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The productivity impact of R&D investment: are high-tech sectors still ahead?

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Our aim is to investigate the relationship between a firm's R&D expenditures and its productivity, looking at sectoral peculiarities. We use a unique longitudinal database consisting of 1809 US and European manufacturing and service firms over the period 1990–2008. Our main findings can be summarised as follows. Consistently with previous literature, the knowledge stock has a significant positive impact on a firm's productivity. More interestingly, the coefficient turns out to be significantly larger in the R&D-user services and high-tech manufacturing sectors than in the non-high-tech manufacturing sectors. Contrary to the 'latecomer advantage' approach, these outcomes suggest that firms in high-tech sectors are still ahead in terms of impact on productivity of R&D investments.

Keywords: R&D; productivity; knowledge stock; panel data

JEL Classification: O33; L25

1. Introduction

The aim of this paper is to investigate the link between R&D and productivity, in order to see whether previous evidence supporting a positive and significant relationship between the two can be confirmed and whether sectoral peculiarities emerge. In particular, we will focus on the role of high-tech manufacturing sectors and R&D-user services as the possible key drivers of a higher impact of R&D over productivity (see below).

Indeed, the interest in the microeconomic impact of R&D expenditures is nowadays quite widespread and previous literature on the subject is solid (see the next Section). In line with previous literature, in this paper we are going to assess the significance and magnitude of the R&D-productivity elasticity, making use of a unique and new large longitudinal firm-level data set.

However, considerably less attention has been devoted to investigate whether the impacts of R&D over productivity are different across economic sectors. Therefore, a first novelty of this paper is its sectoral focus. In this context, we 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

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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?

For instance, some authors have recently claimed that catching-up low-tech sectors invest less in R&D but benefit from a ‘latecomer advantage’ (see [Marsili 2001](#); [Mairesse and Mohnen 2005](#); [Von Tunzelmann and Acha 2005](#)). If such were 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. Actually, this hypothesis contrasts with most of the (scarce) previous empirical evidence, supporting the leading role of high-tech sectors (see the next Section).

Indeed, contrary to the latecomer approach, one can claim that high tech-sectors and R&D-based services may exhibit higher productivity impacts of R&D investments for different reasons.

Firstly, these are the sectors where ‘technological opportunities’ are more frequent, radical and pervasive, while in low-tech manufacturing and traditional services innovation is scarce, incremental and specific; therefore, the same amount of R&D investment is expected to have a larger productivity impact in the formers rather than in the latters (see [Freeman 1982](#); [Pavitt 1984](#); [Winter 1984](#); [Aghion and Howitt 1996](#); [Dosi 1997](#); [Greenhalgh, Longland, and Bosworth 2001](#); [Malerba 2004](#); [Dosi and Nelson 2013](#)).

Secondly, these sectors are characterised by an emerging and increasing demand and the ‘demand-pull’ is a crucial incentive for effective R&D investment in terms of productivity boost, cost reduction, and increasing profits (for recent supporting evidence of the demand-pull hypothesis, see [Cainelli, Evangelista, and Savona 2006](#), on services; [Piva and Vivarelli 2007, 2009a](#) on manufacturing).

Thirdly, it is in the high-tech manufacturing sectors and in the emerging services where innovative complementarities and synergies between R&D, higher skills and organisational change are more likely to happen and to have a more substantial joint impact on productivity levels (see [Milgrom and Roberts 1990](#); [Brynjolfsson and Hitt 2000](#); [Black and Lynch 2001](#); [Bresnahan, Brynjolfsson, and Hitt 2002](#); [Piva and Vivarelli 2004, 2009b](#); [Mohnen and Hall 2013](#)).

The hypothesis assumed and tested in this study is, therefore, that high-tech and R&D-user service firms¹ may show higher productivity impacts of R&D in comparison with non-high-tech manufacturing.

A second novelty of this study can be detected in our use of a large longitudinal database comprising both manufacturing and service firms, while most of previous literature has been limited to the manufacturing sectors. Therefore—as well as investigating possible differences between high-tech and non-high-tech manufacturing sectors—attention will also be devoted to the link between R&D and productivity in those service sectors that invest in R&D. This is particularly important, since in Western economies services represent more than three-quarters of total value added and this share is increasing ([Duchêne, Lykogianni, and Verbeek 2010](#); [Segarra-Blasco 2010](#)). Moreover, the recent literature supports the view that non-manufacturing industries are also heavy users of knowledge inputs (see [Evangelista 2000](#); [Evangelista and Savona 2003](#); [Faiz and Savona 2009](#)).

Finally, a third novelty of this work is to assess the important role of the so-called ‘embodied technological change’. 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 by which firms update their own technologies and increase productivity (see [Freeman, Clark, and Soete 1982](#); [Freeman and Soete 1987](#)). Certainly, it has been shown that embodied technological change play a key role,

especially in traditional sectors (see [Santarelli and Sterlacchini 1990](#); [Conte and Vivarelli, forthcoming](#)). In this study, the role of the R&D input will be jointly assessed with the role of physical capital and this will allow us to better understand the impact of embodied technological change over productivity and how this may differ across sectors.

To anticipate our results in a nutshell, the positive link between R&D and productivity will be fully confirmed, while – as far as the sectoral breakdown is concerned – R&D-user services and high-tech manufacturing sectors will turn out to be characterised by a higher impact of both R&D and physical capital on productivity.

The rest of the paper is organised as follows: the next section provides a concise survey of the previous literature; afterwards, the data used and the adopted methodology are discussed in two separate sections; the following section deals with the empirical results while the final section briefly concludes.

2. Literature

2.1. *R&D and productivity: overall evidence*

As mentioned in the previous section, 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](#)). From the seminal article by [Griliches \(1979\)](#) up to more recent contributions such as those by [Klette and Kortum \(2004\)](#), [Janz, Lööf, and Peters \(2004\)](#), [Lööf and Heshmati \(2006\)](#) and [Rogers \(2006\)](#), previous empirical works have found a significant contribution by R&D to 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.

2.2. *R&D and productivity: sectoral peculiarities*

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 paper, [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,² [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, according to the different specifications and the different econometric estimators adopted. Interestingly, the effect of R&D capital was considerably higher for high-technology firms compared to 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 was either not significant (although positive) or lower (ranging from 0.090 to 0.096), according to the different estimation techniques used.

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 3830 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.

Although using a different proxy for innovation in an extended C–D–M model (see Crépon, Duguet, and Mairesse 2008), Hall, Lotti, and Mairesse (2009) – using data on Italian manufacturing SMEs over the period 1995–2003 – found that product innovation enhances labour productivity considerably and that this impact is larger for firms in the high-tech sectors (1.314) rather than in the low-tech industries (0.900).

Finally, using OECD sectoral microdata from the UK-DTI R&D Scoreboard over the period 2000–2005, Ortega-Argilés et al. (2010) looked at the top 577 EU R&D investors and found that the R&D-productivity coefficient increased monotonically moving 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 (see also Ortega-Argilés, Piva, and Vivarelli (2011), and – using a stochastic frontier approach – Kumbhakar et al. 2012).

Turning our attention to services, previous literature on the link between R&D and productivity is scarce, notwithstanding the increasing role of services in contributing to the aggregate productivity growth of the economies (see Timmer et al. 2010). For instance, Segarra-Blasco (2010), following the Crépon, Duguet, and Mairesse (1998) specification and using Community Innovation Survey (CIS) data over the period 2002–2004 in Catalonia, concludes that a considerable heterogeneity in firms' performance can be found when manufacturing and service industries are compared, while even greater differences appear when high- and low-tech manufacturing firms are compared. His results show that R&D expenditures, outcomes of innovation, physical capital investment, market share and exports have positive effects on labour productivity in both manufacturing and services. In particular, R&D intensity turns out to have the largest impact on labour productivity in the high-tech industries and services (see also Bogliacino and Pianta 2011; Segarra-Blasco and Teruel 2011).³

Overall, previous 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, those studies including cross-section sectoral breakdowns seem to suggest a greater impact of R&D investments on firm productivity in the high-tech manufacturing sectors than in the low-tech ones; moreover, few recent studies seem to suggest a prominent role of R&D user services, as well. These empirical outcomes will be tested again through a panel analysis applied to the original data set described in the next section.

3. Data set

The microdata used in this study were provided by the JRC–IPTS (Joint Research Centre–Institute for Prospective Technological Studies) of the European Commission, while the original data source is the Compustat Global data set provided by Standard&Poor’s. The information provided only concerns publicly-traded companies and is extracted from a variety of sources, including companies’ annual reports, Securities and Exchange Commission (SEC) 10-K and 10-Q reports, daily news services and direct company contacts, using standardised data definitions and collection procedures to assure consistency in the data.

Available data includes:

- Company identification, name and address, industry sector (Global Industry Classification Standard that can be translated into the standard SIC classification);
- Fundamental financial data including income statements, cash flows, taxes, dividends and earnings, pension funds, property assets, ownership data, etc.
- Fundamental economic data, including the crucial information for this study, namely: sales, cost of goods (the difference between the former and the latter allows us to obtain value added), capital formation, R&D expenditures, and employment.

Given the crucial role assumed by the R&D variable in this study, it is worthwhile discussing in detail what is intended by R&D in our database. This item represents all costs incurred during the year that relate to the development of new products and services. It is important to note that this amount is only the company’s contribution and excludes amortisation and depreciation of previous investments, so being a genuine flow of current in-house R&D expenditures. On the whole, the adopted definition of R&D is quite restrictive and refers to the genuine flow of current additional resources coming from internal sources and devoted to the launch and development of entirely new products. In particular, the figure excludes: customer or government-sponsored R&D expenditures; engineering expenses such as routinised ongoing engineering efforts to define, enrich or improve the qualities and characteristics of the existing products; inventory royalties; market research and testing (see also Ortega-Argilés, Piva, and Vivarelli forthcoming, for a detailed description of the database). Obviously enough, this quite restrictive definition of in-house R&D entails a trade-off between its extreme precision and reliability and the exclusion of other important sources of knowledge such as public-backed R&D, external R&D and acquisition of external knowledge through licences and other property rights; the unavailability of this information has to be recognised as a limitation of the adopted database.

The period covered is 1990–2008; however, the number of years available for each company depends upon the company’s history; therefore, the data source is unbalanced in nature and comprises 1809 companies (1170 US firms and 639 European firms) for a total of 16,079 observations. Once we had acquired the rough original data from IPTS, we proceeded to construct a longitudinal database that would be adequate for running panel estimations to test the hypotheses discussed in the previous section. Below we describe in detail the procedure we adopted to construct the data set; for the sake of simplicity we proceed by steps.

First of all, in guiding the extraction of the data from the original JRC–IPTS database, the following criteria were adopted:

- select only those companies with $R\&D > 0$ in at least one year of the available time span;
- select only those companies located in the US and in the EU 27 countries⁴;

- extract information concerning R&D, sales, cost of goods (the difference between sales and cost of goods gives value added), capital formation, R&D expenditures, and employment.⁵

All the value data were expressed in the current national currency in millions (for instance countries which currently use the euro have values in euros for the entire examined period). Then, nominal values were translated into constant price values through gross domestic product (GDP) deflators (source: IMF) centred on the year 2000.⁶ Finally, once we had obtained constant 2000 price values, all figures were converted into US dollars using the purchasing power parity (PPP) exchange rate at year 2000 (source: OECD).⁷

The obtained unbalanced database comprises 2777 companies, over a period of 19 years (1990–2008).

Since one of the purposes of this study is to distinguish between high-tech and medium/low-tech sectors, we labelled as high-tech the following sectors (here, the standard OECD classification was taken as a reference, see [Hatzichronoglou 1997](#)).

- SIC 283: Drugs (ISIC Rev.3, 2423: Pharmaceuticals);
- SIC 357: Computer and office equipments (ISIC Rev.3, 30: Office, accounting and computing machinery);
- SIC 36 (excluding 366): Electronic and other electrical equipment and components, except computer equipment (ISIC Rev.3, 31: Electrical machinery and apparatus);
- SIC 366: Communication equipment (ISIC Rev.3, 32: Radio, TV and communications equipment);
- SIC 372–376: aircraft and spacecraft (ISIC Rev.3, 353: Aircraft and spacecraft);
- SIC 38: measuring, analysing and controlling instruments (ISIC Rev.3, 33: Medical, precision and optical instruments)

Turning our attention to the measure of our key variables (R&D and physical capital), as is common practice in this type of literature (see [Hulten 1990](#); [Jorgenson 1990](#); [Hall and Mairesse 1995](#); [Griliches 2000](#); [Bönte 2003](#); [Parisi, Schiantarelli, and Sembenelli 2006](#)), stock indicators (rather than flows) were inserted as impact variables in the econometric specification introduced below. Indeed, as extensively discussed in the benchmark literature, a firm's productivity is affected by the cumulated stocks of capital and R&D expenditures and not only by current or lagged flows. Within this framework, knowledge and physical capital stocks were computed using the *perpetual inventory method*. In practice, the following two formulas were applied:

$$K_{t0} = \frac{R\&D_{t0}}{(g + \delta)} \quad \text{and} \quad K_t = K_{t-1} \cdot (1 - \delta) + R\&D_t, \quad (1)$$

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

$$C_{t0} = \frac{I_{t0}}{(g + \delta)} \quad \text{and} \quad C_t = C_{t-1} \cdot (1 - \delta) + I_t, \quad (2)$$

where I , gross investment.

where g is generally computed as the *ex ante* pre-sample compounded average growth rate of the corresponding flow variable and δ is a depreciation rate.

However, our data set spans 19 years and is unbalanced in nature. This means that only for a minority of firms information is available throughout the entire period, while many firms have information only for one or more spans over the 1990–2008 period, and these

spans may be either very short or even isolated data. In addition, many firms display left-truncated data; for instance, some European firms have data only for the last decade. As a consequence, applying the formulas (1) and (2) strictly for computing initial stocks (for example using the first available three years to obtain the *ex-ante* growth rates) would have implied the loss of a huge amount of information.⁸ In order to avoid this loss of much of the available data, we adopted the following criteria. First, it was decided to compute a rate of growth using the initial three years of a given spell and then apply it to the initial flow and not to the fourth year (i.e. our t_0 is the very first year of the spell and so g is an ‘ex post’ three-year compound growth rate). Second, we applied this methodology iteratively to all the available spans of data comprising at least three consecutive years.⁹ The combination of these two choices allowed us to keep all the available information, except for isolated data or pairs of data.¹⁰

As a result, when computing R&D and capital stocks according to the procedure described above, only R&D and capital expenditure flow data with at least three observations in consecutive years were retained. This meant that 354 companies (mainly European) had to be dropped because they lacked 3 R&D observations in successive years, while a further 30 companies lacked 3 capital expenditure observations in successive years. Thus, a total of 2393 firms were retained at the end of this stage of the cleaning process.

Turning our attention to the depreciation rates (δ), we differentiated both between R&D and capital and between the high-tech sectors versus the other sectors, bearing in mind a common assumption in the reference literature, which uses $\delta = 6\%$ for computing the capital stock and $\delta = 15\%$ for computing the R&D stock (see [Nadiri and Prucha 1996](#) for the capital stock; [Hall and Mairesse 1995](#) and [Hall 2007](#) for the R&D stock). Indeed, depreciation rates for the R&D stocks have to be assumed to be higher than the corresponding rates for physical capital, since technological obsolescence is more rapid than the scrapping of physical capital. However, depreciation rates for the high-tech sectors have to be assumed to be higher than the corresponding rates for medium and low-tech sectors under the assumption that technological obsolescence – both related to R&D efforts and to the embodied technologies incorporated in physical capital – is faster in the high-tech sectors. Specifically, depreciation rates were assumed to be equal to 6% and 7% with regard to physical capital in the low-medium and high-tech sectors, respectively, while the corresponding δ for R&D stocks were assumed equal to 15% and 18%, respectively.

Once computed according to the formulas (1) and (2) and the adopted g and δ rates, the resulting stocks were checked and negative ones were dropped.¹¹ Moreover, we excluded unreliable data such as those indicating negative sales and cost of goods equal to zero. After this further cleaning, we ended up with 1884 companies.

At this point, in order to check for the presence of outliers, the Grubbs test ([Grubbs 1969](#))¹² was run on the two critical variables in the analysis: the R&D stock (K) and the physical capital stock (C). Since the outlier test has to be applied to the variables used in the regression analysis, the test was run on the two normalised stock variables: K/E and C/E (see Equation (5)). The Grubbs test is defined under the null hypothesis (H_0) that there are no outliers in the data set; the test statistic is:

$$G = \frac{\max_{i=1,\dots,N} |Y_i - \bar{Y}|}{s} \quad (3)$$

with $\bar{Y}$ and s denoting the sample mean and standard deviation, respectively. Therefore the Grubbs test detects the largest absolute deviation from the sample mean in units of the sample standard deviation. With a two-sided test, the null hypothesis of no outliers is

Table 1. Distribution of firms and observations across countries in the final version of the data set.

Country	Firms	Observations
Austria	16	51
Belgium	20	82
Czech Republic	1	4
Denmark	21	152
Estonia	1	3
Finland	41	157
France	54	279
Germany	141	749
Greece	11	41
Hungary	3	12
Ireland	8	55
Italy	5	19
Luxembourg	3	9
Netherlands	25	165
Slovenia	1	4
Spain	3	7
Sweden	62	386
UK	223	1299
USA	1170	12,605

rejected if:

$$G > \frac{(N-1)}{\sqrt{N}} \sqrt{\frac{t_{(\alpha/(2N), N-2)}^2}{N-2 + t_{(\alpha/(2N), N-2)}^2}} \quad (4)$$

with $t_{(\alpha/(2N), N-2)}^2$ denoting the critical value of the t -distribution with $(N-2)$ degrees of freedom and a significance level of $\alpha/(2N)$. After running the Grubbs test, 426 observations turned out to be outliers for the K/E variable and 613 for the C/E variable (54 outliers turned out to be common to both the variables). Therefore at the end of the process we ended up with a final data set comprising 1809 companies (1170 US and 639 EU, for a total of 16,079 observations). Table 1 reports the distribution of the retained firms and observations across countries.

4. Econometric methodology

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](#)).

$$\ln \left(\frac{VA}{E} \right)_{i,t} = \alpha + \beta \ln \left(\frac{K}{E} \right)_{i,t} + \gamma \ln \left(\frac{C}{E} \right)_{i,t} + \lambda \ln(E)_{i,t} + \delta T_t + \phi N_{i,t} + \vartheta S_{i,t} + \eta_i + v_{i,t} \quad \text{with } i = 1, \dots, 1809; t = 1990, \dots, 2008. \quad (5)$$

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. Considering per employee values is a way for taking into account a firm's size and is a standard procedure in the literature (see [Hall and Mairesse 1995](#), 269; [Crépon, Duguet, and Mairesse 1998](#), 123; [Harhoff 1998](#), 35; [Kwon and Inui 2003](#), 5). In this setting, total employment (E) is a control variable and

λ measures the scale elasticity (if greater than zero, it indicates increasing returns). Finally, η is the idiosyncratic individual effect and ν the usual error term.¹³

In all the following estimates, time (T), country/nation (N) and two-digit sector dummies (S) were implemented in order to take into account both common macroeconomic effects and sectoral peculiarities. Yearly, country and sectoral dummies turned out to be significant in both the aggregate and the sectoral estimates. 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.

As expected, all the estimated specifications turned out to be affected by heteroskedasticity (White 1980); hence, robust standard errors were used.

5. Results

Table 2 provides some descriptive statistics regarding the main variables in our study.

As can be seen from Table 2, the highest average productivity values (measured as VA/E) are in R&D-user service sectors and, within manufacturing, in high-tech sectors; while this cannot be considered as supporting our hypothesis of a stronger link between R&D and productivity in these sectors, it is interesting to note that – contrary to what put forward by the ‘latecomer approach’ – high-tech manufacturing and R&D-based services do not show any obvious evidence of decreasing returns in terms of productivity evolution.

As far as the knowledge stock per employee (K/E) is concerned, not surprisingly the leading position is taken by the high-tech manufacturing sectors, followed by the service sectors; other manufacturing sectors reveal instead a lower average value. However, other manufacturing sectors show the highest physical capital per employee (C/E), far larger than the remaining sectors. Finally, with respect to size (measured as number of employees, E), other manufacturing sectors are characterised by the largest companies.

On the basis of the preliminary correlation exercise reported in Table 3 the knowledge capital (K/E) turns out to be the main driver of productivity, with a linear correlation coefficient ρ of 0.451 in the overall sample, and homogeneously larger than 0.4 in the four sectoral groups. However, productivity is also significantly correlated to physical capital, although with a lower ρ (0.277 in the overall sample). These preliminary descriptive and univariate outcomes seems to confirm the expected key roles of R&D expenditures and embodied technological change in affecting labour productivity positively and significantly (as can be seen in Table 3, all the computed correlations turn out significant at the 99% level of confidence).

Table 2. Descriptive statistics: mean and standard deviation in brackets.

	Overall sample (obs. = 16,079)	Manufacturing sectors (obs. = 12,876)	Service sectors (obs. = 3203)	High-tech manufacturing (obs. = 7693)	Other manufacturing (obs = 5183)
VA/E	102.781 (91.008)	99.565 (92.914)	115.709 (81.648)	112.038 (108.275)	81.050 (58.938)
K/E	86.076 (105.899)	82.470 (106.904)	100.574 (100.478)	110.748 (119.007)	40.497 (66.507)
C/E	81.026 (80.542)	84.886 (81.585)	65.512 (74.222)	78.142 (76.709)	94.895 (87.380)
E	11,204 (35,302)	11,951 (35,250)	8199 (35,356)	8179 (23,264)	17,551 (47,237)

Table 3. Correlation matrices.

	$\ln(VA/E)$	$\ln(K/E)$	$\ln(C/E)$	$\ln(VA/E)$	$\ln(K/E)$	$\ln(C/E)$	$\ln(VA/E)$	$\ln(K/E)$	$\ln(C/E)$
	<i>Overall sample</i>			<i>Manufacturing</i>			<i>Services</i>		
$\ln(VA/E)$	1.000			1.000			1.000		
$\ln(K/E)$	0.451 (0.000)	1.000		0.440 (0.000)	1.000		0.474 (0.000)	1.000	
$\ln(C/E)$	0.277 (0.000)	0.252 (0.000)	1.000	0.286 (0.000)	0.269 (0.000)	1.000	0.315 (0.000)	0.244 (0.000)	1.000
				<i>High-tech manufacturing</i>			<i>Other manufacturing</i>		
				1.000			1.00		
				0.446 (0.000)	1.000		0.414 (0.000)	1.000	
				0.306 (0.000)	0.396 (0.000)	1.000	0.297 (0.000)	0.247 (0.000)	1.000

Note: *p*-Values in parentheses.

This initial evidence is confirmed by the econometric analyses reported in Table 4. Specification (5) was tested through pooled ordinary least squares (POLS), fixed (FE) and random effects (REs) models. Hausman tests (reported in the tables) were always supporting the FE estimations as the most reliable and so only FE results are displayed (however, FE and RE outcomes turned out to be fully consistent¹⁴).

Although POLS estimates are reported in the tables for the sake of completeness, the following comments refer only to the outcomes from the more reliable FE models, checking for individual firms' unobservable characteristics.

As can be seen in the first panel of Table 4, related to the overall sample, the knowledge stock has a significant positive impact on a firm's productivity, with an overall elasticity of about 0.089; this general result is largely consistent with the previous literature in terms of the sign, the significance and the estimated magnitude of the relevant coefficient (as mentioned in the second section, in previous studies estimated average elasticities have ranged from 0.05 to 0.25).

However, physical capital turns out to show a similar elasticity (0.093), confirming the important role of 'embodied technological change' in enhancing labour productivity (see the first section).

As far as the employment regressor is concerned, the investigated firms reveal decreasing returns with the (relatively) smaller firms showing higher productivity levels.¹⁵

Finally, diagnosis tests reveal the satisfactory fitness of the chosen models and the usefulness of including the time, sectoral and country sets of dummies (the correspondent three Wald tests turn out to be significant at the 99% level of confidence¹⁶).

In Table 4, a first sectoral comparison is carried out, comparing manufacturing and service sectors. As can be seen, R&D-user services show higher impacts of both knowledge and physical capital, revealing a better capacity in affecting productivity of both tangible and intangible investments. Consistently with the few previous studies including service sectors discussed in the second section, these results confirm the crucial role of services, in particular those which are knowledge intensive,¹⁷ in translating physical and knowledge investments into productivity (see Sirilli and Evangelista 1998; OECD 2004; Timmer et al. 2010).

The last two panels of Table 4 contrasts the high-tech manufacturing sectors (as previously defined, see the third section) with all the other manufacturing sectors. As can be seen, high-tech sectors are found to be more effective in linking knowledge and physical

Table 4. Sectoral decomposition.

	Whole sample		Manufacturing		Services		High-tech manufacturing		Other manufacturing	
	POLS	FE	POLS	FE	POLS	FE	POLS	FE	POLS	FE
Log (R&D stock per employee)	0.205*** (0.006)	0.089*** (0.007)	0.209*** (0.007)	0.073*** (0.008)	0.177*** (0.014)	0.114*** (0.014)	0.236*** (0.011)	0.070*** (0.012)	0.159*** (0.008)	0.053*** (0.009)
Log (Physical stock per employee)	0.115*** (0.006)	0.093*** (0.006)	0.109*** (0.007)	0.086*** (0.007)	0.148*** (0.014)	0.115*** (0.014)	0.117*** (0.011)	0.092*** (0.010)	0.093*** (0.008)	0.070*** (0.008)
Log (Employees)	0.031*** (0.003)	−0.049*** (0.007)	0.025*** (0.004)	−0.078*** (0.009)	0.062*** (0.009)	0.021 (0.014)	0.042*** (0.005)	−0.086*** (0.012)	−0.010* (0.006)	−0.107*** (0.013)
Constant	0.860* (0.493)	3.529*** (0.038)	2.957*** (0.481)	3.559*** (0.036)	3.513*** (0.164)	3.744*** (0.085)	2.840*** (0.493)	3.514*** (0.051)	3.144*** (0.457)	3.758*** (0.049)
Wald time-dummies (<i>p</i> -value)	4.5*** (0.000)	11.4*** (0.000)	4.3*** (0.000)	15.2*** (0.000)	2.7*** (0.000)	3.1*** (0.000)	2.2*** (0.002)	10.2*** (0.000)	2.5*** (0.000)	9.0*** (0.000)
Wald country-dummies (<i>p</i> -value)	52.5*** (0.000)	—	72.8*** (0.000)	—	13.5*** (0.000)	—	11.3*** (0.000)	—	74.7*** (0.000)	—
Wald sectoral-dummies (<i>p</i> -value)	174.2*** (0.000)	—	69.9*** (0.000)	—	94.8*** (0.000)	—	92.3*** (0.000)	—	67.1*** (0.000)	—
<i>R</i> ² (overall)	0.32	0.18	0.31	0.13	0.39	0.28	0.28	0.10	0.40	0.08
<i>R</i> ² (between)	—	0.09	—	0.06	—	0.29	—	0.04	—	0.03
<i>R</i> ² (within)	—	0.12	—	0.10	—	0.13	—	0.11	—	0.10
Hausman test (<i>p</i> -value) ^a	155.01 (0.000)		45.89 (0.000)		19.29 (0.000)		37.73 (0.000)		28.68 (0.000)	
Obs.	16,079		12,876		3203		7693		5183	
Number of firms	1809		1383		426		804		579	

Notes: (Robust in POLS) standard-errors in parentheses. For time dummies, country dummies and sectoral dummies, Wald tests of joint significance are reported. The Hausman statistic results correspond to the comparison of model specification RE versus FE without dummy sets.

^aThe Hausman statistic results correspond to the comparison of model specification RE versus FE without dummy sets.

*Significance at 10%.

***Significance at 1%.

capital stock with productivity. This outcome is consistent with the previous literature (see the second section) and supports a view stressing that R&D investments still have a greater impact on firm productivity in the high-tech sectors than in the low-tech ones. This outcome is in contrast with the hypothesis of the ‘latecomer advantage’ mentioned in the Introduction and points to the presence of ‘increasing returns’ in R&D: the high-tech manufacturing sectors that invest more in R&D are also those getting more in terms of productivity. Therefore, these results confirm our hypothesis (see the Introduction) that higher technological opportunities, increasing demand and stronger complementarities in high-tech sectors offer a better environment for a particularly virtuous link between innovation and productivity.

Tables A1 and A2 replicates the analyses put forward in Table 4, separately for the EU and the USA¹⁸; as can be seen, the outcomes are fully consistent with those displayed in Table 4.¹⁹

6. Conclusions

Although the positive and significant relationship between R&D and productivity has been proved by a long-established stream of literature, very few studies have provided empirical evidence about possible sectoral differences in the productivity impacts obtainable from R&D activities. In order to fill this gap, in this research we conducted a microeconomic panel analysis of the effect of R&D expenditures on firms’ productivity using a unique large longitudinal database comprising US and European R&D investors in both the manufacturing and service sectors. Our main findings can be summarised along the following lines.

Firstly, the positive link between R&D and productivity is fully confirmed; in particular, our results are largely consistent with the previous literature in terms of the sign, the significance and the estimated magnitude of the relevant coefficient.

Secondly, R&D-user service firms appear to be characterised by a higher impact of both R&D and capital investment on labour productivity; this is an interesting result that would deserve further investigation.

Thirdly, manufacturing firms in high-tech sectors achieve more in terms of the link between research activities and productivity, in comparison with their low-tech counterparts. Therefore, consistently with previous literature, our results show that manufacturing firms in high-tech sectors are still far ahead in terms of the productivity impact of their research activities. Interestingly enough, high-tech manufacturing firms also reveal an advantage in the productivity impact coming from investment in physical capital.

These results support the hypothesis put forward in this study that higher technological opportunities, increasing demand and more obvious complementarities in high-tech sectors and R&D-user services offer a better environment for a stronger link between innovation and productivity.

The fact that the positive and significant effect on productivity by R&D expenditures is not equally strong across different economic sectors may lead to an interesting policy implication: in order to maximise their productivity impact, R&D subsidies and incentives should target high-tech manufacturing and R&D-user services, rather than being designed as *erga-omnes* policy instruments.

Of course, this study presents some limitations. In particular, it has been conducted at the firm level and so results cannot be easily extended at the macroeconomic/aggregate level, also taking into account the data limitations in terms of country coverage and the representativeness of our sample, which is unbalanced in favour of large R&D-performing companies and the Anglo-Saxon countries.

Possible extensions of the approach put forward in this paper include future research based on different data sets and the consideration of additional innovation variables other than R&D expenditures.

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Notes

1. As clarified in the data set section, firms included in our data set are active in R&D and so firms in traditional services are excluded from our analysis.
2. As it will be clear in the following, this methodology investigates the impact of R&D and capital stock over productivity levels.
3. Some other few studies used a different methodology from that put forward by [Hall and Mairesse \(1995\)](#) and also adopted in this study: in these studies productivity growth (and not level) is regressed on R&D levels or differences (instead of stock). Interestingly enough, the outcomes of these studies are strongly consistent with the ones discussed so far. For instance, [Wakelin \(2001\)](#) – using data on 170 UK quoted firms during the period 1988–1992 – found a significant impact of R&D on productivity growth, with firms belonging to sectors defined as ‘net users of innovations’ turning out to experience a higher impact; [Tsai and Wang \(2004\)](#) – using a stratified sample of 156 large firms quoted on the Taiwan Stock Exchange over the period 1994–2000 – found that R&D had a significant and positive impact on productivity but this impact was much greater for high-tech firms; finally, [Bogliacino and Pianta \(2011\)](#) – using data obtained from the innovation surveys CIS2, CIS3 and CIS4 conducted in eight major European countries – found a significant impact of in-house R&D expenditures on labour productivity growth only in the high-tech manufacturing and service sectors.
4. While the original database also includes some Japanese and other Asian firms, these are latecomers only included in recent years and characterised by a lower level of reliability.
5. More specifically, the available information for each firm included in the obtained workable data set is as follows: (1) country of incorporation (location of the headquarters); (2) industry code at 2008; (3) R&D expenses; (4) capital expenditures; (5) net turnover; (6) cost of goods sold; (7) employees.
6. For a tiny minority of firms reporting in currencies other than the national one (i.e. 41 British, 9 Dutch, 4 Irish, 2 Luxembourg, 1 German and 1 Swedish firms reporting in US dollars; 7 British, 2 Danish and 1 Estonian firms reporting in euros), we decided to deflate the nominal values through the national GDP deflator as well.
7. This procedure is consistent with that suggested by the Frascati Manual ([OECD 2002](#)) in order to adjust R&D expenditures correctly for differences in price levels over time (i.e. intertemporal differences requiring deflation) and between countries (i.e. interspatial differences requiring a PPP equivalent). In particular ‘... the Manual recommends the use of the implicit GDP deflator and GDP–PPP (purchasing power parity for GDP), which provide an approximate measure of the average real “opportunity cost” of carrying out the R&D.’ ([OECD 2002](#), 217). Nine companies from four countries (Lithuania, Latvia, Malta and Romania) were excluded, due to the unavailability of PPP exchange rates from the OECD. Another 10 companies reporting in euros but located in non-euro countries (Denmark, Estonia and the UK) were excluded as well; finally, 58 European companies reporting in US dollars were kept as such.
8. In the best case, say a firm with a complete set of 19 data over the period, this methodology would have implied the loss of 3 observations out of 19; in the worst case, say a firm characterised by data available only for some spells of three years each, this computation would have implied the loss of all the available information for that particular firm.
9. This means that for firms characterised by breaks in the data we computed different initial stocks, one for each available time span, consistent with [Hall \(2007\)](#); however, differently from [Hall](#)

- (2007), we consider the different spans as belonging to the same firm and so we assign a single FE or RE to all of the spans belonging to the same company in the following econometric estimates.
10. Although departing from the usual procedure, relying on *ex-post* growth rates appears acceptable in order to save most of the available information in the data set; however, the impact of this choice on the values assumed by the stocks is limited, since they are also affected by the flow values and the depreciation rates. Finally, the chosen growth rate affects the initial stock and its impact quickly smoothes out as we move away from the starting year. Options for the choice of g other than the standard one have been implemented by other authors as well. For instance, [Parisi, Schiantarelli, and Sembenelli \(2006\)](#) assume that the rate of growth in R&D investment at the *firm* level in the years before the first positive observation equals the average growth rate of *industry* R&D between 1980 and 1991 (the time-span antecedent to the longitudinal micro-data used in their econometric estimates). 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, 270, footnote 9): ‘In any case, the precise choice of growth rate affects only the initial stock, and declines in importance as time passes ...’.
 11. The occurrence of negative stocks happens when g turns out to be negative and larger in absolute value than δ .
 12. Specifically, the Grubbs test – also known as the maximum normed residual test, ([Grubbs 1969](#); [Stefansky 1972](#)) – is used to detect outliers in a data set, either creating a new variable or dropping outliers from the data set. Technically, the Grubbs test detects one outlier for iteration: the outlier is expunged from the data set and the test is iterated until no outliers remain. The default number of iterations is 16,000.
 13. More comprehensive studies based on different data sets such as the CIS generally consider Equation (5) 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, Duguet and, Mairesse 1998](#)). Unfortunately, our database includes neither non-R&D firms nor data on innovative output and this does not permit a simultaneous system approach.
 14. RE outcomes are available upon request.
 15. It has to be noted 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.
 16. The estimates of the single dummies are not displayed in the tables but are available upon request.
 17. Unfortunately, paucity of data prevents us from conducting a separate empirical analysis for the knowledge intensive sectors.
 18. We thank one anonymous referee for suggesting us these extensions.
 19. Overall, all the key coefficients (but one) turn out to be significant and the ranking showing higher values for services, followed by high-tech manufacturing and then other manufacturing is always confirmed with the only exception of European countries where the crucial role of embodied technological change in the non-high-tech sectors clearly emerges.

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Appendix 1

Table A1. Sectoral decomposition: European countries.

	Whole sample		Manufacturing		Services		High-tech manufacturing		Other manufacturing	
	POLS	FE	POLS	FE	POLS	FE	POLS	FE	POLS	FE
Log (R&D stock per employee)	0.150*** (0.014)	0.058*** (0.011)	0.147*** (0.016)	0.052*** (0.013)	0.126*** (0.023)	0.086** (0.024)	0.172*** (0.032)	0.065*** (0.020)	0.112*** (0.014)	0.035* (0.015)
Log (Physical stock per employee)	0.126*** (0.013)	0.053*** (0.011)	0.135*** (0.014)	0.059*** (0.013)	0.108*** (0.024)	0.045*** (0.022)	0.127*** (0.025)	0.029 (0.022)	0.146*** (0.016)	0.093*** (0.016)
Log (Employees)	0.017** (0.008)	−0.162*** (0.017)	0.023*** (0.008)	−0.166*** (0.022)	−0.017 (0.015)	−0.141*** (0.030)	0.053*** (0.013)	−0.155*** (0.033)	−0.015 (0.009)	−0.209*** (0.028)
Constant	−1.012*** (0.143)	3.744*** (0.079)	2.567*** (0.269)	3.769*** (0.093)	2.666*** (0.315)	3.623*** (0.185)	2.691*** (0.226)	3.499*** (0.166)	3.710*** (0.202)	4.006*** (0.159)
Wald time-dummies (<i>p</i> -value)	1.9*** (0.009)	2.4*** (0.001)	1.7** (0.029)	2.1*** (0.004)	1.1 (0.348)	0.6 (0.902)	2.0*** (0.009)	2.4*** (0.000)	0.8 (0.718)	1.1 (0.397)
Wald country-dummies (<i>p</i> -value)	18.6*** (0.000)	—	26.8*** (0.000)	—	4.09 (0.000)	—	11.5*** (0.000)	—	28.7*** (0.000)	—
Wald sectoral-dummies (<i>p</i> -value)	99.8*** (0.000)	—	14.4*** (0.000)	—	73.5*** (0.000)	—	14.4*** (0.000)	—	12.6*** (0.000)	—
<i>R</i> ² (overall)	0.27	0.09	0.28	0.01	0.31	0.03	0.26	0.01	0.35	0.01
<i>R</i> ² (between)	—	0.00	—	0.00	—	0.02	—	0.00	—	0.00
<i>R</i> ² (within)	—	0.08	—	0.08	—	0.09	—	0.09	—	0.11
Hausman test (<i>p</i> -value) ^a	71.94 (0.000)		45.30 (0.000)		28.22 (0.000)		15.62 (0.000)		43.70 (0.000)	
Obs.	3474		2662		812		1231		1431	
Number of firms	639		469		170		213		256	

Notes: (Robust in POLS) standard-errors in parentheses. For time dummies, country dummies and sectoral dummies, Wald tests of joint significance are reported.

^aThe Hausman statistic results correspond to the comparison of model specification RE versus FE without dummy sets.

*Significance at 10%.

**Significance at 5%.

***Significance at 1%.

Table A2. Sectoral decomposition: USA.

	Whole sample		Manufacturing		Services		High-tech manufacturing		Other manufacturing	
	POLS	FE	POLS	FE	POLS	FE	POLS	FE	POLS	FE
Log (R&D stock per employee)	0.229*** (0.007)	0.098*** (0.008)	0.230*** (0.007)	0.078*** (0.009)	0.215*** (0.018)	0.125*** (0.017)	0.251*** (0.010)	0.069*** (0.013)	0.176*** (0.009)	0.060*** (0.010)
Log (Physical stock per employee)	0.104*** (0.007)	0.100*** (0.007)	0.098*** (0.008)	0.089*** (0.008)	0.146*** (0.018)	0.140*** (0.016)	0.112*** (0.011)	0.101*** (0.011)	0.073*** (0.009)	0.063*** (0.012)
Log (Employees)	0.037*** (0.004)	−0.034*** (0.008)	0.028*** (0.004)	−0.069*** (0.009)	0.087*** (0.010)	0.051*** (0.016)	0.040*** (0.005)	−0.081*** (0.013)	−0.007 (0.007)	−0.087*** (0.015)
Constant	2.802*** (0.208)	3.523*** (0.036)	2.154*** (0.468)	3.560*** (0.040)	3.161*** (0.196)	3.755*** (0.094)	3.147*** (0.074)	3.525*** (0.055)	2.359*** (0.447)	3.763*** (0.054)
Wald time-dummies (<i>p</i> -value)	5.4*** (0.000)	9.6*** (0.000)	4.9*** (0.000)	13.2*** (0.000)	3.4** (0.016)	4.9*** (0.000)	2.2*** (0.002)	8.3*** (0.000)	4.2*** (0.000)	9.9*** (0.000)
Wald sectoral-dummies (<i>p</i> -value)	86.4*** (0.000)	—	73.7*** (0.000)	—	84.7*** (0.000)	—	78.8*** (0.000)	—	79.5*** (0.000)	—
<i>R</i> ² (overall)	0.34	0.21	0.32	0.15	0.40	0.29	0.28	0.12	0.45	0.13
<i>R</i> ² (between)	—	0.17	—	0.10	—	0.35	—	0.07	—	0.08
<i>R</i> ² (within)	—	0.11	—	0.11	—	0.17	—	0.12	—	0.11
Hausman test (<i>p</i> -value) ^a	53.00 (0.000)		40.18 (0.000)		31.01 (0.000)		34.77 (0.000)		14.83 (0.000)	
Obs.	12,605		10,214		2391		6462		3752	
N. of firms	1170		914		256		591		323	

Notes: (Robust in POLS) standard-errors in parentheses. For time dummies, country dummies and sectoral dummies, Wald tests of joint significance are reported.

^aThe Hausman statistic results correspond to the comparison of model specification RE versus FE without dummy sets.

**Significance at 5%.

***Significance at 1%.