.19
	Investment ratio	0.01	0.31
Other Industries	Technical change	0.62	2.91
	Human Capital	0.29	1.48
	Human Capital*Technical change	0.00	1.69
	Investment ratio	0.00	0.14

Regression results are mixed. The technical change index is a positively significant variable for many sectors and therefore, a positive technical change in high-tech firms has a positive impact on non high-tech firms' productivity growth. Human capital seems to affect positively the increase in efficiency, but for some sectors it is not significant. Finally the interaction term between human capital and the spillover measure is significant for some sectors, but the size of the impact seems to be small for most sectors.

5. Concluding remarks

The existence of knowledge spillovers and the extent to which they can have a beneficial effect on firms' productivity has always been a contentious issue. Some researchers suggest that knowledge produced by innovating firms can be absorbed and used immediately by other firms, enhancing their productivity; however, this view has been criticised by those who claim that a firm has to make a considerable investment in R&D before being able to absorb fruitfully knowledge produced elsewhere.

These theoretical debates have started several empirical studies aimed at testing the spillover hypothesis. Several mechanisms of transmission of knowledge have been tested, like intermediate inputs or R&D spending. Usually, the role the human capital may play in enhancing the spillover effect is neglected in this literature. In this paper, we have measured the impact that the interaction between human capital and spillover have on efficiency change in twelve sectors from the Italian manufacturing. We have used an alternative measure of the spillover effect based on the notion that a spillover effect should measure the actual innovative output following the innovative efforts, where the innovative output is the improvement in firms' productive ability. Therefore, the spillover effect has been computed with an index of technical change measuring shifts of the boundary of the production possibility, using FDH. 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 suggested approach to test for eventual knowledge spillovers. However, the results are mixed as in some sectors of the manufacturing, the role of human capital in enhancing the impact of spillovers on productivity seems limited.

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