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R&D and productivity: testing sectoral peculiarities using micro data

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Abstract The aim of this study is to investigate the relationship between a firm's R&D activities and its productivity using a unique micro data panel dataset and looking at sectoral peculiarities which may emerge; more specifically, we used an unbalanced longitudinal database consisting of 532 top European R&D investors over the 6-year period 2000–2005. Our main findings can be summarised along the following lines: knowledge stock has a significant positive impact on a firm's productivity, with an overall elasticity of about 0.104; this general result is largely consistent with previous literature in terms of the sign, the significance and the estimated magnitude of the relevant coefficient. More interestingly, the coefficient increases monotonically when we move from the low-tech to the medium-high and high-tech sectors, ranging from a minimum of 0.03/0.05 to a maximum of 0.14/0.17. This outcome suggests that firms in high-tech sectors are still far ahead in terms of the impact on productivity of their R&D investments, at least as regards top European R&D investors.

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1 Introduction

Recent studies question the role of R&D as a fundamental determinant of a firm's improved economic performance (see Jaruzelski et al. 2005, 2006).[1] Indeed, the literature on the economics of innovation has focused on the role of R&D investment in enhancing a firm's productivity, while the final outcome in terms of sales growth, profits and shareholders' returns obviously depends on many factors other than R&D, such as advertising, economies of scale, the firm's market power, demand evolution and so on. In this article, the scope is limited to an investigation of the R&D/productivity link in order to see whether previous evidence supporting a positive and significant relationship can be confirmed by analysing the recent performance of a panel of 532 top European R&D investors.

Being limited to the investigation of the R&D-productivity link, this paper will not directly deal with the "rate of return" to R&D in terms of the eventual competitive advantage and output expansion. Hence, it is not within the aim and scope of this study to assess how much a dollar spent in R&D would provide in terms of increasing sales or profits, but simply assessing the significance and magnitude of the R&D-productivity elasticity.

A second issue in the current debate is the alleged advantage of low-tech compared with high-tech sectors in achieving productivity gains from R&D investments. The argument here is that catching-up low-tech sectors are investing less in R&D but benefit from a "late-comer advantage" (see Marsili 2001; Von Tunzelmann and Acha 2005; Mairesse and Mohnen 2005). If such was the case, we would expect a weaker relationship between R&D and productivity growth in high-tech sectors in comparison with their low-tech counterparts. This hypothesis contrasts with the previously available empirical evidence.[2] Hence, the second aim of this study is to investigate whether in low (high)-tech sectors there is a difference in the magnitude of the contribution of R&D investment in achieving productivity gains.[3]

The principal innovative aspects of this study are twofold. Firstly, we propose a sectoral breakdown, using firm-level micro data; this approach has very few antecedents

[1] While the Booz–Allen–Hamilton reports have not significantly influenced academia, they have had a great impact on the financial and economic specialised media, under headings such as "No Relationship Between R&D Spending and Sales Growth, Earnings, or Shareholder Returns"; "Lavish R&D Budgets Don't Guarantee Performance", "Money Isn't Everything", etc. Indeed, these reports are based on outcomes from naive bivariate spurious correlations which are affected by serious statistical drawbacks. As clearly stated by Hall et al. (2009, p. 3): "These reports use very simple tools, essentially "cross sectional" correlations without any controls for other firm characteristics that affect measured performance".

[2] See next section for a survey of this literature.

[3] The reader has to be reminded again of the scope of this study: while it is likely that the R&D/output relationship may show decreasing returns (turning out lower in the high-tech sectors), here the scope is to investigate whether this is also true in terms of productivity gains.

(reviewed in the next section). Secondly, we use a unique new longitudinal database comprising very recent data on 532 top European R&D investors which include both manufacturing and services.

To sum up, the objective of this study is to investigate the relationship between a firm's R&D investment and its productivity, using a unique micro data panel dataset and looking at any sectoral differences which may emerge. Section 2 gives a concise survey of the previous literature, while in Sect. 3 the data used and the adopted methodology are discussed, Sect. 4 deals with the empirical results and Sect. 5 briefly concludes.

2 Previous literature

There is a well-established stream of literature analysing the impact of R&D activities on productivity (for surveys of the earlier literature, see Mairesse and Sassenou 1991; Griliches 1995, 2000; Mairesse and Mohnen 2001). As of the seminal article by Griliches (1979), and up to and including more recent contributions such as those by Klette and Kortum (2004); Janz et al. (2004); Rogers (2006) and Lööf and Heshmati (2006), previous empirical works have found a significant contribution by R&D in enhancing a firm's productivity. The estimated overall average elasticities range from 0.05 to 0.25, depending on the methods of measurement and the data used.

Most of these studies focus either on cross-country analyses or on one specific sector, mainly dealing with high-tech sectors such as the pharmaceutical or ICT-related sectors. In contrast, considerably less attention has been devoted to determining whether the productivity gains from R&D are different across industrial sectors. Indeed, technological opportunities and appropriability conditions are so different across sectors (see Freeman 1982; Pavitt 1984; Winter 1984; Aghion and Howitt 1996; Dosi 1997; Greenhalgh et al. 2001; Malerba 2004) as to suggest the possibility of substantial differences in the specific sectoral R&D-productivity links. In this context, this article will try to address the following questions: are the productivity impacts of R&D investments equally significant across sectors? If this is the case, what are the differences in the magnitudes of these effects? Does the productivity of a firm in a high-tech sector benefit more from an increase in R&D than that of one in a low-tech sector, or vice versa?

At the same time, given that R&D input is generally added to labour and capital inputs in a production function framework, distinguishing by sectors will also allow us to better understand the impact of physical capital on productivity and how this may differ across sectors.

Although it targets sectoral differences, this study will be based on firm-level data; to our knowledge, not many studies have investigated the relationship between R&D and productivity on a sectoral basis and of these only a few have used micro data.

Examples are Griliches and Mairesse (1982) and Cuneo and Mairesse (1983), who performed two comparable studies using micro-level data and making a distinction between firms belonging to science-related sectors and firms belonging to other sectors. They found that the impact of R&D on productivity for scientific firms (elasticity equal to 0.20) was significantly greater than for other firms (0.10).

In a more recent article, Verspagen (1995) used OECD sectoral-level data on value added, employment, capital expenditures and R&D investment in a standard production function framework. The author singled out three macro sectors: high-tech, medium-tech and low-tech, according to the OECD classification (Hatzichronoglou 1997). The major finding of the study was that the impact of R&D was significant and positive only in high-tech sectors, while for medium and low-tech sectors, no significant effects could be found.

Using the methodology set up by Hall and Mairesse (1995) and also adopted in this study, Harhoff (1998) studied the R&D/productivity link—using a slightly unbalanced panel of 443 German manufacturing firms over the period 1977–1989—and found a significant impact ranging from a minimum of 0.068 to a maximum of 0.137, accordingly to the different specifications and the different econometric estimators adopted. Interestingly, the effect of R&D capital was considerably higher for high-technology firms rather than for the residual groups of enterprises. In particular, for the high-tech firms, the R&D elasticity always turned out to be highly significant and ranging from 0.125 and 0.176, while for the remaining firms the R&D elasticity resulted either not significant (although positive) or lower (ranging from 0.090 to 0.096), according to the different estimation techniques.

Wakelin (2001) applied a Cobb–Douglas production function where productivity was regressed on R&D expenditures, capital and labour using data on 170 UK-quoted firms during the period 1988–1992. She found R&D expenditure had a positive and significant role in influencing a firm's productivity growth; moreover, firms belonging to sectors defined as "net users of innovations" turned out to have a higher impact of R&D.

Rincon and Vecchi (2003) also used a Cobb–Douglas framework in dealing with micro-data extracted from the Compustat database over the time period 1991–2001. They found that R&D-reporting firms were more productive than their non-R&D-reporting counterparts throughout the entire time period. However, the positive impact of R&D expenditures turned out to be statistically significant both in manufacturing and services in the US, but only in manufacturing in the main three European countries (Germany, France and the UK). Their estimated significant elasticities ranged from 0.15 to 0.20.

Kwon and Inui (2003) analysed 3,830 Japanese firms with no less than 50 employees in the manufacturing sector over the period 1995–1998, also using the methodology set up by Hall and Mairesse (1995). Using different estimation techniques, they found a significant impact of R&D on labour productivity, with high-tech firms systematically showing higher and more significant coefficients than medium- and low-tech firms.

Finally, Tsai and Wang (2004) also applied a Cobb–Douglas production function to a stratified sample of 156 large firms quoted on the Taiwan Stock Exchange. Their estimates made use of a balanced panel over the 7-year period from 1994 to 2000. They found that R&D investment had a significant and positive impact on the growth of a firm's productivity (with an elasticity equal to 0.18). When a distinction was made between high-tech and other firms, this impact was much greater for high-tech firms (0.3) than for other firms (0.07).

Overall, previous general and extensive empirical evidence on the subject supports the hypothesis of a positive and significant impact of R&D on productivity at country, sector and firm level. More specifically, previous studies including cross-section sectoral breakdowns seem to suggest a greater impact of R&D investments on firm productivity in the high-tech sectors rather than in the low-tech ones. These results will be tested again through a panel analysis applied to the unique dataset described in the next section.

3 Data and methodology

We used an unbalanced longitudinal database consisting of 577 top European R&D investors over the 6-year period 2000–2005.[4] This unique database was constructed by merging UK-DTI R&D Scoreboard data and UK-DTI Value Added Scoreboard data.[5] The UK Department of Trade and Industry (DTI) collects detailed and tracked data on the larger European firms in terms of R&D investment and value added (VA); the two separate DTI datasets contain information at the firm level, distinguishing by country and sector.[6] By merging the two databases we obtained the necessary information to compute our dependent variable (labour productivity, defined as the VA per employee ratio), our main impact variable (R&D[7]) and our additional variables (capital and labour). Of the 577 firms, 27 firms belonging to marginal sectors were dropped,[8] six outliers were excluded according to the results of Grubbs' tests centred on the sectoral average growth rates of firms' knowledge stock intensity (K/VA) over the investigated period,[9] and 12 additional firms were dropped for reasons related to the computation of the R&D and capital initial stocks in the year 2000.[10] Finally, M&A were treated in a way that does not compromise the comparability of longitudinal data; specifically,

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[4] The econometric results discussed in the next section are fully consistent with those obtainable from the restricted balanced panel of 105 firms (630 obs.), available upon request. The use of panel data is commonplace in the recent literature, starting from the seminal contribution of Hall and Mairesse (1995); indeed, in order to investigate the link between R&D and productivity, both *between* the firms and *within* the firm variability must be taken into account.

[5] Different editions of the DTI Scoreboards are downloadable from the website: www.innovation.gov.uk/rd_scoreboard.

[6] Although including data from 14 European countries (Austria (3 companies), Belgium (6), Denmark (9), Finland (9), France (43), Germany (45), Ireland (2), Italy (7), Norway (3), Spain (4), Sweden (16), Switzerland (20), the Netherlands (9) and the UK (356)), British firms are over-represented in the DTI databases. For a more detailed view on the country composition of the sample, see Table A2 in Appendix A.

[7] The measurement of R&D investment is subject to accounting definitions for R&D. In particular, for UK companies, the applied definition is that contained in the Statement of Standard Accounting Practice (SSAP) 13: "Accounting for research and development". As far as non-UK companies are concerned, the definition is that contained in the International Accounting Standard (IAS) and corresponding to the R&D component of the accounting category 38: "Intangible assets". Both figures are based on the OECD "Frascati" manual definition of corporate R&D and therefore are fully comparable.

[8] In the following analysis we kept only 28 of the original 39 DTI sectors, having excluded sectors with less than five firms (see Table A1).

[9] For a definition of K, see below. Notice that Grubbs' test—also known as the maximum normalised residual test—assumes normality (which is a desirable property anyway). Accordingly, we ran normality tests on the relevant variables and this assumption was never rejected. Results from both Grubb's and normality tests are available on request.

[10] See Eqs. 2–5 below; in the rare cases 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.

when an M&A occurs, a new entry appears in the database, while the merged firms exit.

It has to be underlined that the final sample of 532 firms still comprises very large top European R&D investors. This obvious sample bias—inherited from the original datasets we used in this study—has two important consequences. Firstly, our results cannot easily be generalised but should be considered pertinent to large firms heavily engaged in R&D activities. Secondly, this kind of "pick the winner" effect is particularly severe in low-tech sectors, where the "real" populations are dominated by small firms which are scarcely or not at all engaged in R&D investment (Becker and Pain 2002).

As far as the sectoral classification is concerned, the original DTI datasets related firms to 39 industrial and service sectors, defined according to the Industry Classification Benchmark (ICB)[11]. As we were interested in singling out sectoral differences in the R&D/productivity relationship, we split our panel into three subgroups of comparable size: high-tech, medium-high-tech and other sectors (medium-low and low-tech sectors).[12] *Ex ante*, we endogenously grouped the sectors according to their overall R&D intensity (R&D/VA), assuming the thresholds of 5 and 15%.[13] *Ex post*, we compared the outcome of our taxonomy with the OECD classification, and we registered a high degree of consistency at least as far as the comparable manufacturing sectors are concerned.[14] The remaining service sectors were allocated accordingly. Table A1 in Appendix A, gives the sectors under analysis grouped in the three technological categories, their R&D intensities and other descriptive information including the corresponding OECD classification.

Turning our attention to the econometric analysis, we started from the following specification, obtainable from a standard production function (see Griliches 1986; Lichtenberg and Siegel 1989; Hall and Mairesse 1995; Verspagen 1995).

$$\ln(\mathrm{VA}/E) = \alpha + \beta \ln(K/E) + \gamma \ln(C/E) + \lambda \ln(E) + \delta T + \lambda C + \vartheta S + \eta_i + \nu_{i,t}$$
$$\text{with: } i = 1, \ldots, 32; \quad t = 2000, \ldots, 2005 \qquad (1)$$

where η is the idiosyncratic individual effect, and ν is the usual error term. All the variables were taken in natural logarithms and deflated according to the different national

[11] The detailed ICB sectoral classification is given on the following website: http://www.icbenchmark.com

[12] Compared with the OECD classification, we grouped low-tech and middle-low-tech sectors together, in order to have enough observations in each of the sectoral groups. We adopted a classification based on R&D intensity, rather than more articulated taxonomies such as that proposed by Pavitt (1984), for different reasons. Firstly, this article, only deals with R&D, leaving apart other dimensions of innovation; secondly, we cannot deal with intersectoral innovation flows that are central in Pavitt's analysis; thirdly, the OECD-type classification is still adequate to guide R&D policy and suggest policy implications at the European level (see Sect. 5).

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

[14] Only two sectors (automobile and food) turned out to be up-graded; this is also a consequence of dealing with top R&D investors.

GDP deflators provided by EUROSTAT[15]. In all the following estimates, time (T), country (C) and two-digit sector dummies (S) were implemented in order to take into account both common macroeconomic effects and sectoral peculiarities. Both yearly, country and sectoral dummies turned out to be significant in both the aggregate and the three sectoral estimates.[16]

In accordance with data availability, our proxy for a firm's productivity is labour productivity, our pivotal impact variable is the knowledge capital (K) per employee, and our second impact variable is physical capital (C) per employee. Taking per capita values is a rather standard procedure in the recent literature (see Hall and Mairesse 1995, p. 269; Crépon et al. 1998, p.123; Harhoff 1998, p. 35; Kwon and Inui 2003, p. 5). Total employment (E) is a control variable, and λ measures the scale elasticity (if greater than zero, it indicates increasing returns).[17]

As is common practice in this type of literature (see Hulten 1991; Jorgenson 1990; Hall and Mairesse 1995; Bönte 2003; Parisi et al. 2006), stock indicators (rather than flows) were inserted as impact variables; indeed—as extensively discussed by the benchmark literature (for a comprehensive reference, see Griliches 2000)—a firm's productivity is affected by the cumulated stocks of capital and R&D expenditures and not only by current or lagged flows. In this framework, knowledge and physical capital stocks were computed using the *perpetual inventory method* based on the following formulas:

$$K_{t0} = \frac{R\&D_{t0}}{(g_{s,c} + \delta_j)} \quad \text{with: } s = 1, \ldots, 28,\ c = 1, \ldots, 14,\ j = 1, 2, 3,\ t0 = 2000 \tag{2}$$

$$K_t = K_{t-1} \cdot (1 - \delta_j) + R\&D_t \quad \text{with: } t = 2000, \ldots, 2005 \tag{3}$$

where $R\&D$ = R&D expenditures
and

[15] Although most of the investigated firms are multinationals operating in different countries, the data come from the consolidated account balances at their headquarters and firms are allocated according to the location of their headquarters; hence, we think that national deflators are adequate to deflate the collected data. In principle, since multinational firms operate in different countries, some kind of purchasing parity power (PPP) adjustment might be desirable; however, this correction is not possible with the available data that are extracted from the headquarter consolidated accounts.

[16] As far as the latter are concerned, this means that even within the sectoral subgroups, specific two-digit technological opportunities and appropriability conditions continue to play an important role.

[17] It has to be admitted that specification (1) is rather standard, although adequate to the scope and aims of this study and consistent with the limitations of our data. More comprehensive studies based on different datasets such as the CIS (Community Innovation Survey) generally consider Eq. refeq1, as one of the three-equation model where the determinants of productivity are studied together with a knowledge production function and a base equation modelling the decision to engage in R&D activities or not (see Crépon et al. 1998). Unfortunately, our database does not include either non-R&D firms or data on innovative output and this does not allow to put forward a simultaneous system approach.

By the same token, the short time span of the dataset (6 years) does not allow to investigate the possible non-stationarity of the data (as in Los and Verspagen 2000) and makes a GMM specification extremely disputable (on this regard see also footnote 29).

$$C_{t0} = \frac{I_{t0}}{(g_{s,c} + \delta_j)} \tag{4}$$

$$C_t = C_{t-1} \cdot (1 - \delta_j) + I_t \tag{5}$$

where I = gross investment (capital expenditures)

As far as the growth rates (g) in (2) and (4) are concerned, we used the OECD ANBERD and the OECD STAN databases respectively. In particular, we computed the compounded average rates of change in real R&D expenditures and fixed capital expenditures in the relevant sectors (s) and countries (c)[18] over the period 1990–1999 (the ten-year period preceding the period investigated in this study).[19]

As far as the depreciation rates (δ) for K and C are concerned, we chose to apply different δ to each of our three sectoral groups (j). In fact, more technologically advanced sectors are characterised (on average) by shorter product life cycles and by a faster technological progress that accelerates the obsolescence of the current knowledge and physical capital.[20] Accordingly, we applied sectoral depreciation rates of 20, 15 and 12% to the knowledge capital and 8, 6 and 4% to the physical capital (respectively for the high tech, medium-high-tech and medium-low/low-tech sectors). The resulting 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 (Musgrave 1986; Bischoff and Kokkelenberg 1987; and Nadiri and Prucha 1996 for physical capital; Pakes and Schankerman 1986; Hall and Mairesse 1995; Hall 2007 and Aiello and Cardamone 2008 for knowledge capital).

4 Results

Table 1 gives some descriptive statistics regarding the main variables in our study (computed at the final year, 2005).

As can be seen, the per-capita R&D stock (K/E) is—not surprisingly—significantly different in the three sectoral groups and turns out to be consistent with our classification based on R&D intensity (R&D/VA). While high-tech firms are characterised by a higher knowledge stock, low-tech firms appear to be larger, much more capital intensive (C/E) and more productive (VA/E). All these characteristics are correlated

[18] See Table B1 in Appendix B for a detailed view of the OECD to ICB sectoral conversion. German sectoral figures were applied to Swiss firms because of the unavailability of OECD data.

[19] While this procedure—based on computing a pre-sample g—is rather standard in the literature (see Hall and Mairesse 1995; Harhoff 1998; Parisi et al. 2006), it obviously involves some degree of arbitrariness. An alternative methodology is to endogeneously compute g using the first periods of the available panel data. However, this procedure has the unpleasant consequence of loosing a large part of the available information (in our case, say 3 years out of the 6 available). In general terms, the choice of a feasible g does not significantly affect the final econometric results of the studies. As clearly stated by Hall and Mairesse (1995, p. 270, footnote 9): "In any case, the precise choice of growth rate affects only the initial stock, and declines in importance as time passes,…".

[20] Physical capital also embodies technology, and rapid technological progress makes scrapping more frequent.

Table 1 Descriptive statistics

Variable	All firms		High-tech		Medium-high		Low-tech	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
VA/*E*	0.068	0.062	0.063	0.037	0.053	0.024	0.095	0.100
K/*E*	0.032	0.049	0.062	0.069	0.021	0.026	0.012	0.013
C/*E*	0.473	1.756	0.158	0.400	0.135	0.176	1.280	3.091
E	36120	62434	40626	73890	22736	38350	48258	69635

Figures are in million euros

with the "pick the winner" bias (see previous section) which is obviously more marked within the low-tech sectors.[21]

Figures 1, 2 and 3 in Appendix A show the density functions for the relevant variables (in natural logarithms, as they will be used in the regressions) in the last available year (2005); overall and macro-sectoral distributions are reported. Tables with the basic statistics regarding the variables are also included to aid better understanding of the data.

As can be seen, the 2005 density functions are in line with the overall figures reported in Table 1. It should be noted that the possibly greater "pick the winner" bias within the low-tech sectors renders these sectors more likely to turn out to be more efficient in terms of the R&D/productivity link.[22] However, this does not seem to be the case, at least from the preliminary results reported in the correlation matrices in Table 2.

On the basis of this preliminary and univariate exercise, and consistently with the previous studies discussed in Sect. 2, the R&D-productivity link turns out to be positive and significant overall, but more obvious once we move from the low-tech to the medium-high-tech and finally to the high-tech sectors. A reverse pattern seems to emerge as far as the productivity impact of physical capital is concerned.

Indeed, this first evidence is confirmed by the econometric analysis reported in Table 3. Specification (1) was tested through pooled ordinary least squares (POLS) and random effects (RE) models. We chose a random rather than a fixed effects specification for various reasons. Firstly, the nature of our unbalanced short panel (six years with an average of 3.4 observations available per firm) severely affects the within-firm

[21] The original DTI dataset selects top UK and foreign R&D investors on the basis of aggregate rankings (in turn based on absolute R&D figures) independently from sectoral representativeness. This implies that only outstanding firms in low-tech sectors are taken into consideration. The cut off point is variable and corresponds to the threshold reached after obtained the targeted number of firms that the Scoreboard is intended to report. For example, in the case of the 2001 R&D DTI Scoreboard, 500 international companies and 597 UK firms were reported in descending order, based on their absolute R&D figures.

[22] As will become clear from the following analysis, this is not at all the case. However, the sample bias affecting our data (which we cannot control for, since our statistical source does not include non-R&D firms) should not make the obtained results more likely, its possible influence actually working in the opposite direction. In fact—as is clear from Table 1 and Figs. 1–3—the selected low-tech firms turn out to be larger and more capital-intensive than their more technologically oriented counterparts. Assuming possible scale economies in R&D activities (see Piga and Vivarelli 2004) and innovative complementarities see (see Catozzella and Vivarelli 2007), this selection bias should render a greater impact of R&D expenditures on productivity more likely in the selected "best" low-tech firms.

Table 2 Correlation matrices

	All firms			High-tech		
	ln(VA/*E*)	ln(*K/E*)	ln(*C/E*)	ln(VA/*E*)	ln(*K/E*)	ln(*C/E*)
ln(VA/*E*)	1.0000			1.0000		
ln(*K*/*E*)	0.3455	1.0000		0.6147	1.0000	
	(0.0000)			(0.0000)		
ln(*C*/*E*)	0.5414	0.0816	1.0000	0.1180	0.2973	1.0000
	(0.0000)	(0.0006)		(0.0000)	(0.0000)	
	Medium-high			Low-tech		
ln(VA/*E*)	1.0000			1.0000		
ln(K/E)	0.5202	1.0000		0.4046	1.0000	
	(0.0000)			(0.0000)		
ln(*C*/*E*)	0.4605	0.2994	1.0000	0.7039	0.3388	1.0000
	(0.0000)	(0.0000)		(0.0000)	(0.0000)	

p values in parentheses

variability component of our data. Secondly, and consistently with the previous observation, the within-firm component of the variability of the dependent variable turns out to be overwhelmed by the between-firms component (the standard deviations being 0.15 and 0.58, respectively).[23] Thirdly, the Hausman test comparing the random and fixed effects models for the whole sample clearly supports the former ($\chi^2 = 4.65$, p value $= 0.79$).

As expected, all the estimated specifications turned out to be affected by heteroskedasticity (White 1980); hence, robust standard errors were used. In particular, in the following regressions we used the Eicker/Huber/White sandwich estimator (see Wooldridge 2002; Arellano 2003 for a detailed analysis of the application of this robust estimator to random-effects methodology; see also Baltagi 2008).

As can be seen, the knowledge stock has a significant positive impact on a firm's productivity with an overall elasticity of 0.104; this general result is largely consistent with the previous literature both in terms of the sign, the significance and the estimated magnitude of the relevant coefficient. 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 0.03/0.05 (barely significant) to a maximum of 0.14/0.17 (highly significant). This outcome—highly significant and confirmed by the two methodologies—is consistent with the previous empirical contributions discussed in Sect. 2.

However, these results do not mean that a dollar spent on high-tech R&D earns more than one spent on low-tech R&D. In fact, it may well be the case that a lower

[23] As robustness checks, between estimates—just using the cross-sectional variation of data—were run and outcomes were consistent and similar to those obtained from the more comprehensive random effects estimates reported in the following Table 3 (results available upon request).

Table 3 Econometric estimates; dependent variable: ln(VA/*E*)

Model specification	Whole sample		High-tech		Medium-high		Low-tech	
	POLS	RE	POLS	RE	POLS	RE	POLS	RE
ln(*K*/*E*)	0.104	0.104	0.169	0.138	0.115	0.126	*0.029*	*0.047*
	(0.009)	(0.017)	(0.019)	(0.030)	(0.014)	(0.031)	(0.015)	(0.026)
ln(*C*/*E*)	0.132	0.123	**0.002**	**0.017**	0.154	0.147	0.245	0.223
	(0.013)	(0.018)	(0.019)	(0.024)	(0.019)	(0.031)	(0.021)	(0.032)
ln(*E*)	−0.078	−0.115	−0.059	−0.118	−0.086	−0.089	−0.092	−0.127
	(0.009)	(0.017)	(0.014)	(0.028)	(0.014)	(0.027)	(0.018)	(0.028)
Wald time-dummies joint significance test	7.67	95.68	2.97	29.93	3.87	32.37	6.46	54.63
(p value)	(0.000)	(0.000)	(0.012)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
Wald sector-dummies joint significance test	46.04	382.93	28.16	43.91	14.05	19.98	36.35	161.23
(p value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.023)
Wald country-dummies joint significance test	8.11	32.70	21.285	85.55	30.11	79.34	6.38	**19.06**
(p value)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.087)
White heterosk. test	869.47		271.27		289.96		326.02	
(p value)	(0.000)		(0.000)		(0.000)		(0.000)	
R^2(overall)	0.663	0.651	0.581	0.556	0.515	0.507	0.802	0.789
R^2 (within)		0.247		0585		0.281		0.336
R^2 (between)		0.668		0.199		0.495		0.791
Observations	1787		600		671		516	
Firms	532		170		196		166	

Robust standard errors in brackets; all coefficients are significant at the 99% level of confidence apart from those in bold (not significant) and those in *italics* (significant at 90%)

R&D-productivity elasticity (say 4% in the low-tech sectors) propagates more deeply into the market thanks—for instance—to a higher demand elasticity.[24]

As far as the other variables are concerned, physical capital also increases a firm's productivity, with an overall elasticity equal to 0.12/0.13. However, this effect is concentrated in low-tech and medium-high tech sectors, while it is not significant in the high-tech sectors. This evidence seems to suggest that "embodied technological change"[25] is crucial in all sectors except for the high-tech ones, where technological progress is mainly introduced through R&D investments and new products rather than new processes.[26]

Finally, the investigated firms reveal decreasing returns with the (relatively) smaller firms showing higher productivity gains.[27] Diagnosis tests reveal the satisfactory fitness of the chosen models and the usefulness of including both the time, sectoral and country sets of dummies.[28]

Table 4 presents the results of a robustness check consisting in replicating the estimates of (1) with all the regressors lagged one period, in order to check for possible endogeneity problems.[29] As can be seen, results remain very stable, with the knowledge stock coefficients monotonically increasing when moving from the low-tech to the high-tech sectors and the reverse happening for the physical capital stock coefficients. The diagnosis statistics do not significantly differ from those reported in the previous table, supporting the validity of the selected econometric models.

Finally, we tried to control for the important role of spillovers. As commonly found in the literature (see Bernstein and Nadiri 1989; Los and Verspagen 2000; Medda and Piga 2007), we proxied intra-sectoral spillovers[30] through total sectoral

[24] As stated in the Sect. 1, this article is not addressed to assess the final outcome of R&D investment in terms of market performance.

[25] 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 crucial role played by embodied technological change in traditional sectors, see Santarelli and Sterlacchini (1990) and Conte and Vivarelli (2005).

[26] As in the case of R&D, the reader has to be reminded of the fact that this result means that capital formation is more effective in increasing labour productivity within the low-tech sectors and not that the rate of return of investment is higher in the same sectors.

[27] It has to be noticed that this is not an argument in favour of the role of R&D in SMEs, since our sample is made up only of large firms.

[28] The estimates of the single dummies and the constant are not displayed in the tables, but are available upon request.

[29] In principle, a GMM specification (see Arellano and Bond 1991; Blundell and Bond 1998) may appear a possible solution to the endogeneity problem. However, this is not the option pursued either in the previous literature (see Sect. 2) or in this paper. Indeed, the sound reasons supporting a specification in stocks make redundant and possibly inadequate the GMM methodology; moreover, the short nature of our panel would imply a substantial loss of observations in running either a GMM-DIF or a GMM-SYS estimation.

[30] With our data, we have no way of controlling for inter-sectoral spillovers; however, given our level of sectoral disaggregation (basically two-digit), it can legitimately be assumed that most spillovers are intra-sectoral. As outlined by the seminal contributions of Cohen and Levinthal (1989, 1990), R&D expenditures are a way to enforce firm's "absorptive capacity" in acquiring knowledge from external sources. In turn,

Table 4 First robustness check with lagged variables; dependent variable: ln(VA/*E*)

Model specification:	Whole sample		High-tech		Medium-high		Low-tech	
	POLS	RE	POLS	RE	POLS	RE	POLS	RE
$\ln(K/E)_{t-1}$	0.100	0.078	0.175	0.157	0.106	*0.056*	*0.031*	*0.024*
	(0.012)	(0.020)	(0.024)	(0.033)	(0.018)	*(0.033)*	*(0.018)*	(0.033)
$\ln(\mathrm{C/E})_{t-1}$	0.149	0.106	*0.004*	*0.005*	0.168	*0.052*	0.277	0.239
	(0.016)	(0.022)	(0.027)	(0.038)	(0.023)	(0.038)	(0.024)	(0.034)
$\ln(\mathrm{E})_{t-1}$	−0.058	−0.058	−0.048	*−0.078*	−0.059	*−0.018*	−0.058	*−0.050*
	(0.011)	(0.021)	(0.017)	(0.032)	(0.019)	(0.043)	(0.021)	*(0.033)*
Wald time-dummies joint significance test	4.08	54.38	2.76	19.33	*1.25*	25.12	6.46	41.92
(p value)	(0.003)	(0.000)	(0.032)	(0.000)	*(0.290)*	(0.000)	(0.000)	(0.000)
Wald sector-dummies joint significance test	34.79	242.45	19.27	35.44	10.65	30.37	28.18	84.25
(p value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wald country-dummies joint significance test	6.74	20.65	7.09	9.22	17.45	89.83	15.03	41.78
(p value)	(0.000)	(0.056)	(0.000)	(0.417)	(0.000)	(0.000)	(0.000)	(0.000)
White heterosk. test	528.56		234.62		214.47		*216.20*	
(p value)	(0.000)		(0.000)		(0.000)		*(0.038)*	
R^2 (overall)	0.683	0.667	0.595	0.580	0.535	0.440	0.841	0.834
R^2 (within)		0.136		0.199		0.080		0.265
R^2 (between)		0.671		0.581		0.449		0.830
Observations	1214		414		464		336	
Firms	403		133		154		116	

Robust standard errors in brackets; all coefficients are significant at least at the 95% level of confidence apart from those in italics (not significant)

Table 5 Second robustness check including spillovers; dependent variable: ln(VA/E)

Model specification	Whole sample		High-tech		Medium-high		Low-tech	
	POLS	RE	POLS	RE	POLS	RE	POLS	RE
ln(K/E)	0.103	0.101	0.169	0.141	0.111	0.122	*0.025*	*0.044*
	(0.009)	(0.017)	(0.019)	(0.032)	(0.014)	(0.031)	(0.016)	(0.026)
ln(C/E)	0.135	0.128	*−0.003*	*0.013*	0.158	0.151	0.252	0.237
	(0.014)	(0.019)	(0.019)	(0.025)	(0.020)	(0.031)	(0.021)	(0.033)
ln($S_{\text{sect\_OECD}}$)	*0.006*	*0.008*	0.022	*0.009*	0.021	0.015	*−0.016*	*0.009*
	(0.005)	(0.004)	(0.010)	(0.007)	(0.008)	(0.006)	(0.010)	(0.010)
ln(E)	*−0.081*	−0.116	−0.058	−0.118	−0.089	−0.092	−0.093	−0.129
	(0.009)	(0.017)	(0.014)	(0.028)	(0.014)	(0.027)	(0.018)	(0.028)
Wald time-dummies joint significance test	7.43	90.05	3.12	28.67	3.70	31.75	6.83	53.60
(p value)	(0.000)	(0.000)	(0.009)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)
Wald sector-dummies joint significance test	45.42	288.59	26.47	41.54	14.74	19.49	35.52	160.35
(p value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
Wald country-dummies joint significance test	8.43	33.52	19.17	79.61	26.95	75.25	6.43	20.56
(p value)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.057)
White heterosk. test	937.27		281.62		331.33		339.95	
(p value)	(0.000)		(0.000)		(0.000)		(0.000)	
R^2 (overall)	0.664	0.653	0.584	0.559	0.521	0.514	0.805	0.791
R^2 (within)		0.247		0.198		0.288		0.344
R^2 (between)		0.668		0.586		0.503		0.793
Observations	1753		589		671		508	
Firms	527		168		196		165	

Robust standard errors in brackets; all coefficients are significant at least at the 95% level of confidence apart from those in italics (not significant)

R&D expenditures. We obtained the relevant national/sectoral figures from the OECD-ANBERD database, which is the only official source to provide reliable and comparable sectoral data concerning company R&D activities. Unfortunately, this statistical source is updated only to 2003 and so we extrapolated figures for 2004 and 2005 using the compounded average rates of change over the previous four-year period. Then flows were transformed into sectoral stocks per employee using the same procedures described in Eqs. 2–5. As can be seen from the following Table 5, although generally positive, the spillover coefficients ($\ln S/E$) are rarely significant; previous results remain virtually unchanged.[31]

5 Conclusions

While the general link between R&D and productivity has been proved by previous literature, very few studies have provided empirical evidence about possible sectoral differences in the productivity gains obtainable from R&D activities. In order to fill this gap, in this research we conducted a detailed analysis of the effect of R&D expenditures on firms' productivity using panel micro-data based on information from the top European R&D investors. The main results can be summarised along the following lines:

Firstly, the positive and significant impact of R&D on productivity is always confirmed. While this result does not fully dispel the concern about the lack of a link between R&D and the ultimate economic performance of a firm (since the latter is dependent on many other factors), it clearly suggests that R&D is a fundamental determinant of possible competitive advantage.

Secondly, firms in high-tech sectors not only invest more in R&D, but also achieve more in terms of productivity gains connected with research activities. Indeed, our results show that firms in high-tech sectors are still far ahead in terms of the productivity impact of their research activities, at least among the top European R&D investors. Moreover, productivity growth in low-tech firms is still heavily dependent on investment in physical capital (*embodied technological change*).

While providing new evidence on the relationship between R&D and productivity, the approach put forward in this article can be further extended by future research. In particular—using different micro datasets—it would be interesting to fully investigate the link between R&D and firm's profitability, properly taking into account other determinants of firm's performance such as firm's market power, demand elasticity and investment in intangibles other than R&D, like advertisement.

Footnote 30 continued
these spillovers may be an important source of firm's productivity gains and so should be controlled for in our empirical exercise.

[31] A further attempt is reported in the Table C1 in Appendix C where we used an alternative spillover indicator, endogenously constructed using our own data. Using DTI data allow us to avoid arbitrary extrapolation procedures; however, paucity of information prevents us from the possibility to extract specific sector/country spillover data. Hence, we used the total R&D stocks in the relevant sectors all over Europe, so also taking into account possible international (but still intra-sectoral) spillovers. The obtained "large firm spillover stock" variable was never significant; however, main results turned out to be robust.

Appendix A: Sample composition and main variable description

See Tables A1, A2 and Figs. 1, 2 and 3.

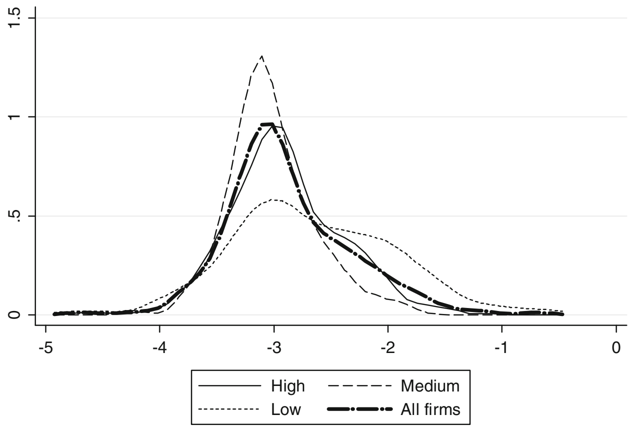
Table A1 Sectoral classification and composition of the samples

	R&D intensity	OECD classification (manufacturing only)	Firms	Observations
High-tech	0.21		170	600
Technology hardware and equipment	0.41	High	22	77
Pharmaceuticals and biotechnology	0.28	High	30	120
Leisure goods	0.25	High	7	25
Aerospace and defence	0.20	High	21	82
Automobiles and parts	0.16	Medium-high	37	140
Software and computer services	0.16		21	56
Electronic and 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 and 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[a]	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 and distribution	0.02		7	22
General retailers	0.02		9	29
Support services	0.02		22	67
Construction and materials	0.02		15	65
Banks	0.02		6	6
Gas, water and multiutilities	0.01		23	75
Oil and 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

[a] In this and the following tables the medium-low/low-tech sectors group is indicated as 'low-tech'

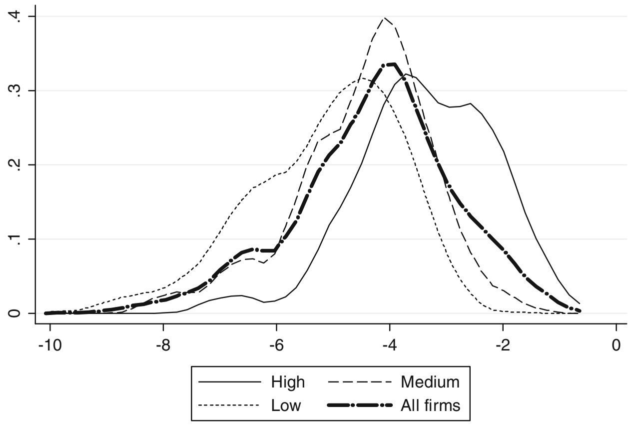
Table A2 Country composition of the sample

Countries	Firms	Observations
Austria	3	8
Belgium	6	20
Denmark	9	28
Finland	9	28
France	43	159
Germany	45	187
Ireland	2	2
Italy	7	27
Norway	3	11
Spain	4	14
Sweden	16	69
Switzerland	20	73
The Netherlands	9	37
UK	356	1124
Total general	532	1787



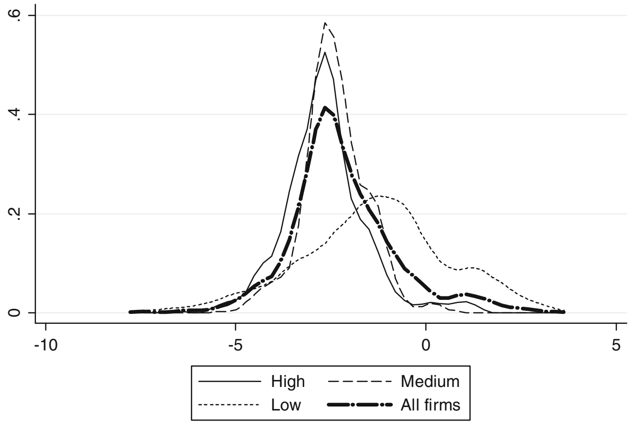
Variable	*All firms*		*High-tech*		*Medium-high*		*Low-tech*	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
ln(VA/E)	-2.879	0.564	-2.901	0.501	-3.031	0.388	-2.651	0.733

Fig. 1 ln(VA/*E*) distribution per sector group in 2005



Variable	All firms		High-tech		Medium-high		Low-tech	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
ln(K/E)	-4.291	1.418	-3.377	1.201	-4.467	1.204	-5.117	1.317

Fig. 2 ln(K/E) distribution per sector group in 2005



Variable	All firms		High-tech		Medium-high		Low-tech	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
ln(C/E)	-2.176	1.422	-2.649	1.077	-2.388	0.844	-1.357	1.931

Fig. 3 ln(C/E) distribution per sector group in 2005

Appendix B

See Table B1.

Table B1 ICB-NACE conversion

	ICB	NACE	
		Code	Division name
High-tech	Technology hardware and 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 and 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 and defence	35	Manufacture of other transport equipment
		75	Public administration and defence; compulsory social security
	Automobiles and parts	25	Manufacture of rubber and plastic products
		34	Manufacture of medical, precision and optical instruments, watches and clocks
			Manufacture of motor vehicles, trailers and semi-trailers
	Software and computer services	72	Computer and related activities
	Electronic and 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 (except 2441)
	Industrial engineering	29	Manufacture of machinery and equipment n.e.c.
		35	Manufacture of other transport equipment
	Health care equipment and 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	26	Manufacture of rubber and plastic products
		74	Other business activities
	Food producers	5	Fishing, fish farming and related service activities

Table B1 Continued

	ICB	NACE	
		Code	Division name
		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 and distribution	11	Extraction of crude petroleum and natural gas; service activities incidental to oil and gas extraction, excluding surveying
	General retailers	52	Retail trade, except of motor vehicles and motorcycles; repair of personal and 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 and materials	26	Manufacture of other non-metallic mineral products
		45	Construction
	Banks	65	Financial intermediation, except insurance and pension funding
	Gas, water and multiutilities	40	Electricity, gas, steam and hot water supply
		41	Collection, purification and distribution of water
	Oil and gas producers	11	Extraction of crude petroleum and natural gas; service activities incidental to oil and gas extraction, excluding surveying
	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

Appendix C: Spillover effects

See Table C1.

Table C1 Spillover effects: European R&D stock (DTI source)

Model specification	Whole sample		High-tech		Medium-high		Low-tech	
	POLS	RE	POLS	RE	POLS	RE	POLS	RE
$\ln(K/E)$	0.104	0.104	0.169	0.138	0.115	0.126	*0.029*	*0.048*
	(0.009)	(0.017)	(0.019)	(0.030)	(0.014)	(0.031)	(0.015)	(0.026)
$\ln(C/E)$	0.132	0.123	*0.002*	*0.017*	0.154	0.147	0.246	0.223
	(0.013)	(0.019)	(0.019)	(0.024)	(0.020)	(0.031)	(0.021)	(0.032)
$\ln(\mathrm{S}_{sect\_DTI})$	*−0.020*	*−0.017*	*0.025*	*−0.034*	*−0.016*	*−0.033*	*0.017*	*0.007*
	(0.063)	(0.053)	(0.125)	(0.085)	(0.113)	(0.060)	(0.083)	(0.078)
$\ln(E)$	*−0.099*	−0.132	*−0.034*	−0.152	*−0.087*	−0.122	*−0.075*	*0.120*
	(0.064)	(0.056)	(0.127)	(0.097)	(0.113)	(0.066)	(0.084)	(0.080)
Wald time-dummies joint significance	3.17	24.37	1.12	14.05	2.18	20.06	3.40	27.58
test (p value)	(0.008)	(0.000)	(0.347)	(0.015)	(0.054)	(0.001)	(0.005)	(0.000)
Wald sector-dummies joint significance test	45.55	277.92	28.08	35.21	14.04	17.04	34.50	87.64
(p value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
Wald country-dummies joint significance test	8.12	32.74	21.14	84.61	30.10	50.69	6.35	18.68
(p value)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.067)
White heterosk. test	895.72		280.70		292.63		346.83	
(p value)	(0.000)		(0.000)		(0.000)		(0.000)	
R^2 (overall)	0.663	0.651	0.581	0.556	0.521	0.507	0.802	0.789
R^2 (within)		0.247		0.200		0.282		0.336
R^2(between)		0.668		0.585		0.494		0.791
Observations	1787		600		671		516	
Firms	532		170		196		166	

Robust standard errors in brackets, all coefficients are significant at least at the 95% level of confidence apart from those in italics (nonsignificant)

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