Exploring the relationship between the educational level of the workforce and the innovative capacity of the firm: A cross-country comparative analysis on a sample of European firms

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Abstract

In this paper, we explore the relationship between the educational level of the workforce and the innovative capacity of the firm, adopting an international comparative perspective and comparing different countries. The data are obtained from the survey European Firms in a Global Society (EFIGE) that was conducted in seven European countries (Austria, France, Germany, Hungary, Italy, Spain, and the UK) during the 2007-2009 period and are analysed with several models of multivariate analysis. Our results show a positive relationship between the ratio of graduated employees and the measures of the innovative capabilities of the firm, even controlling for the share of personnel employed in R&D. This relationship is not linear; in terms of firm innovativeness, we find decreasing marginal returns for the ratio of educated employees and for people involved in R&D. We also find some significant differences across different countries regarding the intensity of the link between the qualification of the workforce and the innovative capacity of the firm.

Keywords: Human capital; R&D; Innovation; D22; O32; J24.

1. Introduction

The importance of human capital for economic growth has been largely emphasized. In the theory of growth, the importance of human capital was almost immediately acknowledged. Although in the 'classic' Solow model of growth (1956) its role remains in a sort of 'black box', Mankiw, Romer, and Weil (1992), extending Solow's model with the explicit inclusion of human capital, manage to explain almost two-thirds of the variability of the growth rate among different national economies. The new theory of growth particularly emphasizes the importance of human capital (Lucas, 1988), giving a microeconomic foundation to the theory. The link between human capital and growth is seen in technological progress and innovation and it clearly has its roots at the firm level. In fact, Mincer (1958, 1962), Schultz (1961), and Becker (1964) develop the concept of human capital, looking at it as an important input to production. But, what is human capital exactly? This term is commonly used by economists and other social scientists with reference to skills, knowledge, and capabilities embodied in people (Abel and Gabe, 2011). Rowley (2001) and Storper and Scott (2009) define human capital as the embodiment of knowledge in terms of the understanding, practices, awareness, and creation of tacit knowledge within people. As knowledge increases, the absorptive capacity of both an individual and a firm also increase (Grant, 1996). However, knowledge and skills are abstract terms that need to be specified to measure them and to capture their sources. Becker (1964) and Mincer (1962), in their theoretical and empirical analyses, focus on the role of formal education in schools, on the work experience, and on the training on the job. The macroeconomic literature traditionally measures human capital using the number of years of schooling or level of formal education (Cohen and Soto, 2007; Romer, 1990a, b). Internationally comparable schooling data are much more easily available than data about the other components of human capital. At a microeconomic level, a greater availability of data allows attention to be focused on training, work experience, etc. The result is that, while there are plenty of studies on the importance of people's education at a macroeconomic level, there is not the same richness of empirical studies at the firm level. Many studies have used workforce education as a control variable to analyse the determinants of productivity or of innovation at the firm level, although it is seldom the main object of analysis. Rarely has the nature of the relationship been deepened or an internationally comparative perspective been adopted.

Our paper tries to fill this relative gap in the literature. We ask whether there is a relationship between the educational level of the workforce and the innovative capacity of a firm. The relationship between education and innovation is evident if we consider employees with high education levels working in R&D laboratories. The importance of R&D for innovation has been widely recognized at both micro and macroeconomic levels (see Romer, 1990 a, b for an example of a micro-founded model of growth). We enquire whether a highly educated workforce is related with innovation, even controlling for R&D activities. Empirically, we try to test if there is a relationship between the share of university graduated employees and the innovativeness of a firm, expressed by the probability of introducing a product innovation and by the percentage of turnover derived from an innovative product, controlling for the share of employees directly occupied in R&D activities and for other factors that may affect innovation. Therefore, this study focuses on the relationship between the workforce's education and innovation, although it has R&D as an essential control variable because our theoretical framework is rooted in the knowledge production function literature. This function states that innovation at the firm level is related to the cognitive capital present in the firm itself, which is calculated not only by the expenses in (or by the personnel dedicated to) formalized R&D but also by the level of internal human capital (Audretsch and Feldman, 2004). Following this definition, we refer later to R&D personnel and the education of the workforce as the cognitive capital of a firm.

The knowledge production function approach also hypothesizes decreasing returns for human capital and R&D. Therefore, it provides a theoretical basis for the hypothesis of the non-linear relationship between the two components of cognitive capital and innovativeness of a firm. In fact, another question we attempt to answer with our empirical study is whether the relationship between the percentage of graduated workforce on one side and the probability to introduce an innovation and the percentage of turnover deriving from the innovation on the other side is constant in its intensity regardless of the percentage of graduated employees or, on the contrary, it varies (decreases) with an increase in this percentage.

Finally, this paper also attempts to shed light on the differences in the relationship between workforce education and innovation from an international perspective. We ask the following question: if the educational level of the workforce is related to the innovativeness of the firm, is the intensity of this relationship significantly different between different countries? The comparative perspective at a micro level represents the main element of novelty of our paper. To our knowledge, there are no other papers comparing the intensity of the relationship between educated people and innovation at a firm level across countries in any influential journals.

The empirical analysis is conducted on data from a survey (EFIGE) conducted in seven European countries during the 2007-2009 period. This survey is described in detail in the third section. To address these issues, we performed a regression analysis comparing several different techniques.

The article is structured as follows. The second section presents a review of the relevant literature on the relationship between human capital and innovation. The third section describes the database and presents the results of the descriptive, bivariate, and multivariate analysis. A conclusion, with a synthesis of the results and some final considerations, ends the paper.

2. Human capital, R&D, and innovation: looking for microeconomic literature

As mentioned in the Introduction, the link between human capital and innovation has been analysed both from the micro and macroeconomic perspectives, focusing on the effects of human capital on firm productivity and innovation (micro level) and on economic growth (macro level), with an evident link between these two aspects underlined by the micro founded models of growth. However, human capital is a concept with many facets; it has been used in different theoretical contexts, and it has been assigned many different functions.

First, we report the content of some studies that can be traced back to two important conceptual frameworks where human capital has a prominent role: the knowledge production function and the evolutionary theory of the firm. In the former context, the complementarities between human capital and other factors crucial for productivity and innovation has been particularly emphasized. In the latter theoretical framework, the role of human capital in developing a firm's ability to absorb innovations from outside has been underlined. Then, we discuss some important empirical contributions regarding the contribution to innovation and firm productivity of single components of human capital (from training to workforce education).

In the context of the knowledge production function (Griliches, 1979), which represents a bridge between the macro and microeconomic levels, bringing the concept of the production function from a macro to microeconomic level, human capital is, together with R&D, an explication of the concept of knowledge. In fact, in this formulation, innovation is the output and knowledge is the input at the firm level. Although the latter is a term with a clear meaning in economics, this needs to be explained empirically. As Audretsch and Feldman (2004) underline, citing Cohen and Klepper (1991 and 1992), the main source of knowledge in firms is generally considered R&D, which is therefore the term that underpins most empirical investigations. Other elements to which the knowledge 'translates' vary depending on the specific objective of the study. In Audretsch and Feldman's (2004) formulation, knowledge production includes, in addition to R&D, human capital as an input of innovation. In empirical studies, such formulation of the knowledge production function has rarely been estimated at the firm level. It has usually been extended to industries, geographic areas, or countries, highlighting the role of spillovers and externalities. The innovation output of each firm depends only partly on internal sources of knowledge. Knowledge functions depend largely on the research done by other firms, by the public and private research centres and on the human capital in the geographically contiguous area of a firm (for an analysis of the Italian case, see Audretsch and Vivarelli, 1996). Therefore, when the link between the input and output of knowledge has been studied at the firm level, the results have commonly been weak; if the unit of analysis was larger, the relationship has been stronger.

In the decades since the introduction of the theoretical model of the knowledge production function, there have been many important contributions, including empirical studies, that substantiated this approach (Griliches and Mairesse, 1983; Hall and Mairesse, 1995; Crepon, Duguet, and Mairesse, 1998). The idea is that a company, an industry, or a geographical area (Jaffe, 1986; Acs, Audretsch, and Feldman, 1992; Feldman, 1994) must invest in R&D expenses (input) to increase the production of innovations (output). These, in turn, imply an increase in the value added through an increase in productivity. In this context, human capital is a complementary input that may also interact with R&D. As an example of an empirical study that analyses the impact on firm performance of both R&D and human capital and of their interaction, Ballot, Fakhfakh, and Taymal (2001) analyse data from France and Sweden and found that R&D and human capital have a positive effect on firm performance, as measured by the value added, and found a positive effect of the interaction between these two factors.

The original formulation of the knowledge production function has been significantly enriched through the consideration of the effects of feedback (Kline and Rosenberg, 1986) as well as by the realization that knowledge spillover can take root only in the presence of a sufficient level of absorptive capacity (Cohen and Levinthal, 1989). This is, in fact, an adequate level of internal knowledge resources that can 'absorb' the external knowledge. According to Mangematin and Nesta (1999), firms with a high level of absorptive capacity will be in a better position to assimilate and utilize external knowledge to increase the innovative performance. Several studies relate the internal and external sources of knowledge with innovative performance (Srivastava et al., 2015; Wang and Libaers, 2016). According to DeCarolis and Deeds (1999), innovation is a result of the internal development of knowledge and of the acquisition and application of external knowledge.

Absorptive capacity appears, therefore, to be one of the most important determinants of the firm's ability to acquire, assimilate, and profitably utilize new knowledge to increase its innovation performance. Accordingly, firms need to increase their absorptive capacities to improve their performance (Cokburn and Henderson 1998). Cohen and Levinthal (1989) claim that the learning capacity of firms depends on their internal capacities, which can be measured by the number of researchers in the R&D department. However, some authors identify internal R&D as the key component of the absorptive capacity of external R&D spillover.

Thus, in the sophisticated context of the evolutionary theory of the firm, the idea of Nelson and Phelps (1966), which was born in the macroeconomic field, that 'internal' knowledge is needed to absorb new knowledge produced outside, is reclaimed, showing a type of inverse causal process between cognitive capital and innovation. Despite these important theoretical improvements, these studies have remained focused on the role of R&D as a primary factor. R&D is capable of generating innovation to support productivity, the competitiveness of products, and economic growth.

Compared to the profusion of studies on the effects of human capital in the macroeconomic sphere or on the effects of R&D at the firm level, there have been fewer empirical studies on the effects of human capital on innovation at the firm level (Schneider, Guenther, and Brandenburg, 2010). In many cases, the highlighted link is indirect in the sense that human capital is seen as a prerequisite for investment in other factors or changes in firms that, in turn, lead to innovation. For example, in a study using Italian data, Arrighetti, Landini, and Lasagni (2011) refer to a vision of a firm based on *capabilities* and stressed the propensity to invest in *intangible assets.* Such assets, which have a strong impact on innovation and firm performance, depend on the level of human capital in the firm as well as on firm size, organizational complexity, and many firm-specific factors.

Using Turkish data, Alpkan at al. (2010) demonstrate that, even if organizational support (identified as an internal climate factor and described as a facilitator for organizations to spur organizational entrepreneurial) and human capital (defined as the sum of the individual knowledge, skills, and abilities of the organizational human resource) exert positive effects on innovative performance, their interaction does not produce higher performance. When human capital is low, organizational support increases innovative performance more (and vice versa). When both are high, a further significant increase in innovative performance seems to be possible within the same period.

Abowd et al. (2002), using US data, show that human capital affects the productivity of businesses directly or in a complementary role with respect to the most advanced technologies, business models, and organizational practices. Piva, Santarelli, and Vivarelli (2005), using Italian data, highlight the link between organizational change and the demand for employees with high levels of *skills.* Other studies underline the importance of the management practices in developing the effectiveness of human capital: Cabello-Medina, López-Cabrales, and Valle-Cabrera (2011) and López-Cabrales, Real, and Valle (2011) find that the human resource management practices enhances the uniqueness of the human capital, which has, rather than its value, a positive effect on firm's innovativeness.

As underlined in the Introduction, human capital has several components. Education, work experience, and training are more frequently identified and analysed. Some empirical studies have analysed the effect of each on them individually on firm performance, while others have underlined their interactions.

Regarding the importance of training, Laursen and Foss (2003) analyse the relationship between training and innovative performance at the firm level; they found that human resources management practices (in particular, internal training and the combination of internal and external training) have a positive effect on innovation performance. Zhou, Dekker, and Kleinknecht (2011) report that training and R&D improve a firm's innovation performance in terms of higher new product sales in the Netherlands. Using data on French firms, Gallié and Legros (2012) also find that training and R&D have positive effects on patenting activity. On the other side, Gonzàlez, Miles-Touya, and Pazò (2016) explore the effect of the investment in R&D and firm-sponsored training on a firm's decision to innovate. Using a sample of Spanish manufacturing, they want to establish whether these investments reinforce or perhaps even complement each other. The results show that simultaneously engaging in R&D and worker training increases the likelihood of innovating significantly. In particular, for small firms, this probability more than doubles when neither activity was performed previously; for larger firms, the corresponding increase exceeds 70%. However, Rogers (2004), using data on Australian firms, shows that there is no significant relationship between training and innovation.

Formal education is, however, considered the main source of general human capital (Schwerdt and Turunen, 2007) because it enables a person to acquire the skills necessary to identify business opportunities (Arvanitis and Stucki, 2012) and increases a firm's absorptive capacity (Goedhuys, Janz, and Mohnen, 2013).

Bartel and Lichtenberg (1987) demonstrate that highly educated employees have a comparative advantage in adopting and implementing new technology. Blundell et al. (1999), in their literature review of the returns on human capital at the macroeconomic (representing the entire economy) and microeconomic (representing the firm and the individual) levels, underline the dual role of a highly educated and skilled workforce, which is able to adapt to new tasks and technologies and is a direct source of innovation because education increases an employee's ability to be innovative in his/her job. They also report the results of several empirical studies, such as that of Bosworth and Wilson (1993), which suggests strong links between the employment of graduates, including professional scientists and engineers, and the adoption and use of high-level technologies in a firm. Additionally, they underline the role of on-the-job training as a component of human capital and, aside from innovation, they also considered the effects of human capital on productivity and profitability.

Nelson and Phelps (1966) and Benhabib and Spiegel (1994) consider that "education enhances the ability to receive, decode, and understand information", which increases the capacity to innovate (creation of activities, products, and technologies) and fosters the adoption of new technologies. According to them, the growth rates of productivity and innovation are positively correlated with the level of education, especially the number of persons with high school or university diplomas. The importance of qualified human resources, together with R&D, to enhance the firm's absorptive capacity and therefore its innovative performance are also emphasized by Lund Vinding (2006) and Muscio (2007).

The study by Bugamelli *et al.* (2012) is also based on EFIGE data. The share of university graduate employees is linked with the introduction of an innovation in a firm as well as with the number of patents filed at the European Patent Office (the relationship found is positive). Expenditures on R&D are not included in the same estimate of the determinants of innovation, although it is placed in relation to human capital in the sense that the latter (measured by the share of graduates) has a positive effect on the expenditures on R&D. The paper by D'Amore, Iorio, and Lubrano Lavadera (2014), which analyses Italian data (a rotating panel of Italian firms for a period of nine years), shares the same theoretical background and some of the same central empirical questions addressed in this study, and they find similar results: a statistically significant and positive relationship between the number of graduates and the number of employees in R&D, on the one hand, and the likelihood of introducing both a product and a process innovation on the other; a non-linear relationship between the graduated workforce and the innovative capacity of the firm.

3. Data and objectives of the empirical analysis: bivariate and multivariate analysis

For our analysis, we use data from the EFIGE survey. EFIGE (European Firms in a Global Economy) is an international research project under the auspices of the European Commission. A large survey with six sections was given to a sample of 14,911 manufacturing firms in seven European countries, with 482 responses from Austria, 2,975 from France, 2,973 from Germany, 488 from Hungary, 3,019 from Italy, 2,832 from Spain, and 2,142 from the United Kingdom. The stratification of the sample was done according to the size and business sector, considering the main geographical areas of each country. The questions are related to the 2007-2009 period.

The goal of this study is to correlate the innovativeness of the firms with a fundamental dimension of the human capital, i.e., the formal education of the workforce. As a measure of innovativeness, we take two variables into consideration, both derived from two specific questions of the EFIGE survey. The first is a dummy variable that assumes a value of 1 if a firm introduced any product innovations in the 2007-2009 period and is 0 otherwise; the second variable is the average percentage of turnover from innovative product sales in the same years[1]. As a measure of the formal education of the workforce, we use the percentage of university graduates in the firm's home country; we also control for another dimension of the firm's cognitive capital, i.e., the percentage of employees involved in R&D activities. We investigate whether and to what extent the education of the workforce is related to innovation at the firm level, the non-linearity of the relationship, and the different intensity of this relationship in different countries[2].

Referring to the review of the literature in the previous section, our theoretical reference is the function of internal knowledge production à la Audretsch and Feldman (2004). In this framework, innovation at the firm level (I) is a function of R&D (RD), the human capital (HK), and an error term:

$$I_i = \alpha RD^{\beta}{}_i HK^{\gamma}{}_i \varepsilon_i$$

The non-linear formulation of the function implies a relationship between human capital and innovation that is not constant but is dependent on the level of human capital itself. The same holds for R&D. This is the reason why we test a non-linear relationship between the two components of the cognitive capital and the innovation and why the more complex (and complete) tested model keeps this non-linear formulation.

We analyse the relationship between innovation and cognitive capital with bivariate and multivariate statistical techniques. Table 1 presents the list of the variables used in the different analyses, including their names, definitions, mean values, standard deviations, minimum values and maximum values.

Table 1 - Definitions and descriptive statistics of the variables

[1] In the EFIGE questionnaire, only those who introduced a product innovation may indicate the percentage of turnover derived from innovative product sales; therefore, for those who did not introduce any product innovations, we assumed that the percentage was zero.

[2] Other surveys, like the Community Innovation Survey, may have equally or more detailed questions about innovation and may cover the service sector too, while EFIGE covers only manufacturing firms. However, the international perspective and the comparative purpose led us to prefer the EFIGE survey because it is conceived with this comparative perspective. Moreover, its dataset is not the result of the harmonization of surveys conducted by single countries; on the contrary, it has a single sampling plan and the interviews are carried out by a single institution, which produces a single dataset.

Variables	Definitions	mean	sd	min	max
innoprod	Dummy = 1 if the 'firm introduced any product innovation in the 2007-2009 period	0.491		0	1
innoturn	Percentage of turnover derived from innovative product sales	10.18	18.80	0	100
innoturn_prop	innoturn/100	0.102	0.188	0	1
gradperc	Percentage of university graduates in the workforce in the firm's home country				
gradperc2	$(\text{gradperc})^2$	271.6	914.3	0	10000
ln_gradperc	natural logarithm (gradperc + 1)	1.661	1.240	0	4.615
rdperc	percentage of employees involved in R&D	7.820	13.77	0	100
rdperc2	$(\text{rdperc})^2$	250.757	1067	0	10000
ln_rdperc	natural logarithm (rdperc + 1)	1.358	1.283	0	4.615
tertiaryperc	percentage of people with tertiary education in the country (average 2007-2008-2009)	25.598	6.852	14.15	35.91
workforce	Number of employees in the firm's home country	65.09	102.0	10	500
age1	Dummy = 1 if the firm was founded since less than 6 years	0.071		0	1
age 2	Dummy = 1 if the firm was founded since between 6 and 20 years	0.352		0	1
age 3	Dummy = 1 if the firm was founded more than 20 years.	0.577		0	1
Italy	Dummy = 1 if the firm is located in Italy	0.205		0	1
France	Dummy = 1 if the firm is located in France	0.201		0	1
Spain	Dummy = 1 if the firm is located in Spain	0.192		0	1
Germany	Dummy = 1 if the firm is located in Germany	0.199		0	1
Austria	Dummy = 1 if the firm is located in Austria	0.030		0	1
Hungary	Dummy = 1 if the firm is located in Hungary	0.033		0	1
UK	Dummy = 1 if the firm is located in United Kingdom	0.140		0	1
pavitt1	Supplier-dominated firms	0.265		0	1
pavitt2	Scale-intensive firms	0.500		0	1
pavitt3	Specialized-suppliers firms	0.189		0	1
pavitt4	Science-based firms	0.0460		0	1
grad_Austria	Austria*gradperc	0.177		0	80
grad_France	France*gradperc	1.790		0	100
grad_Germany	Germany*gradperc	2.290		0	100
grad_Italy	Italy*gradperc	1.413		0	100
grad_Hungary	Hungary*gradperc	0.510		0	80
grad_Spain	Spain*gradperc	2.021		0	100
grad_UK°	UK*gradperc	1.252		0	100
gradperc2_Austria	gradperc2*Austria	4.437		0	6400
gradperc2_France	gradperc2*France	50.252		0	10000
gradperc2_Germany	gradperc2*Germany	71.021		0	10000

gradperc2_Italy	gradperc2*Italy	33.702	0	10000
gradperc2_Hungary	gradperc2*Hungary	18.319	0	6400
gradperc2_Spain	gradperc2*Spain	51.113	0	10000
gradperc2_UK°	gradperc2*UK	42.711	0	10000
N		14759		

°Variables excluded by regressions to avoid the perfect collinearity trap.

Table 2 gives the distribution of firms by country in the sample

Table 2 - Number and percentage of firms by country

	Number of firms	Percentage
Austria	443	3%
France	2973	20.14%
Germany	2935	19.89%
Hungary	488	3.31%
Italy	3021	20.47%
Spain	2832	19.19%
United Kingdom	2067	14.01%
Entire sample	14759	100%

Table 3 gives an introductive, general picture of the innovative performance of the firms included in the sample. For each country and for the entire sample, the first column shows the percentage of firms that claim to have introduced product innovations (that is, when the value of *innoprod* is 1), the second column shows the mean percentage of turnover derived from innovative products (the mean value of the variable *innoturn*) among the innovative firms, and the third column shows the same mean among all firms.

Austria and the United Kingdom are the countries with the highest percentage of firms introducing product innovations, while this innovative performance is well below the average in Hungary, France, and Spain. Among the innovative firms, the percentage of innovative turnover is particularly high in Italy and Austria. The value of the percentage of innovative turnover among all the firms is influenced by both previous values, i.e., the percentage of innovative firms and the percentage of innovative turnover; therefore, it is high in countries where the two previous values are both high (Austria and the UK), although it may be high also when one value is particularly high and the other is close to the average (e.g., Italy, which has a percentage of innovative firms slightly above the average but with a high value of innovative turnover among innovative firms).

Table 3 - Percentage of innovative firms and average percentage of innovative turnover by country

	Percentage of firms that introduced a product innovation (who declared *innoprod* = 1)	Average percentage of turnover from innovative product sales (mean value of *innoturn*) - only innovative firms	Average percentage turnover from innovative product sales (mean value of *innoturn*) - all firms
Austria	59.14%	23.31%	13.41%
France	44.27%	19.18%	8.06%
Germany	49.98%	20.74%	10.10%
Hungary	43.85%	19.27%	8.45%
Italy	49.21%	23.71%	11.67%
Spain	45.59%	20.39%	9.29%
United Kingdom	58.49%	21.74%	12.10%
Entire sample	49.09%	21.25%	10.18%

Table 4 shows the dimension of cognitive capital in the firms and a measure of the global human capital of the nations. The first column reports the average of the percentage of university graduates in the workforce in firm's home country for each country and for the entire sample (*gradperc*), the second column reports the average of the share of employees involved in R&D activities (*rdperc*), and the third column reports the percentage (the average between the values of 2007, 2008, and 2009) of the country's population between 18 and 65 years with tertiary degree education (OECD data). This last measure may provide an idea regarding the extent of externalities derived from an educated population.

Table 4 - Mean values of *gradperc*, *rdperc*, and *tertiaryperc* by country

	Average percentage of university graduates in the workforce in firm's home country (mean value of *gradperc*)	Average percentage of employees involved in R&D activities (mean value of *rdperc*)	Percentage of people with tertiary education in the country (average between the 2007-2008-2009 values) (*tertiaryperc*)
Austria	5.88%	7.62%	26.06%
France	8.90%	7.21%	27.49%
Germany	11.50%	10.89%	25.36%
Hungary	15.40%	3,28%	19.04%
Italy	6.91%	6.87%	14.15%
Spain	10.53%	7.37%	29.60%
United Kingdom	8,95%	7.44%	35.91%
Entire sample	9.45%	7.82%	25.60%

The percentage of university graduates in the workforce is particularly high in Hungary, and Germany and Spain are also above the average. The percentage of employees involved in R&D

activities in Germany is much higher than the average, while it is below the average in Hungary; Italy is almost one percentage point below the average of the sample. The percentages of university graduates in the home country are quite different across countries, with the United Kingdom having a high percentage and Italy and Hungary having a low percentage.

The descriptive statistics of the principle variables under observations have been reported; we now turn to an explorative bivariate analysis. Table 5 shows the Spearman correlations between the variables concerning the innovative performance (*innoprod* and *innoturn*) and the variables expressing the cognitive capital of the firms (*gradperc* and *rdperc*).

Table 5 - Spearman correlations

	Innprod	innoturn	gradperc
innoturn	0.883***	-	
gradperc	0.198***	0.206***	-
rdperc	0.347***	0.362***	0.276***

***Significant at 1%

All correlations are positive and significant at 1%. Thus, there is a positive relationship between the components of the cognitive capital and the innovativeness of the firms. Moreover, there is a strong relationship between the number of graduates and the number of employees in R&D, which is obvious considering that there is a high percentage of graduates with science degrees among those involved in R&D. To highlight the relationship between each of the two components of cognitive capital and innovation, it is necessary to perform a multivariate analysis, which also considers several other 'control' variables that are correlated with both innovation and the cognitive capital of the firm.

In the multivariate analysis we consider the following variables: as the dependent variables, we consider the variables expressing innovative performance (*innoprod* and *innoturn*); as the independent variables under study, we consider the ratio of graduated employees (*gradperc),* its quadratic term (*gradperc2*), and its logarithmic transformation (*ln_gradperc*). The most important control variable is the other component of the cognitive capital, i.e., the ratio of personnel employed in R&D (*rdperc*)[3], including its quadratic term (*rdperc2*) and its logarithmic transformation (*ln_rdperc*). We also control for the number of employees, as a proxy of firm size (*workforce*) and for the age of the firm, i.e., the years since it was founded, expressed in three intervals: less than 6 years (*age 1*), between 6 and 20 years (*age 2*), and more than 20 years (*age 3*). We also introduce dummy variables for the Pavitt sector and for countries, as follows: we compare all countries with the United Kingdom because it may be considered a benchmark due to the contemporary high percentage of innovative firms, the high percentage of innovative turnover in innovative firms, and the high number of observations in the sample. In some models, to test the different relationships between the education of the workforce and the innovation across countries, we introduce the interaction between the dummy variables for countries and *gradperc* (*grad_[name country]*) and between the dummy variables for countries and *gradperc2* (*lngrad_[name country]*)[4]

In the regressions with *innoprod* as a dependent variable, we adopt the probit model because this variable is dichotomous; the dependent variable *innoturn* is a percentage, therefore positive values only from 0 to 100 are assumed. Such data may be properly treated with a Tobit model (as suggested by Long, 1997) or with a generalized linear model (as suggested by Papke and Wooldridge, 1996)[5]. We also estimate a classic OLS linear regression model. Moreover, we have to consider that the process that determines whether a firm is innovative may be different from the

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[3] As emphasized before, *gradperc* and *rdperc* are partly overlapping; part of the university graduates are employed in the R&D function and part of the R&D personnel consists of university graduates. Nevertheless, a regression analysis allows the effect of each variable to be calculated while the others are constant. Therefore, this overlapping does not generate bias in the estimation of the coefficients, although their meaning should be carefully considered. The coefficient of *gradperc* indicates how the dependent variable increases if the percentage of graduated workers (both employed and not employed in R&D) increases *while the percentage of workers employed in R&D is constant* (both graduated and not graduated).
Let us analyse the meaning of this statement in more depth and therefore the meaning of the coefficient for *gradperc*.
The total percentage of graduated workers (*gradperc*) is given by the sum of the percentage of graduated workers not employed in R&D (G_{NRD}) and the graduated workers employed in R&D (G_{RD}).
The total percentage of employees involved in R&D (*rdperc*) is given by the sum of the percentage of graduated workers employed in R&D (G_{RD}) and the workers employed in R&D without a university degree (NG_{RD}).
Gradperc may increase a) because of an increase in the percentage of G_{NRD} or b) because of an increase in the percentage of G_{RD}. If *gradperc* increases, how can *rdperc* remain constant? If a) happens, both G_{RD} and NG_{RD} remain constant; if b) happens, the increase in G_{RD} is compensated by an opposite decrease in the percentage of NG_{RD}.
Let us suppose now that the "true" relation is as follows:
$Y= a + b*G_{NRD} + c*G_{RD} + d*NG_{RD} + \varepsilon$
But we estimate (as we do in the paper, we omit the other covariates here) the following:
$Y = f + g*gradperc + h*rdperc + \varepsilon$
Where g expresses the effect of *gradperc* on y, with *rdperc* being constant. Because of the argument above, this may happen when G_{NRD} increases or when G_{RD} increases and contemporary NG_{RD} decreases by the same amount. Therefore, g is a weighted average (whose weights depend on the composition of the sample) between b (the effect of an increase in G_{NRD}) and c-d (the effect of a contemporary and equal in size increase in G_{RD} and decrease in NG_{RD}).
With a similar argument, we may conclude that h is a weighted average between d and c-b.
[4] We tested other control variables in the models; however, the results are non-significant or missing in several observations, therefore reducing the number of observations without significantly modifying the effectiveness of the estimates.
[5] In STATA 14, we adopt the options family (binomial) and link (logit).

process that determines the percentage of innovative turnover; therefore, we implement a two-part model that is similar to the Heckman selection model because there is a binary variable that has a positive versus zero outcome (in our case to sell an innovative product) and after conditionally regressing on a positive outcome. However, unlike the Heckman model, there is no assumption of correlation between errors of binary and continuous equations. Moreover, the zero values are real values, meaning they are not censored, and they represent an accumulation point for the continuous regression (Cragg, 1971; Belotti et al., 2015). Therefore, this model is more appropriate for our case, where innovation decisions depend on the firm and cannot be considered a censored variable.

Estimates with robust standard errors are always performed when possible.

We estimate several models. Model 1 is the 'basic' model, which includes only first-degree terms for human capital and R&D variables plus the control variables illustrated above. Model 2 aims to explore the non-linearity of the relationship between the component of cognitive capital and innovativeness; the most common way to manage the non-linearity is the introduction of quadratic terms, which is what we do in Model 2. To test the different intensities in different countries of the relationship between the presence of educated employees and the innovativeness of a firm, we introduce the interaction terms between the human capital variable and the dummy variables for single countries in Model 3. To consider the non-linearity of the effects of cognitive capital, we also estimate Model 4, which includes the interaction of the country dummy variables of both the first degree and the quadratic term of *gradperc.* To check the robustness of the results found in Model 3 and Model 4, i.e., the different intensities of the relationship between the ratio of educated people and the innovativeness of the firm across countries, in each country we run the same regression of Model 1, of course excluding the dummy variables for countries and their interaction with *gradperc*: (Model 5). To allow for the comparison of single coefficients and taking into account the non-linearity of the relationship between cognitive capital and innovation, we estimate in each country a model where the variable for cognitive capital is substituted by its logarithm (Model 6).

In the following section, we report the formulas for each model (for simplicity, when the dependent variable is *innoturn,* we report only the linear model), the result of the estimates and a brief comment.

We begin our analysis with Model 1, the basic model.

Model 1

Φ^{-1} ($innoprod_i$) = $\beta_0 + \beta_1$ $gradperc_i$ +β_3 $rdperc_i$ + $\beta_3$$workforce$ + β_4 $age2$ + β_5 $age3$ + $\boldsymbol{\beta_{6\text{-}8}}$ (Pavitt dummies) + $\boldsymbol{\beta_{9\text{-}14}}$ (country dummies) +ε_i

$innoturn_i$ = $\beta_0 + \beta_1$ $gradperc_i$ +β_3 $rdperc_i$ + $\beta_3$$workforce$ + β_4 $age2$ + β_5 $age3$ + $\boldsymbol{\beta_{6\text{-}8}}$ (Pavitt dummies) + $\boldsymbol{\beta_{9\text{-}14}}$ (country dummies) +ε_i

Table 6 reports the marginal effects, calculated at the mean values of each variable, of the five estimations (probit for *innoprod* as the dependent variable, OLS, Tobit, GLM, and two-part model for *innoturn* as the dependent variable) of Model 1.[6]

Table 6. Marginal effects from different estimations of Model 1
Dependent variables: product innovation and turnover from innovative product sales

Covariates	probit Dep.var: innoprod	OLS Dep.var: innoturn	Tobit Dep.var: innoturn	GLM Dep.var: innoturn	twopm Dep.var: innoturn
gradperc	0.011***	0.190***	0.364***	0.015***	0.173***
	(0.001)	(0.018)	(0.029)	(0.001)	(0.020)
rdperc	0.015***	0.250***	0.497***	0.019***	0.259***
	(0.001)	(0.018)	(0.030)	(0.001)	(0.021)
workforce	0.002***	0.006***	0.028***	0.001***	-0.010***
	(0.000)	(0.002)	(0.003)	(0.000)	(0.002)
age2	0.006	-1.502*	-1.868	-0.145*	-3.967***
	(0.045)	(0.750)	(1.488)	(0.073)	(1.164)
age3	0.076°	-2.402***	-2.246	-0.242***	-7.001***
	(0.044)	(0.727)	(1.435)	(0.071)	(1.123)
pavitt2	0.011	-0.169	-0.125	-0.037	-0.660
	(0.027)	(0.374)	(0.822)	(0.045)	(0.700)
pavitt3	0.257***	2.010***	6.125***	0.235***	-0.171
	(0.033)	(0.477)	(0.950)	(0.050)	(0.804)
pavitt4	0.391***	3.334***	8.211***	0.309***	0.110
	(0.059)	(0.935)	(1.574)	(0.077)	(1.225)
Austria	0.109	2.427°	4.791*	0.217*	2.238
	(0.077)	(1.243)	(2.113)	(0.108)	(1.730)
France	-0.398***	-3.943***	-10.807***	-0.460***	-2.335*
	(0.038)	(0.567)	(1.169)	(0.065)	(0.980)
Germany	-0.370***	-3.619***	-7.954***	-0.378***	-2.917**
	(0.038)	(0.571)	(1.124)	(0.060)	(0.923)

[6] The coefficients are reported in Table A1 in the Appendix.

Hungary	-0.385***	-4.259***	-12.916***	-0.475***	1.668
	(0.067)	(1.018)	(2.305)	(0.128)	(1.877)
Italy	-0.201***	0.370	-0.797	0.050	2.604**
	(0.037)	(0.593)	(1.127)	(0.059)	(0.915)
Spain	-0.320***	-2.788***	-7.871***	-0.279***	-0.113
	(0.038)	(0.574)	(1.162)	(0.061)	(0.959)
_cons	-0.191***	9.594***	-9.593***	-2.220***	25.061***
	(0.053)	(0.854)	(1.665)	(0.084)	(1.332)
sigma					
_cons			33.320***		
			(0.510)		
N	14046	13727	13727	13727	13727
adj. R^2		0.080			
pseudo R^2	0.060		0.018		
AIC	18324.5	118354.6	67854.5	7207.8	72693.6
BIC	18437.8	118467.5	67975.0	7320.7	72919.4
rmse		18.02			
F		42.61	63.10		
ll	-9147.3	-59162.3	-33911.3	-3588.9	-36316.8
chi2	805.9			792.4	

Standard errors in parenthesis and ° p<0.10, * p < 0.05, ** p < 0.01, and *** p < 0.001

The first column of Table 6 reports the marginal effects of the probit estimate for *innoprod* as a dependent variable. The other columns report the results of the OLS, Tobit, GLM, and two-part model for *innoturn* as a dependent variable (we report only the results of the second part of the two-part model). Regardless of the measure of innovation and the estimated model, the variables representing the cognitive capital of a firm show similar results. The sign for *gradperc* is always positive and significant (at the 0.1% level of significance); this means that, even after controlling for the employees in R&D, a higher ratio of university graduate employees is associated with a higher level of innovativeness. The positive and significant (at the 0.1% level) sign for *rdperc* is largely expected; firms with a higher ratio of employees involved in R&D have a higher degree of innovativeness (a higher probability of introducing an innovation and a higher impact on a firm's returns from the innovations). Moreover, the effect of the firm size (expressed by the number of employees) is significantly positive with regard to the capacity to innovate except in the two-part model, where the workforce has a negative sign. Regarding the Pavitt classification, we may conclude that the *specialized suppliers* and *science-based* firms are more innovative than the *supplier-dominated* firms, which is expected. Even in this case, the results of the two-part model represent an exception, as Pavitt categories are not significant. These differences between the results of the two-part model and the other estimations can be explained by the peculiarities of this model, which is the only one assuming that the process for generating an innovation is different from the process of determining the percentage of innovative turnover. Once the process that generates a product innovation has been determined, the workforce has a negative effect on the second process, and the Pavitt classification has no significant effect. The age of the firm is another variable whose effect seems different in determining if a firm is innovative or not and the percentage of innovative turnover. In fact, according to the probit estimation, the probability to introduce a product innovation increases with the age of the firm (although this result is significant only at the 10% level and only comparing the firms founded since more than twenty years with those founded since less than six years), while the percentage of the innovative turnover is higher for the youngest firms, according to all estimation models except Tobit (in this last case, the marginal effects have the same sign as the OLS, GLM, and two-part model, although they are not significant).

The signs and significance of the marginal effects for the country dummy variables show that firms in the United Kingdom, i.e., the reference category, have a higher probability of introducing product innovation than France, Germany, Spain, and Hungary, and this result is significant at the 0.1% level. Regarding the percentage of turnover derived from innovations, the results of the OLS, Tobit, and GLM models also indicate that the UK has *ceteris paribus* better results than France, Germany, Spain, and Hungary, although it is overcome by Austria (at the 5% level according to the Tobit and GLM models and at the 10% level according to the OLS model). The results are quite different according to the two-part model; the superiority of the UK in the percentage of innovative turnover with respect to France and Germany is significant at a lower level (5% and 1% levels, respectively). Moreover, it is not significant with respect to Hungary, while according to this estimation, Italy has a higher percentage of innovative turnover with respect to the UK (at the 1% level).

We turn now to Model 2, which, to test the non-linearity of the relationship between the components of cognitive capital and the innovativeness of a firm, adds the quadratic terms of *gradperc* and *rdperc* (called *gradperc2* and *rdperc2*, respectively) to Model 1.

Model 2

$$\Phi^{-1}(innoprod_i) = \beta_0 + \beta_1\, gradperc_i + \beta_2\, gradperc2_i + \beta_3\, rdperc_i + \beta_4\, rdperc2_i + \beta_5\, workforce + \beta_6\, age2 + \beta_7\, age3 + \mathbf{B}_{8\text{-}10}\,(\text{Pavitt dummies}) + \boldsymbol{\beta}_{11\text{-}15}\,(\text{country dummies}) + \varepsilon_i$$

$innoturn_i = \beta_0 + \beta_1\, gradperc_i + \beta_2\, gradperc2_i + \beta_3\, rdperc_i + \beta_4\, rdperc2_i + \beta_5\, workforce + \beta_6\, age2 + \beta_7\, age3 + \mathbf{B}_{8\text{-}10}$ (Pavitt dummies) $+ \boldsymbol{\beta}_{11\text{-}15}$ (country dummies) $+ \varepsilon_i$

As it is well known, in the OLS model, a positive sign of the first-degree term and a negative sign of the quadratic term indicate that the relationship between the independent and the dependent variable has an inverted U-shape, and if the turning point of the curve is posed outside the sample values, the relationship is always positive but decreasing. Unfortunately, in non-linear models (the probit, Tobit, GLM, and two part models), it is not possible to derive the shape of the relationship straightforwardly and immediately from the coefficients of the two terms (Karaca-Mandic, Norton, and Dowd, 2012). However, observing the marginal effects of the variable of interest at several values of the independent variable is needed to test if the first derivative of the dependent variable with respect to such variable is constant or decreasing. Therefore, in Table 7, we report only the estimated coefficients of the OLS model, while in graphs 1-4, we show the marginal effects (with confidence intervals at 95%) of *gradperc* on *innoprod* (probit model) and on *innoturn* (Tobit, GLM, and two-part models) at values of *gradperc* increasing progressively by 10% [7]. Therefore, we can verify if the relationship between the percentage of graduated workers and the firm's innovativeness is decreasing as that percentage rises[8].

Table 7. Coefficients from OLS estimation of Model 2
Dependent variable: turnover from innovative product sales

	OLS Dep.var: *innoturn*
gradperc	0.204*** (0.032)
gradperc2	-0.001 (0.001)
rdperc	0.725*** (0.032)
rdperc2	-0.007*** (0.000)
workforce	0.006*** (0.002)

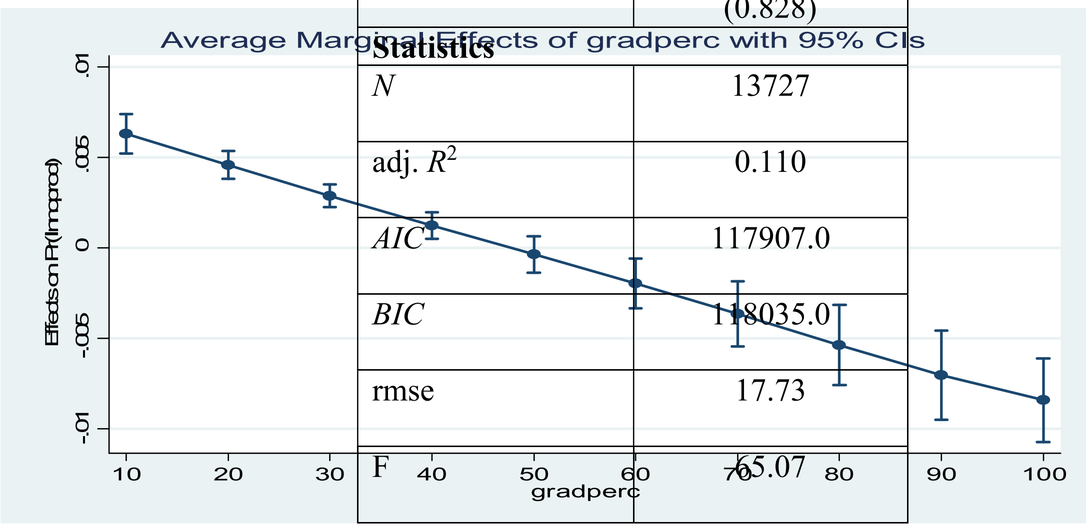
[7] The coefficients obtained by all other estimations of Model 2 are reported in the Appendix in Table A2, while Table A3 reports the corresponding marginal effects at the mean of the variables.

[8] In non-linear models, the relationship between the independent variables and the dependent variable is also non-linear (hence the definition of non-linear models), even if the independent variable is a first-degree term. However, its shape is pre-determined by the model itself. In the probit model, for instance, it is an S-shaped curve. The introduction of quadratic terms allows different shapes of the relationship, which could be analysed through the observation of the marginal effects of x on y for different values of x.

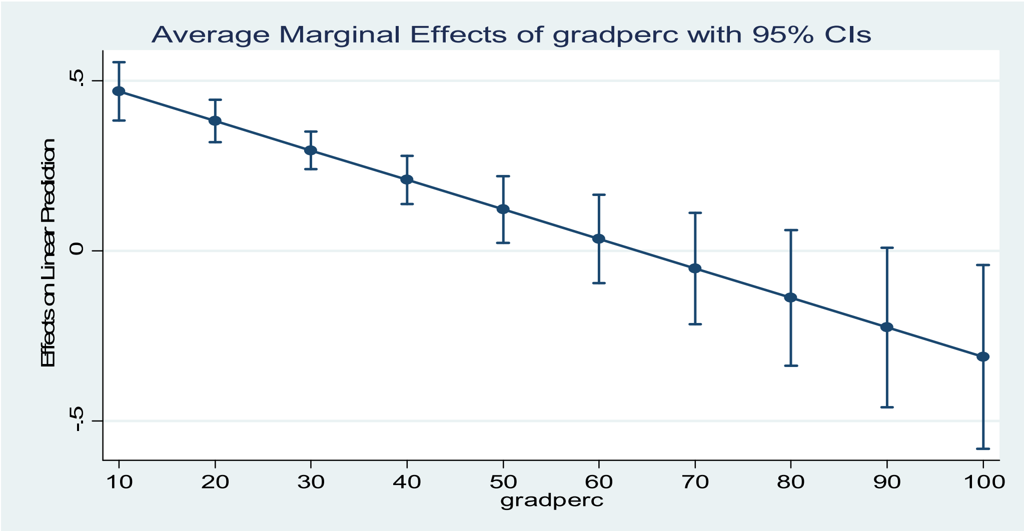
age2	-1.564* (0.735)
age3	-2.508*** (0.712)
pavitt2	-0.013 (0.367)
pavitt3	1.466** (0.469)
pavitt4	2.283* (0.920)
Austria	2.511* (1.193)
France	-4.018*** (0.556)
Germany	-3.814*** (0.560)
Hungary	-3.065** (1.001)
Italy	0.174 (0.583)
Spain	-2.786*** (0.563)
_cons	7.833*** (0.828)
Statistics	
N	13727
adj. R^2	0.110
AIC	117907.0
BIC	118035.0
rmse	17.73
F	65.07

Standard errors in parenthesis
and ° p<0.10, * p < 0.05, ** p < 0.01,
and *** p < 0.001

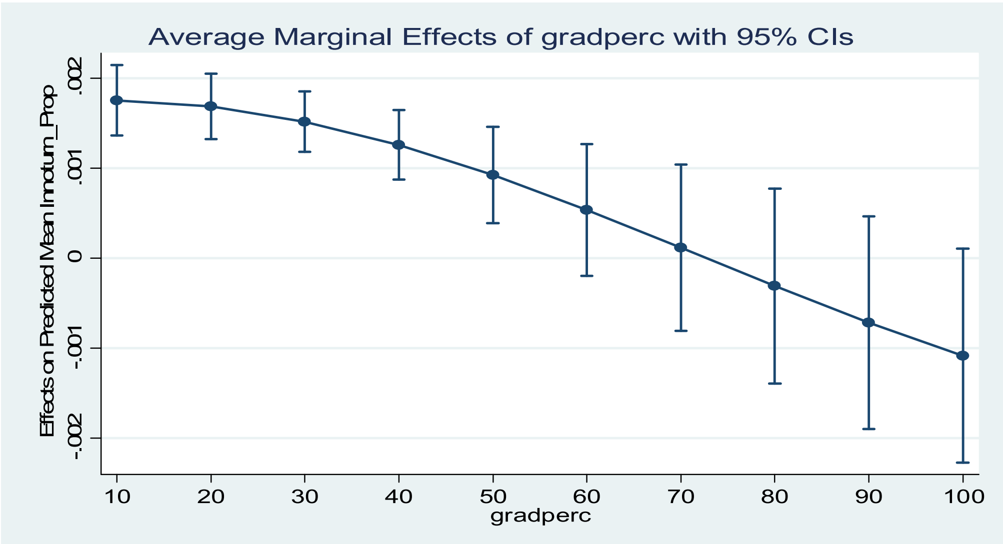
Graph 1.
Probit estimation of Model 2: marginal effects of *gradperc* on *innoprod* for different levels of *gradperc*



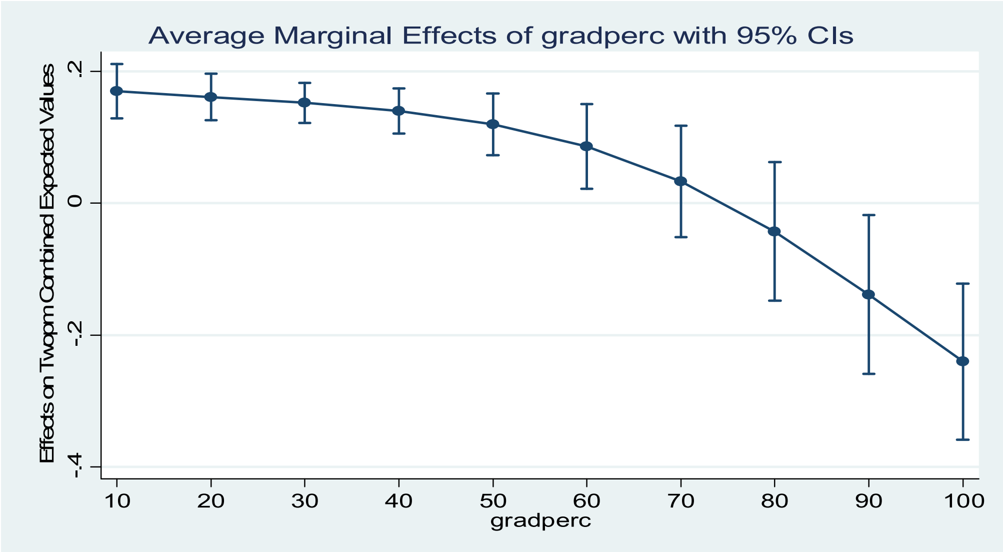
Graph 2.
Tobit estimation of Model 2: marginal effects of *gradperc* on *innoturn* for different levels of *gradperc*



Graph 3.
GLM estimation of Model 2: marginal effects of *gradperc* on *innoturn* for different levels of *gradperc*



Graph 4.
Two-part estimation of Model 2: marginal effects of *gradperc* on *innoturn* for different levels of *gradperc*



As shown in Table 7, in the OLS estimation, the coefficient of *gradperc* is positive, whereas the coefficient of *gradperc*2 is negative, although the latter sign is not significant at the 10% level; therefore, we cannot conclude with an adequate probability that there is a concave relationship between *gradperc* and *innoturn*. In contrast, the effect of *rdperc* on *innoturn* is undoubtedly decreasing because the coefficient for *rdperc* is positive and the coefficient for *rdperc2* is negative, and both are significant at the 0.1% level.

Let us turn now to the analysis of the marginal effects, as calculated by the non-linear estimation models and reported in the graphs. Concerning *innoprod* (probit model), when *gradperc* increases, the marginal effect of *gradperc* on *innoprod* decreases significantly for values of *gradperc* smaller than 50%. Almost all the firms (exactly 97.88% of the total number of firms) have a percentage of employees with university degrees below 50%; therefore, from an empirical perspective, what is estimated to happen for higher values of *gradperc* is not relevant. Therefore, the fact that for higher values of *gradperc* the estimated marginal effect of this variable becomes negative is not concerning. This is the extension that applies to very few concrete cases of a decreasing but positive marginal effect observed in the great majority of cases.

A decreasing marginal effect of *gradperc* is also observed on *innoturn* according to all four estimation models; this effect is statistically undisputable according to the Tobit estimation for the low and middle levels of *gradperc,* which, as mentioned above, concerns almost the entire sample (e.g., the marginal effects for *gradperc* equal to 10% and to 20% are significantly larger than for a *gradperc* value of at least 30% and 40%, respectively). In other cases, the evidence of the effect is less stringent because of the closeness of the punctual estimations for low levels of *gradprc* (GLM and two part model) or because of the amplitude of the confidence intervals for high levels (all four models). However, the OLS model is the only model whose results deny statistical strength to the decreasing marginal effect.

We now analyse Model 3 and Model 4. Both have the aim to compare the intensity of the relationship between the ratio of educated employees and the innovative capacity of the firm across countries. Model 3 imposes linear relationships between the component of cognitive capital and the innovativeness of the firm; therefore, this model simply adds the interactions of country dummy variables with *gradperc* to Model 1. Model 4 imposes non-linear relationships; therefore, it adds the interactions of country dummy variables with *gradperc* and *gradperc2* to Model 2.

Model 3

Φ^{-1} $(innoprod_i) = \beta_0 + \beta_1\, gradperc_i + \beta_2\, rdperc_i + \beta_3\, workforce + \beta_4\, age2 + \beta_5\, age3 + \mathbf{B_{6\text{-}8}}$ (Pavitt dummies) + $\boldsymbol{\beta_{9\text{-}13}}$ (country dummies) + $\boldsymbol{\beta_{14\text{-}18}}$ (dummies *gradperc*_[name country]) $+\varepsilon_i$

$innoturn_i = \beta_0 + \beta_1\, gradperc_i + \beta_2\, rdperc_i + \beta_3\, workforce + \beta_4\, age2 + \beta_5\, age3 + \mathbf{B_{6\text{-}8}}$ (Pavitt dummies) + $\boldsymbol{\beta_{9\text{-}13}}$ (country dummies) + $\boldsymbol{\beta_{14\text{-}18}}$ (dummies *gradperc*_[name country]) $+\varepsilon_i$

Model 4

Φ^{-1} $(innoprod_i) = \beta_0 + \beta_1\, gradperc_i + \beta_2\, gradperc2_i + \beta_3\, rdperc_i + \beta_4\, rdperc2_i + \beta_5\, workforce +$
$+ \beta_6\, age2 + \beta_7\, age3 + \mathbf{B_{8\text{-}10}}$ (Pavitt dummies) + $\boldsymbol{\beta_{11\text{-}15}}$ (country dummies) + $\boldsymbol{\beta_{16\text{-}20}}$ (dummies *gradperc*_[name country]) + $\boldsymbol{\beta_{21\text{-}25}}$ (dummies *gradperc2*_[name country]) $+\varepsilon_i$

$innoturn_i = \beta_0 + \beta_1\, gradperc_i + \beta_3\, rdperc_i + \beta_4\, workforce + \beta_5\, age2 + \beta_6\, age3 + \mathbf{B_{7\text{-}9}}$ (Pavitt dummies) + $\boldsymbol{\beta_{10\text{-}14}}$ (country dummies) + $\boldsymbol{\beta_{15\text{-}19}}$ (dummies *gradperc*_[name country]) + $\boldsymbol{\beta_{21\text{-}25}}$ (dummies *gradperc2*_[name country]) + ε

In these models, the interaction terms between the percentage of graduated employees and the country dummies allow us to observe if the education of the workforce has different effects on innovation in different countries. In the OLS estimation of Model 3, these possible different effects may be deduced by observing the coefficients of the interaction terms, which represent the cross-partial derivative of *innoturn* with respect to *gradperc* and the dummy variable for that country. If the coefficient is significantly positive (negative), an increase in the percentage of graduated workers in that country has a greater (smaller) effect on the percentage of innovative turnover than in the country chosen as a reference. Thus, this model imposes that the relationship between *gradperc* and *innoturn* is represented by different regression lines for different countries; these lines have different vertical intercepts, expressed by the intercepts of the country dummy variables, and different slopes, expressed by the interaction variables. In the other estimations (probit, Tobit, GLM, and two-part models), which are non-linear models, the partial derivatives do not coincide with the coefficients of the interaction terms, and even their signs may not coincide (Ai and Norton, 2003; Karaca-Mandic, Norton and Dowd, 2012). Because only the coefficients of the OLS estimation are intuitive, we only report them in Table 8; as of the estimations of the non-linear models, Graphs 5-9 represent the marginal effect of *gradperc* on *innoprod* (probit model) and on *innoturn* (Tobit, GLM, and two-part models) and the 95% confidence intervals for each of the seven countries calculated at the mean of *gradperc* in the sample[9].

Table 8. Coefficients from OLS estimation of Model 3
Dependent variable: turnover from innovative product sales

	OLS Dep.var: *innoturn*
gradperc	0.325*** (0.051)
rdperc	0.249*** (0.018)
workforce	0.006*** (0.002)
age2	-1.496* (0.749)
age3	-2.365** (0.725)
pavitt2	-0.159 (0.372)
pavitt3	2.082*** (0.476)
pavitt4	3.280*** (0.940)

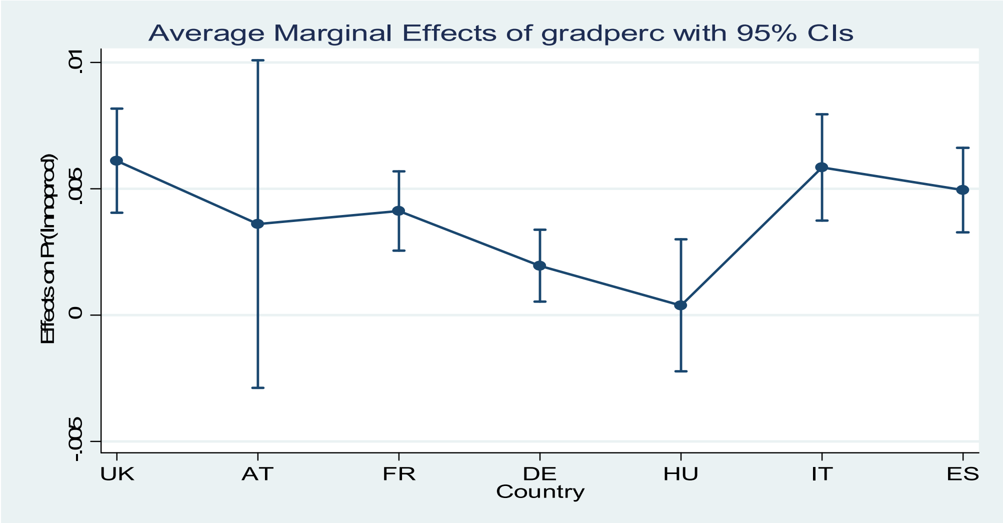
[9] The coefficients obtained by all other estimations of Model 3 are reported in the Appendix in Table A4, while Table A5 reports the correspondent marginal effects at the mean of the variables.

Austria	2.151 (1.359)
France	-2.721*** (0.682)
Germany	-2.032** (0.670)
Hungary	-1.211 (1.347)
Italy	1.854** (0.702)
Spain	-1.254° (0.672)
Austra_gradperc	0.120 (0.171)
France_gradperc	-0.135* (0.066)
Germany_gradperc	-0.167** (0.060)
Hungary_gradperc	-0.253** (0.089)
Italy_gradperc	-0.174* (0.069)
Spain_gradperc	-0.165** (0.059)
_cons	8.334*** (0.895)
Statistics	
N	13727
Adj. R2	0.082
AIC	118326.0
BIC	118484.0
Rmse	18.00
F	30.77
Log likelihood	-59.142.0

Standard errors in parenthesis and ° p<0.10, * p < 0.05, ** p < 0.01, and *** p < 0.001

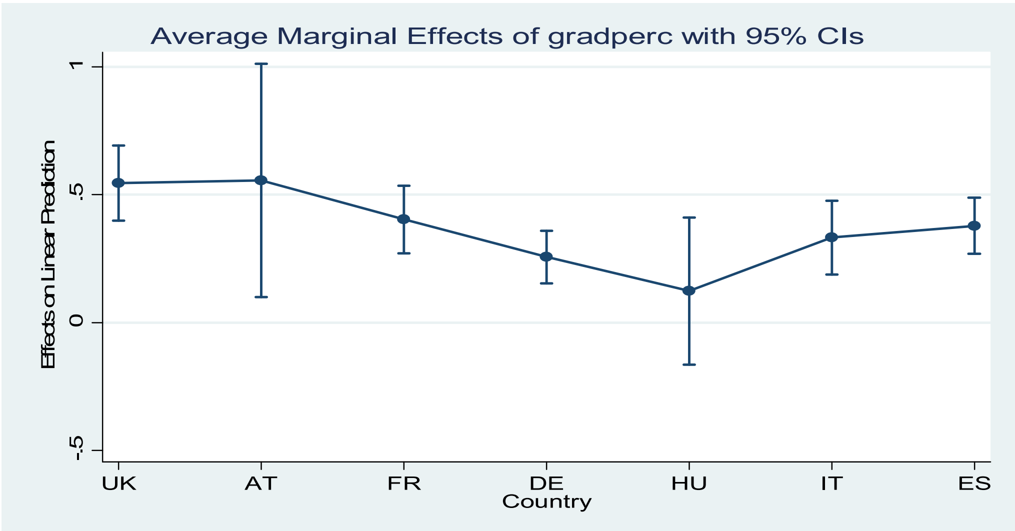
Graph 5.

Probit estimation of Model 3: marginal effects of *gradperc* on *innoprod* for each country



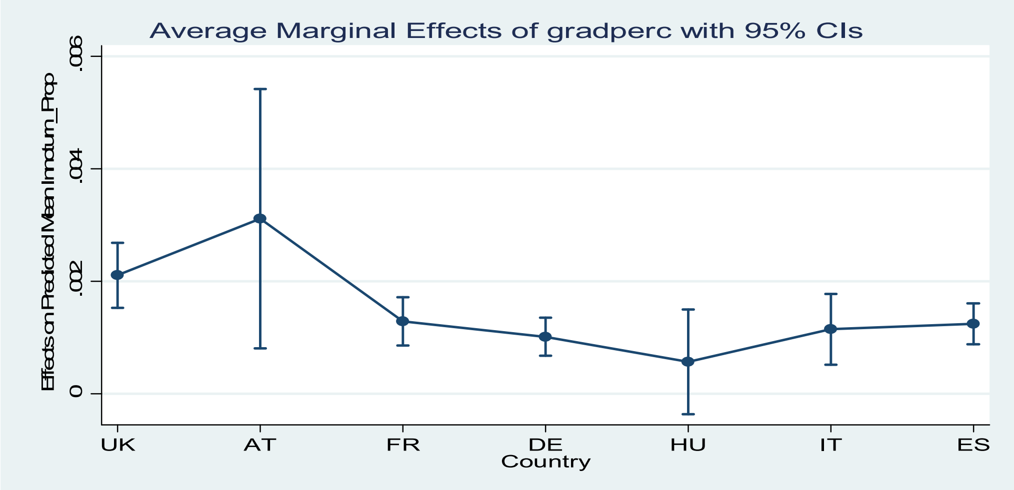
Graph 6.

Tobit estimation of Model 3: marginal effects of *gradperc* on *innoturn* for each country



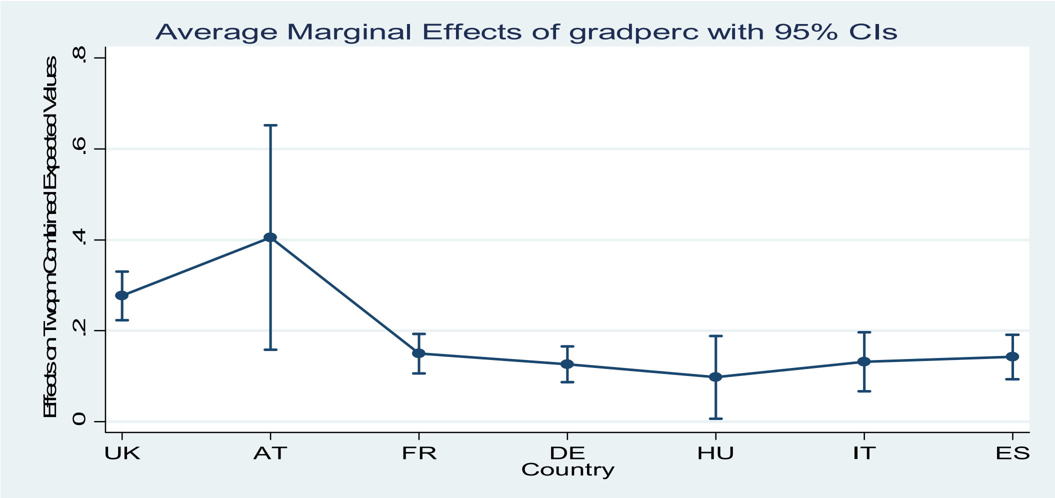
Graph 7.

GLM estimation of Model 3: marginal effects of *gradperc* on *innoturn* for each country



Graph 8.

Two-part model estimation of Model 3: marginal effects of *gradperc* on *innoturn* for each country



In the OLS estimation, the country taken as a reference (and therefore not included in the covariates) is the United Kingdom. All of the variables generated by the interaction of the country dummy variables and *gradperc* have negative and significant signs, with the only exception being Austria, whose coefficient is positive (although not significant). This finding means that the relationship between *gradperc* and *innoturn* is stronger in the UK than in the other countries (except Austria). Thus, an increase in the percentage of graduated workers is related to a greater increase in the percentage of innovative turnover in the UK than in the other countries. If we enlarge our analysis by observing the coefficients of country dummy variables (without interactions with *gradperc*), we notice that Italy has a positive and significant sign, Austria has a positive but not significant sign, and the other four countries have negative and significant signs. Combining this observation with the previous one regarding the coefficients of the interactions and referring to the "geometric" interpretation of this model, we can conclude that the line that relates *gradperc* and *innoturn* is higher in Italy than in the UK for *gradperc* equal to zero, although the line for the UK is more inclined; therefore, it overtakes the lines of Italy. Conversely, the lines for France, Germany, Hungary, and Spain begin below the UK line and rise more slowly. The comparison between Austria and the UK is statistically uncertain because of the large confidence interval for Austria (although the punctual estimation says that the line for Austria is higher and steeper).

Graphs 6, 7, and 8, which represent the marginal effect of *gradperc* on *innoturn* in each country resulting from the estimation of Model 3 with the Tobit, GLM, and two-part models, respectively, provide similar conclusions to those obtain with the OLS estimation. Specifically, the highest punctual estimation of the marginal effect occurs in Austria, although the large confidence interval is too high to make such result statistically robust; the UK follows in the punctual estimation, although the much smaller confidence interval allows a superiority to be established with respect to all other countries (two-part model) or to some of them (GLM and Tobit).

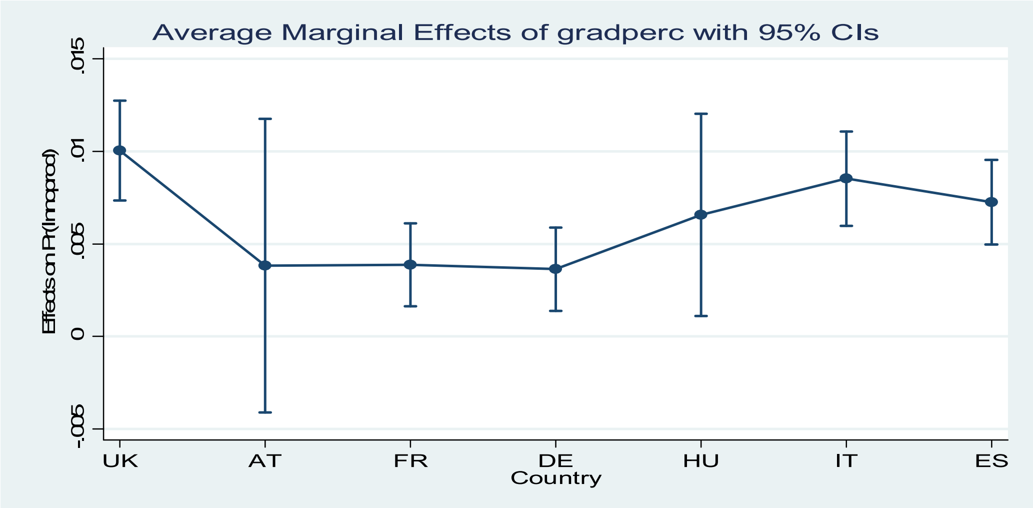
The marginal effects of *gradperc* on *innoprod* are estimated with the probit model and are represented in Graph 5. In this case, the UK has the highest punctual estimation and, at the 5% level, it is significantly higher than in Germany and Italy.

The results obtained from the different estimations of Model 3 are confirmed and are even reinforced by the estimation of the more complex (and therefore more complete) Model 4.

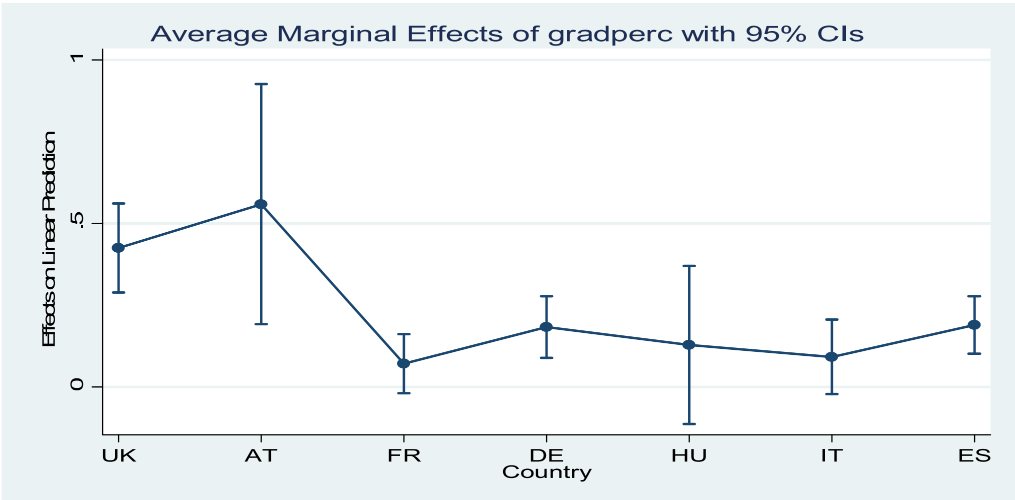
In the OLS estimation, the different relationships between *gradperc* and *innoturn* in different countries are less intuitive than in Model 3; in Model 4, it is assumed that such relationships are represented by U-shaped curves, whose maximum and trends are different in different countries and such differences are expressed by formulas including more than one coefficient. Therefore, the effective differences may not be deducted simply and intuitively by reading the coefficients. This is the reason why we do not report the results for the OLS model for Model 4; we report only graphs 9-13, representing the marginal effect of *gradperc* on *innoprod* (probit model) and on *innoturn* (OLS, Tobit, GLM, and two-part models) with 95% confidence intervals for each of the seven countries calculated at the mean of *gradperc* in the sample[10].

[10] The coefficients obtained by the estimations of Model 4 are reported in the Appendix in Table A6, while Table A7 reports the correspondent marginal effects at the mean of the variables.

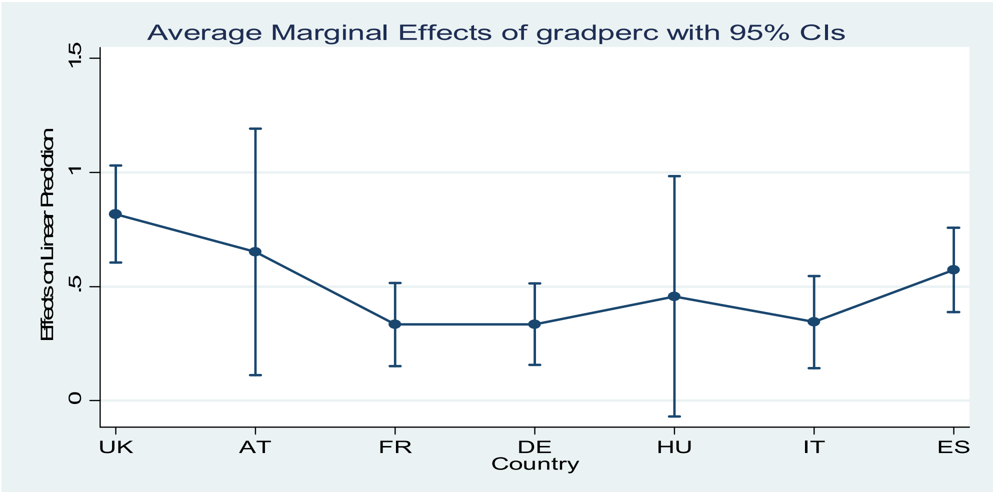
Graph 9.
Probit estimation of Model 4: marginal effects of *gradperc* on *innoprod* for each country



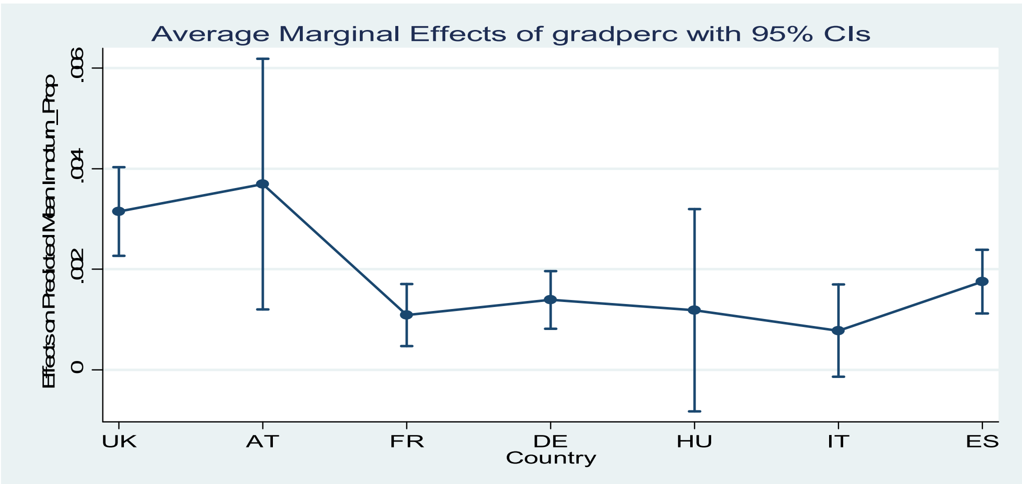
Graph 10.
OLS estimation of Model 4: marginal effects of *gradperc* on *innoturn* for each country



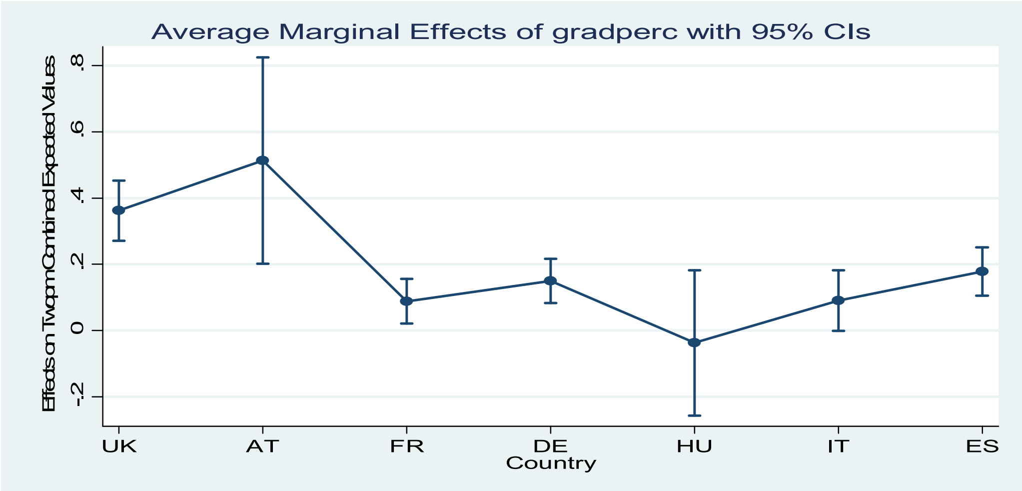
Graph 11.
Tobit estimation of Model 4: marginal effects of *gradperc* on *innoturn* for each country



Graph 12.
Tobit estimation of Model 4: marginal effects of *gradperc* on *innoturn* for each country



Graph 13.
Two-part model estimation of Model 4: marginal effects of *gradperc* on *innoturn* for each country



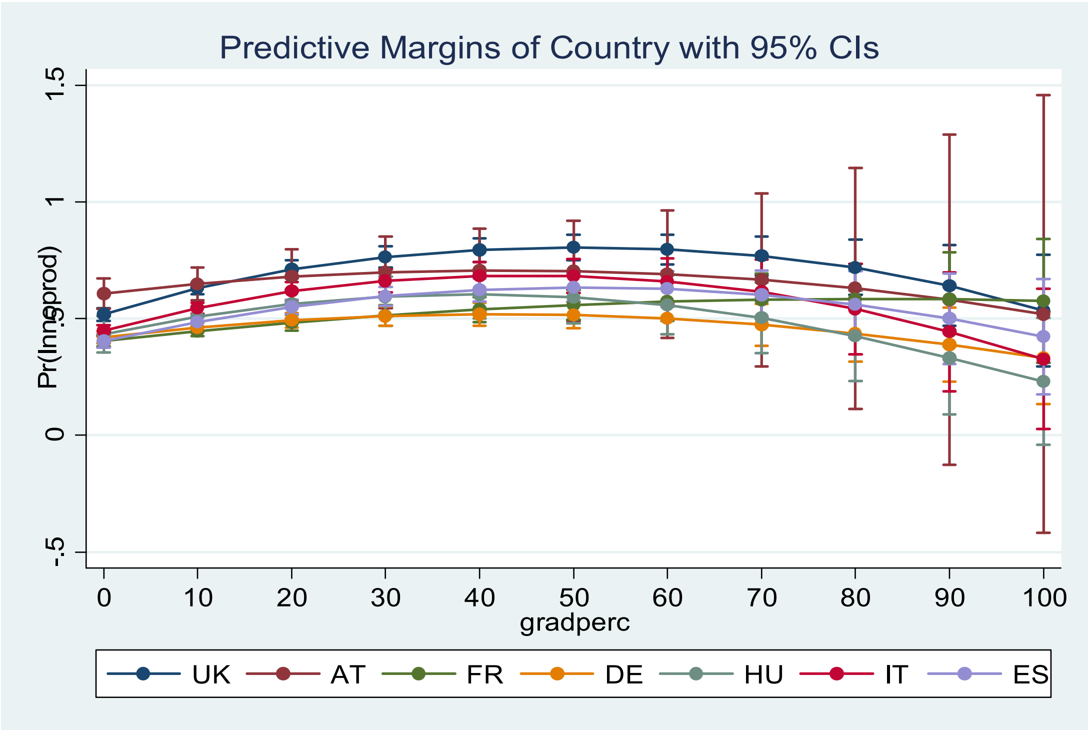
Regarding the marginal effect of *gradperc* on *innoprod* estimated with the probit model and represented in Graph 9, the UK has the highest punctual estimation, which is analogous to Model 3. This effect is significantly higher than in Germany (similar to Model 3) and in France (which "substitutes" Italy).

Regarding the marginal effect of *gradperc* on *innoturn*, as in Model 3, Austria has the highest punctual estimation (except for the Tobit model) but with very large confidence intervals, which do not allow significant comparisons with the other countries. Conversely, such significant comparisons are possible for the UK, where the relationship between the percentage of graduated workers and the percentage of turnover derived from innovative products is significantly higher (at the 5% level) than in France, Germany, and Italy according to all four estimation models, higher than in Spain according to the OLS and two-part models, and higher than in Hungary according to the two-part model.

All of the marginal effects represented and discussed above provide an indication of the different effects of the human capital variable on innovation, although they have the shortcoming of being calculated for a specific value of *gradperc*; the non-linear models allow for different effects at different values of the independent variable. Graphs 14-18 report, for each country, the marginal effects of *gradperc* on *innoprod* (Graph 14) and on *innoturn* (Graphs 15-18) for different values of *gradperc* (progressively increasing of 10%) according to the results of the different estimations of Model 4.

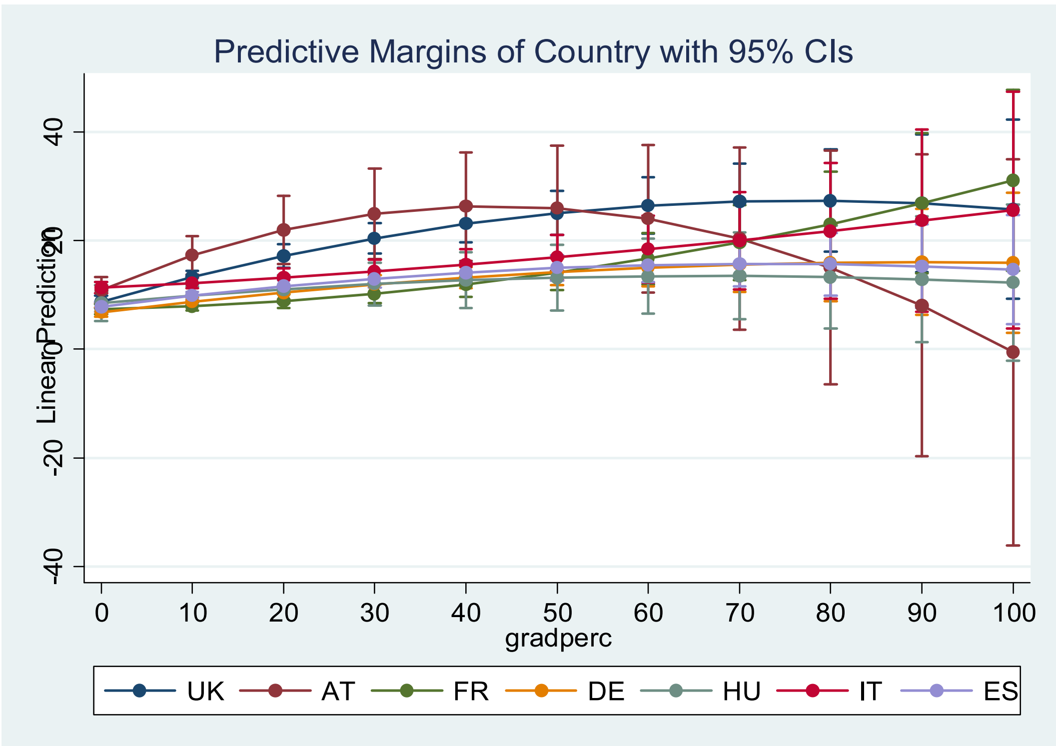
Graph 14

Probit estimation of Model 4: marginal effects of *gradperc* on *innoprod* for each country and different levels of *gradperc*



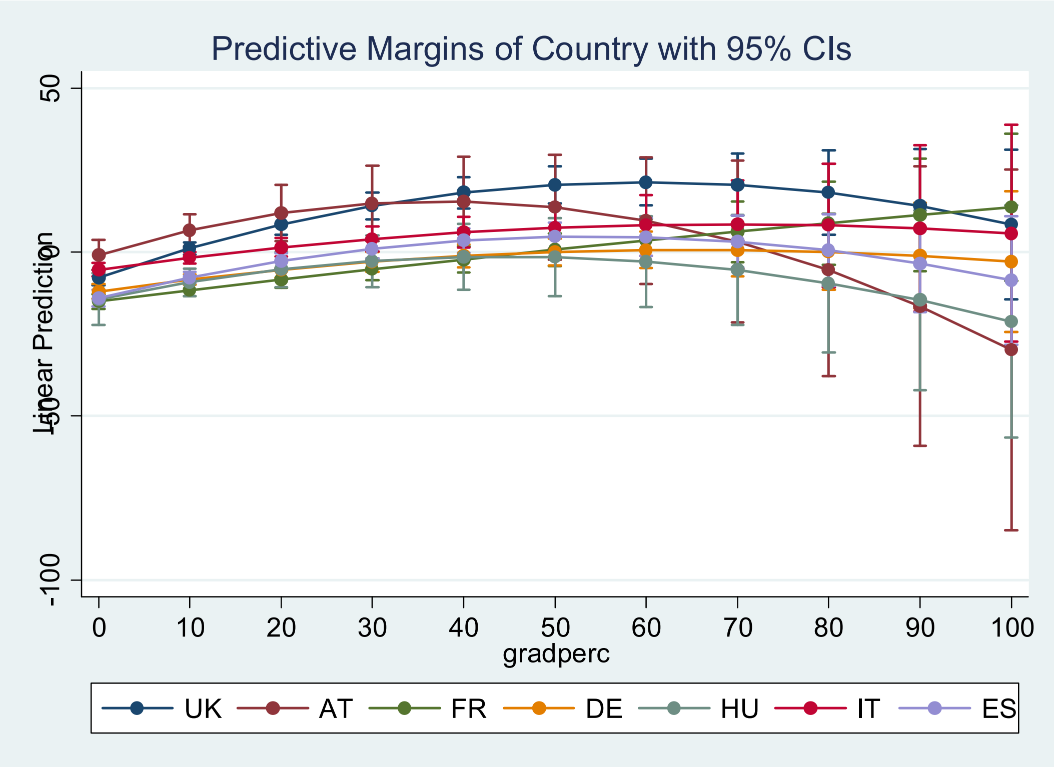
Graph 15

OLS estimation of Model 4: marginal effects of *gradperc* on *innoturn* for each country and different levels of *gradperc*



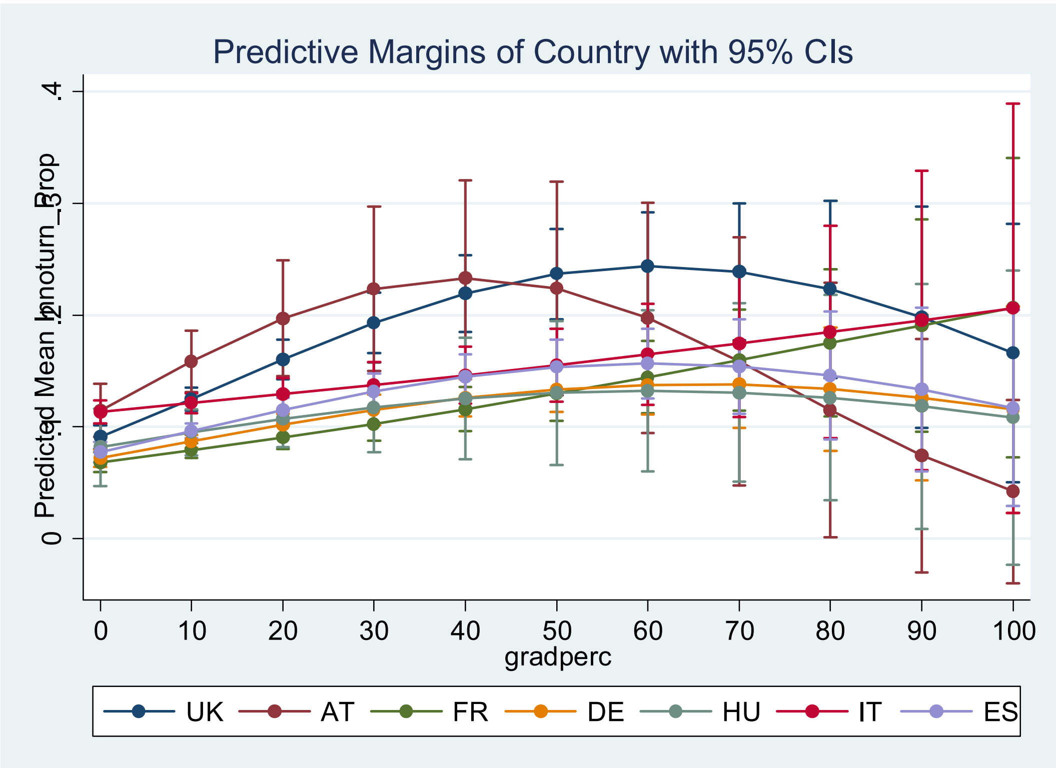
Graph 16

Tobit estimation of Model 4: marginal effects of *gradperc* on *innoturn* for each country and different level of *gradperc*

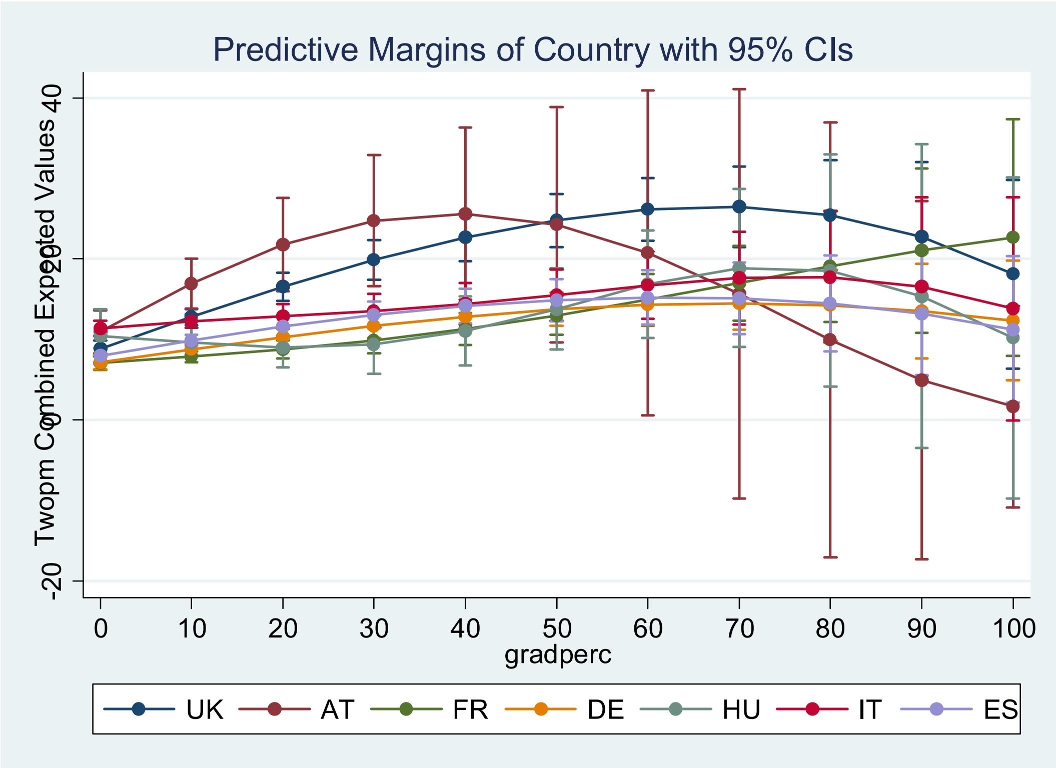


Graph 17

GLM estimation of Model 4: marginal effects of *gradperc* on *innoturn* for each country and different level of *gradperc*



Graph 18
Two-part model estimation of Model 4: marginal effects of *gradperc* on *innoturn* for each country and different levels of *gradperc*



All the estimations show the highest marginal effect of *gradperc* for Austria at low levels of *gradperc* (even with a wide confidence interval), whereas beyond a certain level of *gradperc*, the strongest marginal effect of the percentage of educated people belongs to the UK. The turning point level varies according to the dependent variable and the estimation model. It is between 10% and 20% of *gradperc* for *innoprod* according to the probit model, approximately 30% for *innoturn* according to the Tobit estimation, and approximately 50% according to the OLS, GLM, and two-part model. It is also interesting to observe that Austria and the UK are the countries where the marginal effect of *gradperc* on *innoturn* is more markedly U-shaped with respect to various levels of *gradperc*. Other countries, such as France (in all estimations) and Italy (in all estimations but two-part model), show an increasing marginal effect.

As a robustness test of the results obtained above, we also regress the basic model (without interactions) in each country and then we compare the coefficients of *gradperc.* We also estimate the model for the entire sample to allow comparisons with the global mean value. We estimate Model 5, which is the same as Model 1 except for the country dummy variables, which lose their importance if the regression is run for a single country. Table 9 reports the coefficients of *gradperc* for each country and for the entire sample. To allow for the non-linear effects of *gradperc* on *innoprod* and *innoturn* but allowing the comparison of a single coefficient, we also estimate in each country Model 6, which substitutes *gradperc* and *rdperc* with their logarithm (*ln_gradperc* and *ln_rdperc*, respectively). Table 10 reports the coefficients of ln_*gradperc* for each country and for the entire sample.

Model 5

Φ^{-1} $(innoprod_i) = \beta_0 + \beta_1\ gradperc_{\ i} + \beta_3\ rdperc_{\ i} + \beta_4\ workforce + \beta_5\ age2 + \beta_6\ age3 + \mathbf{B}_{7\text{-}9}$ (Pavitt dummies) $+\varepsilon_{\ i}$

$innoturn_i = \beta_0 + \beta_1\ \mathrm{ln}\_gradperc_{\ i} + \beta_3\ \mathrm{ln}\_rdperc_{\ i} + \beta_4\ workforce + \beta_5\ age2 + \beta_6\ age3 + \mathbf{B}_{7\text{-}9}$ (Pavitt dummies) $+\varepsilon_{\ i}$

Model 6

Φ^{-1} $(innoprod_i) = \beta_0 + \beta_1\ ln\_gradperc_{\ i} + \beta_3\ ln\_rdperc_{\ i} + \beta_4\ workforce + \beta_5\ age2 + \beta_6\ age3 + \mathbf{B}_{7\text{-}9}$ (Pavitt dummies) $+\varepsilon_{\ i}$

$innoturn_i = \beta_0 + \beta_1\ ln\_gradperc_{\ i} + \beta_3\ ln\_rdperc_{\ i} + \beta_4\ workforce + \beta_5\ age2 + \beta_6\ age3 + \mathbf{B}_{7\text{-}9}$ (Pavitt dummies) $+\varepsilon_{\ i}$

Table 9. Coefficients (marginal effects) of *gradperc* obtained by estimating Model 5 for each country and for the entire sample
Dependent variable: introduction of a product innovation and turnover from innovative product sales

	Probit	**OLS**	**Tobit**	**GLM**	**Twopm**
Dep.var.	innoprod	innoturn			
Austria	0.004	0.370*	0.512*	0.003*	0.364**
France	0.003**	0.153***	0.285***	0.001***	0.101***
Germany	0.003***	0.198***	0.320***	0.001***	0.169***
Hungary	-0.000	0.031	-0.043	0.000	0.062

Italy	0.005***	0.119*	0.289***	0.001**	0.115**
Spain	0.005***	0.172***	0.390***	0.001***	0.154***
United Kingdom	0.006***	0.303***	0.528***	0.002***	0.257***
All sample	0.004***	0.174***	0.328***	0.001***	0.146***

Table 10. Coefficients (marginal effects) of *ln_gradperc* obtained by estimating Model 6 for each country and for the entire sample
Dependent variable: introduction of a product innovation and turnover from innovative product sales

	Probit	**OLS**	**Tobit**	**GLM**	**Twopm**
Dep.var.	innoprod	innoturn			
Austria	0.024	2.265*	3.123^{+}	0.021*	2.135*
France	0.018*	0.740*	1.930**	0.006*	0.549*
Germany	0.040***	1.976***	3.683***	0.020***	1.951***
Hungary	0.021	-0.269	-0.448	-0.004	-0.385
Italy	0.051***	0.805*	2.945***	0.008*	0.767*
Spain	0.056***	1.546***	4.653***	0.017***	1.507***
United Kingdom	0.059***	2.479***	5.339***	0.023***	2.223***
All sample	0.036***	1.236***	3.039***	0.012***	1.162***

The results of these estimations are consistent with those obtained from Models 3 and 4. Austria and the UK are the countries with the highest coefficients of *gradperc* when *innoturn* is the dependent variable according to all estimation models and for both the linear and logarithmic specifications. When *innoprod* is the dependent variable, the UK remains the country with the highest coefficient, followed by Italy and Spain[11].

[11] The complete results of the estimations of Model 5 and Model 6 may be obtained by request. Alternative estimations may also be obtained by request. We tested all models with other control variables (e.g., turnover, exports, absolute number of workers involved in R&D, variables about management, etc.) in different combinations with and without the variables presented in the definitive models; the results fundamental to the purpose of our research demonstrated to be substantially robust to such alternative estimations.

The results of the estimations of Models from 3 to 6, therefore, essentially converge in finding different “effectiveness” of “human capital” in different countries. How can this result may be explained? An attempt can be made to relate the different intensities of the education/innovation relationship with the educational level in the entire country. With the partial exception of Austria, whose results are hower not satistically robust, the UK is the country wherethe percentage of educated people in firms is more strictly related to innovation. As reported in Table 4, the UK is also the country with the highest percentage of tertiary education. It appears that the high level of education in the country generates positive externalities, which make the “internal” human capital more effective. However, when considering a single firm, human capital appears to show decreasing returns, which does not happen when considering the entire country; on the contrary, its effectiveness is higher where the global level is higher.

Concluding this discussion, an important warning must be made. As mentioned in the literature review, the causal relationship between human capital and innovation may be twofold, i.e., more educated employees may introduce more innovations, although it is also true that they are needed to absorb and manage innovations. This is the reason why we usually talk about a *relationship* between the percentage of graduated people and the innovativeness of the firm, rather than an *effect* of the former on the latter. Even if the term “effect” is used, we are always estimating a relationship between the two terms because the cross-sectional nature of our data does not allow for the identification of the two directions of the relationship. Therefore, when we compare the different relationship between *gradperc* and *innoturn* in different countries and we conclude that in a country this relation is stronger than in other countries, we mean that an increase in 1% of graduated workers is associated with an increase in the percentage of innovative turnover greater than in other countries. This may be interpreted in two ways: a) in that country, an increase of 1% of graduated workers increases the percentage of innovative turnover greater than in other countries; or b) in that country, an increase of 1% of innovative turnover needs (to be managed) an increase in the graduated employees *smaller* than in other countries. A similar argument may be developed regarding the relationship between *gradperc* and *innoturn*.

4. Conclusions

Several studies have theorized or empirically tested the link between human capital and economic growth at a macroeconomic level. Because of the availability and comparability of the data, the generality of macroeconomic empirical studies *de facto* assimilate the human capital with the formal education. Studies investigating the relationship between the education and the innovation at a microeconomic (firm) level are less frequent. At the firm level, the link between human capital and innovation is often seen as indirect, in the sense that a skilled workforce is considered a precondition for the elements (R&D investments in information technology, business organization, etc.) that generate innovation. However, information about the education of the workforce is often lacking. Therefore, many studies have focused on the relationship with innovation or productivity of different elements of human capital than formal education, such as training or work experience. The intention of this work is to verify whether there is a direct relationship between the education of the workforce and the innovative capacity of the firm empirically, even 'controlling' for other crucial factors for innovation (especially R&D). The analysis, conducted on data from firms in seven European countries in the 2007-2009 period, reveals that an increase in the share of employees with a university degree in the firm is related to an increase in the likelihood of introducing a product innovation and with the share of turnover deriving from such innovations. This study, exploiting the use of different estimation models and international data, attempts to answer other correlated issues. First, we suppose that the component of the human capital we are analysing, i.e., the workforce education, shows decreasing returns with respect to the firm innovativeness, and we find adequate statistical support of this hypothesis. Then, we ask whether the intensity of the relationship between the workforce education and the firm innovativeness at the firm level is significantly different across countries; we find a greater intensity of this relationship in the United Kingdom than in almost all other countries (Austria is generally an exception, although the difference between Austria and the other countries is usually not statistically significant).

This study has some limitations, from the cross-sectional nature of the data to the lack of detailed information on the innovations. The information on the level of education of the workforce is also limited (only the distinction between graduates and non-graduates is made, and therefore the type of degree or the exact level attained is not included). Nevertheless, this analysis offers interesting results, both because the topic has not been frequently explored, especially in an internationally comparative perspective, and because the results may have important implications in terms of *policy*. In fact, from this study, it emerges that the education of the workforce is a key factor to increase a firm's competitiveness because it has a clear relationship with its innovative capacity. Because of the decreasing returns of the human capital, the need to invest in it is particularly strong for firms with a low percentage of educated people. From our analysis, another important conclusion at a country level emerges, i.e., the relationship between education and innovation at the firm level appears particularly high where the education is high in the country. This is probably due to the externality effect. This reinforces the policy indication for governments to not only stimulate the recruitment of educated people but also to act as much as possible to build human capital, enhancing the education level of the country. This appears a fundamental way to maintain the high competitiveness required in today's global economy.

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Appendix

Table A1: Coefficients from different estimations of Model 1
Dependent variables: product innovation and turnover from innovative product sales

Covariates	probit Dep.Var: innoprod	Tobit Dep.Var: innoturn	GLM Dep.Var: innoturn	twopm Dep.Var: innoturn
gradperc	0.011***	0.364***	0.015***	0.173***
	(0.001)	(0.029)	(0.001)	(0.020)
rdperc	0.015***	0.497***	0.019***	0.259***
	(0.001)	(0.030)	(0.001)	(0.021)
workforce	0.002***	0.028***	0.001***	-0.010***
	(0.000)	(0.003)	(0.000)	(0.002)
age2	0.006	-1.868	-0.145*	-3.967***
	(0.045)	(1.488)	(0.073)	(1.164)
age3	0.076°	-2.246	-0.242***	-7.001***
	(0.044)	(1.435)	(0.071)	(1.123)
pavitt2	0.011	-0.125	-0.037	-0.660
	(0.027)	(0.822)	(0.045)	(0.700)
pavitt3	0.257***	6.125***	0.235***	-0.171
	(0.033)	(0.950)	(0.050)	(0.804)
pavitt4	0.391***	8.211***	0.309***	0.110
	(0.059)	(1.574)	(0.077)	(1.225)
Austria	0.109	4.791*	0.217*	2.238
	(0.077)	(2.113)	(0.108)	(1.730)
France	-0.398***	-10.807***	-0.460***	-2.335*
	(0.038)	(1.169)	(0.065)	(0.980)
Germany	-0.370***	-7.954***	-0.378***	-2.917**
	(0.038)	(1.124)	(0.060)	(0.923)
Hungary	-0.385***	-12.916***	-0.475***	1.668
	(0.067)	(2.305)	(0.128)	(1.877)
Italy	-0.201***	-0.797	0.050	2.604**
	(0.037)	(1.127)	(0.059)	(0.915)
Spain	-0.320***	-7.871***	-0.279***	-0.113
	(0.038)	(1.162)	(0.061)	(0.959)
_cons	-0.191***	-9.593***	-2.220***	25.061***
	(0.053)	(1.665)	(0.084)	(1.332)
sigma				
_cons		33.320***		
		(0.510)		
N	14046	13727	13727	13727
pseudo R^2	0.060	0.018		
AIC	18324.5	67854.5	7207.8	72693.6
BIC	18437.8	67975.0	7320.7	72919.4
rmse				
F		63.10		
ll	-9147.3	-33911.3	-3588.9	-36316.8
chi2	805.9		792.4	

Table A2: **Coefficients of different estimations of Model 2**
Dependent variables: product innovation and turnover from innovative product sales

Covariates	probit Dep.Var: innoprod	Tobit Dep.Var: innoturn	GLM Dep.Var: innoturn	twopm Dep.Var: innoturn
gradperc	0.022***	0.555***	0.023***	0.023
	(0.002)	(0.059)	(0.003)	(0.047)
gradperc#gradperc	-0.000***	-0.004***	-0.000***	0.002**
	(0.000)	(0.001)	(0.000)	(0.001)
rdperc	0.055***	1.613***	0.066***	0.535***
	(0.002)	(0.059)	(0.003)	(0.045)
rdperc#rdperc	-0.001***	-0.016***	-0.001***	-0.004***
	(0.000)	(0.001)	(0.000)	(0.001)
workforce	0.002***	0.029***	0.001***	-0.009***
	(0.000)	(0.003)	(0.000)	(0.002)
age2	-0.011	-1.994	-0.154*	-3.887***
	(0.046)	(1.449)	(0.072)	(1.159)
age3	0.058	-2.546°	-0.254***	-6.916***
	(0.044)	(1.397)	(0.070)	(1.119)
pavitt2	0.027	0.446	-0.010	-0.556
	(0.027)	(0.805)	(0.044)	(0.698)
pavitt3	0.213***	4.614***	0.171***	-0.260
	(0.033)	(0.931)	(0.049)	(0.803)
pavitt4	0.305***	5.479***	0.186*	-0.108
	(0.059)	(1.536)	(0.076)	(1.222)
Austria	0.140°	5.070*	0.228*	2.156
	(0.078)	(2.013)	(0.103)	(1.724)
France	-0.429***	-11.192***	-0.482***	-2.439*
	(0.038)	(1.140)	(0.064)	(0.977)
Germany	-0.410***	-8.592***	-0.407***	-2.881**
	(0.039)	(1.095)	(0.059)	(0.920)
Hungary	-0.310***	-10.236***	-0.343**	2.640
	(0.067)	(2.239)	(0.125)	(1.876)
Italy	-0.222***	-1.376	0.021	2.390**
	(0.037)	(1.103)	(0.058)	(0.912)
Spain	-0.354***	-8.114***	-0.289***	0.273
	(0.039)	(1.133)	(0.060)	(0.960)
_cons	-0.368***	-14.534***	-2.493***	24.181***
	(0.054)	(1.633)	(0.083)	(1.357)
N	14046	13727	13727	13727
pseudo R^2	0.097	0.028		
AIC	17613.2	67211.6	7046.2	71935.1
BIC	17741.6	67347.0	7174.2	72191.1
F		95.80		
ll	-8789.6	-33587.8	-3506.1	-35933.6
chi2	1519.8		1453.6	

Table A3: **Marginal effects from different estimations of Model 2**
Dependent variables: product innovation and turnover from innovative product sales

Covariates	probit Dep.Var: innoprod	OLS Dep.Var: innoturn	Tobit Dep.Var: innoturn	GLM Dep.Var: innoturn	twopm Dep.Var: innoturn
gradperc	0.006***	0.189***	0.473***	0.002***	0.167***
	(0.001)	(0.023)	(0.044)	(0.000)	(0.018)
rdperc	0.017***	0.621***	1.367***	0.004***	0.531***
	(0.001)	(0.026)	(0.048)	(0.000)	(0.018)
workforce	0.001***	0.006***	0.029***	0.000***	0.009***
	(0.000)	(0.002)	(0.003)	(0.000)	(0.001)
age2	-0.004	-1.564*	-1.994	-0.013*	-1.630**
	(0.016)	(0.735)	(1.449)	(0.006)	(0.624)
age3	0.021	-2.508***	-2.546°	-0.022***	-2.567***
	(0.016)	(0.712)	(1.397)	(0.006)	(0.604)
pavitt2	0.010	-0.013	0.446	-0.001	0.032
	(0.010)	(0.367)	(0.805)	(0.004)	(0.374)
pavitt3	0.076***	1.466**	4.614***	0.015***	1.499***
	(0.012)	(0.469)	(0.931)	(0.004)	(0.438)
pavitt4	0.109***	2.283*	5.479***	0.016*	1.968**
	(0.021)	(0.920)	(1.536)	(0.007)	(0.700)
Austria	0.050°	2.511*	5.070*	0.020*	2.468*
	(0.028)	(1.193)	(2.013)	(0.009)	(0.976)
France	-0.153***	-4.018***	-11.192***	-0.042***	-4.117***
	(0.014)	(0.556)	(1.140)	(0.006)	(0.526)
Germany	-0.147***	-3.814***	-8.592***	-0.035***	-3.389***
	(0.014)	(0.560)	(1.095)	(0.005)	(0.505)
Hungary	-0.111***	-3.065**	-10.236***	-0.030**	-2.273*
	(0.024)	(1.001)	(2.239)	(0.011)	(0.985)
Italy	-0.080***	0.174	-1.376	0.002	0.222
	(0.013)	(0.583)	(1.103)	(0.005)	(0.499)
Spain	-0.127***	-2.786***	-8.114***	-0.025***	-2.398***
	(0.014)	(0.563)	(1.133)	(0.005)	(0.519)
N	14046	13727	13727	13727	13727
adj. R^2		0.110			
pseudo R^2	0.097		0.028		
AIC	17607.2	117901.0	67203.6	7040.2	71895.1
BIC	17712.9	118006.4	67308.9	7145.6	72000.5
rmse		17.73			
F		65.07	95.80		
ll	-8789.6	-58936.5	-33587.8	-3506.1	-35933.6
chi2	1519.8			1453.6	

Table A4: **Coefficients of different estimations of Model 3**
Dependent variables: product innovation and turnover from innovative product sales

Covariates	probit Dep.Var: innoprod	Tobit Dep.Var: innoturn	GLM Dep.Var: innoturn	twopm Dep.Var: innoturn
gradperc	0.017***	0.546***	0.021***	0.276***
	(0.003)	(0.075)	(0.003)	(0.041)
rdperc	0.015***	0.498***	0.019***	0.257***
	(0.001)	(0.030)	(0.001)	(0.021)
workforce	0.002***	0.028***	0.001***	-0.010***
	(0.000)	(0.003)	(0.000)	(0.002)
age2	0.014	-1.779	-0.144°	-4.070***
	(0.046)	(1.487)	(0.074)	(1.163)
age3	0.081°	-2.164	-0.239***	-7.078***
	(0.044)	(1.434)	(0.071)	(1.123)
pavitt2	0.014	-0.089	-0.036	-0.680
	(0.027)	(0.820)	(0.045)	(0.699)
pavitt3	0.261***	6.245***	0.239***	-0.143
	(0.033)	(0.949)	(0.050)	(0.804)
pavitt4	0.390***	8.173***	0.305***	0.049
	(0.059)	(1.582)	(0.078)	(1.225)
Austria	0.161°	5.422*	0.208	1.145
	(0.093)	(2.475)	(0.127)	(2.104)
France	-0.355***	-9.374***	-0.422***	-1.101
	(0.047)	(1.453)	(0.081)	(1.216)
Germany	-0.263***	-4.803***	-0.271***	-2.005°
	(0.048)	(1.379)	(0.072)	(1.154)
Hungary	-0.189*	-7.159*	-0.247	1.307
	(0.086)	(3.097)	(0.163)	(2.612)
Italy	-0.186***	1.251	0.160*	5.151***
	(0.046)	(1.385)	(0.071)	(1.122)
Spain	-0.302***	-6.216***	-0.202**	2.349°
	(0.049)	(1.447)	(0.074)	(1.244)
Austria#gradperc	-0.007	0.010	0.005	0.234
	(0.010)	(0.244)	(0.010)	(0.165)
France#gradperc	-0.006	-0.143	-0.003	-0.102°
	(0.004)	(0.100)	(0.004)	(0.060)
Germany#gradperc	-0.012**	-0.290**	-0.008*	-0.079
	(0.004)	(0.091)	(0.004)	(0.055)
Hungary#gradperc	-0.016***	-0.423*	-0.013°	-0.005
	(0.005)	(0.165)	(0.007)	(0.114)
Italy#gradperc	-0.001	-0.213*	-0.010*	-0.254***
	(0.004)	(0.104)	(0.004)	(0.064)
Spain#gradperc	-0.003	-0.167°	-0.006	-0.196**
	(0.004)	(0.093)	(0.004)	(0.063)
_cons	-0.246***	-11.505***	-2.295***	23.874***
	(0.056)	(1.771)	(0.090)	(1.408)
sigma				
_cons		33.277***		
		(0.509)		

N	14046	13727	13727	13727
pseudo R^2	0.062	0.019		
AIC	18303.5	67842.2	7214.0	72663.1
BIC	18462.1	68007.8	7372.1	72979.2
F		45.43		
ll	-9130.7	-33899.1	-3586.0	-36289.6
chi2	835.2		810.2	

Table A5: **Marginal effects from different estimations of Model 3**
Dependent variables: product innovation and turnover from innovative product sales

Covariates	probit Dep.Var: innoprod	OLS Dep.Var: innoturn	Tobit Dep.Var: innoturn	GLM Dep.Var: innoturn	twopm Dep.Var: innoturn
gradperc	0.004***	0.190***	0.366***	0.001***	0.162***
	(0.000)	(0.018)	(0.030)	(0.000)	(0.012)
rdperc	0.006***	0.249***	0.498***	0.002***	0.229***
	(0.000)	(0.018)	(0.030)	(0.000)	(0.011)
workforce	0.001***	0.006***	0.028***	0.000***	0.008***
	(0.000)	(0.002)	(0.003)	(0.000)	(0.001)
age2	0.005	-1.496*	-1.779	-0.013°	-1.586*
	(0.017)	(0.749)	(1.487)	(0.006)	(0.633)
age3	0.030°	-2.365**	-2.164	-0.021***	-2.479***
	(0.016)	(0.725)	(1.434)	(0.006)	(0.613)
pavitt2	0.005	-0.159	-0.089	-0.003	-0.137
	(0.010)	(0.372)	(0.820)	(0.004)	(0.379)
pavitt3	0.098***	2.082***	6.245***	0.021***	2.034***
	(0.012)	(0.476)	(0.949)	(0.004)	(0.444)
pavitt4	0.146***	3.280***	8.173***	0.027***	2.877***
	(0.022)	(0.940)	(1.582)	(0.007)	(0.711)
Austria	0.039	3.290*	5.515*	0.030*	3.553**
	(0.030)	(1.517)	(2.335)	(0.015)	(1.366)
France	-0.150***	-4.002***	-10.729***	-0.040***	-3.969***
	(0.014)	(0.575)	(1.166)	(0.006)	(0.542)
Germany	-0.136***	-3.615***	-7.549***	-0.033***	-3.320***
	(0.014)	(0.566)	(1.116)	(0.006)	(0.540)
Hungary	-0.122***	-3.608***	-11.165***	-0.037***	-3.540***
	(0.026)	(1.000)	(2.343)	(0.010)	(0.941)
Italy	-0.072***	0.205	-0.769	0.004	0.298
	(0.014)	(0.622)	(1.136)	(0.006)	(0.574)
Spain	-0.123***	-2.814***	-7.802***	-0.026***	-2.519***
	(0.014)	(0.573)	(1.162)	(0.006)	(0.552)
N	14046	13727	13727	13727	13727
adj. R^2		0.082			
pseudo R^2	0.062		0.019		
AIC	18289.5	118312.0	67826.2	7200.0	72607.1
BIC	18395.2	118417.4	67931.6	7305.4	72712.5
rmse		18.00			
F		30.77	45.43		
ll	-9130.7	-59142.0	-33899.1	-3586.0	-36289.6
chi2	835.2			810.2	

Table A6: **Coefficients of different estimations of Model 4**
Dependent variables: product innovation and turnover from innovative product sales

Covariates	probit Dep.Var: innoprod	OLS Dep.Var: innoturn	Tobit Dep.Var: innoturn	GLM Dep.Var: innoturn	twopm Dep.Var: innoturn
gradperc	0.034***	0.484***	0.971***	0.040***	0.274**
	(0.005)	(0.093)	(0.144)	(0.007)	(0.105)
gradperc#gradperc	-0.000***	-0.003*	-0.008***	-0.000***	-0.000
	(0.000)	(0.002)	(0.002)	(0.000)	(0.001)
rdperc	0.056***	0.720***	1.606***	0.066***	0.520***
	(0.002)	(0.032)	(0.059)	(0.003)	(0.045)
c.rdperc#c.rdperc	-0.001***	-0.007***	-0.016***	-0.001***	-0.004***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
workforce	0.002***	0.006***	0.029***	0.001***	-0.008***
	(0.000)	(0.002)	(0.003)	(0.000)	(0.002)
age2	-0.003	-1.529*	-1.843	-0.149*	-3.879***
	(0.046)	(0.734)	(1.451)	(0.073)	(1.158)
age3	0.062	-2.411***	-2.395°	-0.246***	-6.827***
	(0.045)	(0.710)	(1.399)	(0.071)	(1.118)
pavitt2	0.029	0.022	0.503	-0.008	-0.543
	(0.027)	(0.366)	(0.804)	(0.044)	(0.697)
pavitt3	0.218***	1.584***	4.809***	0.177***	-0.286
	(0.033)	(0.468)	(0.931)	(0.049)	(0.802)
pavitt4	0.310***	2.361*	5.695***	0.197**	0.010
	(0.059)	(0.921)	(1.540)	(0.076)	(1.222)
Austria	0.245*	2.197	6.880**	0.267°	-0.182
	(0.100)	(1.339)	(2.604)	(0.139)	(2.374)
France	-0.310***	-1.384°	-7.301***	-0.316**	0.289
	(0.052)	(0.708)	(1.614)	(0.097)	(1.433)
Germany	-0.267***	-1.896**	-4.234**	-0.259**	-2.277
	(0.054)	(0.723)	(1.587)	(0.090)	(1.392)
Hungary	-0.231*	-0.222	-6.547	-0.118	12.494***
	(0.117)	(1.767)	(4.214)	(0.249)	(3.756)
Italy	-0.188***	2.598***	2.407	0.254**	6.538***
	(0.050)	(0.746)	(1.562)	(0.085)	(1.312)
Spain	-0.311***	-0.932	-6.204***	-0.182°	2.723°
	(0.056)	(0.732)	(1.705)	(0.095)	(1.526)
Austria#gradperc	-0.021	0.233	-0.099	0.004	0.618°
	(0.016)	(0.257)	(0.385)	(0.016)	(0.326)
France#gradperc	-0.022***	-0.452***	-0.627***	-0.024*	-0.372*
	(0.007)	(0.114)	(0.189)	(0.009)	(0.148)
Germany#gradperc	-0.021**	-0.279*	-0.579**	-0.017°	-0.070
	(0.007)	(0.115)	(0.191)	(0.009)	(0.141)
Hungary#gradperc	-0.011	-0.334°	-0.391	-0.022	-1.280***
	(0.011)	(0.176)	(0.364)	(0.019)	(0.353)
Italy#gradperc	-0.005	-0.404**	-0.572**	-0.032***	-0.590***
	(0.007)	(0.125)	(0.204)	(0.009)	(0.148)
Spain#gradperc	-0.010	-0.266*	-0.277	-0.013	-0.246
	(0.007)	(0.110)	(0.190)	(0.009)	(0.151)
Austria#gradperc#gradperc	0.000	-0.005	-0.004	-0.000	-0.009

	(0.000)	(0.004)	(0.006)	(0.000)	(0.006)
France#gradperc#gradperc	0.000**	0.005**	0.008*	0.000*	0.004*
	(0.000)	(0.002)	(0.003)	(0.000)	(0.002)
Germany#gradperc#gradperc	0.000*	0.002	0.005°	0.000	0.000
	(0.000)	(0.002)	(0.003)	(0.000)	(0.002)
Hungary#gradperc#gradperc	0.000	0.002	0.002	0.000	0.019***
	(0.000)	(0.002)	(0.005)	(0.000)	(0.005)
Italy#gradperc#gradperc	0.000	0.004	0.005	0.000*	0.006**
	(0.000)	(0.002)	(0.004)	(0.000)	(0.002)
Spain#gradperc#gradperc	0.000	0.002	0.002	0.000	0.001
	(0.000)	(0.002)	(0.003)	(0.000)	(0.002)
_cons	-0.447***	5.928***	-17.601***	-2.639***	22.197***
	(0.058)	(0.888)	(1.822)	(0.096)	(1.514)
sigma					
_cons			32.393***		
			(0.501)		
N	14046	13727	13727	13727	13727
adj. R^2		0.113			
pseudo R^2	0.098		0.028		
AIC	17609.1	117874.8	67206.5	7061.9	71904.4
BIC	17828.0	118093.1	67432.3	7280.2	72341.0
rmse		17.70			
F		38.32	55.83		
ll	-8775.5	-58908.4	-33573.3	-3502.0	-35894.2
chi2	1544.7			1484.5	

Table A7: **Marginal effects from different estimations of Model 4**
Dependent variables: product innovation and turnover from innovative product sales

Covariates	probit Dep.Var: innoprod	OLS Dep.Var: innoturn	Tobit Dep.Var: innoturn	GLM Dep.Var: innoturn	twopm Dep.Var: innoturn
gradperc	0.006***	0.183***	0.461***	0.002***	0.166***
	(0.001)	(0.024)	(0.045)	(0.000)	(0.019)
rdperc	0.017***	0.616***	1.363***	0.004***	0.526***
	(0.001)	(0.026)	(0.048)	(0.000)	(0.018)
workforce	0.001***	0.006***	0.029***	0.000***	0.009***
	(0.000)	(0.002)	(0.003)	(0.000)	(0.001)
age2	-0.001	-1.529*	-1.843	-0.013*	-1.577*
	(0.016)	(0.734)	(1.451)	(0.006)	(0.624)
age3	0.022	-2.411***	-2.395°	-0.021***	-2.499***
	(0.016)	(0.710)	(1.399)	(0.006)	(0.603)
pavitt2	0.010	0.022	0.503	-0.001	0.051
	(0.010)	(0.366)	(0.804)	(0.004)	(0.373)
pavitt3	0.078***	1.584***	4.809***	0.015***	1.529***
	(0.012)	(0.468)	(0.931)	(0.004)	(0.438)
pavitt4	0.111***	2.361*	5.695***	0.017**	2.055**
	(0.021)	(0.921)	(1.540)	(0.007)	(0.700)
Austria	0.040	3.000*	4.989*	0.026*	3.113*
	(0.028)	(1.412)	(2.153)	(0.013)	(1.333)
France	-0.157***	-4.261***	-11.205***	-0.043***	-4.256***
	(0.014)	(0.570)	(1.137)	(0.006)	(0.541)
Germany	-0.146***	-4.000***	-8.348***	-0.037***	-3.662***
	(0.014)	(0.561)	(1.093)	(0.005)	(0.535)
Hungary	-0.111***	-2.844**	-9.817***	-0.030**	-2.211*
	(0.026)	(1.051)	(2.533)	(0.011)	(1.059)
Italy	-0.079***	-0.212	-1.604	-0.002	-0.175
	(0.014)	(0.615)	(1.108)	(0.006)	(0.571)
Spain	-0.131***	-3.009***	-8.373***	-0.028***	-2.710***
	(0.014)	(0.568)	(1.153)	(0.006)	(0.552)
N	14046	13727	13727	13727	13727
adj. R^2		0.113			
pseudo R^2	0.098		0.028		
AIC	17579.1	117844.8	67174.5	7031.9	71816.4
BIC	17684.8	117950.2	67279.9	7137.3	71921.8
rmse		17.70			
F		38.32	55.83		
ll	-8775.5	-58908.4	-33573.3	-3502.0	-35894.2
chi2	1544.7			1484.5	