QUADERNI DEL DIPARTIMENTO DI SCIENZE ECONOMICHE E SOCIALI

CORPORATE SKILLS AS AN INCENTIVE TO R&D INVESTMENT

Mariacristina Piva e Marco Vivarelli

Serie Rossa: Economia – Quaderno N. 53 luglio 2008

UNIVERSITÀ CATTOLICA DEL SACRO CUORE

PIACENZA

I QUADERNI
Possono essere richiesti a:

Dipartimento di Scienze Economiche e Sociali, Università Cattolica, Via Emilia Parmense 84, 29100 Piacenza tel. 0523 599342. Oppure si può ottenere una copia dall'area di download del Dipartimento al seguente indirizzo: **http://www.unicatt.it/dipartimenti/ScEcoSoc/default.stm**

ALL PAPERS PUBLISHED IN THIS SERIES ARE DOUBLE REVIEWED

"ESEMPLARE FUORI COMMERCIO PER IL DEPOSITO LEGALE AGLI EFFETTI DELLA LEGGE 15 APRILE 2004, N. 106"

CORPORATE SKILLS AS AN INCENTIVE TO R&D INVESTMENT

Mariacristina Piva

Università Cattolica, Dipartimento di Scienze Economiche e Sociali, Piacenza*

Email: mariacristina.piva@unicatt.it

Marco Vivarelli

Università Cattolica, Dipartimento di Scienze Economiche e Sociali, Piacenza*

Max Planck Institute of Economics – Entrepreneurship, Growth and Public Policy Group, Jena

Centre for the Study of Globalisation and Regionalisation (CSGR), Warwick

Institute for the Study of Labour (IZA), Bonn

Email: marco.vivarelli@unicatt.it

Abstract

This paper investigates the determinants of R&D investment at the firm-level. A balanced panel of 215 Italian manufacturing firms over the 1995-2000 period has been used to test the technology-push, the demand-pull and the endogenous skill-bias hypotheses. Econometrically, the GMM-SYS estimator and the Least Squares Dummy Variable Corrected (LSDVC) estimator, a recently-proposed panel data technique particularly suitable for small samples, have been used. Results support the well-established technology-push and demand-pull hypotheses and, furthermore, supply evidence for the role of skill endowment in increasing a firm's R&D investments.

Keywords Skills and innovation, Endogenous skill-bias, Demand-pull, Technology-push, GMM estimator, LSDVC estimator.

JEL Classification: O31

* Università Cattolica, Dipartimento di Scienze Economiche e Sociali, Via Emilia Parmense 84, 29100 Piacenza, Italy

Acknowledgements:

Thanks are due to the research unit of Capitalia for providing the database used in this study.

1. Introduction

It is widely recognized that corporate skills and technological innovation[1] are complementary. However, most previous studies have only focused on one direction of causality, namely on the "skill-biased" impact of innovation (see *infra*). The novelty of this study is the attempt to investigate the reverse link, *i.e.* the possible role of current skills in determining corporate R&D investment. While this reverse effect has recently been investigated at the macroeconomic level (the so-called "endogenous skill bias", see *infra*), we will deal with the micro-determinants of R&D activities.

In particular, the hypothesis put forward in the next sections is that the firm's workforce skill endowment (which in this paper will be measured by the current ratio of white collars to blue collars[2]) may increase the expected returns from technological innovation and so increase the firms' R&D expenditures. More specifically, the basic research question of this paper can be summarized as follows: is a firm's greater skill endowment a good predictor of higher R&D investment, seen as an *"ex ante"* indicator of innovativeness? This skill-led R&D hypothesis will be tested using a balanced panel of 215 Italian manufacturing firms over the 1995-2000 period and will be controlled for the well established theories of *technology-push* and *demand-pull*.

Although specific literature explicitly discussing the possibility that upskilling can induce R&D investment does not exist (at least to our knowledge), there are several managerial and economic studies that propose arguments which indirectly support the hypothesis investigated in this study. In the second section of this paper, we will try to examine these different strands of literature critically.

The third section will describe the microdata used in this study and will discuss the methodology adopted in the econometric estimates, the results of which will be presented in the following section. Finally, some conclusions will be proposed.

2. Previous literature

Traditionally, R&D investment is related to the evolution of demand and to the technological context in terms of path-dependence, opportunity and appropriability conditions.

---

[1] In this paper, innovation is synonymous with "technological innovation" and is directly connected with R&D activities. Other important dimensions of a firm's innovation, such as organisational change, are treated in the general theoretical discussion presented in the next sections, but are not formally taken into account in the following empirical analysis.

[2] From now on, this will be the meaning of "skill endowment"; this is consistent with the previous literature on "skill-biased technological change", where skills are proxied by the ratio between productive and non-productive workers. For the limitations of this index, see footnote 10 below.

As far as demand is concerned, we will test the role of the so-called "*demand pull*" hypothesis. This approach is rooted in the very foundations of the "Economics of Innovation" (see Schmookler, 1966; Freeman, Clark and Soete, 1982; Dosi, 1988) and here it will be sufficient to recall that there are three main arguments for looking at demand as a main driver of R&D investments: 1) a positive demand evolution can increase the expected profitability from technological innovation; 2) an increase in market share increases the degree of innovation appropriability; and 3) a higher cash flow can alleviate possible credit constraints in financing the R&D investment. The empirical evidence in favour of the important role of demand evolution in spurring innovation is vast and previous work has been confirmed by more recent research (see Scherer, 1982; Kleinknecht and Verspagen, 1990; Brouwer and Kleinknecht, 1999; Freeman, 1994; Hall *et al*., 1999, Piva and Vivarelli, 2007a and 2007b).

However, R&D activities do not depend only on market evolution but are also characterised by their own rules of development, as described in the well known "*technology-push*" hypothesis. Indeed, within a firm, R&D activities are highly localised (Atkinson and Stiglitz, 1969) and path-dependent (see Rosenberg, 1982; David, 1985; Hall, Griliches and Hausman, 1986; Arthur, 1988; Ruttan, 1997; Antonelli, 1998). Here we find the concept of the "*technological trajectory*" which is common in the "Economics of Innovation" literature: innovation and R&D activities are characterised by a high degree of cumulativeness and by important irreversibilities which render their dynamics highly persistent (see Nelson and Winter, 1982; Dosi, 1982 and 1998; Vivarelli, Evangelista and Pianta, 1996). These considerations open the way to a dynamic AR(1) specification of the R&D investment decision.

Finally, sectoral peculiarities in terms of different technological *opportunities* and specific *appropriability* conditions are also crucial in affecting R&D investment (Pavitt, 1984; Malerba and Orsenigo, 1996; Breschi *et al*., 2000).

Given this framework shaped by the Economics of Innovation literature, what are the arguments which support the view that higher manpower skills may imply a higher level of R&D investment? In our view, there are different strands of literature that can be recalled to support this hypothesis. They can be grouped together into two broad categories.

A) Individual incentives, organizational change and absorptive capacity

At the level of the single firm, labour skills are crucial in enhancing innovation in terms of individual creativity, organizational change and acquisition of external knowledge. Let us discuss these three dimensions separately.

At the level of the individual worker, skilled employees who feel confident in performing a range of proactive tasks requiring autonomous initiative are surely more likely to be successful in exploring and/or exploiting innovative ideas (Parker, 1998; Axtell *et al*. 2000; West, 2002). By the same token, Morrison and Phelps (1999) have shown that skilled workers who "feel responsibility" are more likely to take charge of workplace change and technological innovation successfully. Conversely, unskilled and passive workers are unlikely to come up with new ideas, since they feel that it someone else's job to do so, while they are unable to make connections between divergent stimuli (see Guthrie, 2001). Finally, skilled people manage to deal with complexity, and job complexity positively interacts with creativity, innovation and suggestion-making as regards how to improve processes and products and to meet identified gaps (see Scott and Bruce, 1994; Oldham and Cummings, 1996; Song, Almeida and Wu, 2003). Indeed, the knowledge management literature has recognized the important role of individual skills in fostering innovation (see Arora, 2002 and Svetlik and Stavrou-Costea, 2007 for a recent survey of the literature).

Moreover, skills enhance collective (organisational) as well as individual innovativeness. Nahapiet and Ghoshal (1998) have shown that knowledge is not just an individual attribute but has a collective, tacit dimension (see also Damanpour, 1991; Gittell, 2000). In this framework, some recent literature shows how team work and innovation are closely related. Parker *et al.* (1997) found that innovation is more likely when team members have a wide range of responsibilities and have more control over the execution of their tasks; Anderson and West (1998) showed that organisational innovation increases when members feel that new ideas are encouraged and expected and when they feel skilled enough to participate in decision-making and voice their suggestions openly; West *et al.* (2004) – using an input/process/output model – singled out twelve managerial steps which should enable the organisation's teams to become innovative.

On the whole, adequate skills emerge as a "*conditio sine qua non*" for enhancing individual and organisational innovativeness. Moreover, technological and organisational changes often go hand in hand. Indeed, a recent strand of literature has emphasised that technological innovation and organisational change are complementary to each other, and that they often generate superadditive effects on a firm's performance, measured in terms of either productivity or profitability (see Pavitt *et al.*, 1989; Milgrom and Roberts, 1995; Black and Lynch, 2001; Piva *et al*., 2005 and 2006).

Conversely, the mismatch between technological change and organisational inertia may generate an adverse impact on a firm's performance (the so-called "Solow paradox"; see Brynjolfsson *et al.*, 1997; Brynjolfsson and Hitt, 2000). Finally, adequate skills make organisational learning more effective and this can be essential in accelerating the development of path-dependent technological trajectories (see Hyland, Gieskes and Sloan, 2001).

On the whole, at the corporate level, skills are the third component of a "triangle" able to sustain better business performance and higher returns (see Caroli, 2001; Bresnahan *et al.*, 2002). In other words, skills are even more valuable when a firm is affected by both technological and organisational change, since the lack of updated and flexible skills may become an important bottleneck for the firm's innovation management strategy[3]. In this context, a firm which invests in R&D and also values the complementary role of organisational change would be particularly sensitive to its own skill endowment.

Of course, human resource management (*HRM*) can actively influence a firm's human capital in order to update skills and enhance a firm's potential in terms of technological and organisational change (see Shipton *et al.*, 2006). Indeed, *HRM* promotes product and process innovation to the extent that people and the networks to which they belong are enabled to create, transfer and institutionalise their firm's internal knowledge (see Wilson, 1992; Senior, 1997; Paton and McCalman, 2000). However, the rapidly-increasing literature linking *HRM* and technological innovation can actually be seen as further confirmation of the role of skills in fostering innovation (see Wang, 2005).

For instance, Michie and Sheehan (1999) – using evidence from the UK's 1990 Workplace Industrial Relations Survey - show that "high road *HRM* practices" are positively correlated to investment in R&D and new technologies such as new machinery and equipment. Laursen and Foss (2003) – on the basis of data from 1,900 Danish firms – come to a similar conclusion showing that the joint adoption of interdisciplinary workgroups, quality circles, job rotation, delegation, and internal and external training significantly increases the likelihood of introducing an innovative product/service. Jiménez-Jiménez and Sanz-Valle (2005) – using a sample of 180 Spanish firms - test whether innovation determines firm's HRM or conversely HRM influences the innovation level of the company. They provide evidence for both hypotheses, even though HRM practices have a stronger effect in promoting company objectives (unfortunately, the issue of which HRM practices are more effective is still unresolved). Shipton *et al*. (2005) – using data from 111 UK companies – conclude that the sophistication and extensiveness of *HRM[4]* positively influences process and product innovation after checking for firms' size and profitability. However, Searle and Ball (2003) – surveying 300 out of the top 500 UK companies – show that organisations use a limited range of *HRM* tools (recruitment, training and performance management) to identify and support innovation. In particular, a proper training emerges as an important complement to innovation activities (see Roffe, 1999 for a review of the literature).

Thus, appropriate *HRM* strategies increase the likelihood of successful innovation. The other side of the coin is simply that an adequate *ex-ante* endowment of skills can increase the expected value of technological innovation because expensive *HRM* policies become much more effective[5] when the recipient workforce is adequately skilled.

Finally, it is well known that firms invest in R&D not only to *produce* technological innovation, but also in order to create internal capacity (see Cohen and Levinthal, 1989) able to *absorb* external knowledge coming from other firms and scientific institutions such as universities and public labs. In other words, firms that conduct their own R&D are better able to identify, assimilate and exploit externally available knowledge. However, "an organisation's absorptive capacity will depend on the absorptive capacities of its individual members" (Cohen and Levinthal, 1990, p. 131). In this framework, skilled labour is a necessary complement to R&D activities in reinforcing the absorptive capacity of a given organisation.

For instance, Leiponen (2005) underlines the fact that skills are an important component of absorptive capacity, being complementary to internal R&D, collaborative R&D joint ventures and a firm's implementation of external knowledge; her results clearly indicate that internal skills (proxied by educational levels) complement external collaboration strategies in positively affecting a firm's operating profit margin. This is an additional channel which renders R&D investment *ex-ante* more profitable for those firms which are well endowed with skilled labour.

---

[3] Uncertainty and fixed costs related to technological and organisational change create incentives for firms characterised by an unskilled workforce to resist innovation. Conversely, the probability of being an early adopter of a profitable innovation is positively correlated with the availability of human capital (see Wozniak, 1987).

[4] Rated on a scale from 1 to 5.

[5] Or even not necessary if the firm's workforce is already skilled enough to effectively implement the expected technological innovation.

To conclude, previous literature suggests that the availability of skills is a crucial factor in enhancing creativity by the single workers, fostering teams' innovativeness and organisational change and increasing capability to absorb external knowledge. For all these dimensions, in most cases the generation of creative ideas and their implementation (see West, 2002) fall outside the narrow remit of technical specialists in R&D departments, involving all of a firm's functions and the entire workforce. In other words, all members of a given organisation should have the necessary skills and motivation to support technological change.

B) Endogenous skill bias and complementarity

Since the '90s, economists have put forward the idea that Information and Communication Technologies (ICT) were conducive to labour upskilling. Evidence supporting the skill-biased technological change (*SBTC*) hypothesis was first provided with regard to the US (Berman *et al.*, 1994; Doms *et al.*, 1997), then to the UK (Machin, 1996), and continental Europe (Machin and Van Reenen, 1998), especially in the manufacturing sector.[6]

Hence, the general consensus was that computerisation and ICT had led to an increase in the demand for skilled labour (generally proxied by non-productive workers, i.e. white-collar workers), and in relative wages. Yet - while the dominant approach has seen skill bias as a consequence of *exogenous* technological change - some authors (Acemoglu, 1996 and 1998; Kiley, 1999; Funk and Vogel, 2004) have put forward the idea that "*endogenous* skill-bias" may in fact have induced a dominant *SBTC* trajectory. In such a view, which is basically macroeconomic and falls within the *endogenous growth* theory, it is the significant increase in the excess supply of college-educated workers in western economies during the second half of the 20th century which has induced *SBTC*. In other words, the attractiveness of investing in *SBTC* would seem to be related to the supply of the factor which complements that technology; in particular, a large number of skilled workers would raise the incentive to invest in that technology which is intensive in the production factor which has become more abundant and cheaper, i.e. skilled labour. Although this view deals with the interaction between the aggregate supply of skills and the aggregate demand for skills, it is suggestive of possible parallel micro-economic dynamics. Indeed, if at the macroeconomic level the abundance of skills is supposed to trigger the adoption of skill-intensive technologies, why should the same not occur at the level of the firm?

For instance, Dunne and Troske (2005), using data from US manufacturing plants, found that the likelihood of adopting a Computer Aided Design (CAD) machine was highly correlated with the proportion of skilled labour within the plant (p.2); by the same token, plants with a greater share of investment in computing equipment in 1992 experienced skill upgrading in the period 1977-1992 (p.7).

Conversely, Mohnen and Röller (2005) found that the lack of skills was the second single most important obstacle to innovation in a wide range of industries in four European countries (the first being financial constraints, *ibidem*, table 2, p. 1443). Furthermore, in Germany employee resistance to innovations can be explained by the sunk costs nature of human capital investments induced by innovations (see Zwick, 2002). Consistent results came from the third Community Innovation Survey (CIS-3): finding or mobilising human resources ranks first in a list of six factors hampering technological innovation in Europe between 1998 and 2000 (see CRIC, 2005, table 4.3, p.47).

Moreover, skilled labour has been found to be a direct complement to R&D activities: in the UK 2001 innovation survey, 88% of firms that were engaged in R&D on a continuous basis employed graduates, while this percentage dropped to 57% for the no-R&D firms (see CRIC, 2005; table 4.5, p.64).

When investing in R&D, a firm's management can well predict that the likely final outcome of the R&D decision, although uncertain and delayed, will be a *SBTC* reinforcing the capital-skill complementarity (Goldin and Katz, 1998). If such is the case, before engaging in R&D investment, managers have to look at the current firm skill endowment; if the latter is adequate, the expected profitability from technological innovation increases because managers can well predict faster implementation times and lower adjustment costs. Analytically, this means that there is a profit function characterised by supermodularity in innovation and skills[[7]]. The fact that "the whole is more than the sum of its parts" makes the more highly skill-endowed firm more inclined to invest in R&D.

Hence, firms that possess high skills should perceive R&D investment as being more profitable, while initially low-skilled firms should be less likely to recognise profitable R&D investment opportunities (see Leiponen, 2000). Going a step further, skill endowment may influence R&D decisions not only because of technological complementarity, but also through its effect on input prices. In fact - following the "induced bias" theory (see Hicks, 1932; Vivarelli, 1995, chap. 2 for a

[6] For some evidence on the German service sector see Falk and Seim, 2001.

[7] In a standard framework, complementarity between technological innovation and skills means that the marginal expected return on innovation (in this case R&D expenditures) increases with the level of skills internal to the firm, or more formally that the cross-partial derivatives of the expected profitability function are positive (see Topkis, 1998).

discussion) - a large *ex-ante* endowment of skilled workers may act as an incentive to invest in those R&D directions which are conducive to skill-intensive technological innovation. In other words, those firms which are already well-endowed with the proper skills will be less reluctant to invest in R&D and will not be afraid to incur any skill shortage or rising wages, once R&D has generated skill-biased innovation.

For instance, using UK data on the relative wages of the relevant occupational categories and on skilled labour shortages, Nickell and Nicolitsas (1997) found that a permanent 10% increase in the number of companies reporting skilled labour shortages in the industry to which a firm belongs would lead to a 10% reduction in the industry's fixed capital investment and a 4% reduction in its R&D expenditure. Vice versa, a large internal endowment of skills should facilitate R&D expenditures at the firm level.

Taking into account the arguments discussed in the sub-sections A and B, the current availability of advanced skills within the firm makes the expected returns from R&D higher for a number of reasons[[8]]:

1. shorter implementation times and lower adjustment costs due to individual and organisational capacity to use the new technologies better;
2. lower need for or lower cost of post-innovation *HRM* practices and training;
3. higher absorptive capacity of externally-available complementary innovations;
4. shorter implementation times and lower adjustment costs due to the technical capital-skill complementarities;
5. lower expected costs due to a possible skill shortage or to possible increases in the wage of the skilled workers.

Obviously, the outcomes from R&D activities remain highly uncertain (see Knight, 1921) and returns from R&D investments may well be negative, or positive but delayed in the very long term; nevertheless, the availability of skills (for the reasons 1 to 5 above) increases - *coeteris paribus* – the ex-ante expected value of R&D returns and so acts as an incentive to R&D investment.

[8] The discussion in sub-sections A and B reveals that although often based on different methodologies, the economics and management literature tends to converge in highlighting the role of skills in making R&D expenditures more valuable.

3. Methodology

Taking the previous theoretical discussion into account, we have to rely on a dynamic specification of the R&D determinants at the level of the firm, where the lagged dependent variable takes into account the *"technology-push"* hypothesis and, in particular, the path-dependent and localised nature of technological change within a firm, and the *Sales* regressor is a direct way to represent the *"demand-pull"* hypothesis[9].

However, taking the discussion in sub-sections A and B into account, the entire firm's innovation strategy may benefit from a strong skill-base, since current employees' higher skills are expected to foster higher R&D expenditures. Hence, we can put forward the following baseline equation (1):

$$RD_t = \alpha + \beta RD_{t-1} + \gamma Sales_t + \delta \left(\frac{WC}{BC} \right)_t + v_t \qquad (1)$$

where the ratio between white (WC) and blue (BC) collar workers is taken as a proxy of the skill endowment within a given firm[10];

The dynamic specification (1) will be tested using a unique longitudinal database, suitable for panel data analysis. This new database is derived from questionnaire surveys collected by the Italian investment bank Mediocredito Centrale (MCC, now Capitalia) and involving representative samples of Italian manufacturing firms with no less than 11 employees. The MCC database used in this study comes from the merge of two different questionnaire waves (first wave in 1997 and second one in 2000), each of them collecting contemporary and retrospective (previous two years) data. In order to obtain a balanced panel dataset, we kept only the overlapping firms declaring continuous data on R&D expenditure, sales and skill endowment in the 1995-2000 period. We ended up with a panel of 215 firms (N) over a 6-year (T) period (N x T = 1290 observations)[11].

---

[9] Sectoral technological opportunities can be taken into account through the insertion of two-digit sectoral dummies, as in the following analysis.

[10] This can be considered a rather rough measure of skills. However, in contrast with case studies, econometric analyses have necessarily to rely on an aggregate measure. Another possible indicator is the percentage of college graduates within a firm's workforce; unfortunately, our dataset provides longitudinal data only for white and blue-collar workers and not for education levels. This prevents the use of this variable in the following panel data analysis. At any rate, the two ratios are generally highly correlated; in our database, the correlation coefficients in the two years (1997 and 2000) where education data are available turn out to be 0.90 and 0.88 respectively.

[11] While choosing an unbalanced panel would have increased the number of observations, it would have implemented unreliable data. In fact, as mentioned in the text, the MCC database is the result of the merging of two questionnaire waves, each of them collecting contemporary and retrospective (previous two years) data. As an expected consequence, most of the dropped firms (in addition to a very large group of respondents not reporting the R&D figures at all) just report two values - 1997 and 2000 - for R&D, while another important group of firms report unreliable repeated values

Monetary variables are expressed at 1995 constant prices; some descriptive statistics are given in Table 1.

Insert Table 1

As can be seen, our sample is made up of medium-large firms with a satisfactory market performance in terms of sales growth; these firms also exhibit an increase in R&D activities and in upskilling[12]. In terms of panel variability, the *between* component emerges as dominating the *within* one (as is common in the case of short panels).

As a preliminary step, we split our sample in two groups according to their skill intensity (below and above the median of WC/BC) and we look for possible differences in the R&D intensity (R&D/Sales) between the two groups in 1997 and 2000[13] (see Figures 1 and 2).

Insert Figures 1 and 2

As can be seen, those firms which are better endowed in terms of skill turn out to be more inclined to invest in R&D; their density functions are more skewed to the right and present substantially higher mean values in the R&D/Sales ratio (2.9% *vs* 1.2% in 1997 and 2.5% *vs* 1.5% in 2000[14]).

Obviously, this univariate analysis provides only tentative evidence and does not yet establish a causal link between skill endowment and R&D expenditure, since the revealed evidence may be driven by unobserved heterogeneity and be affected by the direct and crossover effects of other possible determinants of R&D investment. Therefore, we now turn to the econometric test of (1) for firms (i) over time (t):

$$RD_{i,t} = \alpha + \beta RD_{i,t-1} + \gamma Sales_{i,t} + \delta\left(\frac{WC}{BC}\right)_{i,t} + \left(\eta_i + \lambda_t + \nu_{i,t}\right) \qquad (2)$$

i = 1, …,215;   t = 1995, …, 2000

---

for the two three-year periods. Thus we are convinced that the excluded observations are either useless in a dynamic specification (first group) or massively affected by a measurement error (second group). Descriptive statistics about the excluded firms are available upon request.

[12] As far as the internal composition of the sample is concerned, 70 firms out of 215 belong to a business group, 184 export, 110 belong to either the science-based or the specialised-suppliers Pavitt (1984) categories.

[13] These are the actual years of the questionnaire waves and this means that data collections for 1997 and 2000 are contemporaneous to the two surveys, while data for 1995, 1996, 1998 and 1999 are retrospective; hence figures from 1997 and 2000 are somehow pivotal.

[14] Both the differences are statistically significant at the 99% level of confidence (the relevant t-values are 3.87 in 1997 and 2.79 in 2000).

where variables are expressed in natural logarithms[15], η is the idiosyncratic individual and time-invariant firm's fixed effect and v the usual error term. In addition, λ , the unobservable time effect, has been inserted to control for possible macroeconomic and business cycle effects[16].

The reasons for taking the lagged dependent variable into consideration as a first regressor are both interpretative (see above) and econometric: in fact, the revealed persistence of the R&D variable (ρ = 0.79) also calls for a necessary AR(1) check. Once we have controlled for lagged R&D, sales are considered in order to check for the demand-pull hypothesis.

Finally, our main determinant (WC/BC) is considered in its contemporaneous value[17]. Since R&D may be an antecedent of a skill-biased technological change, a possible endogeneity problem has to be considered. However, our dependent variable measures an initial, pre-innovation investment in R&D, with *ex-ante* R&D expenditure having an uncertain and delayed outcome in terms of subsequent *ex-post SBTC*. Since only subsequent successful technological innovation can have an impact on skill distribution, the possible reverse effect is not between current R&D expenditure and current skill endowment, but between future successful *SBTC* and future skill proportions. This makes the possible insurgence of endogeneity with regard to our main regressor extremely unlikely[18].

However, the need for considering the lagged dependent variable implies another obvious problem of endogeneity. A natural solution for first-order dynamic panel data models is to use GMM (*General Method of Moments*; see Arellano and Bond, 1991; Arellano and Bover, 1995). More specifically, we opted for the GMM-SYS (Blundell and Bond, 1998) methodology that has several advantages in the context of our data. First, it is particularly suitable for a short panel such as the

15 Variables are all log-transformed to reduce possible heteroskedasticity problems.

16 Accordingly, in the following econometric analysis, regressions will include time dummies.

17 As robustness checks, (WC/BC) lags of one and two-periods have been inserted to control for delayed effects, but none of them have turned out to be significant (results available from the authors upon request).

18 Our hypothesis is not in contrast with the *SBTC* one; the two phenomena can in fact originate a sort of circular effect. However, it is reasonable to assume that the final skill-bias effect of current R&D expenditure will be detected well over the short time dimension of the panel used in this study. Indeed, the hypotheses of either endogeneity or weak exogeneity (predeterminedness) of both the skill ratio and sales were rejected by the Hansen tests from the GMM-SYS regressions run under these alternative assumptions and reported in Table A1 in the Appendix. Hence – although the accuracy of the Hansen test in rejecting the validity of the used instruments decreases when the moment conditions increase (see Bowsher, 2002; we thank one of the three referees for raising this methodological issue) – the four alternative specifications estimated in Table A1 do not pass the test. Our interpretation is that – although the strict exogeneity of WC/BC is a stronger assumption than weak exogeneity – the nature of the investigated issue and the structure of our dataset (in particular its short time dimension) call for considering WC/BC as strictly exogenous. However, as can be seen from Table A1, results are very similar to those obtained from the chosen specification reported in Table 2; in particular, the coefficient of WC/BC always turns out to be positive and significant as in the corresponding GMM-SYS estimate in Table 2, albeit overestimated in magnitude.

one used in this study (6 years); second, it is adequate with a highly persistent dependent variable such as R&D; third, it exploits all the information available within the data, both in terms of levels and differences[19].

Unfortunately, this method is only efficient asymptotically and may turn out to be inadequate for small samples. Dealing with 215 firms and 1290 observations is reassuring with regard to this concern; however, to be on the safe side, we also run Least Squared Dummy Variables Corrected (LSDVC) estimates. This is a rather new methodology, suitable for small panels, proposed by Kiviet (1995 and 1999), Judson and Owen (1999), Bun and Kiviet (2003), and extended to unbalanced panels by Bruno (2005a and 2005b)[20].

In the next section estimates are run using the Pooled Ordinary Least Squares (POLS), LSDV, LSDVC and GMM-SYS methodologies. The first method is affected by both heterogeneity and endogeneity; the second takes firms' heterogeneity into account[[21]]; the third and fourth also take endogeneity into account.

4. Results

Table 2 presents the POLS, LSDV, LSDVC and GMM-SYS outcomes. Where appropriate, estimates are checked both for time, in order to take possible aggregate and cyclical effects into account, and two-digit sectoral dummies in order to control for sectoral peculiarities in terms of technological opportunity and technological appropriability. Diagnosis tests regarding the fitness of

[19] Moreover, as can be seen in Table 2, the GMM-SYS specification under the hypothesis of sales and WC/BC both exogenous, passed the AR(1), AR(2) and Hansen tests. We gratefully thank two of the three referees for suggesting the use of the more general and full-information GMM-SYS estimator.

[20] In the case of an autoregressive panel data model, the LSDV estimator is the following:

$$LSDV = (W'AW)^{-1}W'Ay$$

where y is the vector of observations for the dependent variable, W is the matrix of the explanatory variables including the lagged dependent variable and A is the within-transformation which controls for the individual effects. However, in the case of first-order dynamic panel data models, the LSDV estimator turns out to be not consistent and its bias has to be corrected. In their Monte Carlo simulations, Bun and Kiviet (2003) and Bruno (2005a) consider three possible nested approximations of the LSDV bias. In this study we correct for the most comprehensive and accurate one (B_3 in Bun and Kiviet (2003) and Bruno (2005a) notations). Therefore, in the following, the LSDV corrected estimator (LSDVC) is equal to:

$$LSDVC = LSDV - B_3$$

Through their Monte Carlo experiments, Kiviet (1995), Judson and Owen (1999) and Bun and Kiviet (2003) have shown that the LSDVC estimator outperforms GMM estimators such as the Anderson-Hsiao and the Arellano-Bond for small samples. See Bruno (2005b, pp. 5 and ff.) for instructions on Stata command *xtlsdvc*.

[21] In our analysis we control for all the firms' time-invariant fixed effects that might influence a firm's incentive to engage in R&D investment and which may explain why only some firms are innovative (see Cassiman and Veugelers, 2002). While this is an important stream of literature in explaining (through static cross-sections) both why firms engage in R&D activities and why they cooperate in R&D decisions (see Colombo and Garrone, 1996; Piga and Vivarelli, 2003 and 2004), in our dynamic analysis only innovative firms are considered.

the different specifications are satisfactory (see the outcomes of the relevant tests reported in the lower panel of Table 2).

Insert Table 2

As is immediately clear, estimates are affected by a strong path-dependence in R&D expenditure; as expected, the coefficients of the lagged dependent variable are all significant to a 99% degree of confidence with a magnitude ranging from 0.35 to 0.62. This evidence confirms that R&D activities at the level of the single firm follow an autoregressive pattern which is not in contrast with the technology-push hypothesis[22].

As far as sales are concerned, they turn out to positively affect R&D investment. In all the four estimates, the relevant coefficient is significant at the 99% level of confidence and shows a value ranging from 0.33 to 0.56 (0.86 in the long-run). These consistent outcomes can be seen as a further confirmation of the demand-pull hypothesis: together with their auto-regressive nature (see above), R&D investments are also driven by the demand evolution.

After the necessary controls for lagged R&D and current sales, we now turn our attention to the main focus of this work, *i.e.* the impact of skill endowment on R&D investment. As can be seen, the relevant coefficient is positive in all four estimates, with a degree of statistical significance ranging from 90 to 99 per cent, according to the different adopted methodologies (99% in the last, more general, full-information specification). The coefficient is remarkably stable across the more reliable LSDV, LSDVC and GMM-SYS estimates, showing a value ranging from 0.18 to 0.20. This means that doubling the ratio between white and blue collar workers would imply an increase of approx. 20% in R&D investment. In the long run (column 5), the impact coefficient rises to a remarkable 0.48, meaning that in the long run the impact would reach a level of almost 50%. On the whole, the role of firm's skill endowment in influencing the decision to undertake R&D activities emerges as statistically significant and considerable in size.

5. Conclusive remarks

The microeconometric results presented in the previous section are not in contrast with the hypotheses discussed in the introductory sections and pave the way for further studies, based on other samples across different sectors and different countries. In particular, besides finding further

[22] Although suggestive, this result cannot be considered as a definite confirmation of the technology-push theory in all its multi-faceted implications.

support for the well-established technology-push and demand-pull hypotheses, this paper has also tested the role of skill endowment in increasing a firm's R&D investment.

More specifically, together with their auto-regressive nature, R&D activities turn out to be driven by demand evolution. On average, the demand-pull and technology-push effects are both highly significant and similar in terms of their relative magnitudes, with their elasticities ranging from 0.33 to 0.66, according to the different econometric methodologies.

Turning our attention to the main focus of this study, the positive link between the *ex-ante* available skills and R&D investment turns out to be significant in all the adopted specifications and with an impact of about 0.20 in the short-run and 0.50 in the long-run. This evidence suggests a new way of looking at the alleged complementarity between skills and technological innovation. In other words, the co-evolution of the two dimensions has to be thought of not solely as a consequence of *SBTC*, but also vice versa: an adequate *ex-ante* endowment of skills may accelerate R&D investment and so drive innovation *ex-post*. Although our empirical exercise does not allow us to single out the different channels through which upskilling can be pursued, the general microeconometric evidence presented in this study is not in contrast with the managerial and economic literature discussed in the previous sections.

In terms of managerial implications, this means that a successful strategy for improving firm manpower skills (through for example recruitment, training on the job and *HRM)* may also be beneficial to the firm's innovation strategy and ultimately very useful for improving the overall competitive performance of a given firm. As discussed in the introductory sections and confirmed by our results, skills and innovation turn out to be strictly complementary and managers should be aware of this in undertaking any decision relevant to the skills of their own employees.

In terms of (national, regional or sectoral) economic policy implications, our results suggest that successful education and training policies that increase the skill ratio may also act as indirect incentives to R&D investment. This means – for instance – that a subsidy for training activities may have an indirect (both short and long-term) positive impact on the propensity to innovate of a given country, region or sector.

An important limitation of this study that could be overcome by further research concerns the measure of skills that, consistently with previous economic literature, is here simply the ratio between productive (blues collar) and non-productive (white collar) workers. Longitudinal questionnaires with detailed complementary questions about education, profession, qualifications and performed tasks are needed in order to build panel databases able to disentangle the different dimensions of the very general concept of skill.

By the same token, further studies are needed to disentangle the various transmission channels through which higher skills can enhance R&D expenditures and innovation. Although we have provided different arguments supporting the positive relationship between skills and R&D activities, in this study we were not able to see for instance whether this link is based on higher individual creativity, higher propensity for organisational change or better positioning for acquiring external knowledge. Similarly, we can deduce that successful training and *HRM* may have important consequences in terms of better innovative potentialities, but our aggregate estimates cannot directly capture these aspects. In this respect, future questionnaire analyses and case studies should be focused on the particular sources of skill upgrading, as well as on their consequences affecting those specific personal and collective attitudes which may be crucial in fostering innovation.

Another important limitation of this contribution concerns its limited generalisability: as is clear from the methodological section above, our panel data comes from relatively large Italian manufacturing firms (168 employees on average, see Table 1); other studies could test our hypothesis using data from different countries and possibly comprising service sectors and SMEs.

References

Acemoglu, D. (1996), “A microfoundation for social increasing returns in human capital accumulation”, *Quarterly Journal of Economics*, vol.111, pp.779-804.

Acemoglu, D. (1998), “Why do new technologies complement skills? Directed technical change and wage inequality”, *Quarterly Journal of Economics*, vol.113, pp.1055-90.

Anderson, N.R. and West, M.A. (1998), “Measuring climate for work group innovation: development and validation of the team climate inventory”, *Journal of Organizational Behaviour*, vol.19, pp.235-58.

Antonelli, C. (1998), “The dynamics of localized technological changes. The interaction between factor costs inducement, demand pull and Schumpeterian rivalry”, *Economics of Innovation and New Technology*, vol.6, pp.97-120.

Arellano, M. and Bond, S. (1991), “Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations”, *Review of Economic Studies*, vol.58, pp.277-97.

Arellano, M. and Bover, O. (1995), “Another look at the instrumental variables estimation of error-components models”, *Journal of Econometrics*, vol.68, pp.29-51.

Arora, R. (2002), "Implementing Knowledge Management – a balanced score card approach", *Journal of Knowledge Management*, vol. 6, pp. 240-49.

Arthur, B.W. (1988), “Competing technologies: an overview”, in Dosi, G., Freeman, C., Nelson, R., Silverberg, Soete, G. (Eds.), *Technical Change and Economic Theory*, Pinter, London, pp.590-607.

Atkinson, A.B. and Stiglitz, J.E. (1969), “A new view of technological change”, *Economic Journal*, vol.79, pp.573-8.

Axtell, C.M., Holman, D.J., Unsworth, K.L., Wall, T.D., Waterson, P.E. and Harrington, E. (2000), “Shopfloor innovation: facilitating the suggestion and implementation of ideas”, *Journal of Occupational and Organisational Psychology*, vol.73, pp.265-86.

Berman, E., Bound, J. and Griliches, Z. (1994), “Changes in the demand for skilled labor within U.S. manufacturing industries: evidence from the Annual Survey of Manufacturing”, *Quarterly Journal of Economics*, vol.109, pp.367-97.

Black, S.E. and Lynch, L.M. (2001), “How to compete: the impact of workplace practices and information technology on productivity”, *Review of Economics and Statistics*, vol.83, pp.434-45.

Blundell, R. and Bond, S. (1998), “Initial conditions and moment restrictions in dynamic panel data models”, *Journal of Econometrics*, vol.87, pp.115-43.

Bowsher, C.G. (2002), “On testing overidentifying restrictions in dynamic panel data models”, *Economics Letters*, vol.77, pp.211-20.

Breschi, S., Malerba, F. and Orsenigo, L. (2000), “Technological regimes and Schumpeterian patterns of innovation”, *Economic Journal*, vol.110, pp.388-410.

Bresnahan, T., Brynjolfsson, E. and Hitt, L.M. (2002), “Information technology, workplace organization and the demand for skilled labor: firm-level evidence”, *Quarterly Journal of Economics*, vol.117, pp.339-76.

Brouwer, E. and Kleinknecht, A. (1999),“Keynes-plus? Effective demand and changes in firm-level R&D: an empirical note”, *Cambridge Journal of Economics*, vol.23, pp.385-91.

Bruno, G.S.F. (2005a), “Approximating the bias of the LSDV estimator for dynamic unbalanced panel data models”, *Economics Letters*, vol.87, pp.361-6.

Bruno, G.S.F. (2005b), “Estimation and inference in dynamic unbalanced panel data models with a small number of individuals”, *The Stata Journal*, vol.5, pp.473-500.

Brynjolfsson, E. and Hitt, L.M. (2000), “Beyond computation: information technology, organizational transformation and business performance”, *Journal of Economic Perspectives*, vol.14, pp.23-48.

Brynjolfsson, E., Renshaw, A. and Alstyne, M.V. (1997), “The matrix of change”, *Sloan Management Review*, vol.38, pp.22-40.

Bun, M.J.G. and Kiviet, J.F. (2003), “On the diminishing returns of higher order terms in asymptotic expansions of bias”, *Economics Letters*, vol.79, pp.145-52.

Caroli, E. (2001), “New technologies, organizational change and the skill bias: what do we know?” in Petit, P., Soete, L. (Eds.), *Technology and the Future of European Employment*, Elgar, Cheltenham, pp.259-92.

Cassiman, B. and Veugelers, R. (2002), “R&D cooperation and spillovers, some empirical evidence from Belgium”, *American Economic Review*, vol.92, pp.1169-84.

Cohen, W.M. and Levinthal, D.A. (1989), “Innovation and learning: the two faces of R&D”, *Economic Journal*, vol.99, pp.569-96.

Cohen, W.M. and Levinthal, D.A. (1990), “Absorptive capacity: a new perspective on learning and innovation”, *Administrative Science Quarterly*, vol.35, pp.128-52.

Colombo, M.G. and Garrone, P. (1996), “Technological cooperative agreements and firms’ R&D intensity: a note on causality relations”, *Research Policy*, vol.25, pp.923-32.

CRIC (2005), “A literature review on skills and innovation. How does successful innovation impact on the demand for skills and how do skills drive innovation?”, *CRIC report for the Department of Trade and Industry, Centre for Research on Innovation and Competition*, University of Manchester, Manchester.

Damanpour, F. (1991), “Organizational innovation: a meta-analysis of effects of determinants and moderators”, *Academy of Management Journal*, vol.34, pp.555-90.

David, P. (1985), “Clio and the economics of QWERTY”, *American Economic Review Proceedings*, vol.75, pp.332-7.

Doms, M., Dunne, T. and Troske, K. (1997), “Workers, wages and technology”, *Quarterly Journal of Economics*, vol.112, pp.253-90.

Dosi, G. (1982), "Technological Paradigms and Technological Trajectories", *Research Policy*, vol. 11, pp.147–63.

Dosi, G. (1988), “Sources, procedures and microeconomic effects of innovation”, *Journal of Economic Literature*, vol.26, pp.1120-71.

Dunne, T. and Troske, K. (2005), “Technology adoption and the skill mix of US manufacturing plants”, *Scottish Journal of Political Economy*, vol.52, pp.387-405.

Falk, M. and Seim, K. (2001) “Workers’ skill level and information technologies: a censored regression model", *International Journal of Manpower*, vol.22, pp.98-121.

Freeman, C., Clark, J. and Soete, L. (1982), *Unemployment and Technical Innovation*, Pinter, London.

Freeman, C. (1994), “The economics of technical change”, *Cambridge Journal of Economics*, vol.18, pp.463-514.

Funk, P. and Vogel, T. (2004), Endogenous skill bias, *Journal of Economic Dynamics and Control*, vol.28, pp.2155-93.

Gittel, J.H. (2000), “Organizing work to support relational co-ordination”, *International Journal of Human Resource Management*, vol.11, pp.517-39.

Goldin, C. and Katz, L.F. (1998), “The origins of technology-skill complementarity”, *Quarterly Journal of Economics*, vol113, pp.693-732.

Guthrie, J.P. (2001), “High-involvement work practices, turnover, and productivity: evidence from New Zealand”, *Academy of Management Journal*, vol.44, pp.180-90.

Hall, B. H., Griliches, Z. and Hausman, J.A. (1986), "Patents and R&D. Is There a Lag?", *International Economic Review*, vol. 27, pp. 265-83.

Hall, B. H., Mairesse, J., Branstetter, L. and Crépon, B. (1999), “Does cash flow cause investment and R&D? An exploration using panel data for French, Japanese, and United States scientific firms”, in Audretsch, D. and Thurik, R. (Eds.), *Innovation, Industry Evolution and Employment,* Cambridge University Press, Cambridge, pp.129-56.

Hicks, J.R. (1932), *The Theory of Wages*, Macmillan, London.

Hyland, P. W., Gieskes, J. F. B. and Sloan, T. R. (2001), Occupational clusters as determinants of organisational learning in the product innovation process, *Journal of Workplace Learning*, vol. 13, pp. 198-208.

Kiley M.T. (1999), "The supply of skilled labour and skill-biased technological progress", *Economic Journal*, vol.109, pp.708-24.

Kiviet, J.F. (1995), "On bias, inconsistency, and efficiency of various estimators in dynamic panel data models", *Journal of Econometrics*, vol.68, pp.53-78.

Kiviet, J.F. (1999), "Expectation of expansions for estimators in a dynamic panel data model; some results for weakly exogenous regressors", in Hsiao, C., Lahiri, K., Lee, L.F. and Pesaran, M.H. (Eds.), *Analysis of Panel Data and Limited Dependent Variables*, Cambridge University Press, Cambridge, pp.199-225.

Kleinknecht, A. and Verspagen, B. (1990), "Demand and innovation: Schmookler re-examined", *Research Policy*, vol.19, pp.387-94.

Knight, F.H. (1921), "*Uncertainty and Profit"*, Houghton Mifflin, New York.

Jiménez-Jiménez, D. and Sanz-Valle, R. (2005) "Innovation and Human Resource Management fit : an empirical study", *International Journal of Manpower*, vol.26, pp.364-81

Judson, R.A. and Owen, A.L. (1999), "Estimating dynamic panel data models: a guide for macroeconomists", *Economics Letters*, vol.65, pp.9-15.

Laursen, K. and Foss, N. (2003), "New human resource management practices, complementarities and the impact in innovation performance", *Cambridge Journal of Economics*, vol.27, pp.243-63.

Leiponen, A. (2000), "Competencies, innovation and profitability of firms", *Economics of Innovation and New Technology*, vol.9, pp.1-24.

Leiponen, A. (2005), "Skills and innovation", *International Journal of Industrial Organization*, vol.23, pp.303-23.

Machin, S. (1996), "Changes in the relative demand for skills in the UK labor market", in Booth, A. and Snower, D. (Eds.), *Acquiring Skills: Market Failures, Their Symptoms and Policy Responses*, Cambridge University Press, Cambridge, pp.129-46.

Machin, S. and Van Reenen, J. (1998), "Technology and changes in the skill structure: evidence from seven OECD countries", *Quarterly Journal of Economics*, vol.113, pp.1215-44.

Malerba, F. and Orsenigo, L. (1996), "Schumpeterian patterns of innovation", *Cambridge Journal of Economics*, vol.19, pp.47-65.

Michie, J. and Sheehan, M. (1999), “HRM practices, R&D expenditure and innovative investment: evidence from the UK’s 1990 Workplace Industrial Relations Survey (WIRS)”, *Industrial and Corporate Change*, vol.8, pp.211-38.

Milgrom, P. and Roberts, J. (1995), “Complementarities and firms: strategy, structure and organisational change in manufacturing”, *Journal of Accounting and Economics*, vol.19, pp.179-208.

Mohnen, P. and Röller, L.-H. (2005), ”Complementarities in innovation policy”, *European Economic Review*, vol.49, pp.1431-50.

Morrison, E.W. and Phelps, C.C. (1999), “Taking charge at work: extrarole efforts to initiate workplace Change”, *Academy of Management Journal*, vol.42, pp.403-19.

Nahapiet, J. and Ghoshal, S. (1998), “Social capital, intellectual capital and organizational advantage”, *Academy of Management Review*, vol.23, pp.242-66.

Nelson, R.R. and Winter, S.G. (1982), *An Evolutionary Theory of Economic Change*, Balknap Press Harvard University Press, Cambridge (Mass.).

Nickell, S. and Nicolitsas, D. (1997), “Human capital investment and innovation: what are the connections?”, *CEPDP0370 Centre for Economic Performance*, London.

Oldham, G.R. and Cummings, A. (1996), “Employee creativity: personal and contextual factors at work”, *Academy of Management Journal*, vol.39, pp.607-34.

Parker, S.K. (1998), “Enhancing role breadth self-efficiency: the role of job enrichment and other organizational intervention”, *Journal of Applied Psychology*, vol. 83, pp.835-52.

Parker, S.K, Wall, T.D. and Jackson P.R. (1997), “ “That’s Not My Job”: developing flexible employee work orientations”, *Academy of Management Journal*, vol.40, pp.899-929.

Paton, R.A. and McCalman, J. (2000), *Change Management. A Guide to Effective Implementation (2nd ed.)*, Thousand Oaks, Sage.

Pavitt, K. (1984), “Sectoral patterns of technical change: towards a taxonomy and a theory”, *Research Policy*, vol.3, pp.343-73.

Pavitt, K., Robson, M. and Townsend, J. (1989), “Technological accumulation, diversification and organization in UK companies, 1945-83”, *Management Science*, vol.35, pp.81-9.

Piga, C.A. and Vivarelli, M. (2003), “Sample selection in estimating the determinants of cooperative R&D”, *Applied Economics Letters*, vol.10, pp.243-6.

Piga, C.A. and Vivarelli, M. (2004), “Internal and external R&D: a sample selection approach”, *Oxford Bulletin of Economics and Statistics*, vol.66, pp.457-82.

Piva, M., Santarelli, E. and Vivarelli, M. (2005), “The skill bias effect of technological and organisational change: evidence and policy implications”, *Research Policy*, vol.34, pp.141-57.

Piva, M., Santarelli, E. and Vivarelli, M. (2006), "Technological and organizational changes as determinants of the skill bias: evidence from the Italian machinery industry", *Managerial and Decision Economics*, vol.27, pp.63-73.

Piva, M. and Vivarelli, M. (2007a), "Is demand-pulled innovation equally important in different groups of firms?", *Cambridge Journal of Economics*, vol. 31, pp. 691–710.

Piva, M. and Vivarelli, M. (2007b), "Demand-pulled innovation under liquidity constraints", *Applied Economics Letters*, forthcoming.

Roffe, I. (1999), Innovation and creativity in organisations: a review of the implications for training and development, *Journal of European Industrial Training*, vol. 23, pp. 224-41.

Rosenberg, N. (1982), *Inside the Black Box: Technology and Economics*, Cambridge University Press, Cambridge.

Ruttan, V.W. (1997), "Induced innovation, evolutionary theory and path dependence: sources of technical change", *Economic Journal*, vol.107, pp.1520-29.

Scherer, F.M. (1982), "Demand-pull and technological invention: Schmookler revisited", *Journal of Industrial Economics*, vol.30, pp.225-37.

Schmookler, J. (1966), *Invention and Economic Growth*, Harvard University Press, Cambridge (Mass.).

Scott, S.G. and Bruce, R.A. (1994), "Determinants of innovative behaviour: a path model of individual innovation in the workplace", *Academy of Management Journal*, vol.37, pp.580-607.

Searle, R.H. and Ball, K.S. (2003), "Supporting innovation through HR policy: evidence from the UK", *Creativity and Innovation Management*, vol.12, pp.50-62.

Senior, B. (1997), *Organizational Change*, Pitman, London.

Shipton, H., Fay, D., West, M., Patterson, M. and Birdi, K. (2005), "Managing people in promote innovation", *Creativity and Innovation Management*, vol.14, pp.118-28.

Shipton, H., West, M., Dawson, J., Birdi, K. and Patterson, M. (2006), "Human Resource management as a predictor of innovation", *Human Resource Management Journal*, vol.16, pp.3-27.

Song, J., Almeida, P. and Wu, G. (2003), "Learning-by-hiring: when is mobility more likely to facilitate interfirm knowledge transfer?", *Management Science*, vol.49, pp.351-65.

Svetlik, I. and Stavrou-Costea, E: (2007), "Connecting human resources management and knowledge management", *International Journal of Manpower*, vol. 28, pp. 197-206.

Topkis, D.M. (1998), *Supermodularity and Complementarity*, Princeton University Press, Princeton.

Vivarelli, M. (1995), *The Economics of Technology and Employment: Theory and Empirical Evidence*, Elgar, Cheltenham, reprinted 1997.

Vivarelli, M., Evangelista, R. and Pianta, M. (1996), "Innovation and employment: Evidence from Italian manufacturing", *Research Policy*, vol. 25, pp. 1013-1026.

Vivarelli, M. and Pianta, M. (Eds.) (2000), *The Employment Impact of Innovation: Evidence and Policy*, Routledge, London.

Wang, Z. (2005), "Organizational effectiveness through technology, innovation and HRM strategies, *International Journal of Manpower*, vol.26, pp.481-87.

West, M. (2002), "Sparkling fountains or stagnant ponds: an integrative model of creativity and innovation implementation in work groups", *Applied Psychology: An International Review*, vol.51, pp.355-87.

West, M., Hirst, G., Richter, A. and Shipton, H. (2004), "Twelve steps to heaven: successfully managing change through developing innovative teams", *Organizational Journal of Work and Organizational Psychology*, vol.13, pp.269-99.

Wilson, D.C. (1992), *A Strategy for Change*, Routledge, London.

Wozniak, G.D. (1987), "Human capital, information, and the early adoption of new technology", *Journal of Human Resources*, vol.22, pp.101-112.

Zwick, T. (2002), "Employee resistance against innovations", *International Journal of Manpower*, vol.23, pp.542-52.

Table 1. Descriptive statistics (monetary values in millions of Euros)

	Mean (1995)	**Std. dev. (1995)**	**Std. dev. components: *between (B) within (W)***	**Average growth rate (1995-2000)**
Sales	13.72	28.98	30.12 (B) 8.07 (W)	3.40 %
R&D	0.24	.94	1.04 (B) .39 (W)	5.14 %
White Collar / Blue Collar Workers	0.79	1.05	1.31 (B) .73 (W)	2.38%
Employees	168	344.24	368.15 (B) 69.45 (W)	1.06 %

Table 2: Dependent variable: log(R&D)

	(1) POLS	(2) LSDV	(3) LSDVC	(4) GMM-SYS	(5) long-run
Constant	-1.53***			-1.24***	
	(3.22)			(3.34)	
log(R&D-1)	0.62***	0.35***	0.64***	0.58***	
	(28.44)	(11.82)	(17.85)	(5.61)	
log(Sales)	0.33***	0.56***	0.42***	0.36***	0.86***
	(10.74)	(4.62)	(3.39)	(4.11)	(12.23)
log(WC/BC)	0.34***	0.20*	0.18*	0.20***	0.48***
	(3.35)	(1.69)	(1.93)	(3.27)	(4.28)
R^2	0.72				
F test		149.63***			
		(0.00)			
AR(1)				-5.69***	
				(0.00)	
AR(2)				-0.63	
				(0.53)	
Hansen test (df)				17.73 (13)	
				(0.17)	
Observations	1075	1075	860	1075	

Notes:
- t-statistics in brackets for POLS, LSDV and GMM estimates, z-statistics for the LSDVC estimate; p-values in brackets for the F-test, AR(1), AR(2) and the Hansen-test; * = significant at 10%; ** = significant at 5%; *** = significant at 1%.
- in the LSDVC estimate, the bias correction was initialised by the GMM-SYS estimator and bootstrapped standard errors were computed through 200 iterations.
- long-run coefficients (column 5) have been computed on the basis of the more general GMM-SYS outcomes.

Figure 1: Density of the R&D/Sales variable in 1997
(continuous line if WC/BC <= .4827586 (median value); dotted line if WC/BC > .4827586
(Mean value of R&D/Sales = 0.012 if WC/BC <= .4827586 ; Mean value of R&D/Sales = 0.029 if WC/BC > .4827586)

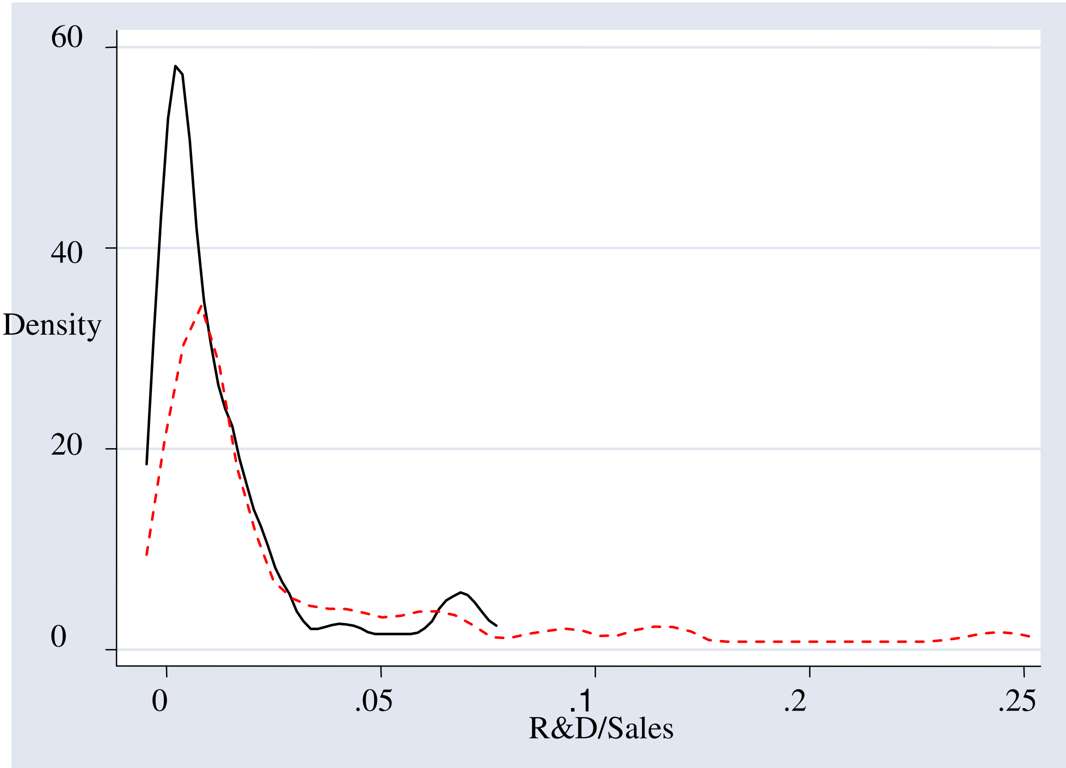
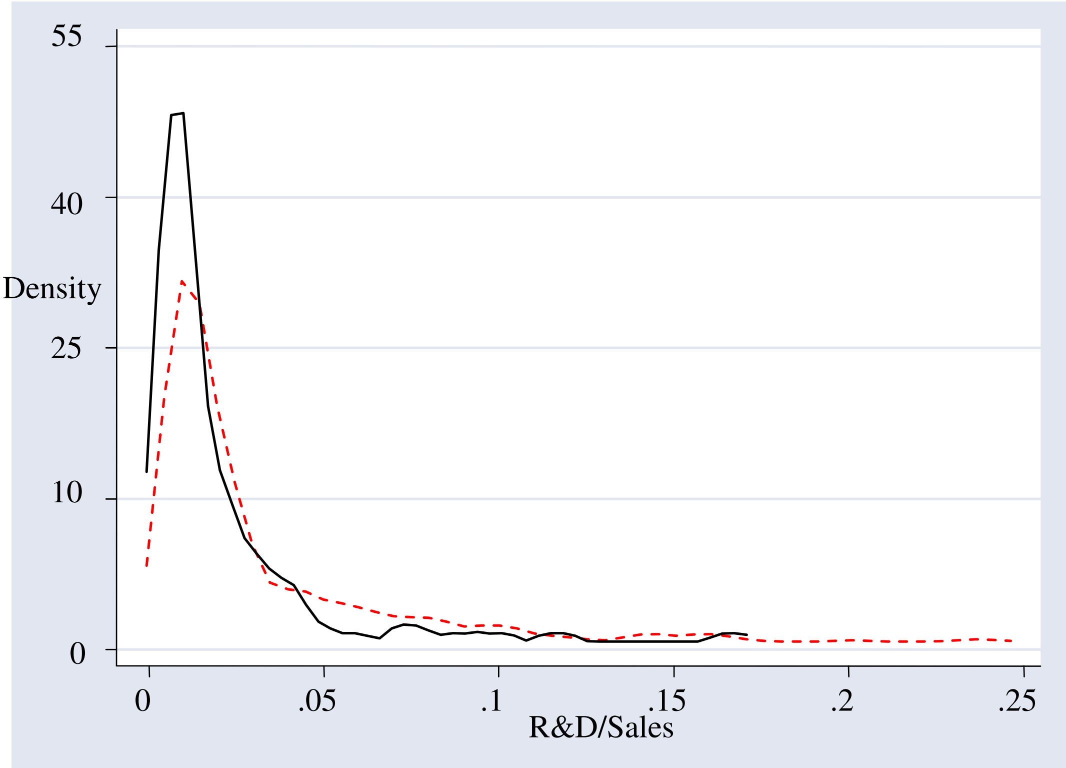


Figure 2: Density of the R&D/Sales variable in 2000
(continuous line if WC/BC <= .5384616 (median value); line if WC/BC > .5384616)
(Mean value of R&D/Sales = 0.015 if WC/BC <= .5384616 ; Mean value of R&D/Sales = 0.025 if WC/BC > .5384616)



Appendix

Table A1: GMM-SYS regressions under alternative assumptions

	(1) Endogeneity of WC/BC	(2) Endogeneity of Sales	(3) Weak exog. of WC/BC	(4) Weak exog. of Sales
Constant	-1.24***	-8.65***	-1.32***	-5.40**
	(3.43)	(2.65)	(3.46)	(2.39)
log(R&D-1)	0.59***	0.56***	0.57***	0.53***
	(5.95)	(8.12)	(5.71)	(8.63)
log(Sales)	0.37***	1.17***	0.39***	0.83***
	(4.35)	(3.20)	(4.46)	(3.35)
log(WC/BC)	0.27**	0.37***	0.42**	0.31***
	(2.33)	(3.31)	(2.28)	(3.84)
AR(1)	-5.93***	-5.08***	-5.81***	-4.87***
	(0.00)	(0.00)	(0.00)	(0.00)
AR(2)	-0.62	-0.63	-0.62	-0.65
	(0.54)	(0.52)	(0.53)	(0.51)
Hansen test (df)	76.31 (26)***	123.43 (26)***	78.28 (31)***	148.89 (31)***
	(0.00)	(0.00)	(0.00)	(0.00)

Notes:
- t-statistics in brackets; * = significant at 10%; ** = significant at 5%; *** = significant at 1%.
- p-values in brackets for AR(1), AR(2) and the Hansen-test; * = significant at 10%; ** = significant at 5%; *** = significant at 1%.