DISCUSSION PAPER SERIES

IZA DP No. 4657

Corporate R&D and Firm Efficiency: Evidence from Europe's Top R&D Investors

Subal C. Kumbhakar
Raquel Ortega-Argilés
Lesley Potters
Marco Vivarelli
Peter Voigt

December 2009

Forschungsinstitut
zur Zukunft der Arbeit
Institute for the Study
of Labor

Corporate R&D and Firm Efficiency: Evidence from Europe's Top R&D Investors

Subal C. Kumbhakar
State University of New York at Binghamton

Raquel Ortega-Argilés
IN+ Center, Instituto Superior Técnico, Lisboa

Lesley Potters
Utrecht School of Economics

Marco Vivarelli
Università Cattolica, Milano-Piacenza, and IZA

Peter Voigt
IPTS, European Commission Joint Research Centre, Sevilla

Discussion Paper No. 4657
December 2009

IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

IZA Discussion Paper No. 4657
December 2009

ABSTRACT

Corporate R&D and Firm Efficiency: Evidence from Europe's Top R&D Investors

The main objective of this study is to investigate the impact of corporate R&D activities on firms' performance, measured by labour productivity. To this end, the stochastic frontier technique is applied, basing the analysis on a unique unbalanced longitudinal dataset consisting of 532 top European R&D investors over the period 2000–2005. R&D stocks are considered as pivotal input in order to control for their particular contribution to firm-level efficiency. Conceptually, the study quantifies the technical inefficiency of a given company and tests empirically whether R&D activities could explain the distance from the efficient boundary of the production possibility set, i.e. the production frontier. From a policy perspective, the results of this study suggest that – if the aim is to leverage companies' productivity – emphasis should be put on supporting corporate R&D in high-tech sectors and, to some extent, in medium-tech sectors. By contrast, supporting corporate R&D in the low-tech sector turns out to have a minor effect. Instead, encouraging investment in fixed assets appears vital for the productivity of low-tech industries. However, with regard to firms' technical efficiency, R&D matters for all industries (unlike capital intensity). 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.

JEL Classification: L2, O3

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

Corresponding author:

Marco Vivarelli
Facoltà di Economia
Università Cattolica
Via Emilia Parmense 84
I - 29100 Piacenza
Italy
E-mail: marco.vivarelli@unicatt.it

1 Introduction

R&D literature generally assumes that corporate R&D activities have a positive impact on firms' productivity (Griliches, 1979). Currently, the alleged advantage of low-tech over high-tech sectors in achieving more 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 would be affected by diminishing returns (see Marsili, 2001; von Tunzelmann and Acha, 2005; and Mairesse and Mohnen, 2005). Following this argument, the relationship between R&D and productivity growth would be 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 appear highly relevant to policy making. 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 specific impact of corporate R&D activities on firms' performance (measured by productivity) by applying the stochastic frontier [SF] technique. R&D activities (approximated by knowledge stocks) are considered pivotal input in order to control for their particular contribution to firm-level efficiency. This study quantifies the technical inefficiency of each company and tests whether R&D activities could explain any possible distance from the efficient boundary of the production possibility set, i.e. the production frontier. 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 (groups) in which the most significant efficiency gains (leverage effects on firms' performance) can be expected from supporting corporate R&D activities.

2 Literature

From a methodological point of view, studies on firms' 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 for any marginal effects of inputs might be biased. The second strand follows the logic of a two-stage approach:[3] cross-sectional or cross-firm productivity estimates are retrieved as a residual from a production function and subject to (regression on) a set of potential determinants of productivity growth (Bos et al., 2007).

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

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

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

Within the first strand, there is a well-established stream of literature analysing the impact of R&D activities on productivity, for instance the seminal article by Griliches (1979) and more recent contributions such as 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 to enhancing firms' 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 pharmaceuticals or any ICT-related sector. By contrast, considerably less attention has been paid to studying whether the productivity returns stemming from R&D activities differ between 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 specific sectoral R&D/productivity links as well.

In this regard, Griliches and Mairesse (1982) and Cuneo and Mairesse (1983) might be taken as examples of the numerous studies focusing on sectoral comparisons by applying a 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 suggests 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 set up by Hall and Mairesse (1995), Harhoff (1998) studied the R&D/productivity link, using a panel of 443 German manufacturing firms over the period 1977-1989, and found that the effect of R&D was considerably higher for high-technology firms rather than for the residual groups of enterprises.[5]

Wakelin (2001), Rincon and Vecchi (2003), and Tsai and Wang (2004) applied a Cobb–Douglas production function to micro-data, regressing productivity on R&D expenditure, capital and labour. Wakelin (2001), using data on 170 quoted UK firms during the period 1988-1992, found that R&D exerted a significant positive influence on a firm's productivity growth. Moreover, firms in sectors defined as 'net users of innovations' turned out to have a higher rate of return on R&D. Rincon and Vecchi (2003), using data extracted from the Compustat database over the period 1991-2001, found that firms reporting R&D were more productive than their non-R&D-reporting counterparts throughout the entire period. The estimated elasticities ranged from 0.15 to 0.20. Finally, Tsai and Wang (2004), using a stratified sample of 156 large firms quoted on the Taiwan Stock Exchange from 1994 to 2000, found that R&D investment had a significant positive impact on the growth of a firm's

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 always was found to be highly significant and ranging from 0.125 to 0.176, while for the remaining firms the R&D elasticity resulted either not being significant (although positive) or systematically lower (ranging from 0.090 to 0.096), according to the different estimation techniques.

productivity (elasticity 0.18). When a distinction was drawn between high-tech and other firms, this impact was much higher for high-tech firms (0.3) than for any other firms (0.07).

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 most vital for low-tech sectors, tend to be less relevant for medium-tech and are insignificant for high-tech sectors (see Ortega-Argilés et al., 2010).

On the whole, previous empirical evidence supports the hypothesis that R&D makes a significant positive impact on productivity at country, sector and firm levels. More specifically, previous studies which give a cross-section sectoral breakdown seem to suggest that R&D investment makes a bigger impact on firms' 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 (see hypotheses above) is questionable. We will test these hypotheses empirically by applying the stochastic frontier technique to a comprehensive sample of companies investing in R&D.

In particular, in this study we will address the following questions: Is the impact of R&D activities on productivity equally significant across sectors? If so, what are the differences in the magnitudes of these effects? Does the productivity of a high-tech firm benefit more from an increase in its corporate R&D than that of a firm in a low-tech sector, or vice versa? Furthermore, we will investigate the impact of physical capital vs. accumulated knowledge on productivity and how this might differ across sectors. For this purpose, R&D activities (accumulated as R&D stocks) will be considered as complementary input to capital and labour use. Finally, the SF approach will be applied to take into account possible (technical) inefficiencies and to check whether they might be attributed either to inappropriate capital accumulation (capacity) or to insufficient R&D spending (capabilities) or to both.

There is a comprehensive literature on empirical analyses of firms' efficiency based on either parametric or non-parametric frontier approaches. These applications cover almost every field of economics.[6] With respect to the impact of corporate R&D on firms' efficiency, Sanders *et al.* (2007) developed a model of firms' 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.[7]

Bos et al. (2007 and 2008) applied SF techniques to investigate the forces driving output growth across countries[8] and EU manufacturing industries.[9] Their model takes account of

6 For example, Hunt-McCool, Koh and Francis (1996) and Stanton (2002) on finance; Adams, Berger and Sickles (1999), Fernández, Koop and Steel (2000a) and Lozano-Vivas and Humphrey (2002) on banking; Wadud and White (2000) and Zhang (2002) on agriculture; Reinhard, Lovell and Thijssen (1999) and Amaza and Olayemi (2002) on environmental economics; Perelman and Pestieau (1994) and Worthington and Dollery (2002) on public economics; or Pitt and Lee (1981) and Thirtle, Bhavani, Chitkara, Chatterjee and Mohanty (2000) on development economics.

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

8 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*.

9 Bos et al. (2008) model both the technology clubs and the parameters within each club as a function of R&D intensity.

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 [TCH], efficiency and effects associated with input usage. Significant differences in efficiency levels, TCH 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 characteristic R&D intensity (low, medium and high) and thus employing accumulated measures for capital use and corporate R&D activities.

3 Data

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.[10] The two separate DTI datasets contain information at firm level, broken down by country and sector.[11] By linking the two databases, the information required for computing the dependent variable (labour productivity, defined as value added (VA) per employee), the main impact variable (R&D[12]) and the firms' capital and labour use were obtained. Of the total of 577 companies, 27 firms from marginal sectors were dropped.[13] 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 the period investigated.[14] Another 12 companies were dropped for reasons related to calculation of the R&D and initial capital stocks in 2000.[15] Finally, controls for mergers and acquisitions (M&A) were carried out in order to ensure the comparability of the longitudinal data.[16]

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 small firms with little or no R&D investment (Becker and Pain, 2002).

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.

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

11 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.

12 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.

13 In this analysis only 28 of the original 39 DTI sectors were retained, as sectors with fewer than five firms were excluded (see Table A1).

14 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.

15 See equations 1 to 4 below; 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 in time zero.

16 M&A were treated as a new entry and the firms that merged were labelled as 'exit' from the dataset.

The original DTI datasets grouped firms into 39 industrial and service sectors, defined in accordance with the Industry Classification Benchmark (ICB).[17] This study splits these into three subgroups of comparable size: high-tech, medium/high-tech and other sectors (medium-low- and low-tech sectors)[18] since the focus was on singling out sectoral differences in the relationship between R&D and productivity. *Ex ante*, the sectors were grouped on the basis of their overall R&D intensity (R&D/VA), assuming thresholds of 5% and 15%.[19] *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.[20] Remaining service sectors were allocated accordingly. Table A1 in the Appendix provides an overview of the sectors analysed, 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[21] 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).

In this paper, we allow for different technological regimes across industries reflected by the characteristic R&D intensity of a given sector. Considering high-, medium- and low-tech sectors separately allows estimating industry-specific frontiers and reflects the corresponding technology most adequately. But, as stressed for instance 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 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.[22]

As mentioned above, we approximate firm's productivity by its labour productivity. The pivotal impact variable is knowledge capital (K) per employee. In addition, capital expenditure (C) per employee is considered as 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 λ accounts for scale elasticity (indicating increasing returns if > 0).

As firms' productivity appears to be affected by the accumulated stocks of capital and R&D expenditure, stock indicators (rather than current or lagged flows) were used as impact

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

18 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.

19 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.

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

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

22 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 a 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.

variables (thus following, for example, Hulten, 1991; Jorgenson, 1990; Hall and Mairesse, 1995; Bönte, 2003; and Parisi, Schiantarelli and Sembenelli, 2006). Accordingly, knowledge and physical capital stocks were computed using the perpetual inventory method based on the following equations:

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

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

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

$$C_{t0} = \frac{I_{t0}}{(g_{s,c} + \delta_j)} \tag{3}$$

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

where: I = gross investment (capital expenditure).

The OECD ANBERD and the OECD STAN database were used to provide growth rates (g) 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*)[23] over the period 1990-1999 (the decade preceding the period investigated in this study).

As far as the depreciation rates (δ) for *K* and *C* are concerned, different δ 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.[24] 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 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.

23 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.

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

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 the functional form of the frontier to be estimated (although it can be flexible), together with assumptions concerning the distribution of the compound error term.

By 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, inbuilt attribution of inefficiencies to exploratory variables, etc.[25]

Looking at trends in firms' productivity, the aim is to separate gains in efficiency from quality improvements by estimating a stochastic production frontier that makes it possible to distinguish between virtual moves towards or away from the frontier (efficiency gains/losses) and changes in the production possibility set, i.e. technical change (shift of the frontier or change in its shape). 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 firms' efficiency will also be estimated. 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 will apply the parametric stochastic frontier technique.[26]

In fact, one major advantage of the SF framework is the three-tier breakdown of productivity growth into (i) technology changes (i.e. shifts of the frontier or changes in its shape over time), (ii) factor accumulation (i.e. scale elasticity-adjusted increases in factor use) and (iii) inefficiency changes (i.e. movements of the observed firm-level input-output combination in relation to the 'optimum' efficient combination benchmarked by the production frontier).

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 deploy and of their production processes and/or attempt to overcome the (external) restrictions which limit their individual businesses compared with their competitors (e.g. institutional/financial framework, infrastructure, etc.).

5 The model

As outlined above, assuming a common frontier across sectors is a sensitive issue. In general, the business framework and the persistent 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 can 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

---

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

26 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 Knox Lovell (2000).

(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 boundary of a common production set that consists of an input vector with three arguments – intangible or knowledge capital – R&D (K) –, physical capital (C) and labour (E) – the output of firm *i* in sector *s* (*s* = 1, 2 or 3 representing high-, medium- and low-tech industries, respectively) at time *t* can be expressed as:

$$Y^*_{ist} = f(K_{ist}, C_{ist}, E_{ist}, t; \beta)\exp\{v_{ist}\}, \ i = 1 \ldots 532; \ \ t = 2000 \ldots 2005 \qquad (5)$$

where Y^*_{ist} is the frontier (maximum) level of output of firm *i* in sector *s* at time *t.* The production technology is expressed by function *f* (.) and parameter vector *β*. Thus, *t* is a time trend variable that 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 $\mathrm{N}(0, \sigma^2_v)$, which reflects the stochastic character of the frontier, accommodates noise in the data and therefore allows for statistical inference.

The frontier defined in equation 5 represents a set of maximum outputs for a range of input vectors. Therefore, at any moment in time, it is estimated from observations of a number of industries. 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 differences between maximum and actual (observable) output is $\exp\{-v_{ist}\}$, then the actual output Y_{ist} produced by each firm *i* in industry *s* at time *t* can be expressed as a function of the stochastic frontier output, as follows:

$$Y_{ist} = Y^*_{ist}\exp\{-v_{ist}\} \qquad (6)$$

or equivalently:

$$Y^*_{ist} = f(K_{ist}, C_{ist}, E_{ist}, t; \beta)\exp\{v_{ist}\}\exp\{-u_{ist}\}, \qquad i = 1 \ldots 532; \ \ t = 2000 \ldots 2005 \qquad (7)$$

where $u_{ist} \geq 0$ is assumed to be i.i.d., with a normal distribution truncated at zero $N(0, \sigma_u^2)$ and independent of the noise term v_{ist}. Assuming that the frontier relationship is log-linear but differs for individual sectoral groups, it therefore follows that:[27]

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

where i = 1…532; t = 2000…2005 and u and v are the error terms representing inefficiency and noise components, respectively. Here the output variable (Y) is the value added (VA) at firm level.

All 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 estimates. This means that even within the sectoral subgroups, specific two-digit technological opportunities and appropriability conditions continue to play an important role.

Equation 8 is modelled on 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 was extended by allowing the noise term to be heteroscedastic to reflect size-related differences. The variance of inefficiency was also allowed to depend on exogenous factors.[28] These factors can be viewed as determinants of inefficiency.[29] Furthermore, marginal effects of these factors on labour productivity were calculated. This could allow detailed investigation of the impact of external factors on inefficiency as the marginal effects are observation-specific.

6 Results

Table 1 presents the econometric estimates of the SF models in comparison with those of the corresponding pooled OLS (POLS) and random-effects (RE) regressions, in order to permit a sensitivity check. As can be seen, the SF estimates provide virtually the same image as the results of the regression analyses.[30]

[insert Table 1 around here]

The knowledge stock has a significant positive impact on a firm's productivity with an overall elasticity ranging from 0.087 to 0.125. This general result is largely consistent with the previous literature both in terms of the sign and the significance and estimated magnitude of the relevant coefficient (see Section 2). More interestingly, the coefficient increases monotonically when we move from the low-tech to the medium-high and the high-tech sectors, ranging from a minimum of 0.048/0.068 to a maximum of 0.160/0.180. This outcome

27 See 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.

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

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

30 In order to allow this comparison, equivalent model specifications were used.

– homogeneous across the three methodologies – is consistent with the previous empirical contributions discussed in Section 2.

Physical capital was found to increase firm's productivity, with an overall elasticity equal to 0.075/0.122. However, this effect is concentrated in low-tech and medium-high tech sectors, while it is not significant in the high-tech sectors. Hence, evidence suggests that "*embodied technological change*"[31] is crucial in all sectors except for the high-tech, where technological progress is mainly introduced through R&D investments and new products rather than new processes. Finally, the investigated firms reveal decreasing returns with (relatively) smaller firms showing higher productivity gains[32].

In order to draw further distinctions and deepen the analysis, for the sample as a whole and for each of the industrial clusters considered (low-, medium- and high-tech), several alternative model specifications along with the corresponding hypotheses were tested. For example, the data were controlled for technological change [TCH], sector-specific effects in terms of technology and efficiency, factor-specific effects, etc. Furthermore, with regard to determinants of inefficiencies (via σ_u), time dummies, 'year' and other exogenous variables were tested. In this respect, *Time* was assumed to capture the learning curve effects and the *Year* dummies to control for the impact of external environment/market conditions on any company's technical efficiency. Table 2 shows the corresponding econometric results and outlines the final restricted SF models.

[insert Table 2 around here]

Evidence based on these final restricted models [FRM], as reported in Table 2, suggests that, as regards productivity gains, capital investments are vital solely for low- and medium-tech sectors (not in high-tech industries). The R&D variable, however, was found to have no direct 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.[33] In the medium-tech sector (if the sample as a whole is considered), both capital and R&D investment are statistically significant (see Table 2: FRMs).

This suggests structuring the discussion of the empirical results around the R&D intensity, starting with a general view and some general remarks (considering all companies) and then successively looking at the high-, medium- and low-tech industries (see below).

31 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, Clark and Soete, 1982; Freeman and Soete, 1987). On the crucial role played by embodied technological change in traditional sectors, see Santarelli and Sterlacchini (1990) and Conte and Vivarelli (2005).

32 This is not an argument in favour of the role of R&D in SMEs since our sample consists mainly of large firms.

33 Note that although these variables were discarded 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 Whole sample

In general, the range and magnitudes of the stochastic production frontier parameters correspond to the estimates of the pooled OLS (POLS) and the random effects (RE) production function, but appear to be somewhat lower (see Table 1). This could be attributable 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) by shaping the frontier and (ii) by systematically affecting firms' technical efficiency.

Sector dummies were used in order to reflect 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 2).

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 at the rate of about 3.3% per year was found. By 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 firms' inefficiency levels.

Companies' R&D intensity and capital intensity were used as explanatory variables of firms' technical (in)efficiency. Both were found to be significant. In fact, companies reporting higher (over-proportional) R&D intensity and/or capital input tend to be more efficient. In other words, these highly R&D-intensive and/or highly capital-intensive companies are likely to operate 'closer' to the frontier (waste less than others). This empirical finding suggests that policies that seek to leverage corporate R&D and capital accumulation tend to have a positive impact on any company's efficiency and, therefore, also its productivity. However, this general conclusion (based on consideration of the sample as a whole) changes somewhat when a closer look is taken at the sub-samples.

Although empirically justified for determining different technological conditions (as pointed out above), a joint Wald test found no significant impact when the set of sector dummies was replaced by dummies representing low-, medium- and high-tech sectors. In other words, it is not sufficient to differentiate among low-, medium- and high-tech sectors when patterns of inefficiencies across companies have to be investigated. Moreover, this finding was confirmed for the sample as a whole and for each industrial cluster. Hence, there is strong evidence of sector-specific effects in terms of efficiency and, therefore, policy measures targeting this issue have to be explicitly sector-specific.[34]

6.1.2 High-tech industries

In contrast to the sample as a whole, physical capital input does not appear to be as vital for high-tech companies (neither as a production factor and, hence, in terms of shaping the production frontier nor by affecting firms' technical efficiency). In other words, the key

34 We also controlled for company-size effects in the statistical noise term and found them to be significant in all FRMs, suggesting heteroscedasticity.

variable in high-tech industries is R&D rather than physical capital input. Accordingly, for the FRM of high-tech industries, the capital stock variable was dropped; both as an input and as an explanatory variable of companies' inefficiencies (see Table 2).[35]

Overall, the elasticity of R&D stocks with regard to productivity for high-tech firms is higher than observed in any other industry or the sample as a whole. Moreover, R&D intensity also overwhelmingly determines technical efficiency in high-tech industries. Over-proportional R&D intensity therefore indicates high efficiency (ceteris paribus).

In a nutshell, as capital does not appear to be a limiting factor for high-tech firms, the companies in the sector which report the highest R&D intensity are supposed to set the technological frontiers and therefore are naturally assumed to operate more (eventually fully) efficiently. This is not trivial as it 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 are vital. In fact, both were found to be significant determinants of the production technology (i.e. to shape the frontier). However, only R&D intensity was found to affect firms' inefficiencies. In general, higher R&D intensity appears to be associated with higher technical efficiency.

Corresponding to the finding made for high-tech industries, the capital intensity of medium-tech industries does not affect companies' technical inefficiency. This suggests that leveraging the amount of capital used in medium-tech companies might trigger an expansion of their production possibilities due to embodied TCH, but any corresponding productivity gain would then rely on innovations made elsewhere (for instance, by the suppliers of the technology purchased) rather than on reductions of waste (increasing efficiency).

6.1.4 Low-tech industries

Comparing the estimates of the sectoral FRMs, the importance of R&D seems to decrease from the high- to the low-tech industries, whereas the importance of capital input rises inversely. In fact, for low-tech firms, the highest marginal return on capital input was estimated, 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 low-tech firms' inefficiencies. Hence, 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 determines labour productivity by means of the applied technology and the production capacity of a certain firm, whereas R&D intensity (accumulated knowledge) has an impact on the firm's performance via its positive effects on technical efficiency (reduction of waste).

Comparing the sectoral FRMs, the highest annual rate of TCH across all sectors was found for low-tech industries (see the corresponding time trend coefficients in Table 2). This likely reflects the mentioned sample bias towards companies performing large-scale R&D. Hence, the R&D-intensive companies representing low-tech industries in the given sample possibly

35 The corresponding p-values were therefore kept in order to illustrate the significance level.

appear somewhat special. Accordingly, the TCH results might not be representative for the low-tech sector in general and should be treated with caution. Nevertheless, 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 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 are easy to interpret. They indicate how much the technical inefficiency will change if the R&D intensity changes by one unit. Alternatively, these marginal effects (when multiplied by 100) can be viewed as the percentage change in output for a unit change in the z variables (determinants of inefficiency). Accordingly, given our model specification, by considering the marginal effects it is possible to predict how much the (labour) productivity of a given company could change if its R&D intensity were increased by 1%.

The results of these calculations support the general finding outlined above: R&D affects firms' performance and, in particular, their inefficiencies differently between high-, medium- and low-tech sectors. Looking at the micro-level evidence, there are even significant differences between companies within each industrial sector. As illustrated by Figure 1 and Table 3, the TE scores of low-tech companies are much more widely dispersed than those of companies in high- or medium-tech industries (see the standard deviation in Table 5 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] This raises the question what role R&D can play in achieving such an efficiency increase.

[insert Figure 1 and Table 3 around here]

Figure 2 and Table 4 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 efficiency/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 4).[39]

[insert Figure 2 and Table 4 around here]

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).

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 the low number of firms in the sample belonging to the corresponding 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.

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'.

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]

[insert Table 5 around here]

Table 5 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) optimum R&D intensity from a technical 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 5, 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 certainly be sector-specific.

7 Conclusions and policy implications

The general link between R&D and firms' productive performance has been established in previous literature, but very few studies have provided empirical evidence of the impact of investment in corporate R&D, knowledge accumulation, R&D intensity and capital intensity on productivity and efficiency. To fill this gap, we studied the effect of different inputs, in particular physical capital and R&D stocks, on firms' productivity and technical efficiency, using a set of micro-data on a sample of top European R&D investors.

In order to address the question of whether supporting policy measures should target specific groups of sectors or industries, three sub-samples were created based on the average R&D intensity in a given sector. Out of the total of 1787 observations, 516 fell into the low-tech sector, 671 into medium-tech and 600 into high-tech. A separate SF model was run for the sample as a whole and for each sub-sample and the corresponding production frontier was estimated. The study controlled for sector-specific differences in terms of the frontier technology, which is allowed to change over time, in order to reflect technological progress and possible changes in the business environment. The signs and magnitudes of the production frontiers are comparable to the results achieved by estimating an average production function (see Table 1).

The main empirical results can be summarised as follows:

- With respect to the production possibilities (shape of the frontier), for low-tech industries capital is crucial, for high-tech industries R&D activities are the key and for medium-tech companies a combination of both determines performance.
- R&D matters for any firm's efficiency, regardless of its R&D intensity or the sector it is operating in. In general, over-proportional R&D intensity (in relation to the means

40 For instance, the comparably high 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 the companies' productivity.

for the corresponding sample) was found to have a positive effect on companies' efficiency, no matter whether low-, medium- or high-tech industries were considered.

- Nevertheless, corporate R&D activities appear to be more important for medium- and high-tech industries than for their low-tech counterparts due to a double-edge effect.[41] Nevertheless, there is evidence that stimulating an increase in R&D intensity in low-tech industries might also be beneficial, as it could help companies fully seize their production possibilities. In fact, the results indicate that a number of companies in low- and medium-tech industries could increase their technical efficiency significantly (and therefore their productivity too) if they were to expand their R&D activities.[42]
- However, the potential of this leverage effect appears to be very different from one industry to another. This calls for a targeted policy approach if the aim is to stimulate corporate R&D in an (cost) effective way.
- Turning the attention to capital expenditures – whereas this input was found to be a crucial production factor in affecting shape and shift of the technological frontier in low- and medium tech industries – there is little evidence that capital intensity affects firms' efficiency levels. In fact, capital intensity matters in terms of firms' efficiency (and in this regard affects its productivity) only if the sample as a whole is considered.
- Accordingly, if the aim is to leverage the productivity of a given firm by policy measures, the results of this study suggest putting the emphasis on supporting R&D activities rather than on capital accumulation. Admittedly, the latter could also leverage productivity (particularly in low- and some medium-tech sectors), given the effects of embodied technological change. However, this productivity effect appears more indirect as the evidence suggests that the technical efficiency of a given company tends to remain unaffected by supporting investment in fixed capital (all other things being equal). By contrast, supporting corporate R&D could lead to both an expansion of the production possibility set (technological progress) and to a reduction of existing inefficiencies and seems therefore more appropriate.[43]

The implications for European research and innovation policy are straightforward. As corporate R&D activities seem to have a positive impact on the productivity and competitiveness of companies across sectors, general support for corporate R&D might be envisaged. However, the results of this study have shown that allocation of support to corporate R&D seems to be as important as its general increase and that 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 primarily to an outward shift of the frontier and thereby help to create and/or conquering new markets (due to a technologically leading position). By contrast, one reason for supporting corporate R&D in low-tech sectors might be the potential of leveraging

41 Intensifying R&D activities in medium- and high-tech industries could affect their productivity in two ways: (1) by shifting the frontier outwards due to technological progress and (2) by leveraging efficiency (reducing waste). In the case of low-tech industries, only the latter was found to be statistically significant.

42 While this result does not fully dispel the concern about the lack of any link between R&D and the ultimate economic performance of a firm (since the latter depends on many other factors), it clearly suggests that R&D is a fundamental determinant of possible competitive advantage.

43 This could focus political efforts on providing access to finance since the crucial point in terms of possible productivity gains is what any additional resources might be spent on, assuming that the companies targeted are in fact restricted in this respect. According to the results of this study, spending these additional resources on R&D would appear the most promising option. But, this is not always the aim and it could be difficult to ensure appropriate use of the resources earmarked, especially once access to money is granted.

efficiency and reducing waste, which are preconditions for keeping any business competitive against its rivals.

However, the policy mix should be sectorally targeted rather than an ‘equal for all industries’ public intervention. This implies measures focusing on R&D, hand in hand with issues such as capital accumulation and applies equally to distribution of subsidies and to the design of fiscal incentives targeting corporate R&D investment.

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. fundamental research) on firms' productivity and technical efficiency. Differences between sectors appear likely in this respect, as high-tech sectors are supposed to be able to push the frontier outwards due to their affinity to conducting fundamental research, whereas low-tech sectors are more inclined to increase their technical efficiency (and thus their productivity) by means of applied research.

References

Acemoglu, D. and Zilibotti, F. (2002): 'Productivity Differences', *Quarterly Journal of Economics,* 116(2), 563-606.

Adams, R., Berger A. and Sickles, R. (1999): 'Semiparametric Approaches to Stochastic Panel Frontiers with Applications in the Banking Industry', *Journal of Business and Statistics,* 17, 349-358.

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

Amaza, P. and Olayemi, J.K. (2002): 'Analysis of Technical Inefficiency in Food Crop Production in Gombe States, Nigeria', *Applied Economics Letters,* 9(1), 51-54.

Barro, R.J. and Sala-i-Martín, X.X. (2004): 'Economic Growth', Cambridge, MA: MIT Press.

Basu, S. and Weil, D. (1998): 'Appropriate Technology and Growth', *Quarterly Journal of Economics*, *113(4), 1025-1054.*

Becker, B. and Pain, N. (2002): 'What Determines Industrial R&D Expenditure in the UK?', National Institute of Economic and Social Research, London.

Bischoff, C.W. and Kokkelenberg, E.C. (1987): 'Capacity Utilisation and Depreciation-in-use', *Applied Economics,* 19, 995-1007.

Bönte, W. (2003): 'R&D and Productivity: Internal vs. External R&D — Evidence from West German Manufacturing Industries', *Economics of Innovation and New Technology,* 12, 343-360.

Bos, J., Economidou, C., Koetter, M. and Colari, J. (2007): 'Do Technology and Efficiency Differences determine Productivity?', Tjalling C. Koopmans Research Institute Discussion Paper Series, No. 07(14).

Bos, J., Economidou, C. and Koetter, M. (2008): 'Technology Clubs and Growth Patterns: Evidence from EU Manufacturing', Tjalling C. Koopmans Research Institute Discussion Paper Series, No. 08(03).

Cameron, A.C. and Trivedi, P.K. (2005): 'Microeconometrics: Methods and Applications', Cambridge: Cambridge University Press.

Cameron, G., Proudman, J. and Redding, S. (2005): 'Technological Convergence, R&D, Trade and Productivity Growth', *European Economic Review,* 49(3), 775-809.

Coelli, T.J., Prasada Rao, D.S. and Battese, G.E. (1998): 'An Introduction to Efficiency and Productivity Analysis', Kluwer Academic Publishers, Boston.

Conte A. and Vivarelli, M. (2005): *'One or Many Knowledge Production Functions? Mapping Innovative Activity Using Microdata',* IZA Discussion Paper No. 1878, Institute for the Study of Labour, Bonn.

Crépon, B., Duguet, E. and Mairesse, J. (1998): 'Research, Innovation and Productivity: an Econometric Analysis at Firm Level', *Economics of Innovation and New Technology,* 7, 115–158.

Cuneo, P. and Mairesse, J. (1983): 'Productivity and R&D at the Firm Level in French Manufacturing', NBER Working Paper No. 1068, National Bureau for Economic Research, Cambridge, MA.

Dosi, G. (1997): 'Opportunities, Incentives and the Collective Patterns of Technological Change', *Economic Journal,* 107, 1530-1547.

Durlauf, S.N. and Johnson, P.A. (1995): 'Multiple Regimes and Cross-Country Growth Behaviour', *Journal of Applied Econometrics,* 10(4), 365-384.

Farrell, M.J. (1957): 'The measurement of productive efficiency', *Journal of Royal Statistical Society*, Series A, General 120, Part 3 (1957), pp. 253–281.

Fernández, C., Koop, G. and Steel, M.F.J. (2000): 'Multiple-Output Production with Undesirable Outputs: An Application to Nitrogen Surplus in Agriculture', *Journal of the American Statistical Association, Applications and Case Studies,* 97, 432-442.

Freeman, C. (1982): 'The Economics of Industrial Innovation', Pinter, London.

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

Freeman, C. and Soete, L.. (1987): '*Technical Change and Full Employment*', Basil Blackwell, Oxford.

Fried, H.O., Knox Lovell, C.A. and Schmidt, S.S. (2008): 'The Measurement of Productive Efficiency and Productivity Growth', Oxford University Press, New York.

Griffith, R., Redding, S. and Van Reenen, J. (2004): 'Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries', *Review of Economics and Statistics,* 86(4), 883-895.

Griliches, Z. (1979): 'Issues in Assessing the Contribution of Research and Development to Productivity Growth', *Bell Journal of Economics,* 10, 92-116.

Griliches, Z. (1986): 'Productivity, R&D and basic research at the firm level in the 1970s', *American Economic Review,* 76(1), 141–154.

Griliches, Z. (1995): 'R&D and Productivity: Econometric Results and Measurement Issues', in P. Stoneman (ed.) '*Handbook of the Economics of Innovation and Technological Change'* , 52-89, Blackwell Publishers Ltd., Oxford..

Griliches, Z. (2000): 'R&D, Education and Productivity', Harvard University Press, Cambridge, MA.

Griliches, Z. and Mairesse, J. (1982): ‘Comparing Productivity Growth: An Exploration of French and US Industrial and Firm Data’, NBER Working Paper No. 961, National Bureau of Economic Research, Cambridge, MA.

Hall, B.H. (2007): ‘Measuring the Returns to R&D: The Depreciation Problem’, NBER Working Paper No. 13473, National Bureau of Economic Research, Cambridge, MA.

Hall, B.H. and Mairesse, J. (1995): ‘Exploring the Relationship between R&D and Productivity in French Manufacturing Firms’, *Journal of Econometrics*, 65, 263-293.

Harhoff, D. (1998): ‘R&D and Productivity in German Manufacturing Firms’, *Economics of Innovation and New Technology,* 6, 29-49.

Hatzichronoglou, T. (1997): ‘Revision of the High-Technology Sector and Product Classification’, OECD, Paris.

Hulten, C.R. (1991): ‘The Measurement of Capital’, in E. R. Berndt and Triplett, J. E. (eds.): ‘*Fifty Years of Economic Management*’, University of Chicago Press, Chicago.

Hunt-McCool, J., Koh, S.C. and Francis, B.B. (1996): ‘Testing for Deliberate Underpricing in the IPO Premarket: A Stochastic Frontier Approach’, *Review of Financial Studies,* 9, 1251-1269.

Janz, N., Lööf, H. and Peters, B. (2004): ‘Firm Level Innovation and Productivity — Is there a Common Story across Countries?’, *Problems and Perspectives in Management*, 2, 1-22.

Jones, C. I. (2005): ‘The Shape of Production Functions and the Direction of Technical Change’, *Quarterly Journal of Economics*, 120(2), 517-549.

Jorgenson, D.W. (1990): ‘Productivity and Economic Growth’, in E. R. Berndt and Triplett, J. E. (eds.): ‘*Fifty Years of Economic Growth*’, 19-118, Chicago University Press, Chicago.

Klette, J. and Kortum, S. (2004): ‘Innovating Firms and Aggregate Innovation’, *Journal of Political Economy*, 112, 986-1018.

Koop, G. (2001): ‘Cross-Sectoral Patterns of Efficiency and Technical Change in Manufacturing’, *International Economic Review,* 42(1), 73-103.

Koop, G., Osiewalski, J. and Steel, M. F. (2000): ‘Modelling the Sources of Output Growth in a Panel of Countries’, *Journal of Business and Economic Statistics,* 18(3), 284-299.

Kumbhakar, Subal C. and Knox Lovell, C.A. (2000): ‘Stochastic Frontier Analysis’, Cambridge University Press.

Lichtenberg, F.R. and Siegel, D. (1989): 'The Impact of R&D Investment on Productivity — New Evidence Using Linked R&D-LRD Data', NBER Working Paper No. 2901, National Bureau for Economic Research, Cambridge, MA.

Limam, Y. R. and Miller, S. M. (2004): 'Explaining Economic Growth: Factor Accumulation, Total Factor Productivity Growth and Production Efficiency Improvement', Department of Economics Working Paper Series, 2004-20, Connecticut University.

Lööf, H. and Heshmati, A. (2002): 'The Link between Firm Level Innovation and Aggregate Productivity Growth', Institutet för studier av utbildning och forskning, Stockholm.

Lööf, H. and Heshmati, A (2006): 'On the Relation between Innovation and Performance: A Sensitivity Analysis', *Economics of Innovation and New Technology*, 15, 317-344.

Los, B. and Timmer, M.P. (2005): 'The appropriate technology explanation of productivity growth differential: An empirical approach', *Journal of Development Economics*, 77(2), 517-531.

Lozano-Vivas, A. and Humphrey, D.V. (2002): 'Bias in Malmquist Index and Cost Function Productivity Measurement in Banking', *International Journal of Production Economics,* 76(2), 177-188.

Mairesse, J. and Mohnen, P. (2001): 'To Be or not To Be Innovative: An Exercise in Measurement', NBER Working Paper No. 8644, National Bureau of Economic Research, Cambridge, MA.

Mairesse, J. and Mohnen, P. (2005): 'The Importance of R&D for Innovation: A Reassessment Using French Survey Data', *Journal of Technology Transfer,* 30, 183-197.

Mairesse, J. and Sassenou, M. (1991): 'R&D and Productivity: A Survey of Econometric Studies at the Firm Level', NBER Working Paper No. 3666, National Bureau for Economic Research, Cambridge, MA.

Malerba, F. (2004): 'Sectoral Systems of Innovation', Università Commerciale Luigi Bocconi, Milano.

Marsili, O. (2001): 'The Anatomy and Evolution of Industries', Edward Elgar, Northampton, MA.

Meeusen, W. and van den Broeck, J. (1977): 'Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error', *International Economic Review*, 18(2), 435-444.

Musgrave, J.C. (1986): 'Fixed Reproducible Tangible Wealth Series in the United States, 1925-91', *Survey of Current Business*, 66, 51-75.

Nadiri, M.I. and Prucha, I.R. (1996): 'Estimation of the Depreciation Rate of Physical and R&D Capital in the U.S. Total Manufacturing Sector', *Economic Inquiry,* 34, 43-56.

OECD (2005). 'OECD Science, Technology and Industry Scoreboard 2005', OECD Publishing, Paris.

Orea, L. and Kumbhakar, S.C. (2004): 'Efficiency Measurement Using a Latent Class Stochastic Frontier Model', *Empirical Economics*, 29(1), 169-183.

Ortega-Argilés R., Piva, M., Potters, L. and Vivarelli, M. (2010): 'Is Corporate R&D Investment in High-Tech Sectors more Effective?', *Contemporary Economic Policy*, forthcoming.

Pakes, A. and Schankerman, M. (1986): 'Estimates of the Value of Patent Rights in European Countries During the Post-1950 Period', *Economic Journal*, 96, 1052-1076.

Parisi, M., Schiantarelli, F. and Sembenelli, A. (2006): 'Productivity, Innovation Creation and Absorption and R&D. Microevidence for Italy', *European Economic Review*, 8, 733-751.

Pavitt, K. (1984): 'Sectoral Patterns of Technical Change: Towards a Taxonomy and a Theory', *Research Policy*, 13, 343-373.

Peneder, M. (2001): 'Entrepreneurial Competition and Industrial Location: Investigating the Structural Patterns and Intangible Sources of Competitive Performance', Edward Elgar, Cheltenham.

Perelman, S. and Pestieau, P. (1994): 'A Comparative Performance Study of Postal Services: A Productive Efficiency Approach', *Annales d'Économie et de Statistique*, 33, 187-202.

Pitt, M.M. and Lee, L.F. (1981): 'The Measurement and Sources of Technical Inefficiency in the Indonesian Weaving Industry', *Journal of Development Economics*, 9, 43-64.

Piva, M. and Vivarelli, M. (2005): 'Innovation and Employment: Evidence from Italian Microdata', *Journal of Economics*, 86, 65-83.

Reinhard, S., Lovell, C.A.K. and Thijssen, G. (1999): 'Sustainable Efficiency of Dutch Dairy Farms: A Parametric Distance Function Approach', Working paper, Agricultural Economics Research Institute, The Hague.

Rincon, A. and Vecchi, M. (2003): 'Productivity Performance at the Company Level', in O'Mahony, M. and van Ark, B. (eds.): '*EU Productivity and Competitiveness: An Industry Perspective. Can Europe Resume the Catching-up Process?'*, 169-208, European Commission, Luxembourg.

Rogers, M. (2006): '*R&D and Productivity in the UK: evidence from firm-level data in the 1990s'*, Economics Series Working Papers No. 255, University of Oxford.

Salter, W. E. G. (1960): '*Productivity and Technical Change*', Cambridge University Press, Cambridge.

Sanders, M., Bos, J. and Economidou, C. (2007): 'R&D over the Life Cycle', Tjalling C. Koopmans Research Institute Discussion Paper Series No. 07-18.

Santarelli, E. and Sterlacchini, A.. (1990): ‘Innovation, Formal vs. Informal R&D, and Firm Size: Some Evidence from Italian Manufacturing Firms‘, *Small Business Economics*, 2, 223-228.

Scarpetta, S. and Tressel, T. (2002): ‘Productivity and Convergence in a Panel of OECD Industries: Do Regulations and Institutions Matter?’, OECD Economics Department Working Papers No. 342.

Stanton, K. R. (2002): ‘Trends in Relationship Lending and Factors affecting Relationship Lending Efficiency’, *Journal of Banking and Finance,* 26(1), 127-152.

Thirtle, C., Bhavani, S., Chitkara, S., Chatterjee, P. and Mohanty, M. (2000): ‘Size Does Matter: Technical and Scale Efficiency in Indian State Tax Jurisdictions’, *Review of Development Economics,* 4 (3), 340-352.

Tsai, K.H. and Wang, J.C. (2004): ‘R&D Productivity and the Spillover Effects of High-Tech Industry on the Traditional Manufacturing Sector: The Case of Taiwan’, *World Economy*, 27, 1555-1570.

Van Reenen, J. (1997): ‘Employment and Technological Innovation: Evidence from U.K. Manufacturing Firms’, *Journal of Labor Economics* 15, 255–284.

Verspagen, B. (1995): ‘R&D and Productivity: A Broad Cross-Section Cross-Country Look’, *Journal of Productivity Analysis*, 6, 117-135.

Von Tunzelmann, N. and Acha, V. (2005): ‘Innovation in ‘Low-Tech’ Industries’ in Fagerberg, J., Mowery, D. C., and Nelson, R. R. (eds.): ‘*The Oxford Handbook of Innovation’*, 407-432, Oxford University Press, New York.

Wadud, A. and White, B. (2000): ‘Farm Household Efficiency in Bangladesh: A Comparison of Stochastic Frontier and DEA Methods’, *Applied Economics,* 32(13), 1665-1973.

Wakelin, K. (2001): ‘Productivity growth and R&D expenditure in UK manufacturing firms’, *Research Policy,* 30, 1079-1090.

Wang, H.J. (2002): ‘Heteroskedasticity and non-monotonic efficiency effects of a stochastic frontier model’, *Journal of Productivity Analysis* 18, 241-253.

White, H. (1980): ‘A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity’, *Econometrica,* 48, 817-838.

Winter, S.G. (1984): ‘Schumpeterian Competition in Alternative Technological Regimes’, *Journal of Economic Behaviour and Organisation,* 5, 287-320.

Worthington, A.C. and Dollery, B.E. (2002): ‘Incorporating Contextual Information in Public Sector Efficiency Analyses: A Comparative Study of NSW Local Government’, *Applied Economics,* 34(4), 453-464.

Zhang, Y. (2002): ‘The Impacts of Economic Reform on the Efficiency of Silviculture: A Non-Parametric Approach’, *Environmental and Development Economics,* 7(1), 107-122.

APPENDIX

Table A1: Sector classification and composition of the sub-samples

	R&D intensity	*OECD classification (manufacturing only)*	*Firms*	*Observations*
High-tech	**0.21**		**170**	**600**
Technology hardware & equipment	0.41	High	22	77
Pharmaceuticals & biotechnology	0.28	High	30	120
Leisure goods	0.25	High	7	25
Aerospace & defence	0.20	High	21	82
Automobiles & parts	0.16	Medium-high	37	140
Software & computer services	0.16		21	56
Electronic & electrical equipment	0.15	High	32	100
Medium-high-tech	**0.08**		**196**	**671**
Chemicals	0.12	Medium-high	42	154
Industrial engineering	0.08	Medium-high	58	209
Health care equipment & services	0.08		14	43
Household goods	0.06	Medium-high	18	51
General industrials	0.05	Medium-high	20	69
Food producers	0.05	Low	31	105
Media	0.05		13	40
Low-tech	**0.02**		**166**	**516**
Fixed line telecommunications	0.03		14	43
Industrial metals	0.02	Medium-low	14	39
Electricity	0.02		13	43
Oil equipment, services & distribution	0.02		7	22
General retailers	0.02		9	29
Support services	0.02		22	67
Construction & materials	0.02		15	65
Banks	0.02		6	6
Gas, water & multiutilities	0.01		23	75
Oil & gas producers	0.01		13	48
Mobile telecommunications	0.01		6	17
Industrial transportation	0.01		11	23
Beverages	0.01	Low	8	20
Mining	0.00		5	19
Total	**0.09**		**532**	**1787**

Note: In this and the following tables the medium-low-/low-tech sectors group is indicated simply as ‘low-tech’.

Table A2: ICB-NACE conversion

	ICB	NACE Code	Division name
High-tech	Technology hardware & equipment	30	Manufacture of machinery and equipment n.e.c.
			Manufacture of office machinery and computers
		32	Manufacture of radio, television and communication equipment and apparatus
	Pharmaceuticals & biotechnology	24	Manufacture of chemicals and chemical products
		73	Research and development
	Leisure goods	32	Manufacture of radio, television and communication equipment and apparatus
		36	Manufacture of furniture; manufacturing n.e.c.
	Aerospace & defence	35	Manufacture of other transport equipment
		75	Public administration and defence; compulsory social security
	Automobiles & parts	25	Manufacture of rubber and plastic products
		34	Manufacture of motor vehicles, trailers and semi-trailers
	Software & computer services	72	Computer and related activities
	Electronic & electrical equipment	31	Manufacture of electrical machinery and apparatus n.e.c.
		32	Manufacture of radio, television and communication equipment and apparatus
Medium-tech	Chemicals	24	Manufacture of chemicals and chemical products
	Industrial engineering	29	Manufacture of machinery and equipment n.e.c.
		35	Manufacture of other transport equipment
	Health care equipment & services	33	Manufacture of medical, precision and optical instruments, watches and clocks
		36	Manufacture of furniture; manufacturing n.e.c.
		85	Health and social work
	Household goods	36	Manufacture of furniture; manufacturing n.e.c.
	General industrials	25	Manufacture of rubber and plastic products
		74	Other business activities
	Food producers	5	Fishing, fish farming and related service activities
		15	Manufacture of food products and beverages
	Media	22	Publishing, printing and reproduction of recorded media
		92	Recreational, cultural and sporting activities
Low-tech	Fixed line telecommunications	64	Post and telecommunications
	Industrial metals	27	Manufacture of basic metals
	Electricity	40	Electricity, gas, steam and hot water supply
	Oil equipment, services & distribution	11	Extraction of crude petroleum and natural gas
	General retailers	52	Retail trade, except motor vehicles and motorcycles; repair of personal & household goods
		93	Other service activities
	Support services	51	Wholesale trade and commission trade, except of motor vehicles and motorcycles
		74	Other business activities
	Construction & materials	26	Manufacture of other non-metallic mineral products
		45	Construction
	Banks	65	Financial intermediation, except insurance and pension funding
	Gas, water & multiutilities	40	Electricity, gas, steam and hot water supply
		41	Collection, purification and distribution of water
	Oil & gas producers	11	Extraction of crude petroleum and natural gas
	Mobile telecommunications	64	Post and telecommunications
	Industrial transportation	60	Land transport; transport via pipelines
		63	Supporting and auxiliary transport activities; activities of travel agencies
		64	Post and telecommunications
	Beverages	15	Manufacture of food products and beverages

Table 1: Results (parameter estimates) from POLS, RE and SF models (dependent variable VA/E)*

	Whole sample			***High-tech***			***Med-high***			***Low-tech***		
Model	**POLS**	**RE**	**SF**	**POLS**	**RE**	**SF**	**POLS**	**RE**	**SF**	**POLS**	**RE**	**SF**
ln (K/E)	0.123	0.125	0.087	0.180	0.160	0.162	0.138	0.146	0.102	0.048	0.068	0.051
	(0.014)	(0.015)	(0.009)	(0.018)	(0.029)	(0.018)	(0.012)	(0.026)	(0.012)	(0.014)	(0.021)	(0.013)
ln (C/E)	0.122	0.117	0.075	-0.011	0.014	0.035	0.133	0.137	0.132	0.230	0.210	0.105
	(0.013)	(0.018)	(0.011)	(0.019)	(0.025)	(0.020)	(0.018)	(0.029)	(0.014)	(0.020)	(0.031)	(0.017)
ln (E)	-0.063	-0.092	-0.043	-0.036	-0.074	-0.007	-0.061	-0.072	-0.035	-0.084	-0.113	-0.087
	(0.007)	(0.013)	(0.006)	(0.010)	(0.019)	(0.009)	(0.012)	(0.022)	(0.009)	(0.014)	(0.022)	(0.010)
Constant	-0.189	0.096	-2.015	-1.863	-1.571	-1.792	-1.412	-1.231	-1.326	-0.598	-1.443	-0.306
	(0.183)	(0.220)	(0.086)	(0.149)	(0.221)	(0.151)	(0.149)	(0.309)	(0.141)	(0.188)	(0.252)	(0.211)
Determinants of												
inefficiency:			-3.992			-7.660			-0.694			---
R&D intensity[1]			(0.830)			(2.285)			(0.192)			---
			-12.715			0.675			---			-0.424
Capital intensity[1]			(2.887)			(0.295)			---			(0.190)
			---			---			---			1.040
Constant												(0.345)
Heteroscedasticity:			-0.255			-0.295			-0.454			-0.714
No of employees			(0.004)			(0.012)			(0.061)			(0.081)
			---			---			1.176			3.930
Constant									(0.548)			(0.721)
Wald test time-dummies (p-value)	8.80	95.28	53.51	3.30	29.53	7.89	3.66	32.22	20.69	7.17	58.15	55.20
	0.000	0.000	0.000	0.006	0.000	0.162	0.003	0.000	0.001	0.000	0.000	0.000
Wald T: sector-Ds in PF	46.62	368.21	1455.85	38.07	54.76	95.15	14.89	19.49	136.22	45.51	186.66	858.23
(p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000	0.000
Wald T: sector-Ds in σ_u			75.90			79.64			59.22			75.45
(p-value)			0.000			0.000			0.000			0.000
White heteroscedasticity test	671.84			188.43			246.47			245.16		
(p-value)	0.000			0.000			0.000			0.000		
R-squared (overall)	0.649	0.639		0.550	0.532		0.484	0.478		0.784	0.773	
R-squared (within)		0.245			0.190			0.283			0.334	
R-squared (between)		0.652			0.540			0.460			0.772	
F(*k*-1, N-(*k*-1))	83.73			46.61			36.51			86.03		
(p-value)	0.000			0.000			0.000			0.000		
Wald chi2(*k*-1)		972.14			673.05			185.74			616.20	
(p-value)		0.000			0.000			0.000			0.000	
Firms		1787			600			671			516	
Observations		532			170			196			166	

[1] 'Intensity' means calculated R&D (capital) stocks per employee, standardised by the sample mean.

Note: Robust standard errors in parentheses; all coefficients are significant at 95 % confidence level (apart from those underlined).

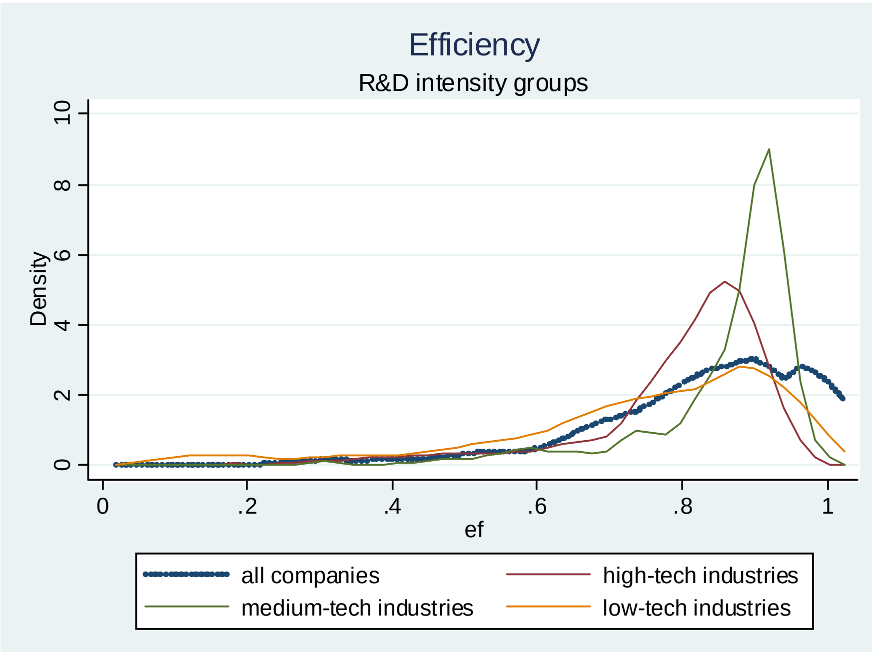
Table 2: Parameter estimates from the final restricted SF model (dependent variable VA/E)*

	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	-3.992	0.000	-5.5144	0.001	-0.6861	0.000	-0.4683	0.000
Capital intensity	-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	

* 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).

Figure 1: Technical efficiency by R&D intensity groups
Figure 2: Impact of companies' R&D intensity on their individual technical inefficiency



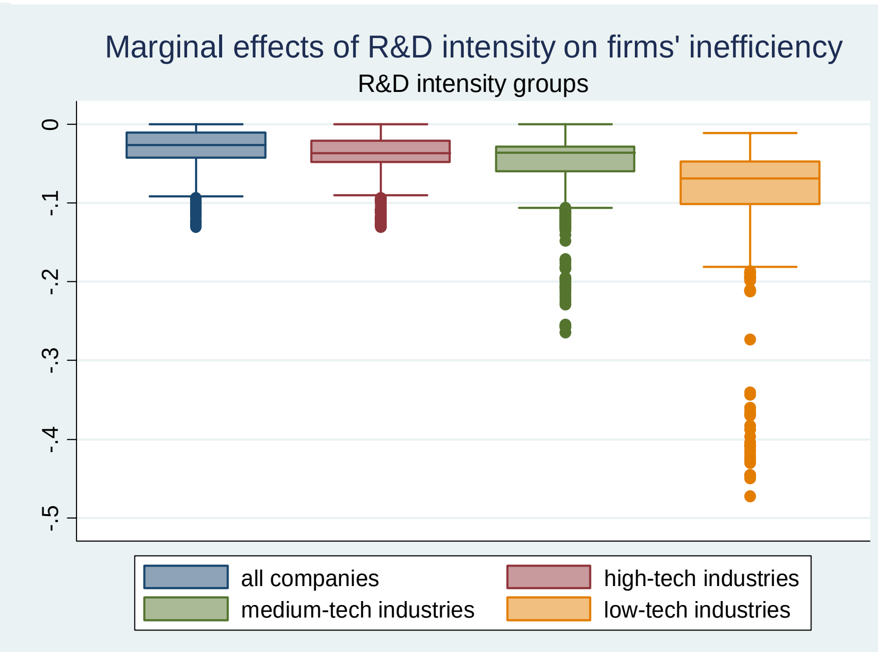


Table 3: Descriptive statistics on firm-level technical efficiency (as illustrated in Figure 1)

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

Table 4: Descriptive statistics for Figure 2 — Marginal effects of R&D intensity on firms' inefficiency per industry cluster

Marginal effects on inefficiency	No of observ.	Mean	Standard deviation	Min	Max
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

Table 5: Overview of TE estimates and marginal effects of R&D intensity on firms' inefficiency per sector

				TE estimates			Marginal effect of R&D intensity on firms' technical efficiency		
	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**