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Innovation and Employment: A firm level analysis with European R&D Scoreboard data

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Abstract

In this article, we analyse the microeconomic relationship between innovation and employment, using company data from the R&D Scoreboard for Europe covering 2000-2008.
A reduced form labour demand equation is estimated. In the equation, R&D can account for both product and process innovation. 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 relationship between total turnover and employment.
The results have important implications for policymakers: R&D and innovation supporting policies should be correctly tailored and monitored since the results depend on the characteristics of the firms benefited. By the same token, calibration of general equilibrium models aimed at quantifying the employment impact of R&D and innovation policies should take into account that an aggregate constant elasticity can be a very rough approximation.
Our results suggest that R&D and innovation policies tailored towards favouring entry of knowledge intensive firms can promote job growth.

JEL Classification: Technological change, corporate R&D, employment, panel data.

Keywords: O33, J20.

1 Introduction

This article deals with the relationship between innovation and employment at the firm level. Our focus is on formalised and structured innovation, i.e. new products and/or processes generated by an initial R&D expenditure. As explained by a large literature following Dosi (1988) and Pavitt (1984), innovation strategies are heterogeneous and there are industries where the basic type of innovative activity is based on embodied technological change or tacit knowledge accumulation, without formal research. Taking these elements into account 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 will be 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 an underlying magmatic heterogeneity exists, which may generate non linearity.[1] 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 factor in fixed supply, 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 statement in the literature that unit (research) costs are decreasing over some interval to the minimum efficient scale. Needless to say, it may be the case that in the long run firms less efficient in exploiting the benefit of research will exit the market, but in the short run this selection may be difficult, due to existence of market niches and informational problems.

How do scale and size effect operate? The former tends to amplify the effect on employment: for any given increase in the sales, if the impact of innovation on productivity is decreasing, then that 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 may prevail: it is a matter of empirical assessment. In our measurement exercise we will focus on Europe

[1] From now on, by non linear we mean that the employment elasticity of R&D is not constant, i.e. a percentage increase in R&D spending returns a non constant percentage increase in employment.

using the European subsample of R&D Scoreboard data, which covers almost all the R&D carried out in Europe[2].

The existing literature is either focused on assuming that labour saving technical change is at work and then estimating how compensation mechanisms operate to re-absorb displaced workers or in estimating some labour demand equation augmented for some innovation proxies. Differentiating ourselves from previous literature, we estimate a reduced form that explicitly incorporates a microfoundation for firm innovation process, namely the decision to invest in R&D. Indeed, since innovation is stochastic, optimal employment depends on the probability to innovate and thus serve a large market and also on the market effects of innovation. Significantly, although analytically simple, our framework is flexible enough to account for product and process innovation. To our knowledge this is an absolute novelty.

Our results confirm that R&D and innovation have a positive employment impact, coherently with a large strand of previous empirical contribution (see Section 2 below). Moreover, we estimate 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 positively affects the elasticity.

The quantification of those non linearities has important implications for innovation and competitiveness policy, in a broad and in a narrower sense. The broad sense is rather obvious: in order to do cost benefit analysis and/or simulation exercises, we need a proper calibration of the employment elasticity of R&D. If this elasticity is not constant, taking the average value may generate non robust predictions.

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 Lisbon-Barcelona Agenda and the follow up, called the Europe 2020[3] agenda- the chosen target is the three percent ratio of R&D on GDP. We claim that at aggregate level the R&D intensity could be seen from two perspectives, as an extensive

[2] Although Scoreboard and BERD data are collected according to very different rules and by different sources, whereas the former comes from groups consolidated balance sheet, and it is limited to internally financed research, and the second looks at research located in Europe regardless of the financing source, they report very similar results (European Commission, 2009). As a result, the database covers almost the overall population of R&D performing firms.

margin or an intensive one. The intensive margin is characterised by adding new actors (firms or sectors, in the sense of a sectoral system of innovation, see Malerba, 2002 and 2004) with high knowledge intensity, while the extensive margin is reached by increasing the weight of existing "big players", i.e. those who outspend the others in research. We claim that policies more oriented towards the emergence of knowledge intensive small firms are better. In fact, increasing weight by *large actors* fosters concentration and market power, slowing down the rate at which innovative gains are transferred to consumers and generating "inflexibility", since reallocation of resource from large actors, in case of failure, is much more problematic. 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 the relevant literature on the relationship between R&D and employment. Section 3 discusses methodology and data. Section 4 the results. Section 5 concludes.

2 Related Literature

The relationship between innovation and employment has received a cyclical interest depending on the rhythm and pace of technological change in the real economy, sometimes also spurred by the fear of technological unemployment in the public opinion. 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 (see the reviews in Chennels and Van Reenen, 2002; Pianta, 2005; Vivarelli, 2007).

Empirically, a number of caveats have been raised on the importance of the level of analysis: at *the firm 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 all the underlying dynamics (Bogliacino and Vivarelli, 2010).

If we focus on the micro level, the existing 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

[3] European Commission (2002), European Council (2002), and European Commission (2010).

innovation. If we consider also the indirect effect, i.e. compensation mechanisms, although there operate forces which push towards reabsorbing displaced workers, the full and instantaneous compensation cannot be assumed ex ante (see again the reviews in 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, see Van Reenen, 1997 for some discussion on the firm level mechanism).

Some theoretical clarification is necessary about how to interpret positive or negative employment elasticity. The classical approach (and the Schumpeterian one) is usually focused on the compensation mechanisms. In a nutshell, technical change is assumed labour saving: by reducing labour input per unit of output, it generates unemployment in the short run, but in the economy there are at work various prices and income effects[4] that tend to reabsorb displaced workers. Empirical work has tried to assess the speed and efficacy of this compensation.

However, one could also argue that in presence of complementarities between labour and research-innovation (which is very likely at least for skilled labour as testified by the huge literature on skilled biased technological change)[5] there are multiple equilibria, characterised by different – but positively related - innovation and employment rates. If this is the case, the rationale of R&D and innovation policy is not (only) the reduction of unemployment, but also the shift of the economy from a low R&D intensity/employment rate equilibrium to another one where both knowledge intensity and the employment rate are higher.[6]

Finally, since we have mentioned the EU competitiveness policies, as stated into the Lisbon-Barcelona agenda and its updated version -Europe 2020- we shall briefly sum up some assessment exercises. There has been a very large interest in the productivity consequences of increasing R&D, but less focus on the employment patterns. As far as the former is concerned, there is now a large consensus that research driven innovation is a major force shaping growth, empirically confirmed by data (for an updated review see Ortega-Argilés et al. 2010). As far as the latter is concerned, there have been some efforts to quantify the impact of

[4] Examples of compensation mechanisms are: an adjustment downwards by the wage, a decrease in price that pushes demand upward, more investment out of increasing profits and so on. For some discussion, see Vivarelli (1995) and (2007).

[5] See among many others Acemoglu (2002), Chennels and Van Reenen (2002), Antonietti (2007), Chusseau et al. (2008).

[6] This is an important claim under a policy perspective: since a higher employment rate improves the financial sustainability of the welfare state, a competitiveness policy based on R&D and innovation will be beneficial also in this aspect.

reaching the targets both at industry level (Bogliacino and Vivarelli, 2010) and through general equilibrium computations (Chevallier et al. 2006; Gelauf and Lejour, 2006; Gardiner and Bayar, 2010). Needless to say, the results are very sensible on the assumptions made, but the all studies agree that the impact would be positive.

3 Methodology and Data

In order to formulate our labour demand reduced form 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.[7]

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 can see our framework captures both product and process innovation.[8]

A point of clarification must be made with regard to this latter distinction. In the theoretical literature product and process innovation are usually distinguished, since the former is assumed to be intrinsically labour friendly and the latter labour saving, because it is associated with substitution of labour with new capital. Indeed, there is evidence that at industry level the mechanisms fits well the data (Bogliacino and Pianta, 2010). However, at micro level the relationship is usually more complicate due to business stealing and market power. For example, if the market is sufficiently competitive, a firm may even reduce the unit labour input by a large amount, but market selection will drive the price downwards and allow the firm to gain market shares and increase employment size. In contrast, whenever product innovation is associated with temporary monopolistic power, employment growth may be reduced. Since there is no *a priori* reason to assume different effects, we take as a first approximation a homogeneous effect of product and process.

[7] 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 relabeling patents with "secrecy" or "learning lags" as the main tools to appropriate rents from innovation.
[8] We clarify that our main interest is in the effect of innovation on labour demand, a somehow smaller objective but that allows disentangling the causality chain. There are of course theoretical studies on the general equilibrium

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

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

where *w, r* are the rental prices of factors, *q* is a probability which depends on output, *Y,* and R&D expenditure and σ is a parameter of substitutability between labour and capital (resp. *K* and *L*).

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

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

readjusting and taking logs, we obtain our main equation:

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

where $\Phi(R\&D_{it}, Y_{it})$ is some non linear function to be estimated.[9]

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:

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

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 nature of innovation.

Writing the FOC from the problem in equation (5) we can write:

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

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

We estimate (3) by fixed effects,[10] to get rid of unobserved heterogeneity, and using a polynomial approximation of $\Phi(R\&D_{it}, Y_{it})$.

relations between innovation and employment, but they are strictly dependent on the assumption justifying non market clearing by price. For an example, see Aghion and Howitt (1998), chapter four.

[9] Given non linearity, it is not possible to introduce some testable restrictions on the coefficients, although it is clear that a couple of them will depend on the parameter of the production function.

3.1. Data

We use data from the R&D Scoreboard. It recollects data for the top R&D spenders; data are consolidated at group level, i.e. including all the subsidiaries. The first edition of the Scoreboard was issued in 2004, the last one in 2009 (European Commission, 2009). Each scoreboard gathers data over the four previous years, and a choice should be made regarding the overlapping information: for this reason whenever a year is covered by more than one edition the last one is considered the dominant source.

The number of firms covered changes through the various editions: 500 EU and 500 non-EU in the first year, rising to 700 EU and 700 non-EU in 2005 and finally arriving at 1000 and 1000 from 2006 onwards. We are using data only for the EU firms. 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.

Scoreboard data cover more than 80% of total R&D expenditure, thus our data base covers most of the R&D doers located in Europe. The definition of R&D is the balance sheet one: it follows the standard IAS 38 – Intangible Assets, which is homogeneous with Frascati Manual (OECD, 2002). It includes the research carried out by the firm, not including any financed by public authorities.[11]

In case of mergers, we define a new firm, i.e. the old firms end their existence in the year of the merger, 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 occurs 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: the former are obviously

[10] The choice of fixed effects is due to the highly unbalanced structure of the panel, which affects the reliability and the robustness of dynamic specifications and GMM techniques. As a result the results may be interpreted as steady state ones.

[11] We should mention that in any case the publicly financed business R&D is a small percentage of the total. According to Community Innovation Surveys (source Eurostat) it is around two-three percent of the total.

correlated with the bargaining power, while the latter is a signal of the health status by the firm, which will also affect the wage level. Operating surplus is negative for many firms, implying that a log transformation would select the sample.[12] Since the tails are so fat that simply taking the level is not feasible, we rescale the variable adding its minimum and taking log. Since we are not interested in interpreting the coefficient, we found this to be the best strategy. To have a rapid appraisal of the validity of the instrument we also tried to match the information on the company wage for a subsample. Using other available sources we were able to collect information for 266 firms and we found a correlation of 0.30 between wage and operating surplus and 0.75 between wage and investment.

In the following Table we report the standard descriptive statistics

Table 1. Descriptive Statistics

	Firms (Average T)	Mean	Standard Deviation Within	Between	Overall
Employment	1485 (6.24)	18221.29	9469.51	42257.79	46150.63
Sales	1486 (6.24)	4072.04	3412.91	12029.58	14403.24
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.

As can be seen clearly 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 very often either go bankrupt or make a huge amount of extra profits.

R&D has a drawback, because it is an input measure and may be criticised for under-representing innovativeness of small firms and technological backward sectors (Smith, 2005). However, although there have been constant improvements in the measurement of innovation output (Oslo Manual, see OECD, 2005) through Innovation Surveys, the latter are not usable

[12] We tried also to estimate with only the firms who have positive values of the operating surplus and results are confirmed.

in panel format, which creates a large array of issues in detecting causality problems, and moreover Innovation Surveys are still experiencing a number of measurement problems. Moreover, R&D Scoreboard has two great advantages: a) it is an objective and not a subjective indicator; 2) it covers almost the total expenditure.

4 Results

4.1. Main results

In the Appendix we provide some diagnostic tests in Table A-2. The fixed effects estimator is supported by the Hausman test. In order to approximate the non linear expression, we chose a quadratic polynomial with an interaction with output. We have tried also a third degree polynomial, but it is rejected (as shown in Table A-2). Our estimated equation is:

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

Table 3 shows our baseline estimation of (3). Since the sample included firms with very high capital investment and R&D investment intensity -mainly research labs- we checked for the presence of outliers. The Grubbs test was negative, thus we used the full sample. As a robustness check, Table A-1 in the Appendix also shows the estimation for the truncated sample (at 100% intensities), presenting only minor differences.

Since we use both interaction and quadratic terms, there may be some risk of multicollinearity. In the following Table 2 we report the correlations among the main coefficients. As can be seen they are considerable but not worrying.

Table 2. Descriptive Statistics

	Sales	Capital Investment	Operating Surplus	R&D
Sales	1			
Capital Investment	0.91	1		
Operating Surplus	0.34	0.32	1	
R&D	0.67	0.64	0.42	1

To test for collinearity in a robust manner, we compute the variance inflation factor (for the OLS estimator), which is non negligible (the average is around twenty). For this reason, we present 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 all estimations we add time dummies to control for supply effects. We also add a dummy for events (mergers, acquisitions, significant change of name etc). Since our main interest is the R&D effect, we avoid including a full set of lags for *OS, Y* and *I,* because this will dramatically increase multicollinearity problems.

Table 3. Dependent Variable: log of employees

	(1)	(2)	(3)	(4)
$\log(Y_{it})$	0.395 (0.008)***	0.322 (0.009)***	0.334 (0.011)***	0.362 (0.011)***
$\log(OS_{it})$	-0.038 (0.013)***	-0.027 (0.012)**	-0.027 (0.012)**	-0.024 (0.012)*
$\log(I_{it})$	0.103 (0.005)***	0.084 (0.005)***	0.084 (0.005)***	0.080 (0.005)***
$\log(R\&D_{it})$		0.131 (0.008)***	0.160 (0.016)***	0.161 (0.016)***
$\log(R\&D_{it-1})$		0.034 (0.007)**	0.034 (0.007)***	0.030 (0.007)
$\log(R\&D_{it-2})$		0.047 (0.006)***	0.047 (0.006)***	0.043 (0.006)***
$\log(R\&D_{it})\log(Y_{it})$			-0.004 (0.002)**	-0.020 (0.002)***
$\log^2(R\&D_{it})$				0.021 (0.002)***
constant	5.896 (0.149)***	5.591 (0.141)***	5.533 (0.144)***	5.442 (0.143)***
Time Dummies	Yes	Yes	Yes	Yes
Events	Yes	Yes	Yes	Yes
N Obs	6992	5130	5130	5130
R2 (overall)	0.809	0.766	0.763	0.758

Source: R&D Scoreboard data. All columns refer to Within Group estimation. Standard Errors in parenthesis; *** significant at one percent, ** at five percent, * at ten percent. Y stands for Sales, OS for operating surplus, I for capital expenditure and R&D for R&D expenditure.

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.[13]

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

In order to compute the implied employment impact, taking into account the scale and size effect, 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:

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

There are three components in the above equation (7):

a) The direct elasticity, invariant to firm characteristics (α_3);

b) The intensive margin, related to R&D intensity ($2\alpha_5 \log\left(\frac{R\&D_{it}}{Y_{it}}\right)$);

c) The extensive margin, which is given by the interaction of the scale and size effects, dependent on the turnover ($(\alpha_4 + 2\alpha_5)\log(Y_{it})$).

Now, assuming that the firm fixes the R&D intensity as a routine, we can depict alternative scenarios (we consider from one to five percent), and then see how the employment elasticity of R&D increases when we enlarge the size. It is worth noting that for a given R&D intensity, if we increase the output, then we implicitly also increase the R&D expenditure level, e.g. if R&D intensity is five percent and if the sales increase by a hundred euros, then research expenditure should increase by five euros. The results are in Figure 1, where we have plotted

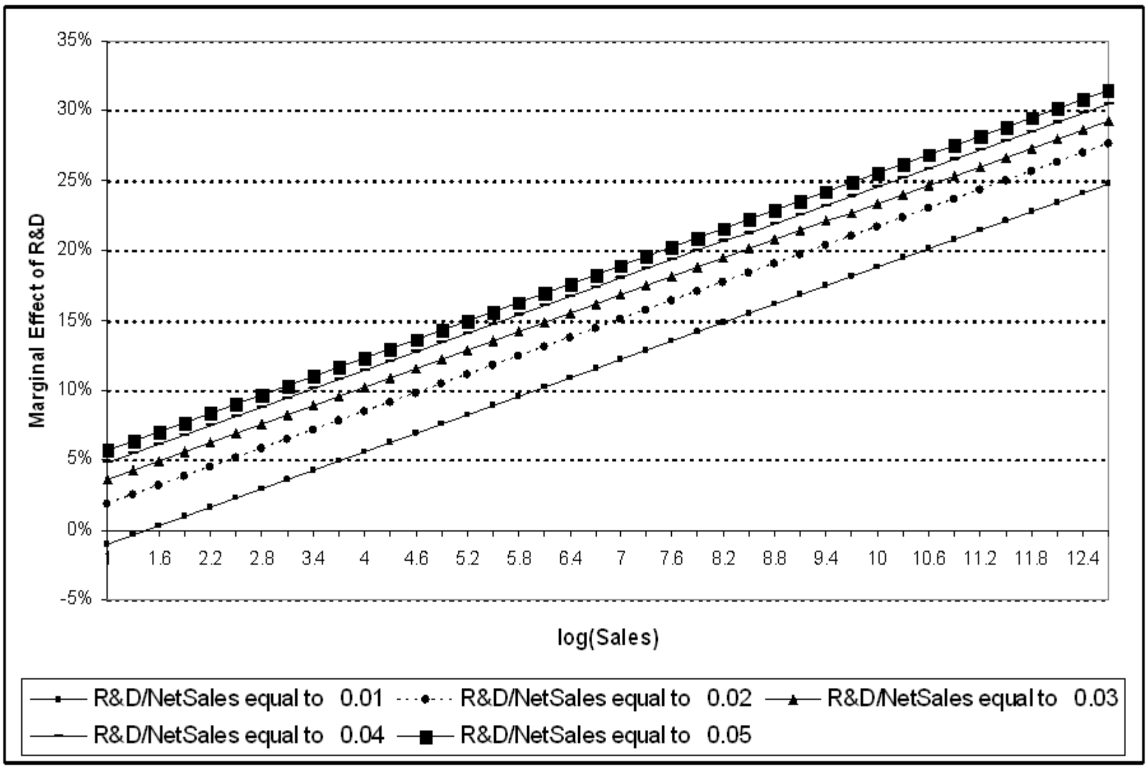
[13] A simple regression on the restricted subsample for which we have data confirms the sign and magnitude of all the coefficients (all but output which has a larger elasticity). Although the sample size is largely reduced and so this regression should be handled with care, this results support the validity of our econometric exercise.

the estimated employment elasticity of R&D for various R&D intensities as a function of turnover (in log scale).

As we said, to our knowledge this is the first paper on microdata which allows for non linear impact, so comparability with previous studies is somewhat difficult. Some back of the envelope calculation is however reassuring. We take as a benchmark the most famous study, i.e. Van Reenen (1997): from his Table 3 we compute the cumulative innovation effect on employment in 0.10-0.17 (we use the last three columns, which are robust regressions instead of OLS). Its sample of firms has an average R&D intensity around one percent and is probably less populated by large multinational firms, so we can take a range of value for (log) sales that goes from 5.2 to 8.2 (the latter being our sample mean). To get a value of the innovation – employment elasticity we should note that $\frac{d\log(L)}{d\log(Innov)} = \frac{d\log(L)}{d\log(R\&D)} / \frac{d\log(Innov)}{d\log(R\&D)}$. The corresponding values in Figure 1 are 0.08 and 0.15. Using an estimate of $\frac{d\log(Innov)}{d\log(R\&D)}$ from the large review in Denicolò (2007) in a range of 0.7 and one we get an estimated value that is between 0.08 and 0.2, which is of the same order of magnitude as the benchmark study.

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.

Figure 1. The marginal effect of R&D.



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

4.2. Robustness Check

We performed a robustness check. First of all, one may also wonder if 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 calculated the log of the total amount of R&D performed by competitors in the same industry (defined as four digits) –it can be added since it is in PPP- and we interact it with the log of R&D.

As expected, results are confirmed and there are additional labour saving consequences. The regression on the full sample and the truncated sample are reported in Table 4 below.

Table 4. Dependent Variable: log of employment.

	(1)	(2)
$\log(Y_{it})$	0.563 (0.011)***	0.359 (0.011)***
$\log(OS_{it})$	-0.028 (0.001)***	-0.024 (0.012)*
$\log(I_{it})$	0.057 (0.006)***	0.080 (0.005)***
$\log(R\&D_{it})$	0.226 (0.039)***	0.266 (0.033)***
$\log(R\&D_{it-1})$	0.020 (0.007)	0.029 (0.007)
$\log(R\&D_{it-2})$	0.037 (0.006)***	0.042 (0.006)***
$\log(R\&D_{it})\log(Y_{it})$	-0.020 (0.003)***	-0.018 (0.002)***
$\log^2(R\&D_{it})$	0.018 (0.002)***	0.020 (0.002)***
$\log(R\&D_{it})\log(S_{it})$	-0.008 (0.002)***	-0.010 (0.002)***
constant	4.893 (0.145)***	5.464 (0.143)***
Time Dummies	Yes	Yes
Events	Yes	Yes
N Obs	4097	5130
R2 (overall)	0.759	0.755

Source: R&D Scoreboard data, full sample for column (1), sample truncated at R&D and capital intensity both less than hundred per cent for column (2). All columns refer to Within Group estimation. Standard Errors in parenthesis; *** significant at one percent, ** at five percent, * at ten percent. 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.

A further robustness check takes into consideration 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 and 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 an estimation in sequence to check for stability.

The main results are confirmed, as can be seen in Table 5. It is obviously difficult to discuss the changes in magnitude due to the large difference in sample size.

Table 5. Dependent Variable: log of non R&D employment.

	(1)	(2)	(3)	(4)
$\log(Y_{it})$	0.605 (0.029)***	0.570 (0.032)***	0.596 (0.036)***	0.623 (0.040)***
$\log(OS_{it})$	-1.885 (0.535)***	-1.800 (0.535)***	-1.626 (0.546)***	-1.547 (0.548)***
$\log(I_{it})$	0.057 (0.006)***	0.053 (0.016)***	0.053 (0.016)***	0.053 (0.016)***
$\log(R\&D_{it})$		0.067 (0.027)**	0.154 (0.061)**	0.158 (0.061)**
$\log(R\&D_{it})\log(Y_{it})$			-0.013 (0.008)*	-0.026 (0.012)**
$\log^2(R\&D_{it})$				0.016 (0.010)*
constant	23.375 (5.514)***	22.512 (5.514)***	20.585 (5.644)***	19.708 (5.671)***
Time Dummies	Yes	Yes	Yes	Yes
Events	Yes	Yes	Yes	Yes
N Obs	1743	1743	1743	1742
R2 (overall)	0.703	0.730	0.774	0.787

Source: R&D Scoreboard data, sample truncated at R&D and capital intensity both less than hundred per cent. All columns refer to Within Group estimation. Standard Errors in parenthesis; *** significant at one percent, ** at five percent, * at ten percent. 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.

5 Conclusions & implications for policy

In this paper we have examined the relation between innovation and employment at firm level, focusing on the most formalised 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 obtain two main results: 1) as expected the employment impact of technological change is positive; 2) the employment elasticity of R&D is not constant, neither with regards to the amount of R&D expended, nor with regards with the size of the firms. In fact we detect a size effect, driven by more efficiency by 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.

Taking into account the standard objection against any policy intervention, namely the need to evaluate and monitor them, and the need to carefully discuss the design in the light of the existing lines of intervention, in order to avoid deadweight losses and additionality, some policy implications follow straightforwardly from this empirical assessment.

First of all, when trying to calibrate models in order to quantify the impact of R&D and innovation supporting policies one has to take into account that using an aggregate constant elasticity may introduce a considerable bias.

Secondly, according to our results the empirical impact of innovation is not invariant along the distribution of firms. From our empirical estimates we infer that promoting employment through the knowledge economy can be done either through the entry of new innovative actors, with higher research intensity or by promoting growth through existing big players. The first of the two strategies shows some advantages: (a) it prevents harmful (to consumers) concentrations; (b) it leaves more flexibility to the system, to allow faster reallocation of resources. While a picking-up-the-winner is not implementable, there are strong arguments in favour of the development of an integrated venture capital market and policies that reduce barriers to entry.

The next steps of the research will be the explicit incorporation of innovative effort carried out through Innovation Survey data, in order to quantify the direct and indirect effect of research expenditure. Moreover, a contemporaneous account of productivity and employment effect would be important for better policy targeting and calibration.

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Annex: Further Robustness Check

In order to test the robustness of our specification, we report the result for the truncated sample in the following Table A-1. We exclude firms for which the R&D or capital investment intensity was larger than one hundred per cent. 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, confirming the specification.

Finally, in Table A-2 we provide some basic specification test for the baseline version. The F-test is the standard general test of significance of the model. The second line reports the F-test for the joint lack of significance of the fixed effect. The third line shows the t-test on the third power of R&D, to control for a good approximation of the non linearity. Finally, the last line is the standard Hausman test that compares fixed effects with the random effects model, showing that the latter should be rejected.

Table A - 1. Dependent Variable: log of employees

	(1)	(2)	(3)	(4)
$\log(Y_{it})$	0.558 (0.009)***	0.523 (0.012)***	0.535 (0.013)***	0.567 (0.014)***
$\log(OS_{it})$	-0.037 (0.012)***	-0.031 (0.011)***	-0.032 (0.011)***	-0.029 (0.011)***
$\log(I_{it})$	0.055 (0.009)***	0.059 (0.006)***	0.059 (0.006)***	0.057 (0.006)***
$\log(R\&D_{it})$		0.084 (0.008)***	0.119 (0.018)***	0.136 (0.018)***
$\log(R\&D_{it-1})$		0.024 (0.007)***	0.024 (0.007)***	0.020 (0.007)***
$\log(R\&D_{it-2})$		0.042 (0.006)***	0.041 (0.006)***	0.038 (0.006)***
$\log(R\&D_{it})\log(Y_{it})$			-0.004 (0.002)**	-0.021 (0.003)***
$\log^2(R\&D_{it})$				0.019 (0.002)***
constant	4.885 (0.140)***	4.692 (0.138)***	4.622 (0.142)***	4.500 (0.142)***
Time Dummies	Yes	Yes	Yes	Yes
Events	Yes	Yes	Yes	Yes
N Obs	6328	4893	4893	4893
R2 (overall)	0.788	0.768	0.764	0.761

Source: R&D Scoreboard data, sample truncated at R&D and capital intensity both less than hundred per cent. All columns refer to Within Group estimation. Standard Errors in parenthesis; *** significant at one percent, ** at five percent, * at ten percent. Y stands for Sales, OS for operating surplus, I for capital expenditure and R&D for R&D expenditure.

Table A- 2. Dependent variable: log of employees. Specification tests.

	(1) Baseline specification
F test	307.50
(p value)	(0.000)
F test: Fixed Effects	57.42
(p value)	(0.000)
T-test on $\log^3(R\&D_{it})$ **in the base specification**	-0.34 (0.730)
Hausman test	3880.50
(p value)	(0.000)

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

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Abstract

In this article, we analyse the microeconomic relationship between innovation and employment, using company data from R&D Scoreboard for Europe covering 2000-2008.
We estimate a reduced form equation in which R&D can account for both product and process innovation. 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 relationship between total turnover and employment.
Our results have important implications for policymakers: R&D and innovation supporting policies should be correctly tailored and monitored since the results depend on the characteristics of the firms benefited. By the same token, calibration of general equilibrium models aimed at quantifying the employment impact of R&D and innovation policies should take into account that the average elasticity can be a very rough approximation.
We claim that our results support the position that R&D and innovation policies should be tailored towards favouring entry by knowledge intensive firms, instead of supporting existing actors.

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