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Corporate R&D and firm efficiency: Evidence from Europe's top R&D investors

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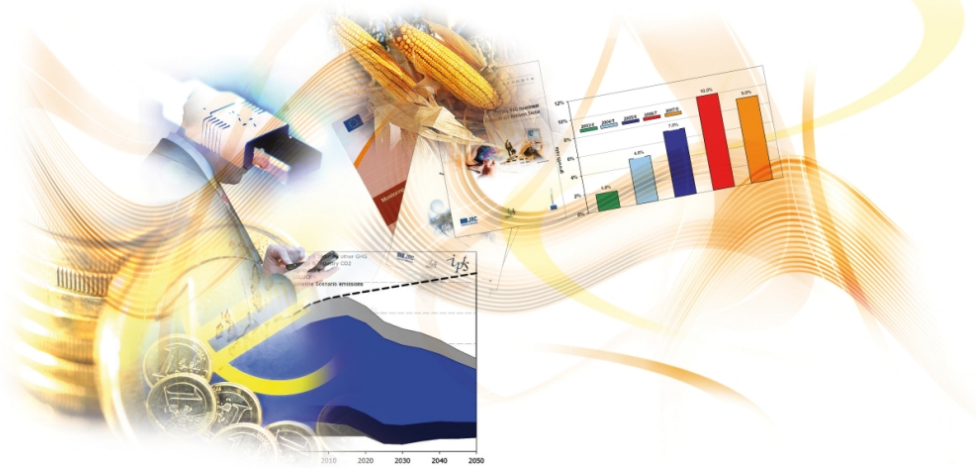

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Abstract

The main objective of this study is to investigate the impact of corporate R&D activities on firm performance, measured by labour productivity. To this end, the stochastic frontier technique is used on a unique unbalanced longitudinal dataset on top European R&D investors over the period 2000–2005. The study quantifies technical inefficiency of individual firms. From a policy perspective, the results of this study suggest that – if the aim is to leverage firms' productivity – emphasis should be put on supporting corporate R&D in high-tech sectors and, to some extent, in medium-tech sectors. On the other hand, corporate R&D in the low-tech sector is found to have a minor effect in explaining productivity. Instead, encouraging investment in fixed assets appears important for the productivity of low-tech industries. Hence, the allocation of support for corporate R&D seems to be as important as its overall increase and an '*erga omnes*' approach across all sectors appears inappropriate. However, with regard to technical efficiency, R&D intensity is found to be a pivotal factor in explaining firm efficiency. This is true for all industries.

JEL Classification: L2, O3

Keywords: Corporate R&D, productivity, technical efficiency, stochastic frontier analysis

1 Introduction

R&D literature generally assumes that corporate R&D activities have a positive impact on firm productivity (Griliches, 1979). Currently, the alleged advantage of low-tech over high-tech sectors in achieving higher efficiency gains from (additional) R&D investment is being debated. The argument is that 'catching-up low-tech sectors' are investing less in R&D but benefit from a 'late-comer advantage', whereas firms in high-tech sectors are affected by diminishing returns (Marsili, 2001; von Tunzelmann and Acha, 2005; Mairesse and Mohnen, 2005). Following this argument, the relationship between R&D and productivity growth are expected to be weaker in high-tech than in low-tech sectors. This hypothesis contrasts with previous empirical evidence[1] that additional R&D activities make a bigger marginal impact in high-tech sectors and that additional capital investment makes a bigger marginal impact in low-tech sectors. Hence, a key point to investigate is whether low-/high-tech sectors are more/less successful in achieving productivity gains from R&D activities.

Empirical evidence in this regard would be highly relevant to policy makers. In fact, leveraging Europe's competitiveness and its proximity to the technological frontier are common policy goals and – given existing budget restrictions – raise the question where support measures could pay off most.

The main objective of this study is to analyse the impact of corporate R&D activities (measured by knowledge stocks) on firm performance (measured by labour productivity). In this regard, we address the following key questions: Is the impact of R&D activities on productivity equal and significant across sectors? If not, how large are the differences in the magnitude of these effects? Does productivity of a high-tech firm benefit more from an increase in corporate R&D compared to a firm in a low-tech sector, or vice versa? Furthermore, we investigate the impact of physical capital vs. accumulated knowledge on productivity and how this effect might differ across sectors. For this purpose, R&D activities are considered as a complementary input to capital and labour. We apply the stochastic frontier [henceforth SF] approach to take into account possible (technical) inefficiencies and to test whether they might be attributed either to inappropriate capital accumulation or insufficient R&D spending or both.

The analysis is based on a unique unbalanced longitudinal dataset consisting of 532 top European R&D investors over the period 2000–2005. The results can be used directly as a basis for policy recommendations as they show the sector in which the most significant efficiency gains (leverage effects on firm performance) can be expected from supporting corporate R&D activities.

2 Literature

From a methodological point of view, studies on firm performance can be divided into two main strands[2]. The first relies on production functions that assume efficient use of the given inputs. If this assumption does not hold true, the parameter estimates and associated marginal effects of inputs might be biased. The second strand follows the logic of a two-stage ap-

[1] See Section 2 for an overview of the relevant literature.

[2] In this paper we only focus on the impact of R&D on firm productivity, while a related stream of literature studies the effect of R&D and innovation on employment (see, for instance, Van Reenen, 1997; Piva and Vivarelli, 2005).

proach[3]; cross-sectional or cross-firm productivity estimates are retrieved as a residual from a production function and subject them to a regression on a set of potential determinants of productivity growth (Bos et al., 2007).

Within the first strand, there is a well-established stream of literature analysing the impact of R&D activities on productivity; for example the seminal article by Griliches (1979) and more recent contributions by Klette and Kortum (2004), Janz, Lööf and Peters (2004), Rogers (2006) and Lööf and Heshmati (2006).4 In general, empirical works have commonly found that R&D activities make a significant contribution in enhancing firm productivity. The estimated overall average elasticities range from 0.05 to 0.25, depending on the measurement methods and the data used.

Most of these studies focus on either cross-country analyses or a specific sector, mainly dealing with high-tech industries (such as ICT) given their importance in increasing productivity growth. By contrast, considerably less attention has been paid to studying whether the productivity growth stemming from R&D activities differ across industries. In fact, technological opportunities and appropriability conditions appear quite different from one sector to another (see Freeman, 1982; Pavitt, 1984; Winter, 1984; Dosi, 1997; and Malerba, 2004), suggesting possible differences in the sectoral R&D productivity link as well.

In this regard, Griliches and Mairesse (1982) and Cuneo and Mairesse (1983) might be taken as examples of studies focusing on sectoral comparisons based on production function methodology. The authors conducted two comparable studies, used micro-level data, and drew a distinction between firms in science-related sectors and those in other sectors. They found that the impact of R&D on productivity was significantly higher for science-based firms (elasticity 0.20) than for others (0.10).

More recently, Verspagen (1995) used OECD sector-level data on value added, employment, capital expenditure and R&D investment in a standard production function framework. The study finds that R&D activities have a positive impact on a firm's output in high-tech sectors only, whereas in medium- and low-tech sectors no significant effects could be found.

Using the methodology proposed by Hall and Mairesse (1995), Harhoff (1998) and Kwon and Inui (2003) analysed the impact of R&D on labour productivity in manufacturing firms and distinguished between low-tech and high-tech industries. Harhoff (1998), using a panel of 443 German manufacturing firms over the period 1977-1989, found that the effect of R&D was considerably higher for high-tech firms compared to the residual groups of enterprises.[5] Kwon and Inui (2003) analysed a sample of 3,830 Japanese manufacturing firms over the period 1995-1998. They used three different estimation techniques (within estimates, first differences and 3-years differences) and found a significant impact of R&D on labour productivity; high-tech firms showed systematically higher and more significant coefficients than medium and low-tech firms.

Similarly, Tsai and Wang (2004), using a stratified sample of 156 Taiwanese quoted large firms observed from 1994 to 2000, found that R&D investment had a significant positive impact on the growth of a firm's productivity (elasticity 0.18). When a distinction was made between high-tech and other firms, this impact was much higher for high-tech firms (0.30) compared to the other firms (0.07).

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3 There are also single-stage approaches for doing this. For a general methodological overview see, for example, Fried et al. (2008) and Kumbhakar and Lovell (2000).

4 For comprehensive literature surveys see, for example, Mairesse and Sassenou, 1991; Griliches, 1995 and 2000; and Mairesse and Mohnen, 2001.

5 In fact, for high-tech firms the R&D elasticity was found to be highly significant ranging from 0.125 to 0.176, while for the remaining firms the R&D elasticities were either not significant (although positive) or systematically lower (ranging from 0.090 to 0.096). These results were based on different estimation techniques.

Finally, a recent study that examined the top EU R&D investors concluded that the coefficient of this impact increases monotonically from low-tech through medium-high to high-tech sectors. For capital input, the results are the opposite; they appear to be quite high for low-tech sectors, tend to be lower for medium-tech and are insignificant for high-tech sectors (see Ortega-Argilés et al., 2010).

On the whole, previous empirical evidences support the hypothesis that R&D makes a significant positive impact on productivity. More specifically, previous studies which give a cross-section sectoral breakdown seem to suggest that R&D investment makes a bigger impact on firm productivity in high-tech sectors than in low-tech sectors. Accordingly, the argument that R&D efforts could eventually make an even higher (additional) impact on low-tech sectors seems to be rejected by previous research. However, we test again these hypotheses by applying the SF technique to a comprehensive sample of companies investing in R&D.

There is a large literature on empirical analyses of firm efficiency based on either parametric or non-parametric frontier approaches. These applications cover almost every field of economics.[6] Piesse and Thirtle (2000) examined the impact of corporate R&D on efficiency of Hungarian firms[7] and found that changes in efficiency were dominated by technological regress, at the rate of 4.8% in agriculture and 8.1% in manufacturing. For explaining inefficiency the authors used different variables for different sectors; such as state subsidies, exports value, and capital-labour ratio in the case of agriculture (capital intensity and subsidy were found significant) and, for manufacturing, the authors controlled for the growing preponderance of white to blue-collar labour with the result that increasing number and salaries of managers reduced firm efficiency.

Sanders *et al.* (2007) developed a model of firm life-cycle that drives and is driven by R&D. Thus, firms virtually have the option of channelling resources either into achieving quality improvements or into R&D activities in order to gain efficiency (e.g., by reducing waste). The authors controlled for size and maturity effects and concluded that young firms facing this trade-off opt for quality instead of efficiency improvements, whereas more mature firms try to do both. This switch is endogenous and depends on past R&D choices.[8]

Following the Orea and Kumbhakar (2004) model, Bos et al. (2007 and 2008) applied SF techniques to investigate the forces driving output growth across countries[9] and EU manufacturing industries.[10] Their model takes account of inefficient use of resources and differences in production technology between countries/industries. Accordingly, for endogenously determined technology clubs/country groups, the model identifies technological change, efficiency, and effects associated with input usage. Significant differences in efficiency levels, techno-

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6 For example, Hunt-McCool et al.(1996) and Stanton (2002) on finance; Adams et al. (1999), Fernández et al. (2000a) and Lozano-Vivas and Humphrey (2002) on banking; Wadud and White (2000) and Zhang (2002) on agriculture; Reinhard et al. (1999) and Amaza and Olayemi (2002) on environmental economics; Perelman and Pestieau (1994) and Worthington and Dollery (2002) on public economics; Pitt and Lee (1981) and Thirtle et al. (2000) on development economics.

7 The analysis is based on accounting data on 117 agricultural enterprises and 43 light manufacturing industries for the period 1985 to 1991.

8 The two hypotheses are tested using a panel of manufacturing industries across six European countries over the period 1980-1997.

9 The study by Bos et al. (2007) is based on 80 countries over the period 1970–2000. The model explicitly accounts for inefficiency, augmented with a latent class structure, which allows production technologies to differ across groups of countries. Membership of these groups is estimated instead of being determined *ex ante*.

10 Bos et al. (2008) model both the technology clubs and the parameters within each club as a function of R&D intensity. This framework makes it possible to explore the components of output growth in each club, potential technology spillover and catch-up issues across industries and countries.

logical change, and capital along with labour elasticities were reported. Evidence suggests that growth is driven mainly by factor accumulation. These findings inspired us to investigate the corresponding effects for sectors distinguished by their specific R&D intensity (low, medium and high) and thus employing accumulated measures for capital use and corporate R&D activities.

Finally, Diaz and Sanchez (2008) analyzed some organizational factors related to managerial ability and its impact on efficiency based on a panel of Spanish manufacturing firms during the period 1995-2001. They found inefficiency to be larger for firms with a high ratio of temporary workers (with firm-size effects playing a role, too). They also found that small and medium size firms are more efficient than large firms, which, is explained by higher organisational complexity and more need of managerial control in the case of larger firms.

3 Data

3.1 Sources

The empirical analysis drew on an unbalanced longitudinal database consisting of 577 top European R&D investors over the six-year period 2000-2005. This unique database was created by merging the R&D scoreboard data of the UK Department of Trade and Industry (DTI) with the UK DTI value-added scoreboard data.[11] The R&D and Value Added Scoreboard are published separately on a yearly basis by the UK Department of Innovation and Skills (former Department of Trade and Industry). It lists the top UK and world companies on either investments in R&D or Value Added, respectively, based on figures from the company annual reports. In short, the scoreboards provide an overview of the top performers on each field. We have merged the data from these two datasets over the years 2000 to 2005 in order to link the cross-sectional Scoreboard waves, thus getting micro-level time series with information yearly R&D investment, capital expenditures, value added and labour at the firm level.

3.2 Definitions and organization of the data

The dataset contains information at firm level, broken down by country and sector.[12] As such, the information required for computing the dependent variable (labour productivity, defined as value added per employee (VA/E)), the main impact variable (R&D[13] per employee) and the firms' capital and labour use were obtained. Of the total of 577 companies, 27 firms from marginal sectors were dropped.[14] Six outliers were excluded, based on the results of Grubbs tests centred on the sectoral average growth rates of firms' knowledge stock intensity (K/VA) over

[11] For the DTI scoreboards, see www.innovation.gov.uk/rd_scoreboard (various editions available).

[12] The DTI collected and tracked data on the largest European firms in terms of R&D investment and value added (VA). Although the DTI databases contain data from 14 European countries (Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland and the United Kingdom), British firms are over-represented in them.

[13] Measurement of R&D investment is subject to accounting definitions for R&D. For UK companies, the definition given in Statement of Standard Accounting Practice (SSAP) 13 'Accounting for research and development' is applied. For non-UK companies, R&D investment is defined in accordance with the International Accounting Standard (IAS) and corresponds to the R&D component of accounting category 38 'Intangible assets'. Both figures are based on the OECD 'Frascati Manual' definition of corporate R&D and are therefore fully comparable.

[14] In this analysis only 28 of the original 39 DTI sectors were retained, as sectors with fewer than five firms were excluded (see Table A2).

the period investigated.[15] Another 12 companies were dropped for reasons related to calculation of the R&D and initial capital stocks in 2000.[16] Finally, controls for mergers and acquisitions (M&A) were carried out in order to ensure the comparability of the longitudinal data.[17]

After all this filtering, a final sample of 532 firms was left, consisting of mainly very large top European R&D investors. The fact that the sample firms are not randomly selected from the population has two consequences. First, the results cannot easily be generally applied to all firms, but should be considered pertinent to large firms heavily engaged in R&D activities. Second, this kind of 'pick the winner' effect is particularly severe in low-tech sectors, where the 'real' population is dominated by (rather small) firms with little or no R&D investment (Becker and Pain, 2002).

The original DTI datasets grouped firms into 39 industrial and service sectors, defined in accordance with the Industry Classification Benchmark (ICB).[18] Since the focus of this is to single out sectoral differences in the relationship between R&D and productivity, sectors were split into three subgroups of comparable size: high-tech, medium/high-tech and other sectors (medium-low- and low-tech sectors)[19]. *Ex ante*, the sectors were grouped on the basis of their overall R&D intensity (R&D/VA), assuming thresholds of 5% and 15%.[20] *Ex post*, the outcome of this taxonomy was compared with the OECD classification and a high degree of consistency was found as far as comparable manufacturing sectors are concerned.[21] Remaining service sectors were allocated accordingly. Table A2 in the Appendix provides an overview of the analysed sectors; grouped into the three technological categories mentioned above.

Recent theoretical and empirical contributions (Basu and Weil, 1998; Acemoglu and Zilibotti, 2001; and Los and Timmer, 2005) have stressed the 'appropriateness' of technology as industries choose the best technology available to them, given their input mix. In fact, industries are members of the same technology club[22] if their marginal productivity of labour and capital are the same for a comparable inputs set. In other words, their input/output combinations can be described by the same production frontier (Jones, 2005).

Accordingly in this paper, we allow for different technological regimes across industries reflected by the specific R&D intensity of a given sector. Indeed, considering high-, medium- and low-tech sectors separately allows estimating industry-specific frontiers and reflects the corresponding technology most adequately. However, as mentioned by Koop (2001), comparison of efficiency scores across sectors will be impossible as these are relative measures obtained from the sector-specific technological frontier. Furthermore, the *ex-ante* division of companies

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15 For a definition of K, see below. Note that the Grubbs test – also known as the maximum normalised residual test – assumes normality (which is a desirable property anyway). Accordingly, normality tests were run on the relevant variables and this assumption was never rejected. Results of both Grubbs and normality tests are available on request.

16 See equations 1 to 4; in the rare cases where a negative g turns out to be larger in absolute value than the depreciation rate δ, the perpetual inventory method generates an unacceptable negative initial stock at time zero.

17 Merger and acquisitions were treated as a new entry and the firms that merged were labelled as 'exit' from the dataset.

18 For the detailed ICB sectoral classification, see http://www.icbenchmark.com.

19 Compared with the OECD classification, low-tech and medium-low-tech sectors were grouped together in order to have enough observations in each sectoral group; out of the total of 1,787 observations, 516 fell into the low-tech sector, 671 into medium-tech and 600 into high-tech.

20 Note that these thresholds are significantly higher than those adopted by the OECD for the manufacturing sectors (2% and 5%, see Hatzichronoglou, 1997). This is the obvious consequence of dealing with the top European R&D investors.

21 Only two sectors (automobiles and food) were upgraded; this is due to dealing with top R&D investors alone.

22 Technology club refers to the technology parameters characterising the corresponding efficient production frontier.

and sectors based on their R&D intensity is also sensitive and, to some extent, arbitrary (see, for example, Hatzichronoglou, 1997; OECD, 2005; or Orea and Kumbhakar, 2004). In fact, R&D itself can affect both the technology parameters and, at the same time, the efficiency *within* each technology club (see section 4).[23]

3.3 Construction of the main variables

As mentioned above, we measure productivity by firm's labour productivity. The pivotal impact variable is knowledge capital (K) per employee. In addition, capital expenditure (C) per employee is considered as a second impact variable. Moreover, per capita values permit both standardisation of data and elimination of firm-size effects (see, for example, Crépon, Duguet and Mairesse, 1998, p. 123). Finally, total employment (E) is used as a control variable and the corresponding parameter accounts for scale elasticity (indicating increasing returns if the scale elasticity is positive).

As firm productivity is affected by the accumulated stocks of capital and R&D expenditure, stock indicators (rather than current or lagged flows) were used as impact variables (thus following, for example, Hulten, 1991; Jorgenson, 1990; Hall and Mairesse, 1995; Bönte, 2003; and Parisi et al., 2006). Accordingly, knowledge and physical capital stocks were computed using the perpetual inventory method based on the following equations:

$$K_{t0} = \frac{R\&D_{t0}}{g_{s,c}(K) + \delta_j}, \tag{1}$$

where: R&D = R&D expenditure and *s = 1,…, 28; c = 1,…,14; j = 1,2,3;* t_0 = 2000

$$K_t = K_{t-1} \cdot (1-\delta_j) + R\&D_t, \quad \text{with t} = 2001, \ldots, 2005 \tag{2}$$

$$C_{t0} = \frac{I_{t0}}{g_{s,c}(C) + \varphi_j} \text{ and} \tag{3}$$

$$C_t = C_{t-1}(1-\varphi_j) + I_t \tag{4}$$

where: *I* = gross investment (capital expenditure).

The OECD ANBERD and the OECD STAN database were used to provide growth rates g(K) and g(C) for *K* and *C*, respectively. In this way we calculated the compound average rates of change in real R&D expenditure and fixed capital expenditure in the relevant sectors (*s*) and countries (*c*)[24] over the period 1990-1999 (the decade preceding the period investigated in this study).

[23] Durlauf and Johnson (1995) endogenised the division rule by applying a regression tree analysis in order to identify multiple technology clubs of cross-country growth behaviour. In their approach, both the parameters and the number of clubs result from applying a sorting algorithm to the whole sample, incorporating cost into sample splits to avoid over-parameterisation. However, for testing the hypotheses outlined above the more general approach suggested here may serve the purpose, since – given the particular context of our study – the technological group as such and not the individual firms in it is what matters most.

[24] See Table A2 in the Appendix for a detailed overview of OECD to ICB sectoral conversion. German sectoral figures were applied to Swiss firms because of the unavailability of corresponding OECD data.

As far as the depreciation rates (δ) and (φ) for *K* and *C* are concerned, different δ and φ values were applied to each of the three sectoral groups (*j*). In fact, more technologically advanced sectors are distinguished (on average) by shorter product life-cycles and faster technological progress that accelerates the obsolescence of knowledge and physical capital.[25] Accordingly, sectoral depreciation rates of 20 %, 15 % and 12 % were applied to the knowledge capital and 8 %, 6 % and 4 % to the physical capital (for the high-, medium-high- and medium-low/low-tech sectors respectively). The resultant weighted averages were 15.6 % for the R&D stock and 6.0 % for the capital stock, respectively. These values are very close or identical to the 15 % and 6 % commonly used in the literature (see Musgrave 1986; Bischoff and Kokkelenberg, 1987; and Nadiri and Prucha, 1996 for physical capital; Pakes and Schankerman, 1986; Hall and Mairesse, 1995; and Hall, 2007 for knowledge capital).

4 Methodology

The idea of defining an efficient frontier function against which to measure the current performance of productive units has been pursued for the last thirty three years. During this period different approaches have been applied to identify efficient frontiers using both parametric and non-parametric methods. Both have strengths and limitations and therefore choosing the most appropriate for a certain research question appears to be a judgment call.

For instance, the parametric approach makes it possible to test hypotheses, take account of statistical noise and provide parameter estimates of production factors, elasticities, etc., for possible further interpretation. But it imposes on a somewhat *ad hoc* basis on the functional form of the frontier to be estimated (although it can be flexible), together with assumptions concerning the distribution of the composed error term. In contrast, the non-parametric approach (a mathematical programming technique), which has been traditionally assimilated into Data Envelopment Analysis [DEA], does not require such assumptions and is comparably easy to calculate. However, limitations remain in terms of considering time series, slacks, relating inefficiencies to exploratory variables, etc.[26]

Looking at trends in firm productivity, we separate gains in efficiency from quality improvements by estimating a stochastic production frontier that distinguishes between virtual moves towards or away from the frontier (efficiency gains/losses) and shifts in the production possibility set, i.e., technical change (shift of the frontier or change in its shape) or catch-up. With regard to our main research question and the length of our time series, we focus on whether, to what extent, and how investments in R&D activities and/or capital stocks affect productivity. In fact, we are more interested in the magnitude of the corresponding effects in each sector / industry.[27]

Furthermore, the impact of the somewhat *ad hoc* selection of explanatory variables (such as capital accumulation, spending on R&D, persisting R&D intensity, sectoral belonging, etc.) on firm efficiency is tested. It is therefore necessary to control for both time and industry-specific effects. Taking the strengths and limitations of the method into account, this study applies the parametric stochastic frontier technique.[28]

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25 Physical capital also embodies technology, and rapid technological progress makes scrapping more frequent.

26 See, for example, Coelli et al. (1998) for a fairly general introduction to efficiency and productivity analysis.

27 For this purpose 'time' was introduced as a shifter in the PF (Hicks- neutral technological change) and was found to be significant. 'Time' was also tested as explanatory in the inefficiency term (found to have an insignificant impact in this regard). See section 5 and the discussion of the empirical results for more details.

28 The stochastic frontier approach was introduced jointly by Aigner et al. (1977) and Meeusen and van den Broeck (1977), based on the seminal work by Farrell (1957). Comprehensive reviews of frontier approaches can be found, for instance, in Kumbhakar and Lovell (2000).

Accordingly, the results of the SF approach can provide valuable insights for policy-making, especially with respect to welfare implications. For instance, among efficient companies, productivity differentials can be reduced by improving the input mix/input qualities or by encouraging faster adoption of innovative technologies. By contrast, companies operating inefficiently could seek to improve the efficiency of the machinery they use and of their production processes and/or attempt to overcome the (external) restrictions which limit their individual businesses compared with their competitors (concerning, for instance, the institutional and financial framework, the infrastructure networks, etc.).

5 The model

As mentioned above the assumption of a common frontier across sectors is a sensitive issue. In general, the business framework and the technology appear to differ from industry to industry, especially if the companies under investigation are heterogeneous. Nevertheless, many studies do assume such a common frontier. In practice, estimating a common production function may lead to biased estimates of labour and capital elasticities. Some previous studies have tried to account for this bias by controlling for the quality of inputs (Koop, Osiewalski and Steel, 2000; Limam and Miller, 2004). Others have explored the possibility of more than one frontier to explain 'excessively' different economies (see Orea and Kumbhakar, 2004, for criticisms of using a single frontier).

This study avoids assuming a common technology by estimating group-specific technology levels and running the corresponding analyses in parallel. The model used for the empirical analyses is outlined briefly below.

A frontier production function defines the maximum output achievable, given the current production technology and available inputs. If all industries produce on the upper boundary of the common production function (i.e., the frontier) with three inputs – intangible or knowledge capital – R&D (K) –, physical capital (C) and labour (E) – the output of firm *i* in sector *s* (representing high-, medium- and low-tech industries, respectively) at time *t* can be expressed as:

$$Y_{ist}^{*} = f(K_{ist}, C_{ist}, E_{ist}, t; \beta)\exp\{v_{ist}\}\ ,\ i = 1\ldots532;\ s=1,\ 2,\ 3;\ t = 2000\ldots2005 \qquad (5)$$

where Y_{ist}^{*} is the frontier (maximum) level of output of firm *i* in industry *s* at time *t.* The output variable (*Y*) is the value added (VA) at the firm level. The production technology is expressed by function *f* (.) and the unknown parameter vector is *β.* The time trend variable, *t*, captures Hicks-neutral technological change (see Barro and Sala-i-Martín, 2004) and v_{ist} is an independent identically distributed (i.i.d.) error term distributed as $\mathrm{N}(0, \sigma_{vs}^{2})$, which reflects the stochastic nature of the frontier.

The stochastic frontier defined in equation 5 represents the maximum possible output given the inputs. It is stochastic because the maximum output is affected by the realization of the noise term which is not in the control of any firm. The idea of the SF approach is to estimate the frontier as well as inefficiency. Conventional growth empirics (Scarpetta and Tressel, 2002; Griffith et al., 2004; and Cameron et al., 2005) that study inefficiency usually benchmark all industries against one — the industry with the highest productivity in the sample. An implicit, but non-trivial, assumption in this literature is that the leading industry itself is the frontier and the single benchmark for all other industries.

However, some industries may not be able to employ existing technologies efficiently (e.g., due to mismanagement) and therefore produce less than the frontier output. If the ratio between maximum and actual (observable) output is exp{-u_{ist}}, then the actual output Y_{ist} produced by each firm *i* in industry group *s* at time *t* can be expressed as a function of the stochastic frontier output, as follows:

$$Y_{ist} = Y^*_{ist} \exp\{-u_{ist}\} \tag{6}$$

or equivalently:

$$Y^*_{ist} = f(K_{ist}, C_{ist}, E_{ist}, t; \beta) \exp\{v_{ist}\} \exp\{-u_{ist}\}, \quad i = 1\ldots532;\ s = 1,2,3;\ t = 2000\ldots2005 \tag{7}$$

where the technical inefficiency term is assumed to be independently and identically distributed as N(0, $\sigma^2_{u_{ist}}$), truncated at zero (i.e., $u_{ist} \geq 0$). Furthermore u_{ist} is assumed to be independent of the noise term v_{ist}.

Assuming that the frontier relationship is log-linear but differs for individual sectoral groups, it follows that:[29]

$$\ln(VA/E)_{ist} = \beta_{0s} + \beta_{1s} \ln(K/E)_{ist} + \beta_{2s} \ln(C/E)_{ist} + \beta_{3s} \ln(E)_{ist} + v_{ist} - u_{ist} \tag{8}$$

where *u* and *v* are the random terms representing inefficiency and noise components, respectively. Following Kumbhakar and Lovell (2000), some explanatory variables (*z*) are introduced to explain inefficiency. This is done by assuming $u_{ist} \sim N^+(0, \sigma^2_{u_{ist}})$ where $\sigma^2_{u_{ist}}$ is specified as

$$\sigma^2_{u_{ist}} = \delta_0 + \sum_{j=1}^{M} \beta_j z_{j,ist} \tag{9}$$

Some of the *z* variables, used in this study, are R&D intensity, capital intensity, time, sectoral dummies, etc. Note that in terms of the notations in equation 6, the output variable (*Y*) is the value added (VA) at firm level.

All the variables are deflated by the national GDP deflators provided by EUROSTAT and implemented as natural logarithms. In all the following estimates, time and two-digit sector dummies were considered in order to control for both common macroeconomic effects and sectoral peculiarities. Indeed, time and the sectoral dummies turned out to be significant in both the aggregate and the three sectoral models. This means that even within the sectoral subgroups, technological differences and appropriability conditions continue to play an important role.

Equation 8 is the baseline SF model introduced by Aigner et al. (1977) and Meeusen and van den Broeck (1977) in a cross-sectional set-up. The baseline model has been extended by allowing the noise term to be heteroscedastic to reflect size-related differences in variances. The variance of inefficiency was also allowed to depend on exogenous factors (z) in equation

[29] See, for example, Griliches, 1986; Lichtenberg and Siegel, 1989; Hall and Mairesse, 1995; and Verspagen, 1995. Note that this study assumed the frontiers to be different for different sectoral groups, reflected by sector-specific coefficients.

(9).[30] These z variables can be viewed as determinants of inefficiency.[31] Furthermore, marginal effects of these factors on labour productivity were calculated (Wang 2002). These observation-specific marginal effects allow detailed investigation of the impact of external factors on inefficiency.

6 Results

As a first step, Equation (8) was estimated using pooled ordinary least squares (POLS), random effects (RE) panel model (ignoring the inefficiency term) and basic stochastic frontier model assuming inefficiency to be independently and identically distributed. In order to conserve space, we are briefly commenting on the results below instead of reporting them in details[32]. The coefficient on the knowledge stock variable is found to be significant in the OLS, RE and frontier models. The overall elasticity ranged from 0.087 to 0.125, thereby meaning that labour productivity is increased by 0.087% (minimum) to 0.125% (maximum) for a 1% increase in knowledge capital stock. This result is largely consistent with the previous literature both in terms of the sign and the magnitude of the relevant coefficient (see section 2).

When the same models were run on each sector, we found that the coefficient increases steadily from the low-tech to the medium-high and the high-tech sectors. The elasticity ranged from a minimum of 0.048 to a maximum of 0.068 in the case of the low-tech, and from between 0.160 and 0.180 in the case of the high-tech sectors. This result holds for POLS, RE and SF models.

Physical capital was also found to increase labour productivity. Its elasticity in the pooled sample ranged from 0.075 to 0.122. However, this effect is mostly concentrated in low-tech and medium-high tech sectors, and is not significant in the high-tech sector. These results suggest that "embodied technological change"[33] is crucial in all sectors except for the high-tech, where technological progress comes through R&D investments and new products rather than new processes.

In order to draw further distinctions and sharpen the analysis for the sample as a whole and for each of the industrial sectors (low-, medium- and high-tech) several alternative frontier models were estimated. In particular, the specifications we tried controlled for technological change, sector-specific effects in terms of technology and efficiency, factor-specific effects, etc. Furthermore, with regard to determinants of inefficiency, time dummies, 'year' and other exogenous variables were tested. *Time* was introduced to capture the learning curve effects and the benefits of experience on individual firm efficiency and the *Year* dummies to control for the impact of external environment/market conditions on technical efficiency. Instead of reporting results from all these models, Table 1 shows the results from the final restricted SF models.

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30 An alternative way to introduce determinants of inefficiency is to make the mean of u a function of exogenous variables.

31 See section 3.4 of Kumbhakar and Lovell (2000) for an extensive discussion on these extensions and problems in ignoring them while estimating inefficiency.

32 These are available from the authors upon request.

33 The embodied nature of technological progress and the effects related to its spread in the economy were originally discussed by Salter (1960). In particular, vintage capital models describe an endogenous process of innovation in which the replacement of old equipment is the main way through which firms update their own technologies (see Freeman et al., 1982; Freeman and Soete, 1987). On the role played by embodied technological change in traditional sectors, see Santarelli and Sterlacchini (1990) and Conte and Vivarelli (2005).

Table 1: Parameter estimates of the final restricted Stochastic Frontier model (dependent variable ln(VA/E))*

	Whole sample		High-tech		Med-high		Low-tech	
Model specification	**coefficient**	**P-Value*** **	**coefficient**	**P-Value*** **	**coefficient**	**P-Value*** **	**coefficient**	**P-Value*** **
ln (knowledge/employee)	0.0870	0.000	0.1536	0.000	0.1038	0.000	---	*0.499*
ln (capital stock/employee)	0.0744	0.000	---	*0.162*	0.1307	0.000	0.1584	0.000
ln (E) [workforce]	-0.0431	0.000	---	*0.613*	-0.0373	0.000	-0.0966	0.000
Time	0.0330	0.000	0.0288	0.000	0.0176	0.003	0.0486	0.000
Constant	-2.0520	0.000	-1.9007	0.000	-1.2650	0.000	---	*0.111*
Sector dummies*	1 462.41	0.000	145.15	0.000	134.40	0.000	1 292.92	0.000
Determinants of inefficiency:								
R&D intensity[1]	-3.992	0.000	-5.5144	0.001	-0.6861	0.000	-0.4683	0.000
Capital intensity[1]	-12.700	0.000	---	*0.083*	---	*0.177*	---	*0.192*
Time	---	*0.265*	---	*0.479*	---	*0.289*	---	*0.400*
Year dummies**	---	*0.707*	---	*0.623*	---	*0.097*	---	*0.342*
Sector dummies**	75.86	0.000	87.50	0.000	61.64	0.000	135.31	0.000
Constant	---	*0.838*	---	*0.984*	---	*0.216*	1.9146	0.000
Heteroscedasticity:								
No of employees	-0.2545	0.000	-0.3020	0.000	-0.4448	0.000	-0.8485	0.000
Constant	---	*0.975*	---	*0.636*	1.1138	0.042	4.7825	0.000
Wald (overall)/prob > chi2	2 639.39	0.000	441.61	0.000	545.48	0.000	27 755.95	0.000
Log likelihood	-449.441		-140.4168		-35.599		-146.69	
Firms	1 787		600		671		516	
Observations	532		170		196		166	

*' "R&D (capital) intensity' refers to per capita R&D (capital stock) as a ratio of the (sub-)sample mean.
** Significance of all variables in the corresponding group was tested jointly (joint Wald test).
*** Variables not found to be significant at α 0.05 have been removed from the estimate (though the corresponding p-values were kept and are reported in the table in order to demonstrate the level of insignificance and/or to justify the removal).

Evidence based on these final restricted models [henceforth FRM], as reported in Table 1, suggests that capital investments have positive effect on labour productivity for low- and medium-tech sectors. On the other hand, the R&D variable was found to have no significant impact on labour productivity in the low-tech sector. Hence, the R&D stock variable was dropped as an input factor for the low-tech sector FRM and the capital (fixed asset) variable was disregarded in the high-tech sector FRM input bundle.[34] In the medium-tech sector both capital and R&D investment are statistically significant.

These results led us to structure the discussion of the empirical findings around the R&D intensity in this manner. We start with a general view and some general remarks (considering all companies) and then successively look at the high-, medium- and low-tech industries.

34 Note that although these variables were not used as input variables for the production frontier, they were, however, used as an explanatory variable of firms' inefficiencies.

6.1 Productivity in the light of corporate R&D activities

6.1.1 Full sample

In general, the range and magnitudes of the stochastic production frontier parameters conform to the estimates of the corresponding pooled OLS (POLS) and the RE models, although the SF parameters appear to be somewhat lower. This could be attributed mainly to the fact that the specification of the SF model (in contrast to the regression analyses) allows capital and R&D stocks to affect labour productivity in two ways: (i) via the frontier and (ii) by systematically affecting technical efficiency.

We added sector dummies in the frontier function to control for sector-specific effects in the technology. This appeared to be particularly important if the sample as a whole is considered since it comprises companies from low-, medium- and high-tech industries. In fact, sector-specific effects were found to be highly significant both in the technology and in firm efficiency (see Table 1).

A linear time trend was used to capture shifts of the production function (technical change) and was found to be significant. Accordingly, for the sample as a whole, technological progress was found to be about 3.3 % per year. In contrast, neither a time trend (approximating learning curve effects) nor year dummies (approximating an eventually changing business environment, market shocks, etc.) were found to affect technical inefficiency.

R&D intensity and capital intensity were used as variables explaining firm inefficiency. Both were found to be significant. In fact, companies reporting higher R&D (capital) intensity (above the mean) tend to be more efficient. In other words, these highly R&D-intensive (capital-intensive) companies are likely to operate 'closer' to the frontier. This empirical finding suggests that policies that seek to leverage corporate R&D and capital accumulation tend to have a positive impact on technical efficiency and, therefore, on productivity. However, this general conclusion (based on consideration of the sample as a whole) changes somewhat when a closer look is taken at the sectoral level. The advantage of analysing the technology at the sectoral level is that all the parameters are allowed to differ by sector – not just the intercept. The Wald test supports the idea of sector-specific technology as opposed to a single technology for all the sectors. In sector-specific regression the parameters associated with the inefficiency function will be different for different sectors. Further, we can also correct for heteroscedasticity which is likely to differ across sectors.

6.1.2 High-tech industries

In contrast to the sample as a whole, physical capital input does not appear to be significant for the high-tech companies (neither in the production function nor in the inefficiency function). This means that marginal product of capital is close to zero which can be used to argue that too much capital is used. Accordingly, for the FRM of high-tech industries, the capital stock variable was dropped both as an input and as an explanatory variable in technical inefficiency (see Table 1).[35]

Overall, the elasticity of R&D stocks with regard to productivity for high-tech firms is higher than that of any other industry or the sample as a whole. R&D intensity is also a determinant of technical efficiency. An increase in R&D intensity increases efficiency, *ceteris paribus*.

[35] However, the corresponding p-values were kept in order to illustrate the significance level.

In summary, capital does not appear to be a limiting factor for high-tech firms; high R&D intensity companies are more efficient. This finding provides a rationale and a toe-hold for policies supporting corporate R&D in high-tech firms.

6.1.3 Medium-tech industries

For medium-tech companies both capital and R&D were found to be significant determinants of the production technology (i.e., the frontier). However, only R&D intensity was found to affect technical inefficiency. In general, higher R&D intensity appears to be associated with higher technical efficiency.

Similar to the finding for high-tech industries, the capital intensity of medium-tech industries does not affect technical inefficiency. This suggests that leveraging the amount of capital used in medium-tech companies might lead to an expansion of their production possibilities due to embodied technological change, but any productivity gain would come from innovations made elsewhere (for instance, by the suppliers of the technology purchased) rather than increasing efficiency.

6.1.4 Low-tech industries

Comparing the estimates of the sectoral models, the importance of R&D seems to decrease from the high- to the low-tech industries; whereas the importance of capital input increases. In fact, for low-tech firms, marginal return on capital input was found to be the highest, but no significant impact of R&D stocks (as an input factor) was found.

However, R&D intensity was found to be significant in explaining inefficiencies of low-tech firms. Thus, investments in physical capital and in corporate R&D are important for low-tech industries, although they seem to affect productivity in different ways. Physical capital stock affected labour productivity via the technology and the production capacity, whereas R&D intensity (accumulated knowledge) affected firm performance solely via its positive effects on technical efficiency.

Comparing the sectoral models, the highest annual rate of technical change across all sectors was found for low-tech industries (see the corresponding time trend coefficients in Table 1). Thus, the R&D-intensive companies representing low-tech industries in the sample appear somewhat special. Accordingly, the technical change results might not be representative for the low-tech sector in general and should be treated with caution. However, annual technological progress of 4.9 % is remarkable (compared with 2.9 % for high-tech sectors and 1.8 % for medium-tech industries).

6.2 Corporate R&D and inefficiency: evidence at the company level

Having discussed productivity and efficiency in the light of corporate R&D activities across sectors, the micro-level evidence will now be considered in detail.[36] For this purpose, firm-specific estimates of the technical efficiency [TE] and the marginal effects of R&D intensity on firms' inefficiencies (for each observation) were calculated.[37] These marginal effects indicate by how much the technical inefficiency will change if the R&D intensity changes. More specifically, these marginal effects (when multiplied by 100) can be viewed as the percentage change in output for a unit change in the determinants of inefficiency (z variables). For exam-

[36] This may also allow checking for a possible sample selection bias due to *a priori* grouping and selecting of companies on the basis of their R&D intensity.

[37] The marginal effects for variable *z* were calculated from $\partial E(u)/\partial z$ (see Wang, 2002, for details).

ple, for R&D the marginal effect can be interpreted as the percentage change (when multiplied by 100) in (labour) productivity for a 1 point change (in a scale of 100) in its R&D intensity. The same thing is true for capital intensity. Since the intensity variables are scaled by their respective means, a value greater (less) than 1 means that R&D intensity is above (below) average. More specifically, a value of 1.05 means 5% above the mean and a value of 0.9 means the intensity is 10% below the average sectoral mean intensity. These percentages can also be viewed as 5 (10) points above (below) the mean (scaled to 100).

The results of these calculations support the general finding outlined above, viz., R&D intensity affects firm performance and, in particular, their inefficiencies differently for high-, medium- and low-tech sectors. Looking at the micro-level evidence, we find significant differences across companies within each sector. As illustrated by Figure 1 and Table 2, the TE scores of low-tech companies are much more dispersed than those of companies in high- or medium-tech industries (see the standard deviation in Table 2 and the less right-skewed graph in Figure 1). Accordingly, the potential for productivity gains from increasing technical efficiency seems to be highest in the low-tech sector.[38]

Figure 1: Technical efficiency by R&D intensity groups

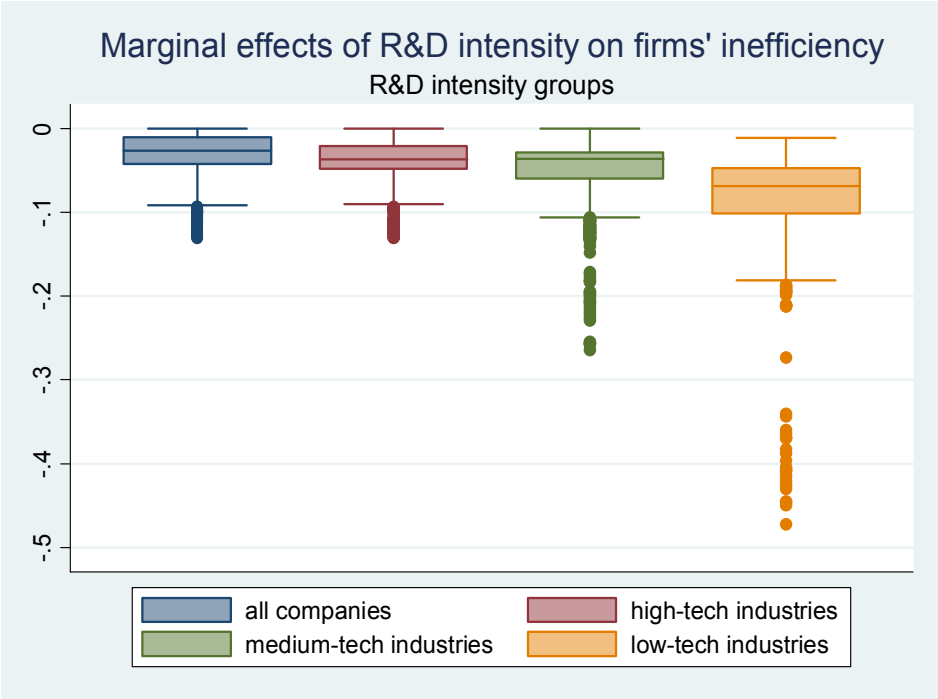

Table 2: Descriptive statistics on firm-level technical efficiency (as illustrated in Figure 1)

Efficiency (TE)	No of observ.	Mean	Standard deviation	Min	Max
Whole sample	1787	0.822	0.1597	0.145	1.000
High-tech	600	0.819	0.1473	0.161	1.000
Medium-tech	671	0.870	0.1182	0.284	1.000
Low-tech	516	0.732	0.2086	0.041	0.970

38 Although the variation of mean TE across sectors is substantial, for some sectors the estimated minimum and maximum TE scores should be treated with caution due to small number of firms in the sample in the sector. For example, the *oil equipment, services and distribution* sector has a mean TE of 13.4% (minimum 4.1% and maximum 20.6%) but comprises only seven companies.

Figure 2 and Table 3 illustrate, for the high-, medium- and low-tech groupings, how firm-level inefficiencies are affected by companies' R&D activities. The majority of companies (across all sectors) display relatively moderate marginal effects, between 0 and 0.1, with a tendency towards higher marginal effects in industries with lower R&D intensity. In fact, some low-tech companies seem to have substantial potential for leveraging their inefficiency/productivity if they were to increase their R&D intensity (see outliers in the graph and the minimum/maximum range of the marginal effects depicted in Table 3).[39]

Figure 2: Impact of companies' R&D intensity on their individual technical inefficiency

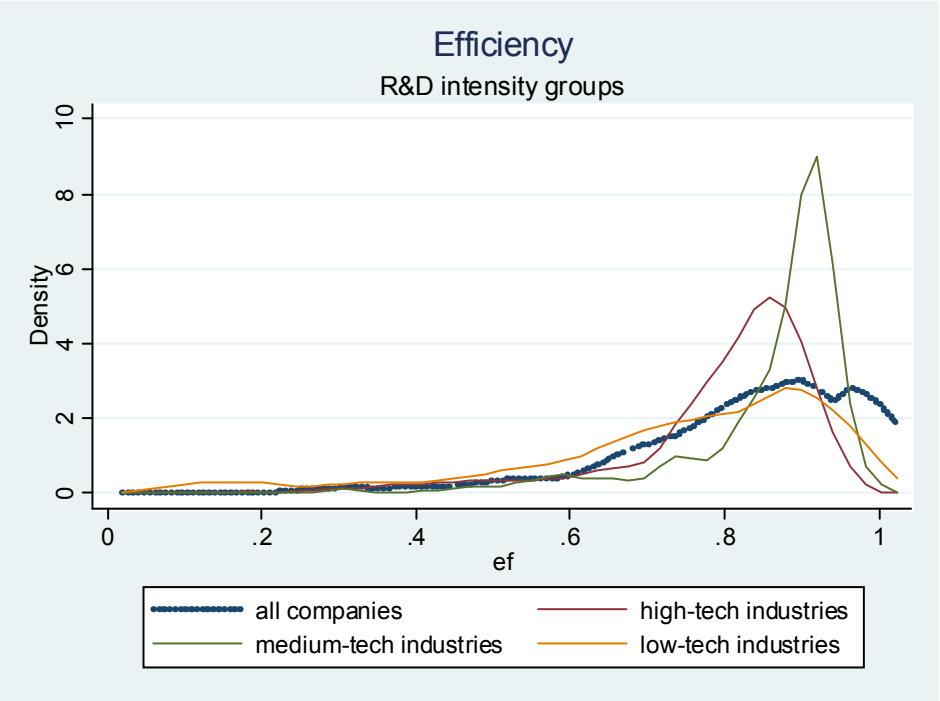

Table 3: Descriptive statistics Figure 2: Marginal effects of R&D intensity on firms' inefficiency

Marginal effects on inefficiency	No of observ.	Mean*	Standard deviation	Max	Min
Whole sample	1787	-0.033	0.0290	-0.131	0.000
High-tech	600	-0.040	0.0304	-0.132	0.000
Medium-tech	671	-0.052	0.0465	-0.264	0.000
Low-tech	516	-0.092	0.0848	-0.473	-0.011

* Average across firms belonging to corresponding subsample.

In this respect, the highest marginal effects of R&D intensity in terms of inefficiency were clearly found in sectors with comparably low mean TE, suggesting underinvestment in R&D. This empirical finding holds true across all industries and is striking, as it provides a toe-hold for targeted R&D policymaking.[40]

[39] The correlation between TE and marginal effects of R&D intensity was found to be rather low (0.28, 0.21 and 0.24 for high-, medium- and low-tech, respectively). This indicates that the lower mean TE and the higher marginal effects of R&D intensity found for low-tech sectors compared with other industries are not an effect of the very nature of this sector. Instead, this seems to be a result of the particularly high heterogeneity between the industries and companies grouped together as 'low-tech'.

[40] For instance, the standard deviation of the marginal effects in the low-tech industries indicates (apart from heterogeneity in the sector) significant underinvestment in corporate R&D activities, which in turn leads to technical inefficiency and, hence, has a negative effect on productivity.

Table A1 in annex shows that for a number of firms the calculated marginal effects of R&D intensity on inefficiency are somewhat low (in some cases even zero). For such companies, this result suggests (nearly) maximum R&D intensity from an efficiency point of view. Accordingly, any further increase in R&D intensity (e.g., triggered by a targeted policy) would make no sense economically. Interestingly, examples of this can be found across all industries (see Table A1, for example the marginal effects on aerospace and defence (0 %; high-tech), general industrials (0 %; medium-tech) and construction and materials (1.4 %; low-tech). This underlines once again the finding pointed out above that R&D policies need to be well targeted and should be sector-specific.

7 Conclusions and policy implications

In this paper we examined the effect of physical capital and R&D stocks on labour productivity and technical efficiency using microdata on a sample of top European R&D investors. To address the question of whether supporting policy measures should target specific sectors or industries, three groups were created based on the average R&D intensity. Separate stochastic frontier models were run for the entire sample as well as for each group. The main empirical results are:

(i) With respect to the production technology, capital is important for low-tech industries, while for high-tech industries R&D activities are the key and for medium-tech companies a combination of both.

(ii) R&D matters for firm efficiency, regardless of its R&D intensity or the sector it belongs. High (above mean) R&D intensity is found to have a positive impact on firm efficiency, no matter whether low-, medium- or high-tech industries are considered.

(iii) R&D activities in medium- and high-tech industries affect their productivity in two ways: (a) by shifting the frontier outwards due to technological progress and (b) by leveraging efficiency (reducing waste). In the case of low-tech industries, only the latter effect was found to be statistically significant.

(iv) A number of companies in low- and medium-tech industries have potential to increase their technical efficiency dramatically provided they were able to expand their own R&D activities.

(v) Capital expenditures were found to have significant positive effect on productivity and shift of the frontier in low- and medium tech industries. There is little evidence that capital intensity affects firms' efficiency levels.

Thus if the aim is to leverage the productivity of a given firm by policy measures, the results of this study suggests putting the emphasis on supporting R&D activities rather than on capital accumulation. The implications for European research and innovation policy are straightforward. Since corporate R&D activities have positive impact on the productivity and competitiveness of companies across sectors, general support for corporate R&D might be envisaged. Results of this study show that allocation of support to corporate R&D is as important as its overall increase. And a cross-cutting approach across all sectors appears to be misleading.

With regard to the effectiveness of R&D policy measures, supporting corporate R&D in high-tech sectors could lead to an outward shift of the frontier and thereby help to create and/or conquering new markets (due to a leading position technologically). By contrast, one reason for supporting corporate R&D in low-tech sectors might be the potential of leveraging efficiency and reducing waste at the firm level, which are preconditions for keeping any business competitive against its rivals.

These outcomes might be seen as a further support in favour of the "Lisbon agenda 2000" to make Europe the most dynamic knowledge economy in the world and for the more specific "Barcelona target" which - two years later - committed the EU to reach the target of an R&D/GDP level of 3%, two thirds of which accounted for the private companies (European Council, 2002; European Commission 2002).

However, our results tell a slightly different story: while an "erga omnes" support to companies' R&D expenditure is welcome in terms of increasing the overall efficiency of European firms, a different policy suggestion emerges if long-term technological progress is assumed to be the main policy goal. From this perspective, the allocation of the R&D efforts is as important as its overall increase and high-tech sectors should be specifically targeted by the European research policy.

Further research – based on larger and more comprehensive samples – is needed to see whether our results can be further substantiated. More research is also needed to measure the effects of different types of R&D (such as applied v. basic research) on productivity and technical efficiency. Differences across sectors appear likely in this respect, as well, since high-tech sectors are supposed to be able to push the frontier outwards due to their ability to conduct basic research, whereas low-tech sectors are more inclined to increase their technical efficiency (and thus their productivity) by means of applied research.

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Annex

Table A1: TE estimates and marginal effects of R&D intensity on firms' inefficiency by sector

				TE estimates			Marginal effect of R&D intensity on firms' technical inefficiency		
	*R&D intensity**	*Firms*	*Observations*	*Mean**	*Min.*	*Max.*	*Mean**	*Min.*	*Max.*
High-tech	**0.21**	**170**	**600**	**0.819**	**0.161**	**1.000**	**-0.040**	**0.000**	**-0.132**
Technology hardware & equipment	0.41	22	77	0.604	0.161	0.885	-0.103	-0.050	-0.132
Pharmaceuticals & biotechnology	0.28	30	120	0.863	0.708	0.943	-0.026	-0.012	-0.035
Leisure goods	0.25	7	25	0.693	0.362	0.906	-0.070	-0.062	-0.074
Aerospace & defence	0.2	21	82	1.000	1.000	1.000	0.000	0.000	0.000
Automobiles & parts	0.16	37	140	0.812	0.565	0.957	-0.038	-0.027	-0.040
Software & computer services	0.16	21	56	0.899	0.863	0.960	-0.019	-0.010	-0.021
Electronic & electrical equipment	0.15	32	100	0.779	0.401	0.909	-0.047	-0.021	-0.051
Medium-high-tech	**0.08**	**196**	**671**	**0.870**	**0.284**	**1.000**	**-0.052**	**0.000**	**-0.264**
Chemicals	0.12	42	154	0.895	0.716	0.996	-0.039	-0.001	-0.063
Industrial engineering	0.08	58	209	0.918	0.771	0.966	-0.030	-0.011	-0.038
Health care equipment & services	0.08	14	43	0.754	0.477	0.930	-0.098	-0.030	-0.141
Household goods	0.06	18	51	0.729	0.414	0.945	-0.112	-0.041	-0.132
General industrials	0.05	20	69	1.000	1.000	1.000	0.000	0.000	0.000
Food producers	0.05	31	105	0.858	0.659	0.936	-0.055	-0.022	-0.063
Media	0.05	13	40	0.640	0.284	0.961	-0.173	-0.044	-0.264
Low-tech	**0.02**	**166**	**516**	**0.732**	**0.041**	**0.970**	**-0.092**	**-0.011**	**-0.473**
Fixed line telecommunications	0.03	14	43	0.783	0.321	0.947	-0.064	-0.041	-0.080
Industrial metals	0.02	14	39	0.837	0.654	0.943	-0.046	-0.025	-0.059
Electricity	0.02	13	43	0.720	0.371	0.911	-0.106	-0.033	-0.146
Oil equipment, services & distribution	0.02	7	22	0.134	0.041	0.206	-0.386	-0.181	-0.473
General retailers	0.02	9	29	0.800	0.588	0.932	-0.055	-0.039	-0.064
Support services	0.02	22	67	0.703	0.297	0.898	-0.090	-0.034	-0.112
Construction & materials	0.02	15	65	0.931	0.821	0.965	-0.017	-0.014	-0.019
Banks	0.02	6	6	0.647	0.411	0.930	-0.414	-0.364	-0.446
Gas, water & multiutilities	0.01	23	75	0.694	0.359	0.954	-0.088	-0.039	-0.103
Oil & gas producers	0.01	13	48	0.787	0.530	0.970	-0.058	-0.028	-0.081
Mobile telecommunications	0.01	6	17	0.550	0.167	0.955	-0.161	-0.011	-0.199
Industrial transportation	0.01	11	23	0.848	0.568	0.943	-0.044	-0.018	-0.052
Beverages	0.01	8	20	0.752	0.481	0.927	-0.073	-0.057	-0.082
Mining	0	5	19	0.471	0.190	0.913	-0.199	-0.186	-0.212
Total	**0.09**	**532**	**1 787**	**0.822**	**0.041**	**1.000**	**-0.033**	**0.000**	**-0.473**

* Average across firms belonging to corresponding subsample

Table A2: Sector classification and composition of the sub-samples (including applied ICB-NACE conversion)

	NACE code	*Division name*	*R&D intensity*	*OECD classification*	*Firms*	*Observations*
High-tech			**0.21**		**170**	**600**
Technology hardware & equipment	30 32	Manufacture of machinery & equipment / Manufacture of office machinery & computers Manufacture of radio, television and communication equipment and apparatus	0.41	High	22	77
Pharmaceuticals & biotechnology	24 73	Manufacture of chemicals and chemical products Research and development	0.28	High	30	120
Leisure goods	32 36	Manufacture of radio, television and communication equipment and apparatus Manufacture of furniture; manufacturing n.e.c.	0.25	High	7	25
Aerospace & defence	35 75	Manufacture of other transport equipment Public administration and defence; compulsory social security	0.20	High	21	82
Automobiles & parts	25 34	Manufacture of rubber and plastic products Manufacture of motor vehicles, trailers and semi-trailers	0.16	Medium-high	37	140
Software & computer services	72	Computer and related activities	0.16		21	56
Electronic & electrical equipment	31 32	Manufacture of electrical machinery and apparatus n.e.c Manufacture of radio, television and communication equipment and apparatus	0.15	High	32	100
Medium-tech			**0.08**		**196**	**671**
Chemicals	24	Manufacture of chemicals and chemical products	0.12	Medium-high	42	154
Industrial engineering	29 35	Manufacture of machinery and equipment n.e.c. Manufacture of other transport equipment	0.08	Medium-high	58	209
Health care equipment & services	33 36 85	Manufacture of medical, precision and optical instruments, watches and clocks Manufacture of furniture; manufacturing n.e.c. Health and social work	0.08		14	43
Household goods	36	Manufacture of furniture; manufacturing n.e.c.	0.06	Medium-high	18	51
General industrials	25 74	Manufacture of rubber and plastic products Other business activities	0.05	Medium-high	20	69
Food producers	5 15	Fishing, fish farming and related service activities Manufacture of food products and beverages	0.05	Low	31	105
Media	22 92	Publishing, printing and reproduction of recorded media Recreational, cultural and sporting activities	0.05		13	40
Low-tech			**0.02**		**166**	**516**
Fixed line telecommunications	64	Post and telecommunications	0.03		14	43
Industrial metals	27	Manufacture of basic metals	0.02	Medium-low	14	39
Electricity	40	Electricity, gas, steam and hot water supply	0.02		13	43
Oil equipment, services & distribution	11	Extraction of crude petroleum and natural gas	0.02		7	22
General retailers	52 93	Retail trade, except motor vehicles and motorcycles; repair of personal & household goods Other service activities	0.02		9	29
Support services	51 74	Wholesale trade and commission trade, except of motor vehicles and motorcycles Other business activities	0.02		22	67
Construction & materials	26 45	Manufacture of other non-metallic mineral products Construction	0.02		15	65
Banks	65	Financial intermediation, except insurance and pension funding	0.02		6	6
Gas, water & multiutilities	40 41	Electricity, gas, steam and hot water supply Collection, purification and distribution of water	0.01		23	75
Oil & gas producers	11	Extraction of crude petroleum and natural gas	0.01		13	48
Mobile telecommunications	64	Post and telecommunications	0.01		6	17
Industrial transportation	60 63 64	Land transport; transport via pipelines Supporting and auxiliary transport activities; activities of travel agencies Post and telecommunications	0.01		11	23
Beverages	15	Manufacture of food products and beverages	0.01	Low	8	20
Mining			0		5	19
Total			**0.09**		**532**	**1787**

The mission of the JRC-IPTS is to provide customer-driven support to the EU policy-making process by developing science-based responses to policy challenges that have both a socio-economic as well as a scientific/technological dimension.

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Abstract

The main objective of this study is to investigate the impact of corporate R&D activities on firm performance, measured by labour productivity. To this end, the stochastic frontier technique is used on a unique unbalanced longitudinal dataset on top European R&D investors over the period 2000–2005. The study quantifies technical inefficiency of individual firms. From a policy perspective, the results of this study suggest that – if the aim is to leverage firms' productivity – emphasis should be put on supporting corporate R&D in high-tech sectors and, to some extent, in medium-tech sectors. On the other hand, corporate R&D in the low-tech sector is found to have a minor effect in explaining productivity. Instead, encouraging investment in fixed assets appears important for the productivity of low-tech industries. Hence, the allocation of support for corporate R&D seems to be as important as its overall increase and an '*erga omnes*' approach across all sectors appears inappropriate. However, with regard to technical efficiency, R&D intensity is found to be a pivotal factor in explaining firm efficiency. This is true for all industries.

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