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**Article**

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# Innovation and employment: A firm level analysis with European R&D Scoreboard data<sup>☆,☆☆</sup>

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## Abstract

This article analyzes the microeconomic relation between innovation and employment, using company data from R&D Scoreboard for Europe covering 2000–2008. A reduced form equation in which R&D can account for both product and process innovation is estimated. The existence of non-constant elasticities is assessed, due to the combination of efficient scale and decreasing return to R&D: in our empirical estimates the scale effect tends to prevail for a given R&D intensity generating an increasing relation between total turnover and employment. These results have important implications for policymakers: innovation supporting policies should be correctly tailored and monitored since the results depend on the characteristics of the benefiting firms. Moreover, R&D intensity on GDP should be managed with care if taken as a policy target, given that the denominator is endogenous and non-linearly dependent on research expenditure.

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*Keywords:* Technological change; Corporate R&D; Employment; Panel data

## Resumo

Este artigo analisa a relação microeconômica entre a inovação eo emprego, utilizando os dados do R&D Scoreboard para a Europa cobrindo 2000-2008. Estima-se uma equação em forma reduzida em que a I&D podem ser responsáveis por inovação de producto ou de processos. A existência de elasticidades não constantes é avaliada, devido à combinação de escala eficiente e retornos decrescentes à I&D: em nossas estimativas o efeito de escala tende a prevalecer para um determinado nível da intensidade de I&D

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gerando uma relação crescente entre volume de negócios total e emprego. Estes resultados têm implicações importantes para os formuladores de políticas: as políticas de apoio à inovação devem ser corretamente adaptadas e monitoradas já que os resultados dependem das características das empresas beneficiárias. Além disso, a intensidade de I&D no PIB como alvo de políticas deve ser gerida com cuidado, uma vez que o denominador é endógeno e não linearmente dependente das despesas de investigação.

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*Palavras chave:* Variação tecnológica; I&D; Emprego; Datos de panel

## 1. Introduction

This article deals with the relation between innovation and employment at the firm level. Our focus is on formalized and structured innovation, i.e. new products and/or processes generated by an initial R&D expenditure. As explained by Dosi (1988) and Pavitt (1984), innovation strategies are more diverse and there exist industries where the basic type of innovative activity is based on embodied technological change or tacit knowledge accumulation, without formal research. Considering these additional elements would return a more detailed picture, but would also complicate the already difficult task of disentangling the channels through which the innovation–employment relationship takes place.

Our proxy for innovation is the research expenditure by firm. While at industry level some pooling effect may operate, resulting in a log linear (i.e. constant elasticity) relation, at firm level there exists an underlying magmatic heterogeneity, which may generate non-linearity.<sup>1</sup> The extent of the latter is determined by at least two main effects: (a) a scale effect: research and development expenditure (R&D) may have decreasing return to scale due to some fixed factor, such as talent (Denicolò, 2007). If this is the case, a firm cannot reproduce in scale the innovative process with constant return, and any new innovation will have a higher employment effect for a constant final demand. (b) A size effect: larger firms (in terms of turnover) may enjoy an advantage in exploiting the benefits of research. This may be interpreted in terms of the standard industrial organization tenet that unit (research) costs are decreasing over some interval up to the minimum efficient scale.

The former tends to amplify the effect on employment: for any given increase in the market, if the impact of innovation on productivity is decreasing, then the impact on jobs should increase at the margin. The latter tends to reduce it: the larger the demand served by the firm, the higher the impact on productivity and the lower the impact on employment. There is no a priori theoretical reason to indicate which of the two will prevail: it is a matter of empirical assessment. In our measurement exercise we will focus on Europe using the European subsample of R&D Scoreboard data, which covers around 80% of world business research and development expenditure.

The quantification of those non-linearities has important implications for innovation and competitiveness policy. First of all, it helps to calibrate better the policy mix, since employment performance can also affect productivity. In fact, in the short run technological unemployment may exist, reducing aggregate demand and thus indirectly lowering productivity via Kaldor–Verdoorn<sup>2</sup> effect and/or the scrapping of specific human capital. Moreover, it may occur that workers have to reallocate to jobs where the labour productivity level is lower. As a result, innovative policies aimed at supporting growth may miss the target because of indirect effects.

The second reason is that in presence of non-linear effects, we can have various instruments to reach the same target, and they may have very different opportunity costs. For instance, in Europe – we refer to the Europe 2020<sup>3</sup> agenda – the chosen target is the three percent ratio of R&D on GDP. Empirically, it is well documented that the typical firm in the industry tends to define its strategy in terms of some routines such as “spend  $\times$  percent of the turnover” (Dosi, 1988). As a result, one may conceptualize the three percent rule as a simple generalization from micro to macro. However, this reasoning is based on a fallacy of composition. The denominator of the target (the product of productivity for employment) is endogenous, in the very spirit of the agenda, since the *aim to increase R&D expenditure is motivated by its impact of productivity and employment*. In other words, not only the quantitative increase in spending matters,

<sup>1</sup> From now on, by non-linear we mean that the employment elasticity of R&D is not constant.

<sup>2</sup> The Kaldor–Verdoorn law postulate a positive relation between growth of output and growth of productivity, due to (dynamic) increasing returns, see Verdoorn (1949).

<sup>3</sup> European Commission (2010).

but also the qualitative composition of it, since the impact on productivity and employment can be very different across firms: in practice, the same gross amount of R&D spending may end up into a different R&D/GDP ratio.

We claim that the R&D intensity could be seen from two perspectives, as an extensive margin or an intensive one. The extensive margin is characterized by adding new actors (firms or sectors, in the sense of sectoral system of innovation, e.g. [Malerba, 2002, 2004](#)) with high knowledge intensity, while the intensive margin is reached by increasing the intensity of existing “big players”, i.e. those who outspend the others in research. There are clear-cut consequences whether we privilege the extensive or the intensive one, in terms of the kind of actors that we directly support (small versus big firms) or indirectly in terms of the institutions that we want to promote. It is now clear that the dynamics of this “intensive” margin depends on the combination of the size and scale effects.

Our results confirm that size impacts negatively through an interaction effect with R&D expenditure, while the scale of R&D has a convex impact. As a result of their magnitude, for a constant R&D intensity (as defined by the ratio between R&D and sales) the marginal effect (in terms of elasticity) of R&D on sales is increasing in the scale of the output of the firm. Moreover, for constant output, R&D intensity matters positively on the elasticity.

In terms of policy, there is a clear trade-off: innovation by large firms has a *ceteris paribus* larger impact on employment, but at the cost of fostering concentration (a large part of the effect is probably driven by business stealing), i.e. hampering the transfer of the gain of innovation to consumers and of pushing the overall economy towards more inflexibility, since the reallocation of workers when a shock hits a small firms is faster. An ideal policy would then try to promote the emergence of small firms with high knowledge intensity: the latter would at least partly compensate the size effect maintaining flexibility and softening concentration. Practical implementation of this policy is difficult at least, and the design is beyond the scope of this paper, but we will comment on the issue in the concluding remarks.

The article proceeds as follows. Section 2 presents some state of the art on the relation between R&D and employment. Section 3 discusses methodology and data. Section 4 the results. Section 5 concludes. Technical parts are included in [Appendix A](#).

## 2. State of the art

The relation between innovation and employment has received a cyclical interest depending on the rhythm and pace of technological change in the real economy. The literature on this topic is now huge and a systematic review is beyond the scope of this article. Nevertheless, we will mention some key issues.

First of all, the controversy is also theoretical: small differences in the framework of analysis give totally different predictions. If we rely on general equilibrium framework, the issue is almost a non-sense, because equilibrium implies full employment, by definition. This does not apply for classical economists, where the reference model assumes a given wage and perfectly elastic supply of labour (through the Malthusian population mechanism). As a result “classical” equilibrium does not necessarily imply absence of unemployment. Classical economists elaborate the theory of compensation mechanisms, putting forth that initial labour saving effects will be recovered by adjustment in demand (coming through prices and/or income effects, as explained in [Vivarelli, 1995](#)). However, even in neoclassical framework, adding small frictions in the wage setting mechanism will generate unemployment, thus technical change can generate alternative long run scenarios depending on the direction of change: e.g. in an efficiency wage case with monitoring, whether the technical change improves monitoring capacity or raise “potential” productivity generates different consequences.

If we depart from equilibrium framework towards evolutionary (out of equilibrium) dynamics, then adjustment lags and continuous processes of variety and selection imply a number of controversial trade-offs. In this situation the time necessary to re-establish full employment can be considerable (a discussion is in [Van Reenen, 1997](#)).

Empirically, the issue is even more controversial: the level of analysis is determinant in the sense that at micro level we should take into account the possibility that the positive employment effect of innovation is simply driven by business stealing; at industry level we can miss information depending on the possible bias towards services or manufacturing; finally at macro level there exist huge measurement problems due to aggregation, besides the obvious impossibility to comprehend the overall dynamics behind ([Bogliacino and Vivarelli, 2012](#)).

If we focus on the micro level, the consensus can be summed up as follows: at firm level technological change creates employment; at industry level the direct employment effect is positive in the case of product innovation (and thus R&D), but can be negative for process innovation. If we consider also the indirect effect, i.e. compensation mechanisms, the full and instantaneous compensation cannot be assumed *ex ante* ([Chennels and Van Reenen, 2002](#);

Pianta, 2005; Vivarelli, 2007, for some recent contributions, Piva and Vivarelli, 2005; Harrison et al., 2008; Hall et al., 2008; Ping et al., 2008; Bogliacino and Pianta, 2010).

Finally, since we mention the EU competitiveness policies (Europe 2020), this exercise may contribute to the assessment exercise of the Agenda. There has been a very large interest on the productivity consequences of increasing R&D, but less focus has been put on the expected change in employment. As the former is concerned, there is now a large consensus that research driven innovation is a major force shaping growth (Ortega-Argilés et al., 2010). As the latter is concerned, there have been some articles trying to quantify the impact of reaching the targets both at industry level (Bogliacino and Vivarelli, 2012) and through general equilibrium computations (Chevallier et al., 2006; Gelauff and Lejour, 2006; Gardiner and Bayar, 2010). Although very sensible to the assumptions, all studies agree that the impact would be positive.

### 3. Methodology and data

In order to formulate our reduced form labour demand to estimate, we start from one of the workhorse of the literature on R&D and innovation, i.e. the “patent race” (Dasgupta and Stiglitz, 1980): firms compete in R&D to gain some market power from an innovation. This market power depends on the appropriability conditions, i.e. the extent of intellectual property rights protection or learning lags, the features of the innovation itself (basically if drastic or not) and the market structure, i.e. barriers to entry in research, competitive pressures from substitutable products and from cumulativeness.<sup>4</sup>

We assume that the firm should decide factor hiring and R&D simultaneously and that the output of innovation activity (new product and/or new process) is stochastic. As we will see, our framework captures both product and process innovation.

Starting from the case in which a firm carries out R&D to introduce a new product, we assume that it has a CES production function, and in case of success, can face a downward sloping inverse demand curve with elasticity  $\varepsilon: P = CY^{-\varepsilon}$ , where  $C$  is a parameter, while, if it fails to innovate, remains price taker. The expected profit of the firm is thus:

$$\max_{K,L,Z} (p + q(R\&D, Y)CY^{-\varepsilon})Y - wL - rK \quad \text{s.t.} \quad Y = [K^\sigma + L^\sigma]^{1/\sigma} \quad (1)$$

where  $w$  and  $r$  are the rental prices of factors,  $q$  is a probability<sup>5</sup> which depends on output and R&D expenditure and  $\sigma$  is a parameter of substitutability between labour and capital.

The labour demand to be estimated can be extracted from first order conditions (FOCs):

$$(p + (1 - \varepsilon)q(R\&D, Y)CY^{-\varepsilon})Y^{1-\sigma}L^{\sigma-1} = w \quad (2)$$

readjusting and taking logs, we get our main equation:

$$\log(L_{it}) = \alpha_0 + \alpha_1 \log(w_{it}) + \alpha_2 \log(Y_{it}) + \alpha_3 \log(\Phi(R\&D_{it}, Y_{it})) + u_i + \eta_{it} \quad (3)$$

where  $\Phi(R\&D_{it}, Y_{it})$  is some non-linear function to be estimated.

Interestingly enough, we arrive at a similar expression also if we assume that the firm tries to improve the productive process. In this case its problem becomes:

$$\min_{K,L} wL + rK \quad \text{s.t.} \quad Y \leq (A_t + q(R\&D, Y)A_{t+1})[K^\sigma + L^\sigma]^{1/\sigma} \quad (4)$$

where  $A_{t+1} > A_t$  represent the result of the innovation and the price is either other firms' marginal costs or the monopoly price, depending on the (drastic versus non-drastic) nature of innovation.

Writing the FOCs from the problem in Eq. (5) we can write:

$$\lambda(A_t + q(R\&D, Y)A_{t+1})Y^{1-\sigma}L^{\sigma-1} = w \quad (5)$$

where  $\lambda$  is the Lagrange multiplier. Again, taking logs and readjusting, we get (3).

<sup>4</sup> Although phrased in terms of patents, Denicolò (2007) addressed all these issues in his general setup. The focus on patents is almost immaterial for our interest and the model can still be considered as a basic reference once relabelling patents with “secrecy” or “learning lags” as the main tools to appropriate rents from innovation.

<sup>5</sup> Needless to say, this probability is heterogeneous and depends on expectations and capabilities by firms. However, since we want to estimate the average impact we neglect this issue as a first approximation.

We estimate (3) by fixed effects, to get rid of unobserved heterogeneity, and using a polynomial approximation of  $\Phi(R\&D_{it}, Y_{it})$ . In Appendix A we provide a justification of the functional form in terms of Taylor expansion at the second order.

As stressed by Van Reenen (1997), the above equation represents the relationship at industry level. If technology adoption was immediate, the employment effect should not be related with the identity of the first mover. However, in the Schumpeterian perspective diffusion may take time, because of intellectual property rights protection or learning lags, secrecy or other informal means of protection, and the first mover will enjoy a market share increase above industry level expansion with a further impact on employment. As a result, it is preferable to include lags of R&D expenditure.

### 3.1. Data

We use data from the R&D Scoreboard. It collects data for the top R&D spenders; data are consolidated at group level, i.e. including all the subsidiaries. We have access to data from the editions of the Scoreboard 2004–2009. Each scoreboard gathers data over the four previous years, and a choice should be taken over the overlapping information: in our case, whenever a year is covered by more than one edition, the last one is considered the dominant source.

The number of firms covered is changing through the various editions: 500 EU and 500 non-EU in the first year, raising to 700 EU and 700 non-EU in 2005 and finally arriving at 1000 and 1000 from 2006 onwards. We are using data for the EU firms only. The Scoreboard provides data for R&D investment, sales, capital expenditure, employees and operating surplus. We end up with an unbalanced panel covering the years 2000–2008. Capital expenditures, sales and operating surplus are recorded from balance sheet, according to the interactional accounting standard definitions (i.e. capital expenditure is the total flow of investment in tangible assets). As a result, the measures are homogeneous across companies. R&D investment is recorded according to the Frascati Manual definition (OECD, 2002). Employees include all formal jobs of the company.

Scoreboard data cover more than 80% of total R&D expenditure, thus our database covers almost the universe of R&D doers located in Europe.

In case of mergers, we define a new firm, i.e. the old firms end their existence in the year of the merge, and a new entity appears. To control for other big events (acquisitions, change of name etc.) we create a dummy variable (equal to one whenever the event occur for the individual firm).

Data are expressed in 2000 Euro at purchasing power parity (PPP) (the source for deflators and PPP is Eurostat).

Scoreboard data do not provide information on wages. However, we have information on capital expenditure and operating surplus that we use as proxies. Increasing/decreasing operating surplus means that the firm is succeeding, and this will translate into higher wages. The opposite happens for capital expenditure: it is usually aimed at saving on labour costs, thus reducing bargaining power and wages. To see consistency of the instruments, we use two indirect strategies. First of all, we look at a similar database at industry level data to see if the correlation is robust. Data are taken from OECD STAN and ANBERD.<sup>6</sup> Spearman rho is .7442 ( $p$ -value = .0000) between log-compensation per employee and log-capital expenditure. Between log-operating surplus and log-compensation per employee it is .7490 ( $p$ -value = .0000).

Secondly, we use a complementary data source at company level. We use microdata for listed companies with headquarter in Europe and positive R&D expenditure,<sup>7</sup> to have a comparable sample for the period covered by our estimation. Of course, listed companies may belong to the same group and cover only a part of our database, where both listed and private firms are included; nevertheless, they can provide an estimation of the relationship among the variables. Spearman rho is .2724 ( $p$ -value = .0000) between log-compensation per employee and log-capital expenditure. Between log-operating surplus and log-compensation per employee it is .1610 ( $p$ -value = .0000). In the literature, an example of the use of various measures of quasi-rents as an instrument to capture wage dynamics in an estimated bargaining

<sup>6</sup> The cleaned database resulting from the merge of sectoral and R&D data includes Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Italy, Netherlands, Portugal, Spain, Sweden and United Kingdom for the period 1996–2005, at two digits level. Sector included are 15–16; 17; 18; 19; 20; 21; 22; 23; 24; 25; 26; 27; 28; 29; 30; 31; 32; 33; 34; 35; 36–37; 55; 72; 73; 74.

<sup>7</sup> The source of the data is Research Insight's Global Vantage Database by Standard and Poor's, updated to the 31st of January 2010. The extraction has been performed using the criteria 'Europe' and 'positive R&D' over the years 2000–2008. All monetary values have been converted to millions of Euro using foreign exchange data of 2008 and then deflated using GDP deflators (base year is 2008), from Eurostat.

Table 1  
Descriptive statistics.

	Firms		Standard deviation		
	(Average $T$ )	Mean	Within	Between	Overall
Employment	1485 (6.24)	18,221.29	9469.51	42,257.79	46,150.63
Sales	1486 (6.24)	4072.04	3412.91	12,029.58	14,403.24
Capital investment	1391 (5.24)	292.08	410.87	1019.12	1207.00
Operating surplus	1486 (5.90)	342.46	1096.86	1481.27	1988.67
R&D	1486 (5.96)	96.66	89.64	333.82	406.22

Source: R&D Scoreboard data, full sample. Expenditure data in million Euros at PPP 2000.

model is [Van Reenen \(1996\)](#). The impact of capital expenditure on wage dynamics is documented at industry level in [Feenstra and Hanson \(1999\)](#).

In practical terms, operating surplus is negative for many firms, implying that a log transformation would induce selection into the sample. Since the distribution is leptokurtic, taking simply the level is not feasible, thus we rescale the variable adding its minimum and taking log. Since we are not interested in interpreting the coefficient, we found this as the best strategy. Capital expenditure, R&D investment and operating surplus are not rescaled by number of employees to avoid introducing a source of endogeneity.

In [Table 1](#) we report the standard descriptive statistics.

As can be seen by the descriptive statistics, the sample shows a very large variability and tends to over-represent large groups (as one can expect, the small firms with high R&D intensity are mainly gazelles or research labs). The large variability of operating profits should not be seen as a surprise given that these very innovative firms quite often either go bankrupt or make a huge amount of extra profits.

An important issue concerns sample selection, namely the external validity of the results. Given the very logic of the Scoreboard (i.e. a ranking), by all means there is a selection, in the sense that this is not a random sample. However, given our interest on the effect of R&D, the issue can be neglected, because we are covering almost the entire population of R&D expenditure in Europe. A simple comparison between R&D Scoreboard and BERD data from secondary sources shows that the concentration of R&D expenditure is so high that what is left aside by the Scoreboard is of second order. The 1000 top investors' expenditure (from the R&D Scoreboard) is as high as the 73% (2004), 75% (2005), 77% (2006), 83% (2007) of the total BERD in US, EU27, Japan, Norway, Switzerland, Iceland and Republic of Korea (Eurostat). If we compare the same top 1000 with the total OECD BERD expenditure we get: 67% (2004), 68% (2005), 70% (2006), and 75% (2007).

Moreover, since we have group data, we are controlling for potential selection due to allocation of R&D expenditure for tax purpose within groups, which standard analyses tend to neglect, but can matter a lot.

#### 4. Results

In [Appendix A](#), we provide some diagnostic tests in [Table A2](#). Fixed effects estimator is supported by the Hausman test. In order to approximate the non-linear function  $\Phi(\cdot, \cdot)$ , we choose a quadratic polynomial with an interaction with output. We have tried also a third degree polynomial, but it is rejected (as shown in [Table A2](#)). In [Appendix A](#), we provide a formal proof of the derivation of (6) from (3). Our estimated equation is:

$$\begin{aligned} \log(L_{it}) = & \alpha_0 + \alpha_1 \log(w_{it}) + \alpha_2 \log(Y_{it}) + \alpha_3 \log(R\&D_{it}) + \alpha_4 \log(R\&D_{it}) \log(Y_{it}) \\ & + \alpha_5 \log^2(R\&D_{it}) + u_i + \eta_{it} \end{aligned} \quad (6)$$

Table 2  
Dependent variable: log of employees.

	(1)	(2)	(3)	(4)	(5)
$\log(Y_{it})$	0.395 (0.008)***	0.322 (0.009)***	0.334 (0.011)***	0.362 (0.011)***	0.234 (0.012)***
$\log(OS_{it})$	-0.038 (0.013)***	-0.027 (0.012)**	-0.027 (0.012)**	-0.024 (0.012)*	-0.031 (0.012)***
$\log(I_{it})$	0.103 (0.005)***	0.084 (0.005)***	0.084 (0.005)***	0.080 (0.005)***	0.057 (0.005)***
$\log(R\&D_{it})$		0.131 (0.008)***	0.160 (0.016)***	0.161 (0.016)***	0.232 (0.015)***
$\log(R\&D_{it-1})$		0.034 (0.007)**	0.034 (0.007)***	0.030 (0.007)***	0.021 (0.006)***
$\log(R\&D_{it-2})$		0.047 (0.006)***	0.047 (0.006)***	0.043 (0.006)***	0.042 (0.006)***
$\log(R\&D_{it})\log(Y_{it})$			-0.004 (0.002)**	-0.020 (0.002)***	-0.041 (0.002)***
$\log^2(R\&D_{it})$				0.021 (0.002)***	0.027 (0.002)***
$\log^2(Y_{it})$					0.027 (0.001)***
Constant	5.896 (0.149)***	5.591 (0.141)***	5.533 (0.144)***	5.442 (0.143)***	5.357 (0.136)***
Time dummies	Yes	Yes	Yes	Yes	Yes
Events	Yes	Yes	Yes	Yes	Yes
<i>N</i> obs.	6992	5130	5130	5130	5130
<i>R</i> <sup>2</sup> (overall)	0.809	0.766	0.763	0.758	0.781

Source: R&D Scoreboard data.

All columns refer to within group estimation. Standard errors in parenthesis. *Y* stands for sales, *OS* for operating surplus, and *I* for capital expenditure and R&D for R&D expenditure.

\* Significant at 10%.

\*\* Significant at 5%.

\*\*\* Significant at 1%.

In Table 2, we report our baseline estimation of (3). Since the sample included firms with very high capital investment and R&D investment intensity – mainly research labs – we check for the presence of outliers. The Grubbs test (Grubbs, 1969) is negative, thus we use the full sample. As a robustness check, in Table A1 we also report the estimation for the truncated sample (at 100% intensities), showing only minor differences.

Since we use both interaction and quadratic terms, there may be some risk of multicollinearity. The variance inflation factor (for the OLS estimator) is indeed a bit high (the average is around twenty). For this reason, we report the estimation sequentially, adding regressors one at a time and we found the results very stable. In column one, we estimate a reduced form of labour demand with operating surplus and capital expenditure as proxies for wages, and output measured by total sales. In column two, we include R&D expenditures (current one and the first two lags). In column three and four we add an interaction term with output and a quadratic term for R&D. In column five we report the estimation including the quadratic term for log-sales. In all estimations we add time dummies to control for supply effects. We add also a dummy for events (mergers, acquisition, significant change of name etc.).

As can be expected, output (i.e. demand) is the larger determinant of employment, while our proxies for wages are significant and their coefficients are stable through alternative specifications. In particular, increasing operating surplus means that the firm is succeeding, and this will translate into higher wages, thus negatively affecting employment. The opposite happens for capital expenditure: since it has labour saving effects, it reduces bargaining power, constraining wages and thus pushing employment.

Coming to our main interest, R&D has a non-linear effect on employment, as expected. First of all, the effect is moulded by time lags, coherently with the Schumpeterian framework. However, contemporaneous terms also matter: as we made clear in the methodological part, the firm should hire factor services before knowing the result of the research, in order to be ready to produce at the new conditions. As a result, while productivity impact of R&D takes



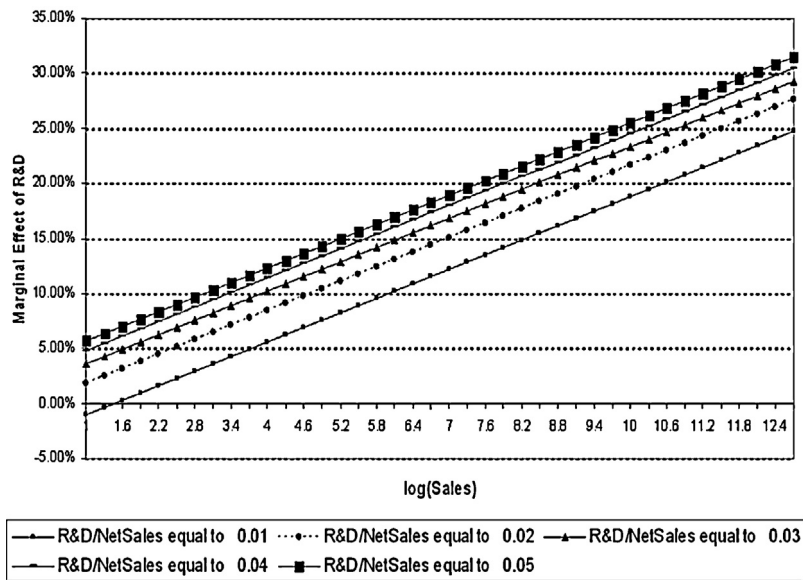


Fig. 1. The marginal effect of R&D.

Source: R&D Scoreboard data, sample truncated at R&D and capital intensity both less than 100%. Data refer to the marginal effect calculated for some given value of the R&D intensity, allowing the sales to change.

significant lags, in the employment case research spans its effects since the beginning. Secondly, the interaction term operates negatively, as expected. Finally our convexity hypothesis – what we called scale effect – is not rejected by data.

In order to compute the implied employment impact, taking into account the size and scale effects, we can rearrange the employment elasticity of R&D in the following way – focusing on the short run effect, neglecting the time persistence of the impact:

$$\frac{\partial \log(L_{it})}{\partial \log(R\&D_{it})} = \alpha_3 + \alpha_4 \log(Y_{it}) + 2\alpha_5 \log(R\&D_{it}) = \alpha_3 + (\alpha_4 + 2\alpha_5) \log(Y_{it}) + 2\alpha_5 \log\left(\frac{R\&D_{it}}{Y_{it}}\right) \quad (7)$$

There are three components in Eq. (7):

- The direct elasticity, invariant to firm characteristics ( $\alpha_3$ ).
- The intensive margin, related to R&D intensity ( $2\alpha_5 \log((R\&D_{it})/Y_{it})$ );
- The extensive margin, which is given by the interaction of the scale and size effects, dependent on the turnover ( $(\alpha_4 + 2\alpha_5) \log(Y_{it})$ ).

Assuming that the firm decides on the R&D intensity by means of a (revisable) routine, we can fix it at alternative levels, and then see how the employment elasticity of R&D increases when we enlarge the size. We should remind that for a given R&D intensity, if we increase the output, then we implicitly increase also the R&D expenditure level. The results are shown in Fig. 1, where we have plotted the estimated employment elasticity of R&D for various R&D intensities as a function of turnover (in log scale).

As one can easily see, both intensive and extensive margins operate in the same direction: for a given size, increasing the R&D intensity raises the employment elasticity. For a given R&D intensity, increasing the size raises the employment impact as well. This leaves the legislator with a clear choice between two very different policy options: on the one hand, favouring entry of research intensive firms; on the other hand, spurring growth of existing firms.

Another way to disentangle the drivers of the employment effect is to separate the direct effect, the scale effect and the size effect. In general these marginal effects are dependent on the amount of R&D and sales of the company. In Table A3 we present an estimation of the three components for a company with a 1% R&D intensity.

Table 3  
Dependent variable: log of employment.

	(1)	(2)	(1)	(2)
$\log(Y_{it})$	0.563 (0.014)***	0.476 (0.032)***	0.232 (0.012)***	0.359 (0.011)***
$\log(OS_{it})$	-0.028 (0.011)**	-0.029 (0.011)**	-0.030 (0.011)**	-0.024 (0.012)*
$\log(I_{it})$	0.057 (0.006)***	0.055 (0.006)***	0.057 (0.005)***	0.080 (0.005)***
$\log(R\&D_{it})$	0.226 (0.034)***	0.264 (0.036)***	0.304 (0.031)***	0.266 (0.033)***
$\log(R\&D_{it-1})$	0.020 (0.007)***	0.019 (0.007)***	0.020 (0.006)***	0.029 (0.007)***
$\log(R\&D_{it-2})$	0.037 (0.006)***	0.038 (0.006)***	0.041 (0.006)***	0.042 (0.006)***
$\log(R\&D_{it}) \log(Y_{it})$	-0.020 (0.003)***	-0.027 (0.004)***	-0.040 (0.003)***	-0.018 (0.002)***
$\log^2(R\&D_{it})$	0.018 (0.002)***	0.020 (0.003)***	0.027 (0.002)***	0.020 (0.002)***
$\log(R\&D_{it}) \log(S_{it})$	-0.008 (0.002)***	-0.008 (0.002)***	-0.007 (0.002)***	-0.010 (0.002)***
$\log^2(Y_{it})$		0.008 (0.002)***	0.027 (0.001)***	
Constant	4.893 (0.145)***	4.715 (0.155)***	5.373 (0.136)***	5.464 (0.143)***
Time dummies	Yes	Yes	Yes	Yes
Events	Yes	Yes	Yes	Yes
<i>N</i> obs.	4893	4893	5130	5130
$R^2$ (overall)	0.759	0.761	0.780	0.755

Source: R&D Scoreboard data, full sample for columns (3) and (4), sample truncated at R&D and capital intensity both less than hundred percent for columns (1) and (2).

All columns refer to within group estimation. Standard errors in parenthesis. *Y* stands for sales, *OS* for operating surplus, *I* for capital expenditure, *S* for R&D expenditure by firms in the same industry and *R&D* for R&D expenditure.

\* Significant at 10%.

\*\* Significant at 5%.

\*\*\* Significant at 1%.

#### 4.1. Robustness check

We performed some robustness check. First of all, one possible objection is that the non-linearities are simply a reflection of some measurement error due to spillovers: given the sequential nature of innovation in many technological trajectories, it may be likely that firms are also investing in R&D as a means to appropriate knowledge generated elsewhere (absorptive capacity). This may result in some labour saving consequences.

In order to control for it, we calculate the log of total amount of R&D performed by competitors in the same industry (defined at four digits) – it can be summed since it is in PPP – and we interact it with the log of R&D.

As shown in Table 3, results are robust and there are additional labour saving consequences. We report the regressions on the full sample and the truncated sample.

A further robustness check regards the potential endogeneity: R&D expenditures are largely due to researchers salaries and this is obviously related to employment. Of course, R&D employees are a minor share of total employment, thus this effect can indeed be negligible. Nevertheless, we have information on R&D employees for a subsample of firms, for which we can run the regression on non-R&D employment.

The sample is considerably restricted and both the Grubbs test for outliers and the variance inflation factor appear more worrying, thus we run the estimation on the restricted sample and neglecting the lags of R&D. As usual, we provide estimation in sequence to check for stability.

The main results are confirmed, as can be seen in Table 4.

Table 4  
Dependent variable: log of non-R&D employment.

	(1)	(2)	(3)	(4)	(5)
$\log(Y_{it})$	0.605 (0.029)***	0.570 (0.032)***	0.596 (0.036)***	0.623 (0.040)***	0.532 (0.073)***
$\log(OS_{it})$	-1.885 (0.535)***	-1.800 (0.535)***	-1.626 (0.546)***	-1.547 (0.548)***	-1.682 (0.555)***
$\log(I_{it})$	0.057 (0.006)***	0.053 (0.016)***	0.053 (0.016)***	0.053 (0.016)***	0.048 (0.016)***
$\log(R\&D_{it})$		0.067 (0.027)**	0.154 (0.061)**	0.158 (0.061)**	0.212 (0.071)***
$\log(R\&D_{it}) \log(Y_{it})$			-0.013 (0.008)*	-0.026 (0.012)**	-0.041 (0.015)**
$\log^2(R\&D_{it})$				0.016 (0.010)*	0.021 (0.011)*
$\log^2(Y_{it})$					0.012 (0.008)
Constant	23.375 (5.514)***	22.512 (5.514)***	20.585 (5.644)***	19.708 (5.671)***	21.200 (5.758)***
Time dummies	Yes	Yes	Yes	Yes	Yes
Events	Yes	Yes	Yes	Yes	Yes
<i>N</i> obs.	1743	1743	1743	1742	1743
$R^2$ (overall)	0.703	0.730	0.774	0.787	0.762

Source: R&D Scoreboard data, sample truncated at R&D and capital intensity both less than hundred percent.

All columns refer to within group estimation. Standard errors in parenthesis. *Y* stands for sales, *OS* for operating surplus, *I* for capital expenditure, *S* for R&D expenditure by firms in the same industry and *R&D* for R&D expenditure.

\* Significant at 10%.

\*\* Significant at 5%.

\*\*\* Significant at 1%.

## 5. Concluding remarks and policy implications

In this paper we have examined the relation between innovation and employment at firm level, focusing on the most formalized and structured part of the innovative activity, carried out through R&D expenditure. We have estimated the employment elasticity of innovation in Europe using a panel built from the R&D Scoreboard data for the period 2000–2008. Our formulation accounts for product and process innovation, using R&D expenditure as a proxy.

In our empirical estimation, we detect a size effect, driven by the greater efficiency of the research conducted by large firms, but also a scale effect, i.e. a decreasing return to R&D expenditure. For a given R&D intensity, the latter tends to prevail, in such a way that for any increase in the market share by a firm, the employment elasticity of R&D tends to increase as well.

Finally, we state below some policy implications.

First of all, the share of R&D on GDP should be taken with caution as a monitoring target, since the denominator is endogenous. We focus on employment – but the same can be stated for productivity: the effect on employment by an increase in R&D is not constant, thus it is very difficult to predict how an increase in absolute spending can transmit into the resulting R&D/GDP observed.

Second, we claim that the employment implication of innovation supporting policies should be correctly calculated. In the medium run destroying too many jobs can be harmful to productivity: although a rapid innovation pace can improve productivity in the sectors in which it occurs, many of the workers may reallocate towards jobs with low technological content (because of specific human capital, absence of capabilities, lack of competitive pressures that spur innovation by firms and so on) counteracting the above effect on the aggregate labour productivity. As a result, innovation policies should be matched with human capital accumulation and welfare policies that help mobility and reallocation of resources.

Third, the same effect on employment can be reached by the entry of new knowledge intensive firms or by the growth of existing ones. The first of the two strategies is superior for two reasons: (a) it prevents harmful concentrations; (b) it leaves more flexibility to the system, given that a large share of these new firms is likely to be small.

## Appendix A. Robustness check

We first prove formally that (6) is a Taylor approximation of (3). Allow  $\Phi(\cdot, \cdot)$  to be a function of innovative input (defined  $x$ ) and production (defined  $z$ ), and define  $\Phi_i(\cdot, \cdot)$  as the partial derivative with respect to the  $i$ th argument. It is reasonable to assume that  $\Phi(0,0) > 0$ , since there is a positive probability to innovate for firms outside the market and also for firms who are not investing, due to spillover and/or imitation. A Taylor expansion at the second order around  $(0,0)$  returns:

$$\begin{aligned} \log \Phi(z, y) = & \log(\Phi(0, 0)) + \frac{\Phi_1(0, 0)}{\Phi(0, 0)}x + \frac{\Phi_{12}(0, 0)}{\Phi(0, 0)}y + (-\Phi^{-2}(0, 0)\Phi_1^2(0, 0) + \Phi^{-1}(0, 0)\Phi_{11}(0, 0))x^2 \\ & + 2(-\Phi^{-2}(0, 0)\Phi_1(0, 0)\Phi_2(0, 0) + \Phi^{-1}(0, 0)\Phi_{12}(0, 0))xy + (-\Phi^{-2}(0, 0)\Phi_2^2(0, 0) \\ & + \Phi^{-1}(0, 0)\Phi_{22}(0, 0))y^2 + o(\|x, z\|^2) \end{aligned}$$

If we now use  $\log(R\&D_{it})$  and  $\log(Y_{it})$  as proxies for innovative input ( $x$ ) and production ( $z$ ) we can re-write:

$$\begin{aligned} \log \Phi(\log(R\&D_{it}), \log(Y_{it})) \cong & \beta_0 + \beta_1 \log(R\&D_{it}) + \beta_2 \log(Y_{it}) + \beta_3 \log^2(R\&D_{it}) + \beta_4 \log(R\&D_{it}) \log(Y_{it}) \\ & + \beta_5 \log^2(Y_{it}) \end{aligned} \quad (A1)$$

Since our main interest is in R&D expenditure, we can neglect  $\beta_5$ . If we replace (A1) into (3) we get (6). In all tables we report the full estimation of (6) with the complete second order expansion, including the second power of log-sales, and the specification is robust.

In order to test the robustness of our specification, we report the result for the truncated sample in the following Table A1. We exclude firms for which the R&D or capital investment intensity was larger than hundred percent. As we can see, magnitude and significance of the coefficients are not affected by the truncation. In fact, the Grubb test does not report any specific outlier. As a further robustness check, we run the regression using the first and second lag for interaction and quadratic term, supporting the specification.

Finally, in Table A2 we provide some basic specification tests for the baseline version. In the first row, we report the  $F$ -test, with the null hypothesis that all the coefficients are not statistically distinguishable from zero. The null hypothesis is rejected at 1% level.

In the second row we report the  $F$ -test that all the fixed effects are equal to zero. The null is again rejected at 1% level.

In the third row we report the  $t$ -test of the coefficient of the cubic term for the R&D expenditure. This is the  $t$ -stat computed when running the baseline specification with the cubic term included among the regressors. The null hypothesis of equality to zero is not rejected.

Finally, we report the Hausman test (Hausman, 1978). In the case in which the regressors are uncorrelated with the unobservable time-invariant variables, the random effect will be a consistent and more efficient formulation, while if the null hypothesis is rejected the fixed effect estimation should be preferred. The null hypothesis is rejected at 1% and we retained the fixed effect formulation.

In Table A3 we report the direct, scale and size effects for a company with a 1% R&D intensity. The reported elasticity should be interpreted as a percentage change in employment. In column (1) we report the sales in Euros, in column (2) the R&D investment, in column (3) the direct effect, in column (4) the scale effect (due to the convexity of R&D costs), and in column (5) the size effect due to the economies of scales.

Table A1  
Dependent variable: log of employees.

	(1)	(2)	(3)	(4)	(5)
$\log(Y_{it})$	0.558 (0.009)***	0.523 (0.012)***	0.535 (0.013)***	0.567 (0.014)***	0.482 (0.032)***
$\log(OS_{it})$	-0.037 (0.012)***	-0.031 (0.011)***	-0.032 (0.011)***	-0.029 (0.011)**	-0.030 (0.011)**
$\log(I_{it})$	0.055 (0.009)***	0.059 (0.006)***	0.059 (0.006)***	0.057 (0.006)***	0.055 (0.006)***
$\log(R\&D_{it})$		0.084 (0.008)***	0.119 (0.018)***	0.136 (0.018)***	0.172 (0.022)***
$\log(R\&D_{it-1})$		0.024 (0.007)***	0.024 (0.007)***	0.020 (0.007)***	0.019 (0.007)***
$\log(R\&D_{it-2})$		0.042 (0.006)***	0.041 (0.006)***	0.038 (0.006)***	0.039 (0.006)***
$\log(R\&D_{it}) \log(Y_{it})$			-0.004 (0.002)**	-0.021 (0.003)***	-0.028 (0.004)***
$\log^2(R\&D_{it})$				0.019 (0.002)***	0.021 (0.003)***
$\log^2(Y_{it})$					0.008 (0.002)***
Constant	4.885 (0.140)***	4.692 (0.138)***	4.622 (0.142)***	4.500 (0.142)***	4.687 (0.155)***
Time dummies	Yes	Yes	Yes	Yes	Yes
Events	Yes	Yes	Yes	Yes	Yes
<i>N</i> obs.	6328	4893	4893	4893	4893
$R^2$ (overall)	0.788	0.768	0.764	0.761	0.763

Source: R&D Scoreboard data, sample truncated at R&D and capital intensity both less than hundred percent

All columns refer to within group estimation. Standard errors in parenthesis. *Y* stands for sales, *OS* for operating surplus, *I* for capital expenditure and *R&D* for R&D expenditure.

\* Significant at 10%.

\*\* Significant at 5%.

\*\*\* Significant at 1%

Table A2  
Dependent variable: log of employees. Specification tests.

	(1) Baseline specification
<i>F</i> test	307.50
( <i>p</i> value)	(0.000)
<i>F</i> test: fixed effects	57.42
( <i>p</i> value)	(0.000)
<i>t</i> -Test on $\log^3$	-0.34
( <i>R\&amp;D_{it}</i> )	(0.730)
Hausman test	3880.50
( <i>p</i> value)	(0.000)

Source: R&D Scoreboard data.

Table A3  
Direct, size and scale effect.

(1) Sales (Euro)	(2) R&D (Euro)	(3) Direct effect (%)	(4) Scale effect (%)	(5) Size effect (%)
100,000.00	1000.00	17.20	11.40	−10.50
110,000.00	1100.00	17.20	11.56	−10.59
121,000.00	1210.00	17.20	11.71	−10.67
133,100.00	1331.00	17.20	11.87	−10.76
146,410.00	1464.10	17.20	12.03	−10.85
161,051.00	1610.51	17.20	12.19	−10.93
177,156.10	1771.56	17.20	12.34	−11.02
194,871.71	1948.72	17.20	12.50	−11.11
214,358.88	2143.59	17.20	12.66	−11.20
235,794.77	2357.95	17.20	12.82	−11.28
259,374.25	2593.74	17.20	12.97	−11.37
285,311.67	2853.12	17.20	13.13	−11.46
313,842.84	3138.43	17.20	13.29	−11.54
345,227.12	3452.27	17.20	13.44	−11.63
379,749.83	3797.50	17.20	13.60	−11.72
417,724.82	4177.25	17.20	13.76	−11.80
459,497.30	4594.97	17.20	13.92	−11.89
505,447.03	5054.47	17.20	14.07	−11.98
555,991.73	5559.92	17.20	14.23	−12.06
611,590.90	6115.91	17.20	14.39	−12.15
672,749.99	6727.50	17.20	14.55	−12.24
740,024.99	7400.25	17.20	14.70	−12.33

Source: Authors elaboration from R&D Scoreboard data (Table 3, column (4)).

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