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# The relationship between the education of the workforce and the innovative capacity of the firms in seven European countries

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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 countries regarding the intensity of the link between the qualification of the workforce and the innovative capacity of the firm: in particular, in the United Kingdom the intensity of such relationship seems greater than in the other countries.*



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 *et al.* (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. 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). However, knowledge and skills are abstract terms that need to be specified to measure them and to capture their sources. 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 also on training, work experience, etc., since the studies by Mincer (1962) and Becker (1964). The result is that, at the firm level, many studies have used workforce education as a control variable to analyse the determinants of productivity or of innovation, but there have been fewer empirical studies specifically focused on the effects of human capital on innovation at the firm level (Schneider *et al.,* 2010).

This 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. R&D is 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 by the expenses in (or by the personnel dedicated to) formalized R&D and 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 that we try to test in this paper of the non-linear relationship between the education of the workforce and the innovativeness of a firm.

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, while there are papers that measure the difference in the quality of human capital across countries and relate it with the difference in economic performance, 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. Review of literature on Human capital, R&D and innovation

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).

In the context of the knowledge production function (Griliches, 1979), which represents a bridge between the macro and microeconomic levels, innovation is the output and knowledge is the input at the firm level. 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. Anyway, in Audretsch and Feldman's (2004) formulation, knowledge production includes, in addition to R&D, human capital as an input of innovation and both inputs present decreasing returns.

Many empirical studies substantiated this approach (Griliches and Mairesse, 1983; Hall and Mairesse, 1995; Crépon *et al.,* 1998). The idea is that a company, an industry, or a geographical area (Jaffe, 1986; Acs *et al.,* 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 *et al.* (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.

Many studies highlighted the role of spillovers and externalities. 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).

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, in this way improving innovative performance (Cokburn and Henderson 1998; Srivastava et al., 2015; Wang and Libaers, 2016)

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. Anyway, the attention remained mainly focused on R&D, identified by Cohen and Levinthal (1998) as the main source of absorptive capacity, partly neglecting the role of human capital.

In many cases, the link between human capital and innovation is seen as 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 *et al.* (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 *et al.* (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 *et al.* (2011) and López-Cabrales *et al.* (2011) find that the human resource management practices enhance 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

Many studies find a positive effect of learning on firm performance (Laursen and Foss, 2003; Zhou *et al.,* 2011; Gallié and Legros, 2012; Gonzàlez *et al.* 2016)

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 *et al.*, 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. Farace and Mazzotta (2015), analysing a sample of small and medium firms in Southern Italy, find that not only the education of the workforce but also of the entrepreneurs is positively inked with the innovative capacity of the firm. Another study of the same authors underlines the positive effect of the founder's education on firm's innovativeness (Farace and Mazzotta, 2017). The paper by d'Amore *et al.* (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.

According to the literature reported above, it emerges that an increase in the quantity of human capital has a positive effect on the output, both of a firm and a country. In such a context, the difference in the per capita GDP of different economies depends, *ceteris paribus*, on different endowments of human capital and the same holds for firms belonging to different countries. The underlying assumption is that an increase in the quantity of human capital (measured as years of schooling or number or percentage of graduated workers, etc.) has the same effect across all firms and countries. But this assumption is not necessarily true: different quality of human capital across countries may imply a different "productivity" of human capital itself (Kaarsen, 2014). Hanushek and Woessmann (2009) find that traditional measures of human capital investment are much less effective than a direct measure of cognitive skills in accounting for differences in economic growth; in their empirical study take into consideration four of the seven countries considered in our study and find that, in the period 1975-2000, higher scores in tests measuring cognitive skills in UK respect to (in decreasing order) France, German and Italy are related to higher average growth rate of GDP per capita.

## 3. Data and empirical 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].

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**

| 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 |
| 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 |

[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.

| | | | | |
|---|---|---|---|---|
| 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.

In the entire sample about half of the firms (49.1%) introduced, in the considered period, a product innovation; Austria and the United Kingdom are the countries with the highest percentage of firms introducing product innovations (respectively 59.1% and 58.5%,) while this innovative performance is well below the average in Hungary, France, and Spain (respectively 43.8%, 44.3% and 45.6%). Among the innovative firms, the percentage of innovative turnover is 21.25% and it is particularly high in Italy (23.7%) and Austria (23.3%). Considering all the firms, the percentage of innovative turnover in the whole sample is 10.2%.

Regarding the dimension of cognitive capital in the firms, in the entire sample the average of the percentage of university graduates in the workforce is 9.5% (this value is particularly high in Hungary and Germany and Spain are also above the average) and the share of employees involved in R&D activities is 7.8% (this value in Germany is much higher than the average, while it is significantly below the average in Hungary). Besides the cognitive capital of the firms, we also had a look at a measure of the global human capital of the nation, considering the percentages of university graduates in the home country according to OECD data in the period of our analysis. The values are quite different across countries, with the United Kingdom having the highest percentage (more than one third of the population has a tertiary degree). This measure may provide an idea regarding the extent of externalities derived from an educated population.

An explorative bivariate analysis, considering correlations and means, shows that 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 (Pavitt, 1984) 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 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,

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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).

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*

$\Phi^{-1}$ ($innoprod_i$) = $\beta_0 + \beta_1$ *gradperc* $_i$ $+\beta_3$ *rdperc* $_i$ + $\beta_3$*workforce* + $\beta_4$ *age2* + $\beta_5$ *age3* + $\boldsymbol{\beta_{6\text{-}8}}$ (Pavitt dummies) + $\boldsymbol{\beta_{9\text{-}14}}$ (country dummies) $+\varepsilon_I$

$innoturn_i = \beta_0 + \beta_1$ *gradperc* $_i$ $+\beta_3$ *rdperc* $_i$ + $\beta_3$*workforce* + $\beta_4$ *age2* + $\beta_5$ *age3* + $\boldsymbol{\beta_{6\text{-}8}}$ (Pavitt dummies) + $\boldsymbol{\beta_{9\text{-}14}}$ (country dummies) $+\varepsilon_i$

Table 2 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.

**Table 2. Marginal effects from different estimations of Model 1**
**Dependent variables: product innovation and turnover from innovative product sales**

| | probit | OLS | Tobit | GLM | two-pm |
|---|---|---|---|---|---|

| Covariates | Dep.var: innoprod | Dep.var: innoturn | Dep.var: innoturn | Dep.var: innoturn | 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) |
| 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 2 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*

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

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

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 *et al.,* 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, increasing or decreasing. We considered the marginal effects (with confidence intervals at 95%) of g*radperc* on *innoprod* (probit model) and on *innoturn* (Tobit, GLM, and two-part models) at values of *gradperc* increasing progressively by 10%.

Such marginal effects are shown in Graphs 1, 2, 3 and 4.

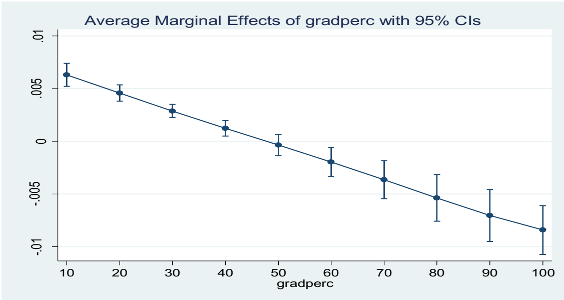
Concerning the effects on *innoprod* (probit model), for values of *gradperc* smaller than 50%, when *gradperc* increases, the marginal effect of *gradperc* on *innoprod* decreases significantly; for values of *gradperc* greater than 50% the marginal effect still decreases but this effect is not significant at 5%. Anyway, 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 much less relevant.

A decreasing marginal effect of *gradperc* on *innoturn* is observed according to all the estimation models. This effect is statistically undisputable according to the Tobit estimation for the low and middle levels of *gradperc,* which, as mentioned above, concern almost the entire sample: the marginal effects for *gradperc* equal to 10% and to 20% are significantly larger than for values of *gradperc* of at least 30% and 40%, respectively). According to the other estimation models, the evidence of the effect is less stringent because of the closeness of the punctual estimations for low levels of *gradprc* and because of the amplitude of the confidence intervals for high levels. However, the OLS model is the only model whose results deny statistical strength to the decreasing marginal effect.

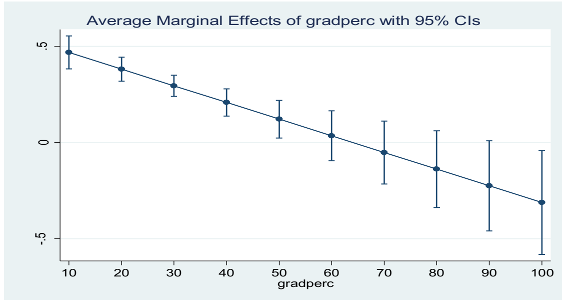
In the OLS estimation, whose results are shown in the first column of Table 3, the coefficient of *gradperc* is positive and the coefficient of g*radperc*2 is negative, although the latter sign is not significant at the 10% level. In contrast, the effect of *rdperc* on *innoturn* is undoubtedly decreasing because the coefficient for *rdperc* is positive and the coefficient for *rdperc2* is negative, and both are significant at the 0.1% level.

We can conclude that we have enough statistical support to the hypothesis that an increase in the percentage of graduated workers has a positive but decreasing effect on the probability to introduce an innovation and on the percentage of innovative turnover.

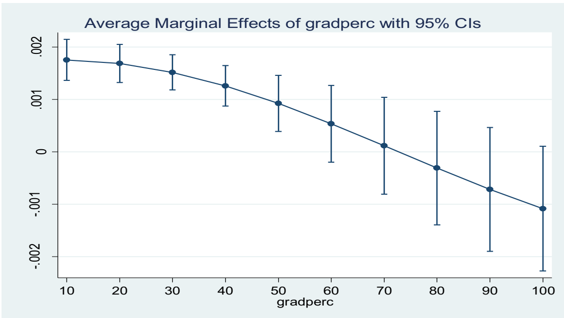
**Graph 1. Model 2: Marginal effects of *gradperc* on *innoprod* at different levels of *gradperc* (Probit)**



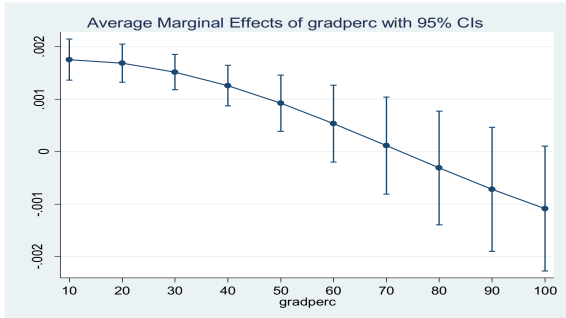

**Graph 2. Model 2: Marginal effects of *gradperc* on *innoturn* at different levels of *gradperc* (Tobit)**



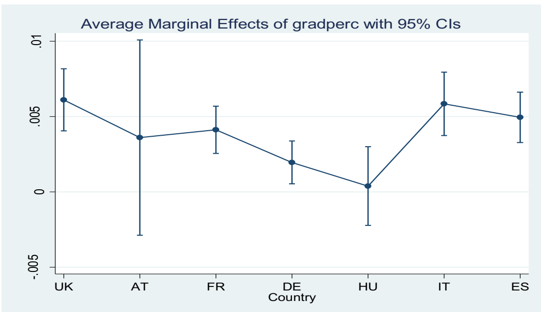

**Graph 3. Model 2: Marginal effects of *gradperc* on *innoturn* at different levels of *gradperc* (GLM)**



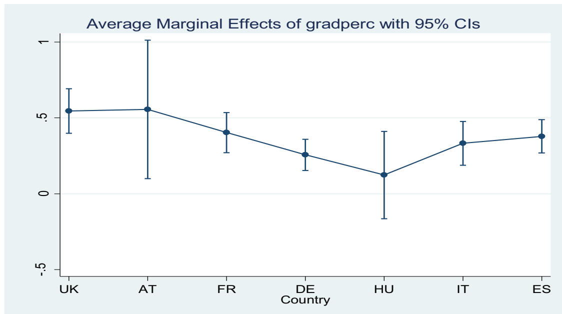

**Graph 4. Model 2: Marginal effects of *gradperc* on *innoturn* at different levels of *gradperc* (two-pm)**



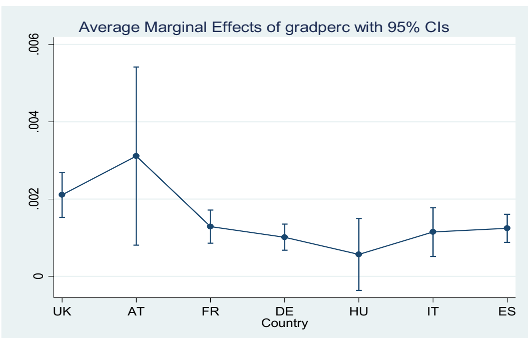

**Graph 5. Model 3: Marginal effects of *gradperc* on *innoprod in different countries* (Probit)**




**Graph 6. Model 3: Tobit – Marginal effects of *gradperc* on *innoturn in different countries* (Tobit)**




**Graph 7. Model 3: Marginal effects of *gradperc* on *innoturn in different countries* (GLM)**




**Graph 8. Model 3: Two-pm – Marginal effects of *gradperc* on *innoturn in different countries***

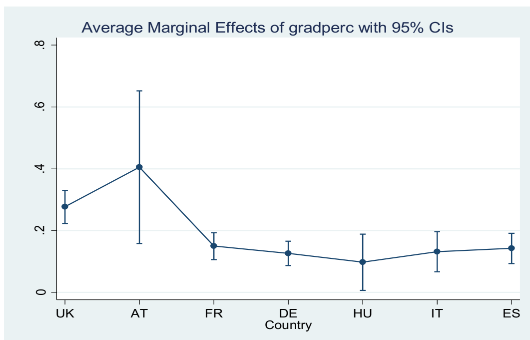


**Table 3. Coefficients from OLS estimation of Model 2 and Model 3**
**Dependent variable: turnover from innovative product sales**

| | Model 2 - OLS<br>Dep.var: *innoturn* | Model 3- OLS<br>Dep.var: *innoturn* |
|---|---|---|
| gradperc | 0.204*** (0.032) | 0.325***(0.051) |
| gradperc2 | -0.001 (0.001) | |
| rdperc | 0.725*** (0.032) | 0.249*** (0.018) |
| rdperc2 | -0.007*** (0.000) | |
| workforce | 0.006*** (0.002) | 0.006*** (0.002) |
| age2 | -1.564* (0.735) | -1.496* (0.749) |
| age3 | -2.508*** (0.712) | -2.365** (0.725) |
| pavitt2 | -0.013 (0.367) | -0.159 (0.372) |
| pavitt3 | 1.466** (0.469) | 2.082*** (0.476) |
| pavitt4 | 2.283* (0.920) | 3.280*** (0.940) |
| Austria | 2.511* (1.193) | 2.151 (1.359) |
| France | -4.018*** (0.556) | -2.721*** (0.682) |
| Germany | -3.814*** (0.560) | -2.032** (0.670) |
| Hungary | -3.065** (1.001) | -1.211 (1.347) |
| Italy | 0.174 (0.583) | 1.854** (0.702) |
| Spain | -2.786*** (0.563) | -1.254° (0.672) |
| Austria_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 | 7.833*** (0.828) | 8.334*** (0.895) |
| | **Statistics** | |
| N | 13727 | 13727 |
| Adj. R2 | 0.110 | 0.082 |
| AIC | 117907.0 | 118356.0 |
| BIC | 118035.0 | 118484.0 |
| Rmse | 17.73 | 18.00 |
| F | 65.07 | 30.77 |

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

We analyse now 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*

$\Phi^{-1}$ (*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*

$\Phi^{-1}$ (*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* + $\mathbf{B_{8\text{-}10}}$ (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]**)** + $\varepsilon$

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, et al., 2012). Therefore, we studied the marginal effect of *gradperc* on *innoprod* (probit model) and on *innoturn* (Tobit*,* GLM, and two-part models), with their 95% confidence intervals, for each of the seven countries, calculated at the mean of *gradperc* in the sample.

Such marginal effects are shown in Graphs 5, 6, 7 and 8.

In the OLS estimation of Model 3, whose results we report in the second column of Table 3, the country taken as a reference (and therefore not included in the covariates) is the United Kingdom. All the variables generated by the interaction of the country dummy variables and *gradperc* have negative and significant signs, with the only exception of 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).

The analysis of the marginal effects of *gradperc* on *innoturn* according to the Tobit, GLM, and two-part models, provide similar conclusions to those obtained 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 and 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. In this case, the UK has the highest punctual estimation and, at the 5% level, it is significantly higher than in Germany and Hungary.

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, even with the OLS estimation, the effective differences may not be deducted simply and intuitively by reading the coefficients. This is the reason why, for all estimation models, we have to study 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.

Such marginal effects are shown in Graphs 9, 10, 11 and 12[6].

Regarding the marginal effect of *gradperc* on *innoprod* estimated with the probit model, 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.

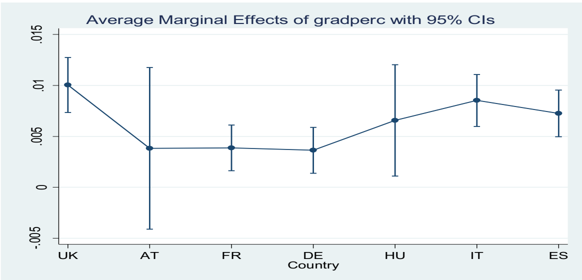
All the marginal effects represented and discussed above provide an indication of the different effects of the human capital variable on innovation, although they have the shortcoming of being calculated for a specific value of *gradperc*; the non-linear models allow for different effects at different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

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

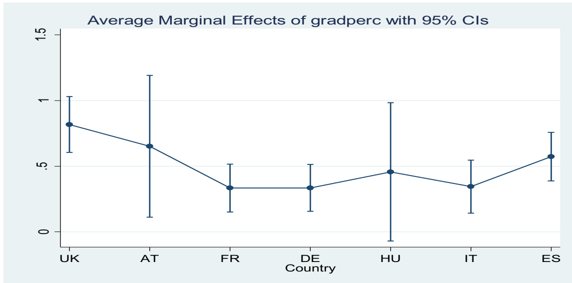
[6] We do not report the result of the OLS estimation, as we remind that, the other kinds of estimation (Tobit, GLM, two-part model) are more suitable than OLS to the nature of the independent variable (*innoturn*). Nevertheless, for Model 1, Model 2 and Model 3, the coefficients of OLS have the quality of an easy readability, therefore we thought it useful to report them. In Model 4 the OLS estimation, remaining not perfectly adequate for the kind of dependent variable, also loses its quality of immediate interpretation. Of course, the coefficients and the marginal effects of OLS for Model n request. The coefficients and the numerical marginal effects of all the estimations are also available on request.

effect of *gradperc* on *innoturn* is more markedly U-shaped with respect to various levels of *gradperc* (this effect is particularly pronounced in the GLM and two-part model). Other countries, such as France (in all estimations) and Italy (in all estimations but two-part model), show an increasing marginal effect. Graph 13 and 14 report such marginal effects according to the GLM and two-part estimation model[7].

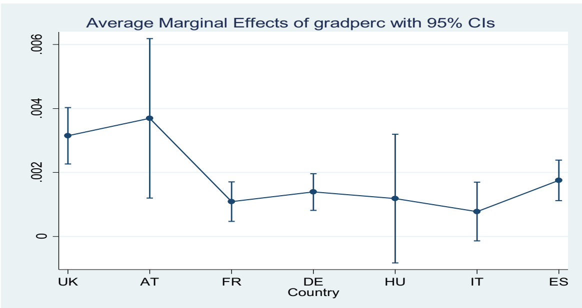
**Graph 9. Model 4. Probit – Marginal effects of *gradperc* on *innoprod* in different countries**



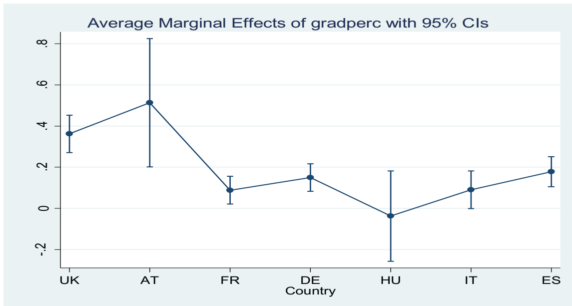

**Graph 10. Model 4. Tobit – Marginal effects of *gradperc* on *innoprod* in different countries**



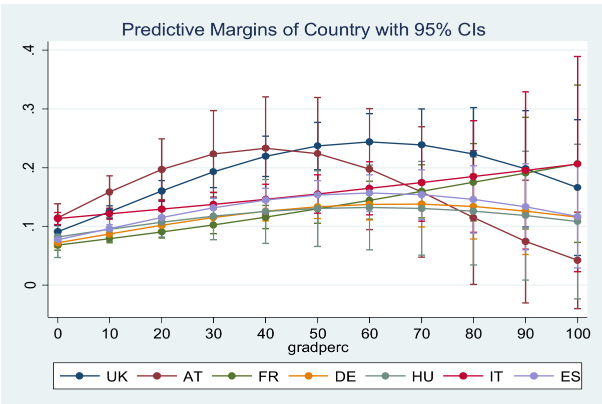

**Graph 11. Model 4. GLM – Marginal effects of *gradperc* on *innoturn* in different countries**



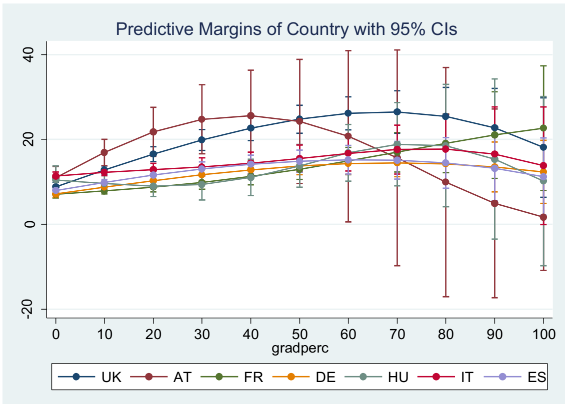

**Graph 12. Model 4. Two-pm– Marginal effects of *gradperc* on *innoturn* in different countries**




**Graph 13. Model 4. GLM – Marginal effects of *gradperc* on *innoturn* at different levels of *gradperc* in different countries**




**Graph 14. Model 4. Two-pm – Marginal effects of *gradperc* on *innoturn* at different levels of *gradperc* in different countries**




[7] We report only the graphs deriving from these two models because the trends and the differences between countries are more pronounced than in the other estimations. The graphs obtained by other models are obtainable on request.

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 4 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 5 reports the coefficients of ln_*gradperc* for each country and for the entire sample.

*Model 5*

$\Phi^{-1}$ $(innoprod_i) = \beta_0 + \beta_1\ gradperc_i + \beta_3\ rdperc_i + \beta_4\ workforce + \beta_5\ age2 + \beta_6\ age3 + \mathbf{B_{7\text{-}9}}$ (Pavitt dummies) $+\varepsilon_i$

$innoturn_i = \beta_0 + \beta_1$ ln_$gradperc_i + \beta_3$ ln_$rdperc_i + \beta_4\ workforce + \beta_5\ age2 + \beta_6\ age3 + \mathbf{B_{7\text{-}9}}$ (Pavitt dummies) $+\varepsilon_i$

*Model 6*

$\Phi^{-1}$ $(innoprod_i) = \beta_0 + \beta_1\ ln\_gradperc_i + \beta_3\ ln\_rdperc_i + \beta_4\ workforce + \beta_5\ age2 + \beta_6\ age3 + \mathbf{B_{7\text{-}9}}$ (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 4. Coefficients (marginal effects) of *gradperc* obtained by estimating Model 5 for each country and for the entire sample**

| | 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 5. Coefficients (marginal effects) of *ln_gradperc* obtained by estimating Model 6 for each country and for the entire sample**

| | 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[8].

The results of the estimations of Models from 3 to 6, therefore, essentially converge in finding different "effectiveness" of human capital in different countries. As stated in the second section of the paper, this result could be explained with different quality of human capital in different countries. It is remarkable that the finding of a paper cited in the literature review (Hanushek and Woessmann, 2009), which reports higher quality of human capital, in terms of cognitive skills, in the UK than in Germany, France and Italy, is consistent with our results.

The different intensities of the education/innovation relationship could also be related with the educational level in the entire country. As reported in Section three, the UK is also the country with the highest percentage of people with tertiary education: it is likely 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

[8] 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.

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 result is consistent with some studies which found a higher quality of the education in United Kingdom than in other countries of our sample.

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. Besides, different "effectiveness" of the human capital in different countries are consistent with previous studies showing different quality of human capital across countries. 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 (in terms of quantity and quality) of the country. This appears a fundamental way to maintain the high competitiveness required in today's global economy.

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