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The research productivity of universities.
A multilevel and multidisciplinary analysis on European institutions

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Abstract
The paper makes use of a novel dataset at European level which includes data on academic staff and students of universities from official National Statistical Authorities, bibliometric indicators on publications, and socio-economic indicators at regional level. The dataset covers all European countries. The unit of analysis is a combination between teaching activities at the level of Field of Education and publications classified by Field of Science, resulting in five major integrated areas of STEM (Science; Engineering, Computer Science; Agriculture; Medicine). Using a multilevel modeling framework and comparing results across disciplinary areas the paper finds strong support for peer effects at institutional level and for the positive effect of international collaborations and attraction of foreign PhD students. It does not find support for economies of scale in research, institutional age, specialization effects and private vs private governance. The external regional environment has an impact on research productivity only in applied disciplines.

Keywords
- Research productivity
- University
- Multilevel modeling
- STEM disciplines
- European universities

1. Introduction

There is large agreement on the notion that research productivity depends on individual-level and institution-level variables. In turn, institution-level variables refer to the research environment (research team, department, or university) and to the external environment (social and economic environment at regional and country level).

There is lower agreement on the general validity of theories of research productivity across disciplines. Does research productivity follow general laws, or is it rather context-dependent with respect to specific scientific disciplines? General theories of research productivity at individual level (for example, Lotka's law, or the Matthew effect, or the life cycle theory) claim general validity across most, if not all, scientific disciplines. The issue of whether disciplinary differences matter for the general theory of productivity has been explored several times, since the pioneering comparative studies of Biglan (1973), Becker (1994) and Becker and Trowler (2001). On the empirical side, however, there is no general agreement. On the one hand, models of productivity have a large number of putative antecedents, so that the replication and comparison of results across disciplines is difficult. On the other hand, existing empirical studies that use cross-disciplinary datasets have taken only one level of observation and/or are based on a single country. Thus, for example, disciplinary differences are examined for individual researcher productivity in Mexico (Gonzalez-Brambila and Veloso, 2007) or at aggregate level for programs and departments in the United States (Baird, 1991; Adams and Griliches, 1998), Portugal (Sarrico et al. 2009) or South Korea (Shin and Cummings, 2010).

In order to improve upon the state of the art there is a need for: (i) including antecedents that are based on the literature, in order to enhance comparability and cumulativity of results; (ii) integrating cross-disciplinary data on research and teaching; (iii) using cross-country datasets; (iv) adopting a multilevel framework, either individual-institution level, or institution-external environment level.

In this paper we contribute to the state of the art in all these directions. We examine systematically cross-discipline variations in a multilevel model of research productivity at university level. The multilevel approach allows to identify the institutional level at which the production of research is affected by various determinants, namely the department (or disciplinary area) level and the university level, on the one hand, and the external regional economic and social environment, on the other hand. In this paper we examine two levels (university and region) separately in five broad disciplinary areas. By running the multilevel model separately across disciplinary areas we are also in the position to examine the issue of disciplinary differences to a great detail. In turn, our results give a contribution to the general theory of research productivity.

The paper exploits a novel dataset combining census-based information on all Higher Education Institutions (HEIs) in Europe, including data on students and academic staff with data on publications and citations. We are able to aggregate into separate broad disciplinary areas academic staff (classified according to Field of Education) and their publications and citations (classified according to Subject Categories). We examine *separately* all STEM fields, namely Science, Engineering, Computer science, Agriculture, and Medicine. We use several measures of research productivity, not just one. Our dependent variables are size-independent measures of research performance showing the percentage of total output at university level which is published in the top 10% or top 25% of publications, or receive citations from the top 10% or top 25% of publications, respectively, using Scopus data. Because the dependent variables are size-independent we interpret them as indicators of productivity, or research performance that does not depend on the number of researchers.

The independent variables include a rich array of determinants, which allow the testing of the most important hypotheses developed in the literature. We arrange the independent variables into a multilevel model. We find a number of results that confirm the state of the art, but also some findings that go against the received wisdom. Taken together, given the broad scope of our dataset

and the coverage of all STEM disciplines, we are somewhat closer to a robust and general theory of determinants of research productivity at university level.
The paper is structured as follows. Section 2 reviews the literature about the determinants of research productivity and develops specific hypotheses. Section 3 describes in detail the dataset. Section 4 shows the main findings and Section 5 discusses the findings against the state of the art and concludes.

2. State of the art and development of hypotheses

The issue of research productivity has attracted lot of attention in recent decades. In this section we review the literature and summarize the evidence related to the variables that will be investigated in our models. For each of them we formalize the assumptions about the sign of the coefficients in the regression models. In defining the hypotheses we follow the nomenclature and the numbering used in our previous study on the field of Medicine (Bonaccorsi and Secondi, 2017). At the same time we modify some of the assumptions we made in that study in the light of the evidence and integrate and update the literature on the basis of most recent studies.

2.1 Size of university

Are researchers affiliated to large universities more productive, or more capable to publish in good journals and receive citations from good journals? The role of size in influencing the research productivity has been repeatedly examined in the theoretical framework of increasing returns to scale, using a production function approach or a cost function approach. Brinkman and Leslie (1986) provide a survey of the pioneering studies, while Cohn and Cooper (2004), Johnes (2006), Brandt and Schubert (2013) and Hernandez-Villafuerte et al. (2017) update the last studies. At university level the economies of scale may be due to indivisibilities of research services and infrastructures (library, computer facility) and to visibility and prestige of the institution. Since universities jointly produce teaching and research it is necessary to distinguish between two types of economies of scale: ray economies and product-specific economies of scale.
The former take into account both types of outputs. de Groot et al (1991), Koshal and Koshal (1999), Leband and Lentz (2003), Worthington and Higgs (2011), Wolszczak-Derlacz and Parteka (2011) and Zhang et al. (2016) all found ray economies of scale at university level. Johnes and Salas Velasco (2007) found positive but only modest ray economies of scale at university level. Duch Brown et al. (2010) confirmed the effect only for newly created universities. Ray economies are defined in an interval of output which specifies the potential for cost reduction: in most studies this interval goes up to 100%-200% of the mean output of the sample, suggesting large potential for gains in efficiency by increasing the size of universities.
Yet ray economies of scale do not permit to disentangle the causes of economies of scale. This is why many studies examine product specific economies of scale across separate categories of outputs, namely teaching (in total or disaggregated by undergraduate and postgraduate) and research. Leband and Lentz (2003) found product-specific economies of scale across all types of outputs (undergraduate, postgraduate and external research funding). Most studies, however, find product-specific economies of scale in one area alone.
While for teaching there is some agreement on the importance of product-specific economies of scale, in the case of research, on the contrary, the empirical findings are much more controversial. Brinkman (1981), Glass et al. (1995), Kotrlik et al. (2002) and Thanassoulis et al. (2011) found economies of scale in research at university level, but several other studies did not confirm these findings. For example, Adams and Griliches (1998) estimated an elasticity of 1.0 between size of universities and research production. Other authors who found constant returns to scale are Cohen (1981; 1984), Bonaccorsi and Daraio (2005), Worthington and Higgs (2011), Abramo et al. (2012). In a study on the increase in efficiency of UK universities between 1980 and 1993 Flegg et al.

(2004) found a significant improvement of technical efficiency, but only a minor role for scale efficiency.
Two notable recent exceptions are van Raan (2013) and Frenken et al. (2017) who find a superlinear scaling relation between size of universities and their volume of citations and interpret this finding as evidence of increasing returns to scale. Since these authors use the total volume of publications as indicator of size, it is not clear whether a superlinear scaling shows a bibliometric property of scientific publication, or a feature of the organization of research at university level. Under increasing returns to scale we should observe better efficiency in the use of *inputs*, that is, some indicator of academic staff should be used as a proxy for size.
Summing up, there are compelling theoretical reasons and convincing empirical findings for economies of scale at university level only for undergraduate teaching. With respect to research, the prevailing view is that the organization at the level of research team is subject to economies of scale, but only up to a very small size, which is exhausted with the units of staff needed for research teams. Beyond this level there are no advantages in the size of the research team and there are decreasing returns to scale in excessively large teams. This prevents teams to grow too large. Funding agencies have recently taken this finding into account in monitoring the PIs who receive very large grants (Berg, 2012; Fortin and Currie, 2013). When research teams are aggregated at department level and university level, the prevaling view is that the returns to scale are constant, with a few studies showing increasing returns.
In our previous study we hypothesized a positive impact of university size on research productivity but this hypothesis was not supported by data on the field of Medicine (Bonaccorsi and Secondi, 2017). On the contrary, we found strong support for the hypothesis of a nonlinear relation, as measured by regressing the square of the number of students.
We then assume
H1 (a) There is no relation between the size of university (as measured by the number of enrolled students) and research productivity at field level.
H1 (b) There is a nonlinear relation between the size of university and research productivity at field level, as witnessed by a positive relation with the square of the number of students.

2.2 PhD intensity

The impact of PhD students on research productivity of universities is a controversial issue. On the one hand, in fact, PhD students can be considered an *input* to the research activities of universities. The universities with a larger percentage of PhD students out of the total student population are institutions that invest more heavily in research, offering their faculty an environment with more opportunities for postgraduate education than undergraduate.
At the individual level there is a strong relation between the quality of PhD education and subsequent research performance. PhD programs in prestigious departments positively affect subsequent productivity (Wood, 1990; Washburn et al. 2006; Rey Rocha et al. 2006). Research productivity is influenced by the quality of mentoring programs (Gardiner et al. 2007; Muschallik and Pull, 2015), the mentor experience (Baird, 1991; Allison and Long, 1990), the supervisor creativity (Mumford et al. 2002; Goodall and Bäker, 2015) and publication output (Fiedler et al. 2008; Besancenot et al. 2009). Similar effects have been found for the quality of postdoc experiences (Horta, 2009). Insofar as PhD students publish their results during their doctoral period, according to this perspective universities with a higher PhD density would get a benefit in terms of research productivity.
On the other hand, however, PhD students absorb resources from academic staff in terms of postgraduate education, so they might be considered part of the *output*, not the input, of universities. It must be recognized that doctoral education is supported, in many European countries, as the final degree of higher education, without the implication that PhD students must contribute actively to the scientific output. Using the ratio between PhD students and total student population as an

indicator at country level Bonaccorsi (2009) found large heterogeneity across European countries. While there is a group of countries (namely, UK, the Netherlands and Switzerland) in which postgraduate education is concentrated in top level universities, in other European countries the population of PhD students is spread thinly across all universities. This means that the *overall* effect of PhD intensity on research performance is ambiguous.
As a matter of fact, in our previous study in the Medicine field we found no effect of PhD intensity. We therefore propose the following hypothesis.
H2 (a) There is no relation between PhD intensity at university level and research productivity at field level.

2.3 Research quality and peer effects

A long standing research tradition addressed the issue of the relative importance of scientific merit and institutional reputation for academic careers. This issue was initially formulated by Robert Merton in the context of a general theory of scientific production based on priority and recognition. Within this tradition, several authors started to investigate whether researchers were recruited on the basis of research merit only. If this were the case, then their productivity would be independent on the quality of the departments in which they operate. This effect is labeled *selection effect*. A different possibility is that researchers are recruited according to other criteria, most likely on the basis of the reputation of the department in which they had their doctoral degree or postdoc experience. In this case the question is whether their productivity is influenced by the research environment in which they operate *after* the selection. This is labeled *departmental effect*.
Early studies in the Mertonian tradition found strong confirmation of the departmental effect (Cole, 1970; Cole and Cole, 1973; Allison and Stewart, 1974; Long and McGinnis, 1981; Allison and Long, 1990; see also Faia, 1975; Reskin, 1977). This effect is interpreted as an example of *peer effect*, or productivity externality: researchers improve their productivity when they are surrounded by productive colleagues. They adapt to the research environment. These findings are interpreted as confirmation of the relative importance of institutional factors, as opposed to individual and psychological factors, in influencing research productivity. These institutional factors are conceptualized within a model of accumulative advantage: researchers who receive an early legitimation by the scientific reward system, in terms of priority recognition and funding, strenghten over time their advantage.
The importance of peer effects has been confirmed repeatedly in later studies of research productivity. These studies found that research productivity is higher in highly active research departments (Baird, 1991; Ramsden, 1994; Hesli and Lee, 2001), prestigious departments (Blackburn et al. 1978; Davis and Patterson, 2000; Maske et al. 2003), departments that assign high priority to research (White et al. 2012), departments with a larger number of highly productive researchers (e.g. Ramon y Cayal grant assignees: Ramos et al. 2007) or of researchers who actively publish (Washburn et al. 2006). On the other side, research productivity is lower when the number of non-publishing colleagues is large (Taylor et al. 2006; Fabel et al. 2008): in other words, “active researchers with less productive peers are less productive themselves” (Fabel et al. 2008, 518). Controlling for endogeneity issues, the intensity and quality of publications of colleagues, or the quality of work environment, have positive impact on research productivity (Creswell, 1985; Wood, 1990; Carayol and Matt, 2006; Gonzalez and Veloso, 2007). This effect is even stronger when the research environment includes star scientists, or extremely productive researchers with a large impact on the directions of research (Johnes, 1988; Nederhof and Van Raan, 1993; Zucker et al. 1998).
H2 (b)[1] *There is a positive relation between the quality of research at university level and research productivity at field level.*

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[1] The sequence of numbering is slightly modified in order to follow the numbering adopted in Bonaccorsi and Secondi (2017, Table 6) with respect to Medicine and compare the results in other STEM fields. With respect to the previous study, for this hypothesis we

2.4 Age of university

In our previous study we had hypotesized that the age of the university could be considered a proxy for institutional visibility and prestige and could be associated to institutional policies for the attraction of productive researchers.

Our assumption was rooted in the Mertonian tradition that investigated extensively the advantages that scientists affiliated to prestigious (old) universities may derive in addition to their intrinsic merits, in terms of acceptance of papers by journals or funding of projects. This literature found that the affiliation to prestigious universities is indeed a major source of advantages, as it has been illustrated in the previous section.

Interestingly, the data disconfirmed the assumption of a positive impact of the age of the university, while offered strong support for the relation between research quality at university level and research performance at field level, as assumed in H 2(b) above. According to Frenken et al. (2017) the relation between university age and research performance is even negative. This means that the age of the university, at best, is not a sufficient statistics for its prestige and visibility in research. We then modify our hypothesis, as follows.

H3 There is no relation between the age of the university and research productivity at field level.

2.5 Internationalization of PhD students

While PhD intensity is not per se associated with research productivity (according to the H2 (a) outlined above), the attraction of PhD students from abroad is associated to it. As illustrated by the literature on mobility, there is an increasing share of postgraduate students searching a PhD programme abroad. Recent studies based on GlobSci, a large scale survey of scientists in 16 countries and in four disciplines (Biology, Chemistry, Earth and environmental sciences, Materials science), show that the main reasons for international mobility are scientific and that mobile researchers are more productive and establish larger collaboration networks (Franzoni, Scellato and Stephan, 2014; 2105; Scellato, Franzoni and Stephan, 2015; Geuna, 2015). According to MORE, a survey on EU-US post-PhD mobile researchers, it is mobility during the PhD that motivates researchers to remain mobile in the postdoc period (Veugelers and Van Bouwel, 2015).

According to a recent JRC Report “better quality universities and those with a higher reputation are associated with a higher share of mobile students, while research orientation and excellence are more relevant for degree mobile PhD students” (Sánchez-Barrioluengo and Flisi, 2017, 2). These arguments are consistent with the findings on attractiveness of European universities for foreign academic staff (i.e. permanent personnel) based on ETER data in Lepori et al. (2015): foreign staff are attracted by the research intensity of the host country (as measured by R&D/GDP ratios) and the research reputation of the university. Overall there are strong elements to assume the following.

H4(a) There is a positive relation between the share of foreign PhD students out of total student population at university level and the research productivity at field level.

2.6 International co-authorship

It has been observed, as a long term trend in scientific production, a steady increase in co-authorship and team production, as measured by the average number of authors per paper (Wuchty et al. 2007). The main explanation for this increase is that larger teams of authors allow a better division of scientific work, particularly in laboratory experimentation (Davis and Patterson, 2000; 2001; Maske et al. 2003; Cimeleur et al. 2015). A related argument is that larger teams mobilize heterogeneous but complementary disciplinary resources, supporting interdisciplinary research.

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adopted as independent variable by using %TOP251DEC, or the Percentage share of sub-sub subjects in the first decile of the TOP 25% SNIP publications, over the total number of subjects where the university has publications in the GRBS dataset.

The question is whether co-authorship increases *individual* productivity, that is, scientific production per capita, after discounting for the number of authors. In a largely cited paper, for example, Hollis (2001) showed that co-authorship in Economics led to an increase in frequency and quality of publications, but a decrease in individual productivity after discounting for the number of authors.

The issue is subtle and, again, involves significant endogeneity. As Ynalvez and Shrum (2011) note, the relation between scientific collaboration and productivity is still poorly understood. Ductor (2015) has re-examined the paper by Hollis (2001) and has suggested that for authors the set of research opportunities and the selection of co-authors are endogenous. In other words, authors decide whether to pursue research ideas alone or to look for co-authors. The negative effects found by Hollis (2001) might be explained in terms of congestion externality of good ideas: authors may keep good ideas for themselves after saturating the opportunities for collaboration. After controlling for these effects, Ductor (2015) found that co-authorship has a positive impact not only on total production but on individual productivity.

The idea that co-author selection is endogenous is at the core of recent work emphasizing the role of the quality of the overall networks of collaboration. Using a model of assortative matching, Besancenot et al. (2009; 2017) and Krapf (2015) show that the size and quality of co-author networks have a positive impact on productivity. This is an indication of the selective effect of co-authorship on individual productivity. On the other hand, it is known that internationally co-authored papers are cited more frequently (Beaver and Rosen, 1979; Katz and Martin, 1997; Lee and Bozeman, 2005), an indication of better quality. The above arguments strenghten the idea that international collaborations and co-authorships are a good antecedent of research productivity.

H4(b) There is a positive relation between the share of publications co-authored with foreign authors at university level and the research productivity at field level.

2.7 Governance of university

By governance we mean here the legal status of universities, which can be classified in Public, Private, and Private-Government dependent. There are few studies comparing public and private universities with respect to the research orientation, intensity, or productivity. Teixeira et al. (2014) showed that private universities increased their importance, particularly in Eastern European countries, focusing mainly on educational needs not covered by the public sector. Consequently, private universities underinvested in research. On the basis of this evidence in our previous study we hypothesized a negative relation with research productivity for private universities, or a positive relation for public ones. This hypothesis was not confirmed by the data. We then now take a more agnostic position, by assuming the following.

H5(a) There is no relation between the public or private nature of universities and the research productivity at field level.

2.8 Generalist vs specialist model of university

Academic research can be carried out in a variety of institutional settings. In addition to the distinction between public and private governance, an important distinction can be drawn between generalist and specialist universities. Generalist universities cover the entire spectrum of disciplines, while specialist universities focus on one or a few fields, most frequently in applied fields such as Engineering (Technical universities, or Polytechnics), Medicine (Medical schools) in STEM, as well as Business or Law in SSH. Does the institutional arrangement have an impact on research productivity? Is it better for researchers, say, in Engineering, to work at a Technical university in which the vast majority of colleagues are engineers, or rather to work at a generalist university in which they may walk down the street and meet philosophers and mathematicians? This issue has been explored by the large literature on economies of scope in research productivity (see among the most recent studies Cherchie et al. 2008; De Witte et al. 2013; Hernandez-Villafuerte et al. 2017). Economies of scope refer to the efficiency gains in shifting from single production to multiple production of outputs. These effects are studied at aggregate level, that is, departments or more commonly institutions (universities). Economies of scope are examined for the joint production of research and teaching, or for the joint production of research in various disciplinary fields. According to this literature economies of scope can be found in either cases. Contrary to the prevailing literature, however, Abramo et al. (2014) found no effect of the breadth of disciplines on research productivity for Italian universities. With respect to disciplinary fields, most studies find that having several disciplines under the same organization produces advantages for research, in particular for inter-disciplinary or multi-disciplinary research. In generalist universities researchers find complementary competences. The breadth of scientific competences among the faculty contributes to intramural research collaboration. Following the prevailing literature, we assume the following.

H5(b) There is a positive relation between the generalist nature of universities and the research productivity at field level.

2.9 Teaching load

There is an overwhelming evidence that the teaching load dedicated to undergraduate students has a negative impact on research productivity.

Teaching load is measured in terms of student/staff ratio, or number of courses/staff ratio. A large number of studies have found a negative and significant relation with several measures of research productivity (Blackburn et al. 1978; Fox, 1992; Golden and Carstensen, 1992; Maske et al. 2003; Taylor et al. 2006; Ramos et al. 2007; Hesli and Lee, 2011; White et al. 2012). Ramsden (1994) found a positive relation between research productivity and a low commitment to teaching. Conversely, several studies find a positive relation between research productivity and indicators of research orientation, such as time spent in research (Chen et al. 2006; Carayol and Matt, 2006; Brew et al. 2016) and subjective belief on the dominant importance of research (Sax et al. 2002; White et al. 2012; Nasser, 2017). Van Heeringen and Dijkwel (1987) found that highly productive researchers may spend up to 80% of their time in research.

According to Fox and Milbourne (1999) a 10% increase in the number of teaching hours results in a 20% decrase in research output. The estimate by Washburn et al. (2006) is that additional 3 hours per week class result in a 9.6% decrease in productivity and that additional summer class results in a 17.7% decrease.

To our knowledge, only Fabel et al. (2008) report a non-significant relation. In institutional contexts in which the teaching load is regulated at national level or supported by legislative provision, it may well be that the variability across academicians is artificially limited, resulting in non significant results. This is the case of Italy, according to Abramo et al. (2012), in which the legislation mandates a yearly commitment of 350 hours for all academic staff.

H6 There is a negative relation between the average teaching load at university level and the research productivity at field level.

2.9 Hospital

In the case of Medicine, there are good reasons to assume that the presence of a hospital within the university has a positive influence on research performance. Hospitals provide an essential facility for the experimentation and testing of medical research in a clinical setting. The empirical data supported this assumption in our previous study (Bonaccorsi and Secondi, 2017).

In a multidisciplinary context it is not possible to generalize, since other disciplinary areas covered in the analysis, i.e. Science, Enginering and Computer Science, and Agriculture, have not a relation with clinical research. We therefore take a neutral attitude here, as follows.
H7 There is no relation between the presence of a hospital at university level and the research productivity at field level.

2.10 External variables at regional level

A multilevel modeling framework allows the estimation of the impact of variables at regional level conditional on the impact of variables at university level, that is, internal to the units under observation.
The theoretical underpinnings of this assumption is the relation between universities and regional economies, a topic largely examined in the literature on economic geography and regional economics. The literature is very large and has been growing in recent years due to the interest in regional innovation policies, so it cannot be reviewed here. There are two main streams of analysis, i.e. the relation between the presence of universities in a region and knowledge spillovers, on the one hand, and human capital creation, on the other hand. Knowledge spillovers refer to the exchange of knowledge and the interaction between universities and companies. Human capital creation describes the cumulative impact of universities on the skills of the local workforce and the general population thanks to educational activities. Following the extensive survey of the literature in Bonaccorsi (2016) we assume a positive relation between research performance and the following variables at regional (NUTS 2) level available from Eurostat:

i) GDP per capita
ii) Gross expenditure on R&D (GERD)
iii) Share of tertiary education

The GDP per capita is a proxy of the overall development of the regional environment. Operating in regions with more developed economies offers advantages of various types to researchers, making available complementary resources (e.g. infrastructure, administration, transport).
In turn, the expenditure in R&D is expected to contribute to the absorptive capacity at regional level. A region with larger expenditure will have a larger number of R&D-performing firms, that are more likely to activate research collaborations with universities, generating knowledge exchanges and spillovers.
Finally, the larger the proportion of population with higher education, the larger the human capital available. Regions with more educated population are more attractive for researchers and students. We therefore assume the following hypotheses.

H8 (a) There is a positive relation between GDP per capita at regional level and research productivity at field level.
H8 (b) There is a positive relation between Gross expenditure on R&D (GERD) at regional level and research productivity at field level.
H8 (c) There is a positive relation between the share of population with tertiary education at regional level and research productivity at field level.

2.11 Research productivity across disciplines

This question has raised attention repeatedly, but has not been addressed systematically in the context of the theory of research productivity. Several authors have noted that disciplines follow different patterns of scientific productivity (Ramsden, 1994; Davis and Patterson, 2000; Piro, Aksnes and Rorstad, 2013; Brew et al. 2016). In the literature on efficiency of universities, it has been noted that the definition of efficiency, or input-output relation, may take different meanings according to the composition of universities in terms of disciplines (Dundar and Lewis, 1995;

1998). Universities are "complex sets of institutions operating at different scale size and different output mixes" (Thanassoulis et al. 2011).
These differences translate into returns to scale, an issue somewhat explored in the literature. As an example, Adams and Griliches (1998) found constants returns to scale for the majority of disciplines (Agriculture, Biology, Chemistry, Engineering, Medicine and Physics) but slower returns to scale for Computer Science and Mathematics. According to Olivares and Wetzel (2011) economies of scale and scope exist at different levels across disciplines. Therefore, as noted by Sarrico et al. (2009), the lack of consideration of the disciplinary composition, or subject mix, may lead to spurious conclusions.
These differences are of large importance when the dependent variables are defined in absolute terms, as for example in terms of number of publications or number of citations. The literature has clearly shown large differences in bibliometric indicators, such as average number of co-authors (i.e. very high in Physics, high in Medicine, low in Mathematics), or total number of publications per year or total citations received (Adams et al. 2005; Marx and Bornmann, 2014; Abramov et al. 2017). Models of productivity that ignore the composition effects deriving from these bibliometric differences are flawed (Sarrico et al. 2009).
Since we work with size-independent variables, there is no theory suggesting why different disciplines should differ in their ability to reach top level quality, that is, being regularly published in, and being cited by, good journals. We are able to compare five broad STEM areas: Science, Computer Science, Engineering, Agriculture and Medicine. In these areas the main research output is the journal article, the language is English, the journals are international and peer-reviewed.
We might, however, observe whether there are observable differences between pure disciplines (Science) and applied disciplines (Engineering, Computer Science, Agriculture, and Medicine). This distinction is admittedly crude, as there are pure topics in applied disciplines (e.g. Theoretical computer science) and applied topics in pure disciplines (e.g. Health applications in Physics). Nevertheless it can be accepted as a first level approximation. One important difference can be identified in the relation between academic research and external stakeholders, which is more important in applied disciplines, in which contract research from companies and third party funding are a significant source of funding. These sources are generated in more advanced regional contexts. We therefore assume that external variables at regional level (GDP per capita, R&D expenditure, and tertiary education) are more important for these disciplines than for Science.
H9 The impact of external variables at regional level is larger in applied disciplines (Engineering and Computer Science, Agriculture, Medicine) that in pure disciplines (Science).

3. Data sets and model specification

We constructed an original data set by integrating various sources of data. We focused on five large disciplinary areas within STEM: Science (FoE 5), Engineering (FoE 6) and Computer Science (FoE 7), Agriculture (FoE 8), Medicine (FoE 9). For each of these areas we aggregated data on academic staff from the mentioned Fields of Education (FoE) with data on publications in the Subject Categories that have a correspondence with the discipline. We also add a pooled model in which the various disciplines are aggregated and a dummy for disciplines is added (baseline= Agriculture).
First, we refer to the Global Research Benchmarking System (GRBS) dataset provided by the United Nation University – International Institute for Software Technology (UNUIIST) based on Scopus publications in 251 Subject Categories covering all science and technology fields[2] and selecting

[2] The 2011 GRBS release covers 24,936 source titles from the Scopus database. Publication types included are articles, reviews, and conference papers. In GRBS, source titles (journals, conference proceedings and book series) are classified into discipline-specific tiered outlets based on their Source Normalized Impact per Paper (SNIP) values in each of the following 15 Top level GRBS categories: i) Agricultural & Biological Sciences; ii) Biochemistry, Genetics and Molecular Biology; iii) Chemistry; iv) Computer Science; v) Earth and Planetary Sciences; vi) Economics and Business Sciences;

variables focusing on university research output, as detailed in Table 1. The GRBS dataset is illustrated in detail in Haddawy et al. (2017) and has been used in several published papers in recent years (Zhu et al. 2014; Bonaccorsi et al. 2016; 2017; Bonaccorsi and Secondi, 2017). The mentioned papers describe the correspondence between FoE (data on academic staff and students) and FoS (data on publications). GRBS data used for this paper refer to the cumulative publications and citations in year 2008-2011 (Haddawy et al. 2017).
We use variables based on SNIP, or Source Normalized Impact per Paper. According to the proponent of SNIP, Henk Moed, this indicator overcomes some of the limitations of Impact Factor (Moed, 2010). It is well known that journal-based indicators are imperfectly correlated to indicators based on individual papers (e.g. top cited papers). The GRBS dataset does not include data on individual papers, but has the advantage of providing aggregate data at the level of universities whose disambiguation with respect to the Census of European higher education institutions has been carried out following the ETER nomenclature. In addition, for large scale analyses at institutional level the strenght of the statistical relation between indicators based on individual papers or journals is less severe.

Second, we integrated data at university level by the information available in the ETER (European Tertiary Education Register) database which provides official data delivered by National Statistical Authorities on all higher education institutions in Europe related to the number of students, graduates, international doctorates, staff as well as details on fields of education, income and expenditure and their structural characteristics such as foundation year, legal status (distinguished into public, private and private-government dependent universities) and presence of university hospital. [3] In recent years ETER, promoted by the Directorate General for Education and Culture of the European Commission, has become an established source for comparative and aggregate analyses of European higher education institutions. While the ETER dataset includes university and non-university higher education institutions, in this paper we only use data on universities, or PhD awarding institutions. Given the significant institutional heterogeneity of European higher education systems (Agasisti and Haelermans, 2016), we rely on official data by National Statistical Authorities, which follow the standardization rules established by Unesco, OECD and Eurostat. We make use of the earliest data available to be compared to GRBS data, that is, 2008 ETER data.
Third, we considered the Scimago data (SIRWorld Report 2011, period analyzed 2005-09) to capture information on disciplinary concentrations/specialization of institution scientific output (generalist vs. specialized institutions) and international collaboration.
Last, in order to take into consideration the context where universities are located, we added variables at NUTS-2 level by using official data available from Eurostat. We considered the NUTS-2 level as the most appropriate detailed territorial level to which refers our analysis, due to the presence of singleton clusters, therefore meaning NUTS-2 regions with only one university, in each of the 5 data sets.
Our units of observation are, therefore, sub-units of the university composed by academic staff who teach in one broad Field of Education (FoE) and publish papers in all scientific disciplines related to the broad areas, following a correspondence with Subject categories of journals, conventionally classified in Fields of Science (FoS). Each of these units of observation can be considered, therefore, as a “university active in the field”. Since not all universities are active in all STEM fields, the number of observations is variable across fields. In particular we have data on 511 universities active in Science (FoE05), 323 in Computer Science (FoE06), 416 in Engineering (FoE07) 325 in Agriculture (F08) and 337 in Medicine (F09).

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vii) Engineering; viii) Environmental Sciences; ix) Health Professions & Nursing; x) Materials Sciences; xi) Mathematics; xii) Medicine; xiii) Multidisciplinary; xiv) Other Life and Health Sciences; xv) Physics and Astronomy.

[3] With respect to staff the ETER project implemented better harmonization of data on medical staff in order to ensure full comparability across countries. We made use of the latest version of ETER data. Remaining measurement errors in the counting of academic staff would affect the estimate for Medicine only.

To our knowledge, this is the first effort to examine data at the level of universities that jointly: (a) cover all European countries; (b) combine teaching and research for the identification of academic staff; (c) offer a disaggregation by discipline; (d) uses several measures of research productivity. Table 1 below summarizes the variables used in this study for model specification and estimation.[4]

[4] A complete description of the data sets and the related available variables can be found in Haddawy et al. (2017) and Bonaccorsi and Secondi (2017).

Table 1 – Variables used for the analysis. Name, description and sources

VARIABLE NAME	DESCRIPTION	SOURCE
pub10F__ pub10F__p	– *PUB10F__*: Number of Pubs published in source titles that are within top 10% of that subject area, based on the SNIP value [Ranked Outlets] of the last year in the time window and for the specific area ISCED-F__ (for the five disciplinary areas from FoE 05 Science to FoE 09 Medicine) – *pub10F09p*: Percentage of Total Pubs published in source titles that are within top 10% of that subject area, based on the SNIP value for the specific area ISCED-F__ (for the five disciplinary areas from FoE 05 Science to FoE 09 Medicine)	GRBS
pub25F__ pub25F__p	– *pub25F__*: Number of Pubs published in source titles that are within top 25 % of that subject area, based on the SNIP value of the last year in the time window (for the five disciplinary areas from FoE 05 Science to FoE 09 Medicine) – *pub25F__p*: Percentage of Total Pubs published in source titles that are within top 25 % of that subject area, based on the SNIP value of the last year in the time window (for the five disciplinary areas from FoE 05 Science to FoE 09 Medicine)	GRBS
cit10F__ cit10F__p	– *cit10F__*: Number of Cites received from publications in journals that are within top 10% based on SNIP value (for the five disciplinary areas from FoE 05 Science to FoE 09 Medicine) – *cit10F__p*: Percentage of Total Cites received from publications in journals that are within top 10% based on SNIP value (for the five disciplinary areas from FoE 05 Science to FoE 09 Medicine)	GRBS
cit25F__ cit25F__p	– *cit25F09*: Number of Cites received from publications in journals that are within top 25 % based on SNIP value (for the five disciplinary areas from FoE 05 Science to FoE 09 Medicine) – *cit25F09p*: Percentage of Total Cites received from publications in journals that are within top 25 % based on SNIP value (for the five disciplinary areas from FoE 05 Science to FoE 09 Medicine)	GRBS
SIZE	Total number of enrolled students ISCED5-8	ETER
PHDINT.TOT	Phd intensity (students ISCED8/students ISCED5-8)	ETER
PHDINT.ISCEDF__	Phd intensity (students ISCED8/students ISCED5-8) within each disciplinary area FoE__ (for the five disciplinary areas from FoE 05 Science to FoE 09 Medicine)	ETER
TOP251DEC P_TOP251DEC: (absolute and % terms)	– Number of sub-sub-subjects where the HEIs is in the first decile of the world rank of institutions with the highest share of publications in source titles that are within top 25% of that subject area, based on the SNIP value (except the one considered) (P_TOP251DEC: Percentage share of sub-sub-subjects in the first decile TOP25%SNIP over total number of sub-subjects where the HEIs has publication in GRBS) (except the one considered)	Elaboration from GRBS
BAS.FOUNYEAR	Foundation year	ETER
FOREIGN8_TOTST	Share of foreign PhD students	Elaboration from ETER
IC	International Collaboration Institution's output ratio produced in collaboration with foreign institutions. The values are computed by analyzing an institution's output whose affiliations include more than one country address	SCIMAGO
BAS.LEGALST	Legal status (0: Public universities; 1: Private universities; 2: Private-government dependent universities)	ETER
SPEC	Specialization Index The Specialization Index indicates the extent of thematic concentration /dispersion of an institution's scientific output. Values range between 0 and 1, indicating generalist vs. specialized institutions respectively. This indicator is computed according to the Gini Index used in applied economics and statistics.	SCIMAGO
RATIO_S_AS	Total students enrolled/ Total academic staff (HC)	ETER
BAS.UNIHOSP	University hospital (1: Yes; 0: No)	ETER
GDPHAB	Gross domestic product (GDP) at current market prices by NUTS-3 regions (PPS per inhabitant, year 2010)	EUROSTAT
Ter2564	Population aged 25-64 with tertiary education attainment by NUTS-2 regions - % (year 2010)	EUROSTAT
GERD	Total intramural R&D expenditure (GERD) by NUTS 2 regions - % of GDP (year 2010)	EUROSTAT

Table 2a and 2b show descriptive analyses for the selected variables in terms of tendency and dispersion measures – by distinguinshing both for the entire data set (Multi FoEs) and the five disciplinary areas (from F05 to F09) – while Figure 1 shows the empirical observed variability for the following performance indicators used to define the dependent variables in the estimated models:

(a) *Pub10F__p*: percentage of Total Publications published in source titles that are within top 10% of the specific ISCED-F__ subject area based on the SNIP value (for each of the five disciplinary area, from F05 Science to 09 Medicine);
(b) *Pub25F__p*: percentage of Total Publications published in source titles that are within top 25% of the specific ISCED-F__ subject area, based on the SNIP value of the last year in the time window (for each of the five disciplinary area, from F05 Science to 09 Medicine);
(c) *Cit10F__p*: percentage of Total Cites received from publications in journals that are within top 10% based on SNIP value (for each of the five disciplinary area, from F05 Science to 09 Medicine);
(d) *Cit25F__p*: percentage of Total Cites received from publications in journals that are within top 25 % based on SNIP value (for each of the five disciplinary area, from F05 Science to 09 Medicine).

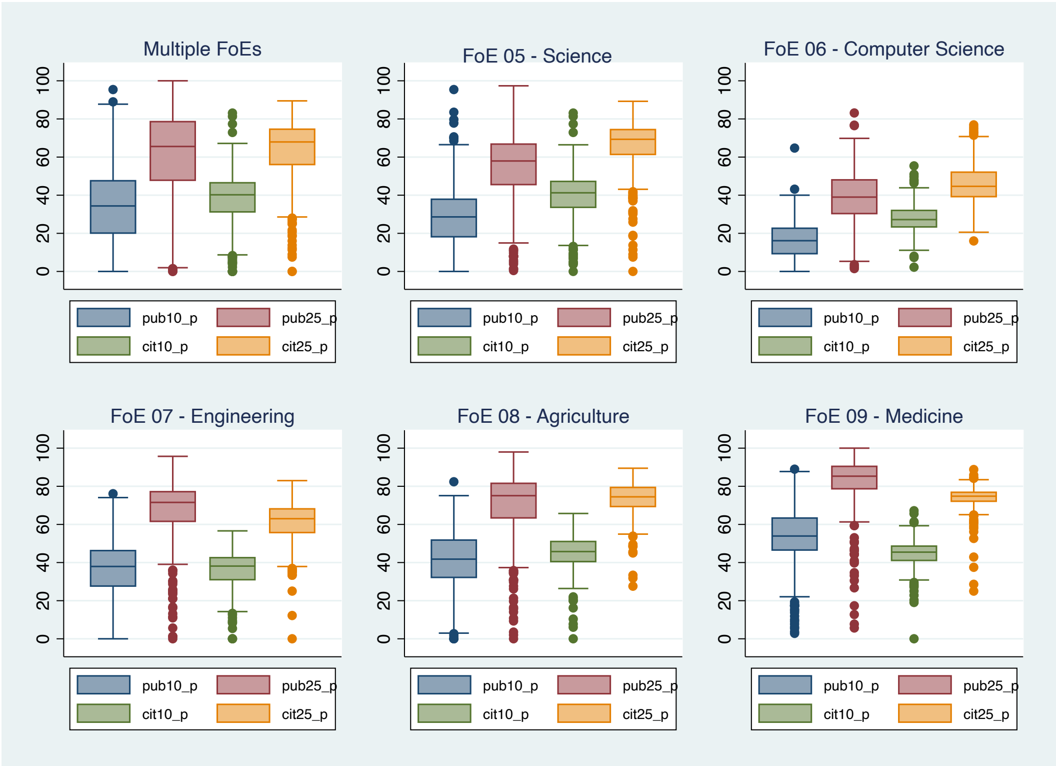
Table 2.a – Summary statistics for the productivity indicators, university-level and contextual-level variables: Multi FoEs (entire data set), FoE 05 – Science, FoE 06 – Computer Science

Variable name	Multi disciplinary areas (FoEs)				FoE 05 - Science				FoE 06 – Computer Science			
	mean	sd	cv	p50	mean	sd	cv	p50	mean	sd	cv	p50
Pub10F	572.523	1131.106	1.976	147.998	28.055	15.141	0.540	28.598	16.493	9.049	0.549	16.142
Pub10F__p	34.256	18.217	0.532	34.352	28.055	15.141	0.540	28.598	16.493	9.049	0.549	16.142
Pub25F	958.506	1726.952	1.802	292.999	54.590	18.055	0.331	57.949	38.553	13.721	0.356	39.000
Pub25F__p	61.903	21.253	0.343	65.554	54.590	18.055	0.331	57.949	38.553	13.721	0.356	39.000
Cit10F	2388.910	5208.904	2.180	456.006	4137.462	6610.904	1.598	1401.966	197.391	285.431	1.446	98.003
cit10F__p	38.654	11.041	0.286	40.205	39.482	11.484	0.291	41.245	27.826	7.310	0.263	27.206
Cit25F	3793.916	8119.973	2.140	747.516	6460.549	9948.979	1.540	2372.973	314.002	442.033	1.408	159.006
cit25F__p	64.126	13.891	0.217	67.929	66.121	12.461	0.188	69.303	46.001	10.480	0.228	44.648
Size (000)	22.537	17.177	0.762	19.547	20.328	16.597	0.816	17.301	24.197	18.177	0.751	20.865
PhDinttot	0.068	0.061	0.905	0.057	0.066	0.071	1.063	0.051	0.068	0.049	0.720	0.062
Phdint.Iscedf__	0.080	0.158	1.967	0.041	0.104	0.174	1.669	0.062	0.100	0.220	2.2021	0.035
Top251dec	4.801	6.785	1.413	2.000	3.853	6.232	1.617	1.000	5.322	7.077	1.330	2.000
P_top251dec	8.123	9.532	1.174	6.024	7.243	9.610	1.327	4.301	7.720	7.768	1.006	6.250
Base.founyear	1839.071	207.658	0.113	1925	1861.550	192.122	0.103	1949	1830.353	214.423	0.117	1923
Foreign8_totst	0.263	0.180	0.684	0.251	0.254	0.188	0.738	0.238	0.276	0.183	0.662	0.261
IC	41.360	9.541	0.231	41.560	40.478	10.320	0.255	40.610	41.682	8.866	0.213	41.875
Baslegalst=0 (Public)	0.974				0.972				0.975			
Baslegalst=1 (Private)	0.006				0.006				0.003			
Baslegalst=2 (Private-governm.)	0.020				0.022				0.022			
SPEC	0.630	0.118	0.187	0.620	0.659	0.123	0.187	0.650	0.612	0.109	0.178	0.605
Ratio_S_AS	13.811	7.205	0.522	13.123	13.989	7.261	0.519	13.544	13.733	7.510	0.547	12.892
Bas.Unihosp	0.475				0.410				0.484			
Gdp_hab	29086.860	14845.900	0.510	27400.000	28078.840	12985.790	0.462	27100.000	28515.100	11208.050	0.393	27700.000
Ter2564	1.953	1.245	0.638	1.640	1.887	1.245	0.660	1.570	2.028	1.237	0.610	1.640
Gerd	29.458	9.710	0.330	29.371	29.117	9.765	0.335	29.122	29.784	9.570	0.321	30.100

Table 2.b – Summary statistics for the productivity indicators, university-level and contextual-level variables: FoE 07 – Engineering, FoE 08 – Agriculture, FoE 09 - Medicine

Variable name	FoE 07 - Engineering				FoE 08 - Agriculture				FoE 09 - Medicine			
	mean	sd	cv	Median	mean	sd	cv	Median	mean	sd	cv	Median
Pub10F	36.046	14.366	0.399	37.934	197.800	264.164	1.336	106.002	1248.620	1932.396	1.548	401.006
Pub10F__p	36.046	14.366	0.399	37.934	40.663	15.446	0.380	41.789	52.621	15.383	0.292	53.919
Pub25F	67.195	15.611	0.232	71.538	337.692	434.592	1.287	185.001	1876.087	2785.097	1.485	655.002
Pub25F__p	67.195	15.611	0.232	71.538	69.574	17.444	0.251	75.073	81.797	14.420	0.176	85.306
Cit10F	1275.253	2110.636	1.655	438.001	641.736	855.984	1.334	349.008	4943.179	7882.681	1.595	1345.037
cit10F__p	36.210	9.548	0.264	38.150	45.068	9.117	0.202	45.750	44.720	7.121	0.159	45.454
Cit25F	2009.578	3193.280	1.589	722.500	1016.656	1331.661	1.310	572.998	8042.426	12661.460	1.574	2259.027
cit25F__p	60.975	10.438	0.171	63.004	73.329	8.633	0.118	74.477	73.655	6.475	0.088	74.797
Size (000)	22.265	17.328	0.778	19.310	24.085	18.470	0.767	20.788	23.149	15.151	0.655	20.310
PhDinttot	0.068	0.069	1.020	0.055	0.069	0.050	0.736	0.059	0.069	0.057	0.822	0.060
Phdint.Iscedf__	0.049	0.110	2.227	0.026	0.064	0.153	2.410	0.028	0.074	0.104	1.408	0.036
Top251dec	4.457	6.655	1.493	2.000	5.283	7.047	1.334	2.000	5.713	7.041	1.232	3.000
P_top251dec	7.147	8.209	1.149	4.878	8.174	8.639	1.057	6.667	11.051	12.400	1.122	7.937
Basefounyear	1845.237	202.927	0.110	1937	1822.355	216.801	0.119	1919	1822.474	217.694	0.119	1920
Foreign8_totst	0.262	0.181	0.688	0.257	0.252	0.173	0.685	0.231	0.277	0.171	0.618	0.268
IC	40.830	9.734	0.238	41.065	42.236	9.142	0.216	42.400	42.229	8.930	0.211	42.570
Baslegalst=0 (Public)	0.980				0.975				0.967			
Baslegalst=1 (Private)	0.002				0.006				0.012			
Baslegalst=2 (Private-governm.)	0.017				0.019				0.021			
SPEC	0.635	0.116	0.183	0.630	0.612	0.114	0.186	0.600	0.614	0.116	0.189	0.600
Ratio_S_AS	13.960	7.376	0.528	13.477	13.982	7.310	0.523	13.483	13.265	6.479	0.488	12.141
Bas.Unihosp	0.455				0.497				0.567			
Gdp_hab	27450.710	11227.250	0.409	27250.000	27569.020	10853.270	0.394	27300.000	34747.600	23984.970	0.690	28500.000
Ter2564	1.926	1.216	0.631	1.640	1.914	1.212	0.633	1.640	2.052	1.318	0.642	1.600
Gerd	28.924	9.242	0.320	28.901	29.403	9.434	0.321	29.371	30.393	10.548	0.347	30.100

Figure 1. Empirical distributions of the selected productivity indicators



The data sets we constructed both for the pooled areas (multiple-disciplinary FoE) and for each disciplinary area separately (F05-F09) explicitely include a hierarchical structure with two different levels of details, i.e. departments affiliated to a university (level-1 units) in each of the broad disciplinary area, located in specific NUTS-2 regions (level-2 units).
Since the indicators – whose empirical distribution is visible in Figure 2 – represent relative values (and lie between 0 and 1 or 0 and 100 in percentage terms), we introduced the empirical logit transformation (Hox et al, 2010) to convert a limited dependent variable into an unlimited dependent variable in order to properly introduce them in the hierarchical regression models. Moreover, the pertinence of this transformation – characterized by a strictly monotonicity due to the logarithmic functional form, which does not influence the magnitude of productivity indicators across universities while preserving symmetry in the ranking – was already verified by Bonaccorsi and Secondi (2017) for the FoE 09 (Medicine) disciplinary area.
Bearing these peculiarities in mind, we referred to the multilevel approach and specifically to the random-intercept models which account for the introduction in the linear model specification of a region-specific (i.e. each NUTS-2 region included in the data sets) intercept. Without loss of generality, for each disciplinary area (FoE 05 Science, FoE 06 Computer Science, FoE 07 Engineering, FoE 08 Agriculture and FoE 09 Medicine) and for each of the four productivity research indicators – detailed above from *(a)* to *(d)* – we specified and estimated the following hierarchical model:

$$Y_{ij} = \alpha + \sum_{r=1}^{R} \beta_r X_{rij} + \sum_{s=1}^{S} \gamma_s Z_{sj} + u_j + e_{ij} \qquad i = 1,\ldots N; j = 1,\ldots.J \qquad (1)$$

where Y_{ij} is the value of the productivity measure observed for the i-th level-1 unit (disciplinary area F_ within a specific university) located in the j-th NUTS-2 region (level 2 unit). Moreover, two sets of explanatory variables were introduced: X_{rij} (with $r=1,\ldots,R$) are explanatory variables referring to level-1 statistical units, Z_{sj} (s=1,…,S) are level-2 explanatory variables (with $s=1,\ldots S$) referring to the NUTS-2 region. Lastly e_{ij} and u_j are level 1 and level-2 errors, respectively, for which normal distributions $u_j \sim N(0,\psi)$ and $e_{ij} \sim N(0,\theta)$ are assumed. As a result, from the specification illustrated in equation (1), each NUTS-2 region in the model is identified in the regression model with a region-specific intercept $\alpha + u_j$ with the random intercept u_j accounting for the combined effects of omitted regional characteristics (or unobserved heterogeneity).

By referring to the random-intercept specification, two main methodological conditions are satisfied. On the one hand, the random intercept explicitely allows us to take into consideration the hierarchical structure of our data as well as to account for the unobserved heterogeneity (Raudenbush and Bryk, 2002; Skrondal and Rabe-Hesketh, 2004; Goldstein, 2011). On the other hand, the multilevel approach enable us to properly deal with the violation of the independence conditions which originates from the grouped-structure of the data (Agresti, 2002) and specifically from the presence of more than one university within the same (NUTS-2) region[5].

With the aim of examining the role that hierarchy plays in explaining the overall variability of each productivity measures and therefore obtaining information about the proportion of the residual variance that can be attributed to the groups (Kreft et al., 1998), our model estimations are accompanied with the computed values of the Intraclass Correlation Coefficient (ICC) obtained as the ratio between the estimation of the level-2 variance and the overall variance, obtained by making the sum of the two error component variances, that is $\rho = \frac{\psi}{\psi + \theta}$. It is important to note that the presence of singleton clusters (only one university within a unique NUTS-2 region) did not enable us to obtain complete information on the within-cluster correlation even though, as highlighted by Rabe-Hesket and Skrondal (2008), their presence does not compromise the estimation process since they still contribute to the unknown parameters estimation as well as to the estimation of the variances ψ and θ related to the two error components.

4. Model estimation and findings

The estimations results of the random-intercept models assuming as dependent variables the four size-independent productivity measures are reported in Tables 3-7 below. On one hand, Table 3 shows the estimated random-intercept coefficients for the multi disciplinary (FoEs) data set and the four selected indicators. On the other hand, Tables from 4 to 8 show the estimated coefficients (referring to level-1, level-2 covariates and the estimated random parameters) distinguishing (by column) for each productivity indicators and for the five scientific areas (FoE 05 Science, FoE 06 Computer Science, FoE 07 Engineering, FoE 08 Agriculture, FoE 09 Medicine)[6]. It is worth noting that due to the cross-sectional nature of our data sets, the regression model estimates provide information on the association between the selected covariates and the dependent variables, while causality relationships cannot be extrapolated. Lastly, in the Appendix of Supplementary Statistical Analysis, the correlation matrices and the values of the Variance Inflation Factors (VIFs) verifying the absence of collinearity

[5] Clustered data could also be modelled by referring to the multiple linear models and specifically to the OLS estimator with robust-clustered standard errors. With the aim of taking properly and correctly into account the hierarchical structure of our data, we firstly tested the degree of dependence by estimating unconditional Hierarchical Linear Models where no predictors were included in the model, but a random effect for the intercept was included. From this model, we estimated the ICC and it was used together with the LR test (Multilevel models vs Linear models) to address whether multilevel models are preferred to multiple linear models. The value of the Intraclass Correlation Coefficient (McNeish, 2014; Hox, 1998) and the results of the LR tests lead us to prefer the random-intercept models for the performance indicators PUB10 and PUB25. However, bearing in mind that standard errors and the Type-I erros may be underestimated by using OLS estimator when the clustering is minimal (McNeish, 2014) and considering the presence of singleton clusters in our data set, we referred to the random-intercept specification for all the four studied indicators. However, for completeness of analysis and in order to make appropriate comparisons, the results of the OLS models with the clustered standard errors (at NUTS-2 level) are reported in the Appendix of the Supplementary Statistical Analysis.

[6] It is worth noting that we carried out a two-step estimation strategy by firstly estimating the models with level-1 variables only while adding in the second step the contextual (NUTS-2 level) variables. The models were fitted with Maximum Likelihood using the 'xtmixed' command of Stata 16.1.

are reported[7].

Table 3 - Determinants of research productivity for the pooled sample (FoEs).

	PUB10			PUB25			CIT10			CIT25		
	Coef.	Std. Err.	P>z	Coef.	Std. Err.	P>z	Coef.	Std. Err.	P>z	Coef.	Std. Err.	P>z
Size	-0.006	0.003	**	-0.006	0.003	**	-0.003	0.002	**	-0.005	0.002	***
(Size^2)	0.000	0.000		0.000	0.000		0.000	0.000	**	0.000	0.000	***
Phdinttot	-0.428	0.384		0.005	0.380		-0.433	0.230	*	-0.416	0.239	*
P_top251dec	0.020	0.002	***	0.028	0.002	***	0.009	0.001	***	0.011	0.001	***
Basfounyear	0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000	
Foreign8_totstud	1.169	0.157	***	0.969	0.155	***	0.101	0.093		-0.212	0.097	**
IC	0.014	0.003	***	0.010	0.003	***	0.005	0.002	***	0.001	0.002	
Baslegalst (ref. Public universities)												
1: Private universities	0.758	0.228	***	0.417	0.227	*	0.097	0.137		0.044	0.143	
2: Private-government dependent universities	0.148	0.190		-0.003	0.189		-0.124	0.113		-0.247	0.118	**
Spec	-1.815	0.258	***	-1.420	0.255	***	-1.144	0.152	***	-0.970	0.159	***
Ratio_S_AS	0.014	0.004	***	0.013	0.004	***	-0.002	0.002		-0.005	0.003	**
Basunihosp	-0.032	0.051		-0.039	0.051		-0.025	0.030		0.015	0.032	
Gdphab	0.000	0.000	***	0.000	0.000	***	0.000	0.000		0.000	0.000	
Ter2564	-0.014	0.003	***	-0.012	0.003	***	-0.002	0.002		0.004	0.002	**
Gerd	0.046	0.017	***	0.033	0.017	*	0.016	0.010		-0.004	0.010	
FoE (ref: FoE 08 Agriculture)												
F0E 05 - Science	-0.578	0.059	***	-0.720	0.059	***	-0.195	0.035	***	-0.327	0.037	***
FoE 06 – Computer Science	-1.426	0.064	***	-1.520	0.063	***	-0.800	0.038	***	-1.180	0.040	***
FoE 07 – Engineering	-0.135	0.061	**	-0.081	0.060		-0.363	0.037	***	-0.560	0.038	***
FoE 09 - Medicine	0.482	0.064	***	0.744	0.064	***	-0.020	0.039		-0.013	0.041	
Constant	-0.213	0.330		1.077	0.326	***	0.403	0.195	**	1.819	0.203	***
Random effect parameters												
Sigma (u)	0.156	0.032		0.168	0.032		0.000	0.000		0.047	0.037	
Sigma (e)	0.647	0.014		0.640	0.014		0.398	0.008		0.411	0.009	
ρ	0.055	0.022		0.064	0.024		0.000	0.000		0.013	0.020	

Notes: ***p-value<0.01; **p-value<0.05; *p-value<0.10 - Dependent variables indicated in the first row

[7]The VIF values are computed on the basis of the OLS model with clustered standard errors (at NUTS-2 level), whose results are reported in the Appendix.

Table 4. Determinants of research productivity by scientific area. Dependent variable: Percentage of total publications in top 10% SNIP Journals.

	F5 **Science**			**F6** **Computer Science**			**F7** **Engineering**			**F8** **Agriculture**			**F9** **Medicine**		
	Coeff	SE	Sig	Coeff	SE	Sig	Coeff	SE	Sig	Coeff	SE	Sig	Coeff	SE	Sig
Size	-0.007	0.006		-0.008	0.007		0.004	0.005		-0.012	0.005	**	-0.021	0.008	***
(Size^2)	0.000	0.000		0.000	0.000		0.000	0.000	*	0.000	0.000	**	0.000	0.000	**
Phdinttot	0.104	0.643		-2.727	1.639	*	-0.719	0.584		-0.060	1.038		-0.733	0.928	
P_top251dec	0.037	0.004	***	0.000	0.009		0.007	0.005		0.021	0.005	***	0.013	0.003	***
Basfounyear	0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000	
Foreign8_totstud	0.309	0.333		1.097	0.396	***	1.554	0.283	***	2.005	0.339	***	1.257	0.314	***
Ic	0.016	0.005	***	0.009	0.008		0.013	0.005	**	0.014	0.006	***	0.016	0.005	***
Baslegalst (ref. Public universities)															
1: Private universities	0.554	0.407		0.992	0.844		0.706	0.587		1.001	0.387	***	0.612	0.365	*
2: Private-government dependent universities	0.116	0.419		0.250	0.446		0.148	0.334		0.073	0.398		0.028	0.362	
Spec	-2.284	0.521	***	-1.246	0.709	*	-2.339	0.487	***	-1.880	0.503	***	-1.331	0.482	***
Ratio_S_AS	0.012	0.008		0.013	0.012		0.018	0.008	**	-0.006	0.009		0.024	0.008	***
Basunihosp	0.061	0.108		0.160	0.138		-0.195	0.095	**	-0.196	0.100	**	0.130	0.087	
Gdphab	0.000	0.000		0.000	0.000	**	0.000	0.000	***	0.000	0.000	***	0.000	0.000	
Ter2564	-0.009	0.007		-0.012	0.008		-0.027	0.005	***	-0.025	0.006	***	-0.001	0.006	
Gerd	0.038	0.041		-0.012	0.045		0.063	0.031	**	0.028	0.034		0.091	0.032	***
Constant	-0.491	0.697		-1.907	0.875	**	0.544	0.607		-0.101	0.642		-0.623	0.585	
Random effect parameters															
Sigma (u)	0.361	0.078		0.000	0.000		0.037	0.524		0.171	0.088		0.194	0.065	
Sigma (e)	0.617	0.038		0.750	0.036		0.563	0.042		0.515	0.036		0.456	0.031	
ρ	0.099	0.11		0.000	0.000		0.004	0.120		0.099	0.100		0.153	0.099	

Notes: ***p-value<0.01; **p-value<0.05; *p-value<0.10

Table 5. Determinants of research productivity by scientific area. Dependent variable: Percentage of total publications in top 25% SNIP Journals.

	F5 Science			F6 Computer Science			F7 Engineering			F8 Agriculture			F9 Medicine		
	Coeff	SE	Sig	Coeff	SE	Sig	Coeff	SE	Sig	Coeff	SE	Sig	Coeff	SE	Sig
Size	-0.012	0.006	**	0.003	0.006		0.011	0.005	**	-0.014	0.005	***	-0.028	0.008	***
(Size^2)	0.000	0.000		0.000	0.000		0.000	0.000	***	0.000	0.000	**	0.000	0.000	**
phdinttot	0.553	0.680		0.395	1.385		-0.430	0.559		0.130	1.034		-0.495	1.036	
P_top251dec	0.042	0.005	***	0.009	0.007		0.003	0.005		0.016	0.005	***	0.034	0.004	***
Basfounyear	0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000	
Foreign8_totstud	0.007	0.329		1.462	0.334	***	0.836	0.271	***	2.291	0.340	***	1.458	0.347	***
Ic	0.007	0.005		0.009	0.006		0.008	0.005		0.011	0.006	**	0.015	0.006	***
Baslegalst (ref. Public universities)															
1: Private universities	0.563	0.438		-0.636	0.712		0.141	0.561		0.628	0.366	*	0.428	0.413	
2: Private-government dependent universities	0.037	0.429		-0.131	0.377		0.046	0.319		-0.183	0.399		-0.107	0.398	
Spec	-2.051	0.538	***	-1.229	0.590	**	-1.693	0.465	***	-1.691	0.494	***	-1.562	0.543	**
ratio_Stud_AS	0.016	0.009	*	0.019	0.010	*	0.014	0.007	*	-0.005	0.009		0.022	0.009	**
basunihosp	0.085	0.113		0.035	0.116		-0.094	0.091		-0.213	0.100	**	0.056	0.097	
Gdphab	0.000	0.000		0.000	0.000	***	0.000	0.000		0.000	0.000	***	0.000	0.000	*
Ter2564	-0.004	0.007		-0.024	0.007	***	-0.009	0.005	*	-0.021	0.007	***	-0.014	0.006	**
Gerd	0.003	0.037		0.057	0.039		0.040	0.029		0.027	0.036		0.097	0.034	***
Constant	1.428	0.713		-1.464	0.731	**	1.467	0.580	**	0.981	0.638		1.624	0.648	**
Random effect parameters															
Sigma (u)	0.193	0.155		0.186	0.096		0.000	0.000		0.265	0.067		0.144	0.098	
Sigma (e)	0.7	0.046		0.604	0.039		0.539	0.023		0.473	0.036		0.526	0.035	
ρ	0.07	0.112		0.087	0.088		0.000	0.000		0.239	0.112		0.069	0.094	

Notes: ***p-value<0.01; **p-value<0.05; *p-value<0.10

Table 6. Determinants of research productivity by scientific area. Dependent variable: Percentage of total citations from top 10% SNIP Journals.

	F5 Science			F6 Computer Science			F7 Engineering			F8 Agriculture			F9 Medicine		
	Coeff	SE	Sig	Coeff	SE	Sig	Coeff	SE	Sig	Coeff	SE	Sig	Coeff	SE	Sig
Size	-0.008	0.004	*	-0.002	0.004		0.001	0.003		-0.005	0.003	**	-0.007	0.003	**
(Size^2)	0.000	0.000	*	0.000	0.000		0.000	0.000		0.000	0.000	*	0.000	0.000	
phdinttot	0.037	0.459		0.202	0.880		-0.977	0.364	***	-0.685	0.520		-0.299	0.393	
p_top251dec	0.019	0.003	*	-0.005	0.005		0.003	0.003		0.007	0.003		0.002	0.001	*
Basfounyear	0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000	
Foreign8_totstud	-0.249	0.222		-0.232	0.211		0.130	0.178		0.669	0.170	***	0.492	0.134	***
Ic	0.002	0.004		0.003	0.004		0.009	0.003	***	0.010	0.003	***	0.005	0.002	**
Baslegalst (ref. Public universities)															
1: Private universities	0.350	0.296		-0.152	0.457		-0.484	0.365		0.038	0.200		0.159	0.153	
2: Private-government dependent universities	-0.034	0.290		-0.237	0.242		-0.005	0.208		-0.286	0.201		-0.097	0.154	
Spec	-1.941	0.364	***	-0.730	0.377	*	-1.373	0.304	***	-0.938	0.254	***	-0.226	0.203	
ratio_Stud_AS	0.004	0.006		0.003	0.007		-0.015	0.005	***	-0.007	0.005		0.005	0.003	
basunihosp	0.029	0.076		0.053	0.074		-0.097	0.059	*	-0.069	0.051		0.021	0.037	
Gdphab	0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000	
Ter2564	0.002	0.004		0.003	0.004		-0.008	0.003	**	-0.004	0.003		0.001	0.002	
Gerd	-0.002	0.025		0.012	0.024		0.033	0.020	*	0.021	0.017		0.022	0.014	
Constant	0.877	0.482		-0.516	0.469		0.317	0.379		0.135	0.322		-0.442	0.248	*
Random effect parameters															
Sigma (u)	0.123	0.103		0.000	0.000		0.073	0.081		0.000	0.000		0.092	0.029	
Sigma (e)	0.475	0.03		0.406	0.020		0.343	0.022		0.275	0.013		0.190	0.014	
	0.062	0.104		0.000	0.000		0.044	0.097		0.000	0.000		0.191	0.112	

Notes: ***p-value<0.01; **p-value<0.05; *p-value<0.10

Table 7. Determinants of research productivity by scientific area. Dependent variable: Percentage of total citations from top 25% SNIP Journals.

	F5 Science			F6 Computer Science			F7 Engineering			F8 Agriculture			F9 Medicine		
	Coeff	SE	Sig	Coeff	SE	Sig	Coeff	SE	Sig	Coeff	SE	Sig	Coeff	SE	Sig
Size	-0.012	0.004	***	-0.006	0.004		0.003	0.003		-0.005	0.003	*	-0.007	0.003	**
(Size^2)	0.000	0.000	***	0.000	0.000		0.000	0.000		0.000	0.000	*	0.000	0.000	*
Phdinttot	-0.054	0.476		0.196	0.922		-0.643	0.357	*	-0.473	0.555		-0.293	0.364	
P_top251dec	0.019	0.003	***	0.003	0.005		0.011	0.003	***	0.010	0.003	***	0.003	0.001	**
Basfounyear	0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000	
Foreign8_totstud	-0.546	0.226	**	-0.811	0.221	***	-0.188	0.179		0.787	0.181	***	0.377	0.123	***
Ic	-0.007	0.004	*	-0.001	0.004		0.004	0.003		0.010	0.003	***	0.006	0.002	***
Baslegalst (ref. Public universities)															
1: Private universities	0.510	0.308	*	-0.178	0.478		-0.639	0.358	*	-0.062	0.212		0.140	0.143	
2: Private-government dependent universities	-0.106	0.300		-0.416	0.253		-0.051	0.206		-0.454	0.214	**	-0.185	0.142	
Spec	-1.856	0.377	***	-0.291	0.395		-0.693	0.300	**	-1.051	0.271	***	-0.243	0.189	
Ratio_Stud_AS	-0.002	0.006		-0.003	0.007		-0.020	0.005	***	-0.003	0.005		0.004	0.003	
Basunihosp	0.123	0.079		0.052	0.078		-0.054	0.058		-0.063	0.054		0.035	0.034	
Gdphab	0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000	**
Ter2564	0.010	0.004	**	0.012	0.005	***	-0.002	0.004		-0.004	0.003		-0.002	0.002	
Gerd	-0.025	0.025		-0.003	0.025		0.004	0.020		0.000	0.018		0.021	0.012	*
Constant	2.510	0.498	***	0.597	0.491		1.183	0.376	***	1.189	0.344	***	0.980	0.229	***
Random effect parameters															
Sigma (u)	0.000	0.000		0.000	0.000		0.121	0.048		0.043	0.098		0.076	0.026	
Sigma (e)	0.509	0.020		0.426	0.020		0.325	0.020		0.289	0.020		0.179	0.012	
	0.000	0.000		0.000	0.000		0.121	0.093		0.022	0.098		0.154	0.101	

Notes: ***p-value<0.01; **p-value<0.05; *p-value<0.10

Overall, there are four groups of factors that are associated to research productivity across most disciplines and indicators. These factors are located only at university level, not at the regional level. They can be grouped as follows:

(a) Governance of university
(b) Size of university
(c) Overall quality of research of the university
(d) Internationalization of the university

Within variables related to governance of universities, we find little effect of the public/private dichotomy (only four positive coefficients for the public governance, one for the private), while we find a strong effect of the generalist model. Universities that cover a large spectrum of disciplines are associated to better research productivity in all five areas and across most indicators (14 cases of negative coefficients for the SPEC variable, generally highly significant). This finding is remarkable given that in at least two of the disciplines covered by the sample (Engineering and Medicine) there is a competing model of specialist university institution (i.e. Technical University or Polytechnics, Medical School). This finding is a confirmation of the validity of the European model of generalist university.
Second, we find support for the notion that the size of university is not systematically associated to research productivity, as the SIZE variable is negatively associated in nine cases and positively only in four cases. This confirms the state of the art in the literature, that finds product-specific economies of scale at the level of universities for teaching, but not for research. For SIZE we assumed and tested the existence of a non linear relationship by considering in the model both the explanatory variable (Size_000) and an artificial variable represend by the squares of Size variable (Size2_000). In these cases the signs of the estimated size^2 variable determine whether the function is bowl shaped (opens up) relative to the x-axis or mound shaped, i.e. opens down (Agresti, 2018)[8]. Interestingly, we found positive coefficients in eight cases for the squared size variable (SIZE 2_000) conferming not only the existence of a nonlinear relation between size and research productivity but also – in six cases – the existence of a bowl-shaped (U-shaped) relationship between size and research productivity which takes its minimum at $x = -\beta_{Size}/2\ \beta_{Size^2}$ (Agresti, 2018).
Third, and perhaps more interestingly, we find strong support for a positive effect played by the quality of the academic environment at university level, or overall quality of the affiliation (11 positive and highly significant coefficients). Does the research productivity of a given disciplinary area (say, Computer Science) depend on the quality of research of the *overall* university in all STEM disciplines? The answer is a strong yes. We find positive and significant coefficients for all dependent variables in the pooled model and for most dependent variables in the disciplinary models for the share of sub-sub-subjects in the first decile of the top 25% SNIP over the total number of sub-subjects in which the university is active (P_TOP251_DEC). This variable can be considered a proxy of the overall scientific quality of the university, across all fields.
Fourth, we find support for the role of internationalization of the university, as proxied by the share of publications produced in collaboration with foreign institutions (IC) and the share of foreign PhD students (FOREIGN8_TOT), with 14 and 12 positive and significant coefficients. The latter finding is particularly interesting when compared with the almost complete lack of significance of the intensity of PhD students (PhDinttot), that is, the proportion of PhD students out of the student population. Having many PhD students is not associated to research productivity, while having many *foreign* PhD students is.
These findings are confirmed by examining the sample in which all fields are pooled together (Table 3). The dummies that describe disciplinary fields (baseline= Agriculture) are in general significant and have all the same sign with respect to the baseline. This supports the notion that

[8] Bowl-shaped functions, also called convex functions, have the square-term positive. Mound-shaped functions, also called concave functions, have the square-term negative.

disciplinary differences are not found in the relative performance, or the ability to reach the top quality in one's own world level scientific competition.
It is useful to review the findings that show no statistical relation with research productivity. They refer to the legal basis of the governance of the university (private vs public), the year of foundation, the presence of a hospital. In these cases we find confirmation for our agnostic hypotheses of no relation.[9] With respect to the literature, these findings do not offer support to the generalization of the findings by Teixeira et al. (2014) about the superiority of public universities in research productivity.
On the contrary, we find disconfirmation for the teaching load variable, which is found positive in six cases and negative in one case. This variable, however, refers to the *average* student load at university level. While it is still a relevant variable (for example because its variability depends on the application of restricted access policies at university level), it may well be that the truly important determinant is teaching load at field, or discipline, level.
Another variable for which we do not find significant relation with research productivity is PhD intensity, as measured by the share of PhD students out of the total student population at university level. In postgraduate education a model of distributed excellence seems at play, insofar as PhD students are not concentrated in top programs, but are spread thinly across all universities. This is consistent with the findings of Bonaccorsi (2009) who identified two models of PhD education in European countries, one based on concentration into research intensive universities (following the model of Graduate schools), the other on the diffusion of small number of PhD students across all universities, irrespective of their research intensity
Finally, it is interesting to note that the variables that describe the external environment find weak support. Overall, we find only 21 significant positive coefficients (out of 60 possible cases, that is five disciplinary areas* four dependent productivity variables* three independent external variables) for the three variables describing the regional context in the multilevel model (GDP per capita, R&D expenditure, and tertiary education).
It is however interesting that almost all these positive coefficients for the external variables (except one) are concentrated in the applied discipline (Engineering and Computer Science, Agriculture, and Medicine), as predicted by correctly by H9. Pure STEM disciplines (Science) seem to be less dependent on the external economic and social regional environment than applied ones.
Table 8 offers an overview of statistically significant coefficients for the five disciplinary areas. Inspection of this table shows that there are not structural differences across the STEM disciplines in the pattern of statistically significant coefficients. All five disciplinary areas share the same relevance of factors associated to the governance of universities (positive impact of the generalist model), the size of universities (no or weak economies of scale) and the impact played by peers in creating the overall quality of the research at university level. The only important variability refers to external variables such as GDP, R&D expenditure or tertiary education, which are important only for applied disciplines.

[9] In all these cases in our previous study (Bonaccorsi and Secondi, 2017) we had assumed positive relation, which was not confirmed by data on Medicine. The larger dataset on all STEM fields confirms that the initial assumptions of positive relation were wrong.

Table 8. Summary of statistically significant results. Determinants of research productivity across scientific areas.

	FoE 05 Science				FoE 06 Computer science				FoE 07 Engineering				FoE 08 Agriculture				FoE 09 Medicine			
	Pub10	Pub25	Cit10	Cit25	Pub10	Pub25	Cit10	Cit25	Pub10	Pub25	Cit10	Cit25	Pub10	Pub25	Cit10	Cit25	Pub10	Pub25	Cit10	Cit25
Size		- (**)	- (*)	+ (***)						+ (**)		- (**)	- (**)	+ (***)	- (**)	- (*)	- (***)	+ (***)	- (**)	- (**)
Squared Size (Size^2)			+ (*)	+ (***)					- (*)	- (***)			+ (**)		+ (*)	+ (*)	+ (**)	+ (**)		+ (*)
Phdinttot					- (*)						- (***)			+ (*)						
P_top251dec	+ (***)	+ (***)	+ (*)	+ (***)								+ (*)	+ (***)	+ (***)		+ (***)	+ (***)	+ (***)	+ (*)	+ (**)
Basfounyear																				
Foreign8_totstud				+ (***)	+ (***)	+ (***)		- (***)	+ (***)	+ (***)		+ (***)	+ (***)	+ (***)	+ (***)	+ (***)	+ (***)	+ (***)	+ (***)	+ (***)
Ic	+ (***)			- (*)							+ (***)	+ (**)	+ (***)	+ (**)	+ (***)	+ (***)	+ (***)	+ (***)	+ (**)	+ (***)
Baslegalst (ref. Public universities)																				
1: Private universities				+ (*)									+ (***)	+ (*)			+ (*)			
2: Private-government dependent universities																- (**)				
Spec	- (***)	- (***)	- (***)	- (***)	- (*)	- (**)	- (*)		- (***)	- (***)	- (***)		- (***)	- (*)	- (***)	- (***)	- (***)	- (**)		- (*)
Ratio_Stud_AS		+ (*)				+ (*)			+ (**)	+ (*)	- (***)							+ (***)	+ (**)	
Basunihosp									- (**)		- (*)		- (**)	- (**)						
Gdphab					+ (*)	+ (*)			+ (***)				+ (***)	+ (***)				+ (*)		+ (**)
Ter2564				+ (**)		- (*)		+ (***)	- (***)	- (*)	- (**)		+ (***)	- (***)				- (**)		
Gerd									+ (**)		+ (*)						+ (***)	+ (***)		+ (*)

Notes: ***p-value<0.01; **p-value<0.05; *p-value<0.10

5. Discussion and concluding remarks

The findings lend support to a theory of research productivity in which institutional factors play a role. They are not found, however, in structural or historical factors such as the university age, size, or governance (private or public). Rather, institutional factors that matter refer to the overall quality of the scientific environment at university level. We find strong support for peer effects, as measured by the ability of the overall university to compete at top quality level across most STEM disciplines, and for the role of international orientation, as measured by the attractiveness of PhD programs for foreign students and the extent of international co-authorship. Researchers, in all STEM fields, are more productive if they are affiliated to universities that have a better overall (not field-specific!) research productivity and are more internationally attractive. We also find a positive effect of the generalist model of university. Institutions do matter.

With respect to STEM disciplines, it seems that generalist universities of any size, in any region, can succeed in producing high quality research, published in top journals and cited by authors from top journals. Universities seem to have some strategic degrees of freedom in choosing their own research profile and hiring academic staff according to their strategy. In turn, the overall quality of academic staff in terms of research has a positive feedback on research productivity of individuals. These findings are important in the light of the debate on the US-Europe transatlantic gap in research excellence and the distributed excellence model of European universities (Albarran et al. 2010; Bonaccorsi et al. 2016; 2017; Jonkers and Sachwald, 2018). These findings are found robust across five STEM disciplinary fields, either in separate regressions and in a pooled model.

On the contrary, the impact of external or regional environmental factors is moderate, and relevant mostly for applied disciplines. This finding has important policy implications in the European context, given the presence of large regional differences in economic and social development. It shows that, in principle, there are not insurmountable obstacles for research groups located in backward regions to be integrated into international scientific communities and compete on the same basis as their colleagues in more advanced regions. The degree to which these opportunities are exploited in order to promote regional and local growth will depend, however, on a host of institutional factors, including national institutions, that lie beyond the scope of this study.

This research has important limitations. First, it simply ignores Social Sciences and Humanities (SSH), for which bibliometric indicators are affected by well known limitations. The degree to which SSH follow the same rules as STEM is a matter of debate. Second, we do not examine determinants at research team, or department level, but only at university level. Therefore we offer a partial theory of research productivity at institutional level. Future research might explore a multilevel framework with three levels (disciplinary area, university, and region). Finally, as already stated, given a cross-section research design we cannot establish causal relations but only conditional correlations.

Summing up, we find evidence that a more general theory of research productivity at university level for STEM disciplines is validated when differences across disciplinary areas are examined.

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APPENDIX – SUPPLEMENTARY STATISTICAL ANALYSES

Table 1 – Correlation matrix: FoE 05 - Science

	L_Pub10_p	L_Pub25_p	L_Cit10_p	L_Cit25_p	size	phdint_tot	P_top251dec	basfounyear	Foreign8_totstud	IC	SPEC	Ratio_Stud_AS	GDP_hab	Ter_2564	Gerd
L_Pub10_p	1														
L_Pub25_p	0.86	1													
L_Cit10_p	0.84	0.77	1												
L_Cit25_p	0.69	0.75	0.87	1											
size	0.15	0.09	0.14	0.09	1										
phdint_tot	0.16	0.13	0.09	0.05	-0.20	1									
P_top251dec	0.54	0.56	0.44	0.41	0.04	0.11	1								
basfounyear	-0.18	-0.15	-0.17	-0.16	-0.32	-0.07	-0.05	1							
Foreign8_totstud	0.33	0.24	0.20	0.08	-0.15	0.28	0.21	-0.03	1						
IC	0.45	0.35	0.32	0.17	-0.02	0.43	0.30	-0.16	0.53	1					
SPEC	-0.49	-0.37	-0.43	-0.34	-0.36	-0.11	-0.27	0.41	-0.34	-0.48	1				
Ratio_Stud_AS	-0.05	-0.02	-0.04	-0.08	0.53	-0.47	-0.07	0.11	-0.23	-0.32	0.16	1			
GDP_hab	0.24	0.17	0.15	0.11	-0.04	0.24	0.23	-0.07	0.42	0.35	-0.11	-0.19	1		
Ter_2564	0.24	0.21	0.21	0.20	-0.09	0.26	0.33	0.00	0.62	0.39	-0.21	-0.22	0.64	1	
Gerd	0.24	0.20	0.19	0.13	0.03	0.24	0.25	-0.16	0.22	0.32	-0.26	-0.27	0.23	0.30	1

Table 2 – Correlation matrix: FoE 06 – Computer Science

	L_Pub10_p	L_Pub25_p	L_Cit10_p	L_Cit25_p	size	phdint_tot	P_top251dec	basfounyear	Foreign8_totstud	IC	SPEC	Ratio_Stud_AS	GDP_hab	Ter_2564	Gerd
L_Pub10_p	1														
L_Pub25_p	0.76	1													
L_Cit10_p	-0.05	0.08	1												
L_Cit25_p	-0.42	-0.27	0.55	1											
size	0.01	0.06	-0.01	-0.04	1										
phdint_tot	0.00	0.08	0.05	0.05	-0.23	1									
P_top251dec	0.07	0.19	0.03	0.12	0.05	0.25	1								
basfounyear	0.01	0.04	-0.10	-0.12	-0.30	-0.05	-0.12	1							
Foreign8_totstud	0.21	0.27	-0.04	-0.14	-0.25	0.45	0.20	0.09	1						
IC	0.16	0.26	0.12	0.04	-0.10	0.53	0.40	-0.09	0.45	1					
SPEC	-0.15	-0.20	-0.16	-0.08	-0.24	-0.33	-0.46	0.38	-0.19	-0.43	1				
Ratio_Stud_AS	0.03	-0.02	-0.09	-0.11	0.56	-0.59	-0.24	0.11	-0.29	-0.38	0.28	1			
GDP_hab	0.16	0.17	-0.05	-0.04	0.00	0.27	0.19	0.00	0.31	0.30	-0.12	-0.24	1		
Ter_2564	0.06	0.11	0.00	0.07	-0.14	0.48	0.34	0.08	0.61	0.45	-0.18	-0.31	0.58	1	
Gerd	-0.02	0.09	0.02	0.04	-0.01	0.33	0.22	-0.07	0.18	0.29	-0.14	-0.29	0.21	0.34	1

Table 3 – Correlation matrix: FoE 07 – Engineering

	L_Pub10_p	L_Pub25_p	L_Cit10_p	L_Cit25_p	size	phdint_tot	P_top251dec	basfounyear	Foreign8_totstud	IC	SPEC	Ratio_Stud_AS	GDP_hab	Ter_2564	Gerd
L_Pub10_p	1														
L_Pub25_p	0.76	1													
L_Cit10_p	0.66	0.55	1												
L_Cit25_p	0.34	0.48	0.73	1											
size	0.10	0.13	0.13	0.10	1										
phdint_tot	0.04	-0.01	0.05	0.03	-0.22	1									
P_top251dec	0.26	0.23	0.30	0.36	0.08	0.10	1								
basfounyear	-0.21	-0.22	-0.24	-0.21	-0.30	-0.05	-0.12	1							
Foreign8_totstud	0.40	0.28	0.21	0.05	-0.19	0.25	0.28	0.00	1						
IC	0.36	0.27	0.39	0.26	-0.05	0.45	0.40	-0.14	0.45	1					
SPEC	-0.50	-0.45	-0.52	-0.39	-0.28	-0.11	-0.46	0.39	-0.33	-0.49	1				
Ratio_Stud_AS	-0.07	-0.05	-0.24	-0.27	0.55	-0.48	-0.19	0.11	-0.23	-0.38	0.24	1			
GDP_hab	0.21	0.12	0.16	0.04	0.01	0.21	0.19	-0.05	0.37	0.33	-0.20	-0.23	1		
Ter_2564	0.12	0.11	0.14	0.10	-0.10	0.25	0.36	0.04	0.63	0.42	-0.24	-0.27	0.59	1	
Gerd	0.19	0.14	0.28	0.20	0.00	0.25	0.26	-0.14	0.22	0.34	-0.25	-0.34	0.26	0.32	1

Table 4 – Correlation matrix: FoE 08 – Agriculture

	L_Pub10_p	L_Pub25_p	L_Cit10_p	L_Cit25_p	size	phdint_tot	P_top251dec	basfounyear	Foreign8_totstud	IC	SPEC	Ratio_Stud_AS	GDP_hab	Ter_2564	Gerd
L_Pub10_p	1														
L_Pub25_p	0.88	1													
L_Cit10_p	0.81	0.68	1												
L_Cit25_p	0.75	0.75	0.88	1											
size	-0.07	-0.19	-0.04	-0.07	1										
phdint_tot	0.31	0.34	0.29	0.29	-0.25	1									
P_top251dec	0.41	0.37	0.39	0.44	0.05	0.16	1								
basfounyear	-0.03	0.04	-0.09	-0.03	-0.27	-0.05	-0.04	1							
Foreign8_totstud	0.57	0.64	0.53	0.56	-0.20	0.41	0.28	0.02	1						
IC	0.53	0.52	0.54	0.54	-0.08	0.46	0.36	-0.09	0.48	1					
SPEC	-0.42	-0.36	-0.46	-0.45	-0.27	-0.20	-0.37	0.34	-0.32	-0.44	1				
Ratio_Stud_AS	-0.26	-0.30	-0.26	-0.24	0.58	-0.57	-0.16	0.09	-0.24	-0.38	0.22	1			
GDP_hab	0.28	0.28	0.17	0.20	0.01	0.25	0.17	-0.05	0.27	0.28	-0.09	-0.23	1		
Ter_2564	0.35	0.41	0.35	0.39	-0.09	0.44	0.31	0.04	0.67	0.42	-0.23	-0.24	0.58	1	
Gerd	0.25	0.24	0.28	0.23	0.03	0.35	0.25	-0.13	0.22	0.32	-0.24	-0.29	0.28	0.36	1

Table 5 – Correlation matrix: FoE 09 – Medicine

	L_Pub10_p	L_Pub25_p	L_Cit10_p	L_Cit25_p	size	phdint_tot	P_top251dec	basfounyear	Foreign8_totstud	IC	SPEC	Ratio_Stud_AS	GDP_hab	Ter_2564	Gerd
L_Pub10_p	1														
L_Pub25_p	0.81	1													
L_Cit10_p	0.72	0.63	1												
L_Cit25_p	0.57	0.65	0.82	1											
size	-0.10	-0.12	-0.17	-0.15	1										
phdint_tot	0.23	0.23	0.24	0.25	-0.23	1									
P_top251dec	0.40	0.58	0.29	0.31	-0.07	0.15	1								
basfounyear	0.03	0.03	0.05	-0.03	-0.41	-0.05	0.10	1							
Foreign8_totstud	0.49	0.45	0.49	0.42	-0.24	0.41	0.21	0.06	1						
IC	0.46	0.43	0.38	0.41	-0.05	0.57	0.20	-0.13	0.49	1					
SPEC	-0.28	-0.22	-0.15	-0.17	-0.42	-0.20	-0.01	0.34	-0.24	-0.45	1				
Ratio_Stud_AS	-0.10	-0.06	-0.16	-0.18	0.34	-0.64	0.04	0.07	-0.22	-0.39	0.17	1			
GDP_hab	0.11	0.12	0.15	0.19	-0.08	0.29	0.08	0.02	0.27	0.20	0.11	-0.28	1		
Ter_2564	0.36	0.31	0.40	0.33	-0.28	0.47	0.29	0.08	0.67	0.43	-0.10	-0.37	0.54	1	
Gerd	0.25	0.24	0.20	0.21	-0.01	0.31	0.18	-0.10	0.07	0.36	-0.20	-0.36	0.07	0.25	1

Table 6 – OLS estimates with clustered (NUTS-2 level) standard errors – FoE 05 Science

	PUB10			PUB25			CIT10			CIT25		
logit_pub10_f05p	Coef.	Std. Err.	P>t	Coef.	Std. Err.	P>t	Coef.	Std. Err.	P>t	Coef.	Std. Err.	P>t
Size (000)	-0.007	0.005		-0.013	0.005	***	-0.007	0.003	**	-0.012	0.004	***
size2_000	0.000	0.000		0.000	0.000	*	0.000	0.000	**	0.000	0.000	***
phdinttot	0.288	0.680		0.632	0.756		0.035	0.442		-0.054	0.569	
p_top251dec	0.040	0.009	***	0.043	0.006	***	0.019	0.005	***	0.019	0.005	***
basfounyear	0.000	0.000		0.000	0.000	**	0.000	0.000		0.000	0.000	*
foreign8_totstud	0.504	0.440		0.073	0.452		-0.195	0.352		-0.546	0.374	
ic	0.014	0.008	*	0.006	0.009		0.002	0.005		-0.007	0.005	
Baslegalst=0 (Public)												
Baslegalst=1 (Private)	0.706	0.363	*	0.605	0.262	**	0.394	0.128	***	0.510	0.112	***
Baslegalst=2 (Private-governm.)	0.047	0.199		0.014	0.186		-0.041	0.153		-0.106	0.129	
spec	-2.558	0.685	***	-2.104	0.756	***	-1.944	0.560	***	-1.856	0.587	***
ratio_StudDoc	0.015	0.011		0.017	0.011		0.003	0.007		-0.002	0.008	
basunihosp	-0.014	0.087		0.072	0.079		0.014	0.057		0.123	0.064	*
gdphab_2010	0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000	
ter2564	-0.013	0.008		-0.005	0.008		0.001	0.006		0.010	0.005	*
gerd	0.021	0.035		-0.003	0.038		-0.005	0.024		-0.025	0.027	
Constant	-0.127	0.757		1.547	0.758	**	0.881	0.595		2.510	0.594	***
R2	0.474			0.393			0.325			0.294		

Notes: ***p-value<0.01; **p-value<0.05; *p-value<0.10

Table 7 – OLS estimates with clustered (NUTS-2 level) standard errors – FoE 06 Computer Science

	PUB10			PUB25			CIT10			CIT25		
	Coef.	Robust SE	P>t	Coef.	Robust SE	P>t	Coef.	Robust SE	P>t	Coef.	Robust SE	P>t
Size (000)	-0.008	0.007		0.002	0.006		-0.002	0.004		-0.006	0.004	
size2_000	0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000	
phdinttot	-2.727	1.969		0.290	1.537		0.202	0.803		0.196	0.991	
p_top251dec	0.000	0.008		0.009	0.010		-0.005	0.007		0.003	0.005	
basfounyear	0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000	
foreign8_totstud	1.097	0.416	**	1.437	0.426	***	-0.232	0.234		-0.811	0.231	***
IC	0.009	0.010		0.010	0.010		0.003	0.007		-0.001	0.005	
Baslegalst=0 (Public)												
Baslegalst=1 (Private)	0.992	0.441	**	-0.625	0.346	*	-0.152	0.208		-0.178	0.216	
Baslegalst=2 (Private-governm.)	0.250	0.232		-0.134	0.281		-0.237	0.096	**	-0.416	0.139	***
spec	-1.246	0.639	*	-1.254	0.657	*	-0.730	0.494		-0.291	0.382	
ratio_StudDoc	0.013	0.014		0.020	0.013		0.003	0.007		-0.003	0.007	
basunihosp	0.160	0.155		0.022	0.129		0.053	0.076		0.052	0.077	
Gdphab	0.000	0.000	**	0.000	0.000	**	0.000	0.000		0.000	0.000	
ter2564	-0.012	0.009		-0.024	0.010	**	0.003	0.005		0.012	0.004	***
Gerd	-0.012	0.041		0.062	0.046		0.012	0.021		-0.003	0.026	
Constant	-1.907	0.895	**	-1.449	0.794	*	-0.516	0.445		0.597	0.564	
R^2	0.134			0.247			0.059			0.114		

Notes: ***p-value<0.01; **p-value<0.05; *p-value<0.10

Table 8 – OLS estimates with clustered (NUTS-2 level) standard errors – FoE 07 Engineering

	PUB10			PUB25			CIT10			CIT25		
	Coef.	Robust SE	P>t	Coef.	Robust SE	P>t	Coef.	Robust SE	P>t	Coef.	Robust SE	P>t
Size (000)	0.004	0.005		0.011	0.004	**	0.001	0.003		0.002	0.003	
size2_000	0.000	0.000	*	0.000	0.000	***	0.000	0.000		0.000	0.000	
phdinttot	-0.720	0.438		-0.430	0.349		-1.004	0.308	***	-0.750	0.385	*
p_top251dec	0.007	0.007		0.003	0.006		0.003	0.004		0.011	0.004	**
basfounyear	0.000	0.000	*	0.000	0.000		0.000	0.000		0.000	0.000	
foreign8_totstud	1.554	0.304	***	0.836	0.291	***	0.127	0.174		-0.225	0.190	
ic	0.013	0.006	**	0.008	0.005		0.009	0.004	**	0.004	0.004	
Baslegalst=0 (Public)												
Baslegalst=1 (Private)	0.706	0.136	***	0.141	0.135		-0.478	0.087	***	-0.612	0.113	***
Baslegalst=2 (Private-governm.)	0.147	0.123		0.046	0.330		-0.009	0.109		-0.070	0.130	
spec	-2.340	0.450	***	-1.693	0.488	***	-1.378	0.301	***	-0.714	0.369	*
ratio_StudDoc	0.018	0.010	*	0.014	0.008	*	-0.014	0.005	***	-0.020	0.006	***
basunihosp	-0.195	0.083	**	-0.094	0.077		-0.097	0.061		-0.058	0.058	
Gdphab	0.000	0.000	***	0.000	0.000		0.000	0.000		0.000	0.000	
ter2564	-0.027	0.006	***	-0.009	0.007		-0.008	0.003	**	-0.001	0.003	
gerd	0.063	0.032	*	0.040	0.024	*	0.034	0.022		0.005	0.020	
Constant	0.544	0.531		1.467	0.495	***	0.307	0.363		1.233	0.421	***
R2	0.581			0.282			0.357			0.280		

Notes: ***p-value<0.01; **p-value<0.05; *p-value<0.10

Table 9 – OLS estimates with clustered (NUTS-2 level) standard errors – FoE 08 Agriculture

	PUB10			PUB25			CIT10			CIT25		
	Coef.	Robust SE	P>t	Coef.	Robust SE	P>t	Coef.	Robust SE	P>t	Coef.	Robust SE	P>t
Size (000)	-0.013	0.006	**	-0.016	0.005	***	-0.005	0.003	**	-0.005	0.003	*
size2_000	0.000	0.000	**	0.000	0.000	***	0.000	0.000	**	0.000	0.000	
phdinttot	-0.264	0.964		-0.508	1.215		-0.685	0.398	*	-0.505	0.467	
p_top251dec	0.021	0.006	***	0.017	0.005	***	0.007	0.002	***	0.010	0.003	***
basfounyear	0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000	
foreign8_totstud	2.007	0.304	***	2.323	0.381	***	0.669	0.165	***	0.792	0.192	***
ic	0.016	0.008	**	0.014	0.006	**	0.010	0.004	**	0.010	0.003	***
Baslegalst=0 (Public)												
Baslegalst=1 (Private)	1.010	0.460	**	0.644	0.419		0.038	0.068		-0.064	0.056	
Baslegalst=2 (Private-governm.)	0.053	0.171		-0.204	0.301		-0.286	0.111	**	-0.452	0.124	***
spec	-1.975	0.478	***	-1.903	0.499	***	-0.938	0.239	***	-1.043	0.267	***
ratio_StudDoc	-0.006	0.009		-0.008	0.010		-0.007	0.005		-0.003	0.005	
basunihosp	-0.200	0.095	**	-0.245	0.114	**	-0.069	0.045		-0.064	0.051	
Gdphab	0.000	0.000	***	0.000	0.000	***	0.000	0.000		0.000	0.000	
ter2564	-0.025	0.007	***	-0.021	0.008	***	-0.004	0.004		-0.004	0.004	
Gerd	0.025	0.034		0.022	0.043		0.021	0.015		0.000	0.014	
Constant	0.010	0.741		1.269	0.783		0.135	0.311		1.190	0.340	***
R2	0.542			0.570			0.477			0.507		

Notes: ***p-value<0.01; **p-value<0.05; *p-value<0.10

Table 10 – OLS estimates with clustered (NUTS-2 level) standard errors – FoE 09 Medicine

	PUB10			PUB25			CIT10			CIT25		
logit_pub10_f09p	Coef.	Robust SE	P>t	Coef.	Robust SE	P>t	Coef.	Robust SE	P>t	Coef.	Robust SE	P>t
Size (000)	-0.020	0.007	***	-0.027	0.007	***	-0.005	0.003		-0.007	0.003	**
size2_000	0.000	0.000	**	0.000	0.000	***	0.000	0.000		0.000	0.000	*
phdinttot	-0.824	1.113		-0.536	1.575		-0.323	0.456		-0.321	0.428	
p_top251dec	0.013	0.004	***	0.034	0.004	***	0.003	0.001	**	0.003	0.001	**
basfounyear	0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000	
foreign8_totstud	1.290	0.422	***	1.468	0.487	***	0.529	0.166	***	0.414	0.144	***
Ic	0.015	0.007	**	0.015	0.007	**	0.004	0.003		0.006	0.002	**
Baslegalst=0 (Public)												
Baslegalst=1 (Private)	0.671	0.143	***	0.472	0.162	***	0.154	0.056	***	0.130	0.058	**
Baslegalst=2 (Private-governm.)	0.036	0.096		-0.110	0.097		-0.078	0.059		-0.177	0.041	***
spec	-1.305	0.478	***	-1.573	0.466	***	-0.163	0.207		-0.225	0.192	
ratio_StudDoc	0.023	0.008	***	0.022	0.009	**	0.003	0.004		0.003	0.004	
basunihosp	0.125	0.084		0.056	0.084		0.014	0.034		0.030	0.033	
Gdphab	0.000	0.000		0.000	0.000	**	0.000	0.000		0.000	0.000	**
ter2564	-0.002	0.007		-0.015	0.008	*	0.001	0.003		-0.002	0.003	
Gerd	0.089	0.036	**	0.093	0.040	**	0.025	0.022		0.022	0.026	
Constant	-0.616	0.557		1.650	0.590	***	-0.489	0.227	**	0.984	0.228	***
R2	0.454			0.539			0.325			0.320		

Notes: ***p-value<0.01; **p-value<0.05; *p-value<0.10

Table 11 – VIF values: estimated disciplinary models (FoE 05 – FoE 09)

	FoE 05 - Science		FoE 06 – Computer Science		FoE 07 - Engineering		FoE 08 - Agriculture		FoE 09 - Medicine	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
Size (000)	2.36	0.42	2.51	0.40	2.42	0.41	2.69	0.37	2.10	0.48
phdinttot	1.51	0.66	2.52	0.40	1.57	0.64	1.93	0.52	2.27	0.44
p_top251dec	1.31	0.76	1.56	0.64	1.54	0.65	1.37	0.73	1.24	0.81
basfounyear	1.40	0.71	1.43	0.70	1.40	0.72	1.35	0.74	1.34	0.75
foreign8_totstud	2.22	0.45	1.94	0.52	2.14	0.47	2.43	0.41	2.50	0.40
Ic	2.00	0.50	1.82	0.55	1.96	0.51	1.77	0.56	2.13	0.47
baslegalst										
Baslegalst=1 (Private)	1.08	0.92	1.26	0.79	1.08	0.93	1.04	0.96	1.13	0.89
Baslegalst=2 (Private-governm.)	1.03	0.97	1.05	0.96	1.04	0.96	1.06	0.95	1.05	0.96
Spec	2.45	0.41	2.13	0.47	2.40	0.42	2.27	0.44	2.35	0.42
ratio_StudDoc	2.41	0.41	3.09	0.32	2.71	0.37	3.22	0.31	2.37	0.42
basunihosp	1.79	0.56	1.77	0.57	1.80	0.55	1.81	0.55	1.63	0.61
Gdphab	1.90	0.53	1.67	0.60	1.68	0.59	1.78	0.56	1.79	0.56
ter2564	2.59	0.39	2.82	0.35	2.57	0.39	3.04	0.33	3.15	0.32
Gerd	1.26	0.79	1.27	0.79	1.30	0.77	1.34	0.75	1.35	0.74