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ACADEMIC KNOWLEDGE AND ECONOMIC GROWTH: ARE SCIENTIFIC FIELDS ALL ALIKE?[1]

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ABSTRACT

The paper elaborates and tests the hypothesis that there are different types of academic knowledge that exert different effects on economic growth. Knowledge items differ with respect to the specificities of both their generation and exploitation processes. Building upon these bases, the paper articulates the crucial distinction between knowledge as a capital good, necessary to produce all the other goods at lower costs and knowledge as a final good that affects directly the utility of consumers. We use OECD data about the disciplinary composition of the R&D expenses in higher education and total factor productivity growth in the years 1998-2008 in 13 countries to test the hypothesis. The results confirm the strong differences in the contribution of each discipline to growth accounting.

KEY WORDS: TYPES OF KNOWLEDGE, KNOWLEDGE EXTERNALITIES, OUTPUT ELASTICITY OF KNOWLEDGE TYPES.

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1. INTRODUCTION

The paper elaborates and tests the hypothesis that there are different types of academic knowledge that exert different effects on total factor productivity and economic growth. The aim of the paper is to contribute the debate on the accountability of the academic system grafting the recent advances of the economics of knowledge into the economics of the academic system.

The role that Science plays in modern societies goes well beyond its impact on the performances of national economies. Advances in medicine or in basic sciences can and should be advocated regardless of their direct or indirect impact on economic growth, since they generally foster the development of human society. However, in the current debate scientific activity is also regarded as a fundamental ingredient to foster the economic development of countries and regions. The National Innovation Systems literature has greatly highlighted the role that academic institutions play in the generation and diffusion of new valuable knowledge and new technologies, that are eventually able to benefit national firms in the implementation of their innovation strategies (Freeeman, 1987; Lundvall, 1992). As a consequence the economic performances of countries have been strongly linked to the quality and efficiency of their academic system. In this paper we follow this specific line of analysis and investigate which type of academic knowledge is better able to contribute to the economic development of countries. More specifically we will focus on the contribution of academic knowledge to the portion of economic growth that is generally attributed to technological change, i.e the growth of Total Factor Productivity (TFP).

Section 2 shows how the recent advances of the economics of knowledge enable to appreciate the differences among types of knowledge with respect to both the characteristics of the knowledge generation and exploitation processes. Building upon these bases, it is possible to introduce the distinction between knowledge as a capital good and knowledge as a final good. Knowledge as a capital good has larger chances of appropriation and wider scope of application as it feeds directly the generation of technological knowledge and the introduction of technological and organizational innovations that in turn account for the technological and economic development of national economies, as proxied by total factor productivity (TFP) growth. When knowledge has a limited scope of appropriation and application it is mainly a final good, consumed directly by final users, and it is likely to exert smaller effects on TFP growth. This distinction is relevant with respect to the variety of academic fields. Scientific knowledge generated by hard sciences is likely to contribute most to TFP growth as it feeds directly eventual introduction of technological innovations in a wide array of industries. The role of social sciences can be fully appreciated as soon as their role in feeding organizational innovations and improvements in business practices is properly identified and highlighted and, in turn, the crucial role of the latter in economic growth is acknowledged. Academic knowledge in humanities and medical sciences should be regarded as final goods that contribute directly the increase of the utility of final consumers rather than to boost the economic growth of the system.

In order to provide a first tentative test of these hypotheses, section 3 presents an econometric approach, using OECD data about the disciplinary composition of the R&D expenses in higher education (HERD) in the years 1998-2008 in 13 countries to measure the differences in the contribution to TFP growth of each of these disciplinary fields. The results confirm that academic disciplines display wide differences in their capability to contribute TFP growth.

The conclusions summarize the result and highlight the policy implications. As long as the academic system is considered to play a central role in fostering economic growth, a careful scrutiny is necessary, in order to understand which are the academic fields that are better able to contribute economic growth. Public support to the academic system should not be spread uniformly across academic disciplines but rather focus these specific fields. The benefits of academic disciplines that contribute directly to increasing the well-being of citizens should be appreciated on their own merit.

2. THE ANALYSIS

2.1 UNIVERSITY AND KNOWLEDGE GENERATION

The academic system plays a central role in economic growth as the prime provider of the scientific knowledge that feeds the innovation process (Etzkowitz, Leydesdorff, 2000). The academic system is regarded as the institutional locus dedicated to generating new scientific knowledge that might be eventually used by firms to generate technological knowledge that would possibly translate in the introduction and diffusion of technological and organizational innovations that increase the total factor productivity of the production process (Feller, 1990).

There is a direct and positive relationship between: a) the amount of scientific knowledge made available –mainly- by the academic system; b) its use to generate technological knowledge in the business sector; c) its exploitation by means of the introduction of innovations, and d) the eventual increase of TFP. This approach builds upon the implicit assumption that scientific knowledge is a capital good, i.e. a crucial and necessary input into the production of other goods. This literature pays little attention to the heterogeneity of academic knowledge. It does not elaborate the distinction between knowledge as an intermediary and capital good and knowledge as a final good and actually assumes that all knowledge is a capital good.

The Arrovian contributions to the economics of knowledge provided the explicit foundations of the analysis of knowledge as a capital input. The early identification of the major limitations of knowledge as an economic good, such as non-appropriability, non-divisibility, non-rivalry in use, non-exhaustibility of knowledge, information asymmetries between potential vendors and customers and the consequent market failures, with high risks of undersupply, provided the necessary tools to introduce a political economy of knowledge. The early economics of knowledge articulated the need for a strong public policy to remedy the intrinsic risks of undersupply and advocated the opportunity of a systematic public intervention on the supply side with the direct provision of public subsidies to the academic system (Dasgupta and David, 1987 and 1994).

The public support to the academic system and the build-up of a public academic system are advocated to balance the lack of incentives to generate knowledge. The basic argument can be synthesized as it follows. The public support would enable to implement a structured mechanism of institutional incentives by means of which talented and creative agents would be willing to publish and hence make publicly available the results of their cognitive efforts in order to be included in the academic system and receive a salary. The academic system becomes the provider of knowledge externalities to the rest of the economic system. The mechanism is likely to be effective as long as the expenses of the academic system, covered by public subsidies, are compensated, possibly more than compensated, by the positive effects of knowledge externalities spilling from the academic system to the rest of the economic system, in terms of an increase of the output levels (Antonelli, 2008a).

The role of the academic system has become even stronger since the last decades of the XX century. After a long period of time during which the generation of technological knowledge has been concentrated within the R&D laboratories of large firms, in fact, the progressive demise of the corporation as the central mechanism for the generation and exploitation of technological knowledge (Coriat and Weinstein, 2012; Keller and Block, 2013) and the fading of the distinction between scientific and technological knowledge has led to the appreciation of the role of the academic system as the main engine of the generation of knowledge at large. The academic system is more and more regarded as the institutional locus for the generation of both scientific and technological knowledge (Mansfield, 1991, 1995; Mansfield and Lee, 1996).

The new centrality of the academic system has called increasing attention both in the economic and policy debate on the amount of both public and private resources devoted to support the academic system, its accountability in terms of the relationship between input and output and its organization (Nelson, Rosenberg, 1994). The general consensus about the need to increase the amount of resources devoted to the academic system has progressively called more attention upon its accountability (Murphy, 1995). Much effort has been made to elaborate analytical tools and interpretative frameworks to better appreciate the actual output of the academic system (Cave, Weale, 1992; Cave, Hanney, Henkel and Kogan, 1997; Crespi, Geuna, 2008). This undertaking has been especially productive at the microeconomic level with important contributions that have made it possible to better appreciate the measures of academic output at the individual, departmental and university level (Johnes, 1988, 1990, 1992, 1997; Johnes and Johnes, 1993).

The organization of the academic system has also received much attention exploring whether the joint performance of research and training were more productive than the specialization. Increasing attention has been paid to assess whether the dissemination of academic knowledge could be left to traditional tools such as the publication of scientific papers and the training of Phds not only for academia, but also and primarily for their enrolment in productive activities in the economic system, or better implemented strengthening the direct interactions and possibly transactions between the academic system and the business sector. Private funding of academic research with the so-called academic outsourcing where corporations rely on academic departments to perform research activities, has been more and more regarded as an effective tool to better exploit the research capabilities of the academic system and to shorten the time lags between inventions and innovations. Along the same lines the acquisition of academic start-up companies by large incumbents is becoming a major mechanism for knowledge transfer between the academic and the business system. At the same time the amount of academic outsourcing and academic start-ups that departments are able respectively to attract and to generate, seems to become reliable indicators of the actual –social and economic- relevance of their academic output (Geuna, 1999; Etzkowitz, Leydesdorff, 2000; Antonelli, Patrucco, Rossi, 2010).

The enquiry about the efficiency of the academic system has been directed mainly, if not exclusively, towards the assessment of its internal efficiency, as distinct from its general, or external efficiency. Much efforts, in fact, have been directed to identify new metrics so as to assess the quantity and quality of knowledge generated, in order to establish appropriate measures of the relationship between the amount of economic resources transferred to the academic system and the amount of knowledge generated (Auranen, Nieminen, 2010). Yet from an economic viewpoint it is not sufficient to assess the internal efficiency of the academic system in terms of the relationship between economic inputs and knowledge outputs. It seems in fact more important to assess whether the amount of knowledge –efficiently- generated by the academic system is actually useful to support economic growth.

Following this line of analysis it is clear that a major problem of coordination and composition may take place. The state provides subsidies to implement a public academic system to remedy to the –possible- undersupply of knowledge, but the academic system insists in the generation of knowledge that is not useful for economic growth. The mismatch between the objectives of public policy and its effects may become gradually evident and the consensus to a public academic system would decline, even if the academic system were able to generate efficiently large amounts of knowledge with a limited amount of public economic resources.

As long as knowledge is regarded as a heterogeneous production input, the effects of the efficiency in its generation are relevant not only internally but also externally. The exploration of the composition of the knowledge generated by the public academic system and the actual assessment of its external efficiency become necessary. Only when the levels of both internal and external efficiency are high it is possible to support the hypothesis that the supply of knowledge generated by the public academic system is actually able to compensate for the Arrovian knowledge undersupply and to match efficiently the 'correct' levels of the derived demand for knowledge of the rest of the economic system.

The two notions of internal and external efficiency would automatically coincide only if knowledge were a homogenous good. As soon as we appreciate that knowledge is a composite bundle of a variety of different kinds of knowledge(s), the problem of the composition of the bundle becomes crucial. The academic system may generate too much of one kind of knowledge and too little of another. The system would suffer both from the undersupply of the relevant knowledge and the oversupply of knowledge that is not directly useful to support growth.

The assessment of the external efficiency of the academic system has been somewhat overlooked. In order to assess whether the public academic system is actually working as a complementary mechanism able to compensate for the undersupply of knowledge by the private sector, it is in fact necessary to assess what is the relationship between the amount of public subsidies paid to the academic system and its revenue measured by the effects of knowledge externalities spilling from the academic system to the business sector in terms of total factor productivity growth and hence additional economic output.

As soon as we understand that knowledge is not a homogenous bundle of standardized items it becomes clear that its heterogeneity risks to undermine the working of the elegant Arrovian mechanism and raises a major problem of coordination between the composition of the supply of knowledge by the academic system and the actual content of the derived demand expressed by the rest of the economic system.

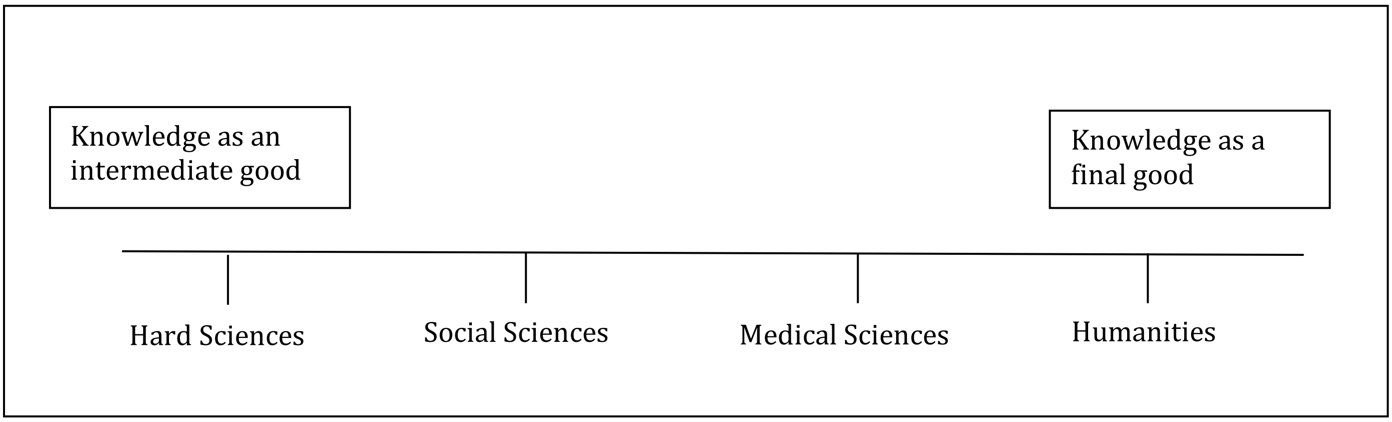
2.2. THE HETEROGENEITY OF ACADEMIC KNOWLEDGE

The grafting of the recent advances in the economics of knowledge enables to contribute this debate from a different viewpoint. The economics of knowledge has made much progress in the appreciation of the variety of different types of knowledge. Knowledge is indivisible, but not homogenous. Knowledge differs not only with respect to the characteristics of the generation process, but also to the scope of application: whether it is an input into the production of other goods, or it can be regarded as a final good, and the levels of appropriability. Knowledge as a capital and intermediary good has a wide scope of application and supports the generation of a large variety of different kinds of technological knowledge(s) that enable the introduction of a wide array of innovations. Knowledge is a capital good when it has sufficient levels of appropriability to provide incentives to firms to use it as an input into the recombinant generation of technological knowledge. Too low levels of appropriability prevent firms to invest in its transformation into technological knowledge for the high risk of disclosure. Knowledge is an intangible capital/intermediary input when it exerts direct and positive effects on the recombinant knowledge generation function and, via the introduction of innovations, is the ultimate cause of TFP growth. When, instead, knowledge has a smaller scope of application and has levels of appropriability so low to reduce the incentives to use it as an input, it affects mainly the utility function of final consumers, rather than the knowledge generation function, and exerts weak effects on total factor productivity growth, it might be considered as a final good. In the literature discussed so far instead the supply of new knowledge would increase the satisfaction of consumers only indirectly, as it helps to increase the efficiency of the production process of other goods, including other final goods (Antonelli and David, 2015; Antonelli and Link, 2015).

The Arrovian undersupply of knowledge as an intangible capital good has far deeper consequences than the undersupply of knowledge as a final good. In the first case its undersupply affects a wide variety of industries with negative consequences along all the intersectoral input-output matrices. Market failure in this case has broader effects that go beyond the static inefficiencies and share some of the features of the Schumpeterian dynamic inefficiency. The undersupply of knowledge, in fact, impedes the realization of the potential growth of the system. The undersupply of knowledge translates directly in the undersupply of output via the reduction of the general efficiency of the production process. In the second case, the negative consequences of the market failure concern only the market for final goods.

The application of the tools of the economics of knowledge to academic knowledge yields interesting results: indeed it is possible to locate different types of disciplines along a continuum where at one extreme we find knowledge that has the features of intermediary/capital good and at the other extreme we find knowledge that can be classified as a final good (see Figure 1). As we will see different kind of academic knowledge can be included in this continuum in different positions.

Figure 1. The continuum of academic knowledge



Hard sciences such as physics, chemistry, biology, mathematics and the broad spectrum of engineering fields seem characterized by the wide scope of application and the high levels of appropriability. The complementarity and cumulability between scientific knowledge and technological knowledge are very high: inventions do feed the recombinant generation of technological knowledge and support the introduction of innovations. The generation of technological knowledge and the introduction of both technological and organizational innovations impinge upon the advances in technological knowledge that in turn rely upon the advances of scientific knowledge. Research and development activities (R&D) performed and funded by the business sector concern mainly if not exclusively hard sciences. The growing reliance of corporations upon academic outsourcing and the acquisition of academic start-ups to access new scientific in hard sciences increases the overlapping between sheer academic activities and corporate R&D. All advances of academic knowledge in hard sciences are most likely to exert a strong and direct effect on economic growth, via the increase of TFP. Among the different academic disciplines there is little doubt that hard sciences are the ones that are closer to the definition of knowledge as an intermediate/capital good, i.e. a production input into the production of all the other goods with direct effects on their efficiency (Stephan, 2011). The cliometric evidence of the Italian economic growth in the years 1900-1959 confirms that the growth of hard sciences within the Italian academic system, as measured by the number and disciplinary characterization of academic chairs, exerted the strongest effects on output and total factor productivity (Antonelli, Crepax, Fassio, 2013; Antonelli Fassio, 2014).

Social sciences play a central role in the introduction of organizational knowledge a special kind of technological knowledge that is directly useful to introduce new business practices and organizational innovations. The introduction of more efficient and effective methods of conducting business encompassing a broad array of activities, ranging from corporate management practices, marketing, advertisement, procurement, industrial relations and finance, relies upon the advances in academic knowledge made possible by social sciences. Research activities aiming at the introduction of new business routines and organizational innovations are poorly appreciated by R&D statistics. Nevertheless large and novel evidence provided by business schools confirms the key role of social sciences as the provider of organizational knowledge that helps improving the efficiency of production and administrative processes in all industries and sectors of economic activity (Evangelista, Vezzani, 2010; Van Reenen, 2011). As a matter of fact the scope of application of social sciences appears to be even higher than that of hard sciences as organizational innovations and new business practices matter not only in the high-tech sectors but also in traditional fields of activities where technological innovations are less relevant for the conduct of business activities. The appropriabilty of organizational innovations and new business methods is quite low, but the implementation of organizational innovations and new business practices require such large amounts of tacit and highly localized knowledge and competence on the specific conditions of the firms and the types of organization to which they apply, to make it hard for uncontrolled spillovers to leak to third parties. As a consequence also social sciences knowledge is close to the definition of knowledge as an intermediary good, since advances in social sciences can be regarded as inputs into the production of all the other goods (Stephan, 1996; Foray, 2004).

Medical sciences are clearly most relevant from a social viewpoint as they feed the introduction of new medical practices and pharmaceutical products that help fighting diseases, stretching the duration of life and improving its quality. Some medical research has a quite high degree of appropriability, as in the pharmaceutical industry, and some of the results of medical research can also be used as production goods in other economic activities, as it is the case in biotechnology where the development of new materials might lead to the eventual use in very different fields and industries. Notwithstanding these relevant exceptions, the scope of application of medical sciences is quite narrow as it is mainly limited to the health industry. Moreover the likelihood that advances in medical sciences affect directly economic growth seem lower also for the institutional setup of the health industry that in most countries is organized as a public service with specific accountability rules that reduce the possibility to appreciating their economic effects (Grebel, 2011). As a consequence we consider that knowledge in medical sciences shares some features of knowledge as an intermediate good, but is closer to the definition of knowledge as a final good along our continuum.

Finally, human sciences seem to be characterized by a limited scope of direct application to the production of goods and very low levels of appropriability. The direct application to economic activities of such advances concerns mainly cultural and entertainment industries, but also in this case the public support to these activities makes it harder to establish their real contribution in terms of value added. The use of human sciences has a strong impact on the utility of consumers: human sciences should be regarded mainly as final goods, rather than productive ones, and therefore along our continuum they are the closest to the definition of knowledge as final good.

Furthermore the case of human sciences calls for a critical attention to the common implicit assumption found in the literature that knowledge is an input into the production of other goods and not a final good. As a matter of fact knowledge in human sciences may be regarded as a final good that consumers are eager to acquire simply because culture increases the quality of life, and not because it provides competitive advantages in the labour markets. From this viewpoint it would become necessary to discriminate between the cases in which human sciences can be considered as a final good and the cases in which they should be regarded as a production input.

The intrinsic characteristics of the four types of knowledge described so far differ substantially. Their analysis supports the general hypothesis that knowledge is not a homogenous good. Building upon these bases it seems possible to move away from the effort to analyze the internal efficiency of academic departments in terms on the relationship between input and outputs measured in terms of the amount of knowledge generated with given investments, towards an original approach to measure the external, rather than the internal, efficiency of the academic system.

The analysis carried out so far enables to try and assess the external efficiency of academic knowledge, that is, to implement the effort to try and measure the differentiated effects of the different types of knowledge on the growth of the economy and of its efficiency as measured by total factor productivity.

2.3 THE HYPOTHESES

An important literature has explored the differentiated effects of the different sources of technological knowledge to total factor productivity of economic systems and their business sector (Guellec and Van Pottelsberghe de la Potterie, 2003 and 2004; Coccia, 2011; Pop Silaghi, Alexa, Jude, Litan, 2014). The grafting of the new tools of the economics of knowledge and the new understanding of the relationship between knowledge and the growth of TFP enables to push further this line of analysis exploring the differentiated effects of the different types of academic knowledge and to put forward our hypothesis. The argument rests on three points: i) knowledge cannot be any longer considered as an undifferentiated basket of a homogenous good; ii) knowledge differs in many ways, in terms of generation, use and exploitation. The plural, knowledge(s) –types of knowledge-, should replace the singular, knowledge; iii) the knowledge(s) identified as intermediary and capital goods have high levels of appropriability and such a wide scope of application to the generation of technological and organizational knowledge that can be considered as inputs that enter the recombinant knowledge generation process and the eventual introduction of specific innovations that foster TFP growth and hence output; iv) the effects of academic knowledge as a final good on the recombinant generation of technological knowledge and hence on TFP growth are weaker as they affect mainly the utility of final consumers; v) the academic remedy to the Arrovian undersupply, -i.e. the supply of academic knowledge made available by academic publications and trained personnel- yields stronger positive effects when it consists of knowledge as a capital good, than when it consists of knowledge as a final good..

In sum, spelling out our hypothesis, knowledge generated in hard and social sciences exhibits the typical characteristics of an intangible capital good and intermediary input necessary to produce all the other goods at lower costs. Knowledge generated in humanities and medical sciences seems closer to a final good that affects directly the utility of consumers, as such it can be regarded as a final output with limited possibilities to be used as an intermediary input.

We expect that advances in hard and social sciences push the generation of technological knowledge and the eventual introduction of technological and organizational innovations that make possible to increase TFP and consequently output and labor productivity. We expect to test a positive and significant relationship between the amount of efforts in the generation of hard and social sciences and TFP growth. Advances in medical and human sciences are less likely to engender the generation of technological knowledge and the eventual introduction of technological and organizational innovations that enable to increase TFP levels. Advances in medical and human sciences contribute directly the increase of output as they are primarily final goods that provide substantial direct contributions to welfare and human happiness. Their appreciation would be stronger with the use of hedonic prices that might grasp their effects on the quality of life. They are, however, less likely to affect the increase of TFP with standard growth accounting.

2.3. THE RESEARCH STRATEGY

We want to explore here the differences across types of academic knowledge in terms of causal effects on economic growth, via TFP growth, and we have put forward the hypothesis that the advances in hard sciences and social sciences are likely to exert a stronger effect on TFP and economic growth than the advances in medical and human sciences. To test our hypothesis it is necessary to identify the contribution of each scientific discipline and its economic impact.

The identification of the impact of each academic field on the economic performances of a country is extremely difficult from an empirical viewpoint, since it is likely that such effect will interact with many other variables (such as the institutions, the cultural environment, the industrial specialization of a country). Moreover the existence of relevant complementarities between academic disciplines may affect the final impact of each of them on productivity growth: accounting for these complementarities would require a much richer analysis that we do not implement here, for the sake of simplicity. Indeed our aim in this paper is to provide a first tentative measurement, keeping our analysis at a very simple level, in order to check first of all for the presence of differences among disciplines in their impact on TFP growth.

Since we expect that the economic effects of the expenditures in academic research will affect economic growth mainly through increases in TFP we specify the following equation:

$$TFP = HS^{c} SS^{d} MS^{e} HU^{f} \tag{1}$$

Where *HS* stands for expenditures in hard sciences, *SS* for social sciences, *MS* for medical sciences, and *HU* for humanities. The exponents c, d, e, f, measure the elasticity of total factor productivity to the production factors considered.

Our hypothesis is that in equation (1) *c* differs from *d* that differs from *e* and *f*. More specifically we expect that $c \geq d > e \geq f$.

3. THE EMPIRICAL ANALYSIS

3.1 DATA AND DESCRIPTIVE EVIDENCE

In order to be able to investigate the relationship between the heterogeneous stock of knowledge, dispersed among the different disciplines, and the aggregate economic performances of countries, the ideal way would be to take advantage of the information on the disciplinary composition of Higher Education R&D expenditures, as provided by the OECD. However this dataset is rather incomplete and often discontinuous for many of the most important advanced economies, also in recent years.[2] In order to overcome this strong limitation we chose to combine data on total HERD with the data on the disciplinary composition of the stocks of graduate students in OECD countries. Indeed the stock of graduate students can be regarded as a reliable proxy for the disciplinary composition of the R&D activities conducted by the higher education system. We consider graduates as an indirect measure of the resources dedicated to their formation, hence of the supply of knowledge provided by the different national university systems. These data are available for a richer set of countries through the UNESCO-OECD-Eurostat (UOE) database, which collects education statistics from many of the OECD member countries: specifically we used the database "Graduates by field of education". This database allows to obtaining the number of graduates in each scientific discipline for each country and in each year for the time period 1998-2008.

[2] More specifically the OECD data on HERD distinguished by disciplines is not available for France, Germany, Italy, Switzerland, United Kingdom, United States and some other OECD countries.

For the purpose of our analysis we apply the main categories we identified in the previous section We could identify four main fields: hard sciences disciplines (including engineering and architecture, as well as life sciences, physics, mathematics, statistics and informatics), social sciences (social and behavioral sciences, journalism and communication, business and administration and law), humanities (including arts, humanities, and education-related courses) and medical sciences (medicine, health-related courses and social services).[3]

We combine the data on the number of graduates in each of these four disciplines with the yearly expenditures for the total economy in Higher Education R&D (HERD), taken from the OECD-ANBERD (ANalytical Business Enterprise Research and Development database) deflated by the Purchasing Power Parity deflator, in order to obtain four proxies of the R&D expenditures in each of the disciplinary field by country.

$$HS_{it} = HERD_{it} * (hs\_grad_{it} / total\_grad_{it}) \qquad (2)$$

Where i indicates a specific country and t denotes a specific year. HS_{it} is our proxy of the expenditures in HERD in hard sciences, $HERD_{it}$ is the total amount of expenditures in HERD, hs_grad_{it} is the number of graduates in each of the disciplinary fields (in this case hard sciences) and $total\_grad_{it}$ is the total number of graduates. The same procedure is replicated for the other three disciplinary fields. In this way we distribute the expenditures in HERD for each year according to the country-level disciplinary distribution of graduates in each year. Our hypothesis is that the number of graduates should be a good proxy of the size of the academic institutions that educate them. Since a large part of the expenditures in R&D consist of wages paid to specialized personnel we expect that in a country in which the share of graduates in a specific field is very high also the number of academic personnel in that discipline will be high, as well as the share of public

[3] See the Appendix A for a detailed description of the disciplines included in each of these broad categories.

R&D expenditures in that specific academic field. However since there are reasons to believe that in some cases the distribution of expenditures in R&D and that of the number of graduates by scientific field might not perfectly overlap, in the following sections we will also try to check for the robustness of our measure, taking advantage of the limited data available on HERD divided by disciplinary fields.

Figure (2) displays the average ratio of HERD expenditure over employment in each country, while Figure (3) provides the average shares of graduates in the four disciplines over the total number of graduates for the period 1998-2008. While the higher shares of graduates in hard sciences are displayed in Germany, France, Switzerland, Czech Republic and Japan, the higher share of graduates in social sciences is in the United States, followed by France, Australia and Japan.

We then combined this data with other economic variables, which will allow to analyze the relationship between the educational variables and the economic performances of countries. We collected from OECD-STAN (STructural ANalysis database) data on the value added of the total economy, the real stock of capital, the number of employees engaged, in order to calculate TFP:

$$\ln\left(TFP_{it}\right) = \ln Y_{it} - \alpha \ln K_{it} - \beta \ln L_{it} \tag{3}$$

Where, assuming constant returns to scale, β is set equal to 0.7 and α is set to 0.3, following Hall and Jones (1999). We also use OECD data to include the following additional variables: the share of employment in manufacturing activities and in high tech economic activities, the total number of patent applications, the level of openness to trade for each country, the number of international students enrolled in tertiary education and the number of researchers employed in HERD. Finally we also included the number of scientific and technical journal articles from the World Bank data.

The countries included in our database were chosen according to the availability of complete series of education-related data and economic variables[4]. Our final selection yielded a fairly balanced panel with 13 countries and 11 years. In Appendix A the construction and the composition of the database are explained in more details.

3.2. THE ECONOMETRIC MODEL

The final specification of our model is therefore:

$$\ln(TFP_{it}) = a + \gamma_1 \ln\left(\frac{HS_{it}}{L_{it}}\right) + \gamma_2 \ln\left(\frac{SS_{it}}{L_{it}}\right) + \gamma_3 \ln\left(\frac{MS_{it}}{L_{it}}\right) + + \gamma_4 \ln\left(\frac{HU_{it}}{L_{it}}\right) + \sum_n \theta_n X_{it} + u_i + \lambda_t + \varepsilon_{it} \tag{4}$$

Following an established tradition of empirical research we include, as a key control variable, the number of patent applications in order to account for the research efforts of private companies. Indeed the interaction between the investments in public R&D and the innovative investments made by companies are likely to influence the final impact of each discipline on productivity growth (Guellec and Van Pottelsberghe de la Potterie, 2004). The number of patent applications is a better proxy, than using private R&D, of the full range of innovative activities made by firms to generate technological knowledge, including, next to formal research, the efforts that are necessary to absorb external knowledge and to extract tacit knowledge from learning processes and the role of the stocks of R&D activities [5].

[4] The 13 selected countries are: Australia, Belgium, Czech Republic, France, Germany, Hungary, Italy, Japan, New Zealand, Spain, Switzerland, United Kingdom, United States.

[5] There is a large literature that confirms the advantages of patents as a reliable indicator of the amount of resources invested in the knowledge generation process. See Griliches (1979 and 1990) and Pakes and Griliches (1984).

Next to patents, as further controls we use the share of manufacturing over total employment and the openness to trade in order to account for the specific structure of each economy considered. The error term is composed of three parts, u_i, λ_t, ε_{it} that represent respectively country specific, common stochastic and idiosyncratic shocks.

We implement fixed effects for the estimation of our models: as we said previously a great difficulty in assessing the impact of different fields of academic knowledge relies on the multiple variables that might interact with knowledge itself, such as the institutional environment, the entrepreneurial culture or the industrial specialization of a country. All these factors are likely to be correlated with the variables of interest of our model: hence adopting fixed effects should allow to take into account the unobserved heterogeneity at the country level. Moreover the time-varying control variables in *X* (share of manufacturing in employment, openness to trade, number of patent applications) will allow to account also for possible changes that occur in the time-interval considered and that might also be correlated with the expenditures in HERD.

A final note has to do with the choice of the time lags used in the specification: it is likely that the effect on economic performances of different disciplines might occur with different time-lags. However historical evidence shows that even important advances in specific fields of science might take a very long time before their effects can be observed. While the time-lag specification seems a relevant issue for historical studies that cover long periods of observation, this dimension is not very suitable for our dataset, in which the cross-country variability is more relevant than the time dimension, since we cover only 11 years. For this reason our specification uses contemporaneous levels of the academic variables and we do not investigate the issue of time-lags choice, while we focus more on the appropriate measurement of our variables of interest and on the relevant causality issues.

3.3 THE RESULTS

Columns 1-3 of Table (1) show the results of the fixed effects estimation of our baseline specification of equation (4). In column (1) we start introducing all the control variables and the total amount of HERD expenditures. The coefficient of the HERD is positive and significant confirming that HERD expenditures in general are an important factor that fosters the growth of TFP. The other control variables have the expected coefficients: patent intensity and manufacturing share of employment have a positive but not significant coefficient, while openness to trade shows a positive and significant effect.

In column (2) we introduce our proxies of HERD expenditures distinguished by disciplinary fields. The estimates confirm our hypothesis concerning the coefficients of the number of graduates from the different disciplines: specifically we notice that hard sciences (HS) and especially social sciences (SS) display positive and significant coefficients, while medical sciences (MS) and human sciences (HU) have non significant coefficients. As regards the other control variables, the manufacturing share of employment exhibits a negative but not significant coefficient, confirming that the specialization of advanced countries is now centered on knowledge intensive business services, patent intensity is now significant and positive, together with openness to trade that is always positive and significant.

Taking into account the descriptive statistics of Figure (3), we want to check whether our results could be induced by some relevant outliers, i.e. countries which might influence the overall results of the estimates. Specifically we want to test whether the coefficients for the social sciences depend from the inclusion in our sample of the United States, which in Figure (3) happened to display the highest share of graduates in social sciences. This might generate a problem since the United States are clearly among the countries with the highest level of GDP per capita and Total Factor

Productivity. Column (3) of Table (1) provides the results of the estimate after the exclusion of the observations belonging to United States from our sample. The results show that the signs and the significance of the coefficients do not change, on the contrary the coefficient for social sciences slightly increases, thus rejecting the hypothesis that United States would have boosted the coefficient of social sciences.

3.4 FIRST ROBUSTNESS CHECK: THE EFFECTS OF SCIENTIFIC DISCIPLINES IN THE TECHNOLOGY PRODUCTION FUNCTION

As a robustness check we try and estimate the output elasticity of the R&D expenditures in the different scientific fields. We rely on the technology production function introduced by Griliches (1979), as it follows:

$$Y = K^{a} L^{b} HS^{c} SS^{d} MS^{e} HU^{f} \tag{5}$$

Where *K* stands for the stock of capital, *L* for labor, *HS* for expenditures in hard sciences, *SS* for social sciences, *MS* for medical sciences, and *HU* for humanities. The exponents *a*, *b*, *c*, *d*, *e*, *f* measure the output elasticity of the production factors considered.

In order to give a rough proxy of the effect that the endowments of knowledge in different disciplines have on the aggregate performances of economic systems we chose to measure the output elasticity of the proxies of HERD expenditures in each different field. As we previously said we adopt the technology production function as follows:

$$Y_{it} = AK_{it}^{\alpha} L_{it}^{\beta} HS_{it}^{\gamma_1} SS_{it}^{\gamma_2} MS_{it}^{\gamma_3} HU_{it}^{\gamma_4} e^{(u_i+\lambda_t+\varepsilon_{it})} \tag{6}$$

where, on the left-hand side is the value added of the total economy (expressed in real terms and in Purchasing Power Parities dollars) while among the independent variables we include the standard material inputs (capital stocks and labor, i.e., employment) and the proxies for the HERD expenditures in each of the disciplines we identified previously: Hard Sciences (HS), Social Sciences (SS), Medical Sciences (MS) and Humanities (HU). The exponents α, β, γ_1, γ_2 , γ_3 and γ_4 measure the output elasticity of the production factors considered.

Since we want to estimate the impact of each of these factors on the aggregate labor productivity, we transform our model in labor intensities and take logs as follows:

$$\ln\left(\frac{Y_{it}}{L_{it}}\right) = a + \alpha \ln\left(\frac{K_{it}}{L_{it}}\right) + \gamma_1 \ln\left(\frac{HS_{it}}{L_{it}}\right) + \gamma_2 \ln\left(\frac{SS_{it}}{L_{it}}\right) + \gamma_3 \ln\left(\frac{MS_{it}}{L_{it}}\right) + \\ + \gamma_4 \ln\left(\frac{HU_{it}}{L_{it}}\right) + \sum_n \theta_n X_{it} + u_i + \lambda_t + \varepsilon_{it} \qquad (7)$$

All the coefficients are expressed in terms of labor intensity[6], while X is the usual set of control variables.

Table (1) shows the results of the fixed effects estimation of our baseline specification of equation (7). In column (4) we start introducing all the control variables and the total amount of HERD expenditures. The coefficient of the HERD is positive and significant confirming that HERD expenditures in general are an important factor that fosters the growth of labor productivity. The other control variables have the expected coefficients. Capital intensity has a positive and

[6] We assume constant returns to scale. We tested whether the results of the estimations changed when we relaxed this assumption and the results were unaffected by the model choice. Therefore we chose to adopt a more simple and parsimonious specification as in equation (7).

significant coefficient, patent intensity and manufacturing share of employment have a positive but not significant coefficient, while the openness to trade shows a positive and significant effect.

In column (5) and (6) we introduce our proxies of HERD expenditures distinguished by disciplinary fields. The estimates confirm our hypothesis concerning the coefficients of the number of graduates from the different disciplines: specifically we notice that hard sciences (HS) and especially social sciences (SS) display positive and significant coefficients, while medical sciences (MS) and human sciences (HU) have negative and not significant coefficients. The other control variables are left largely unaffected by the introduction of our main variables of interest: capital intensity is still positive, manufacturing share of employment is always not significant, the positive coefficient of patent intensity is here significant at the 10% level, while openness to trade is always positive and significant. Also in this case our results are robust to the exclusion of observations from the US, as shown in column (6)

3.5 SECOND ROBUSTNESS CHECK: CORRECTING FOR COST DIFFERENCES ACROSS DISCIPLINES

So far our strategy has relied on the assumption that the distribution of graduates among academic disciplines in each country should be a good proxy of the distribution of the expenditures in HERD. We believe that this is a realistic assumption for the following reasons: the student/professor ratio should not vary too much across scientific fields, therefore a higher number of graduates in a specific discipline should be associated with a higher number of academic personnel in that discipline. Moreover since Higher Education R&D expenditures consist for a large part of labor costs paid to the academic personnel (researchers and professors) we believe that in countries with a high share of graduates in a specific discipline (and hence with a high number of researchers in that discipline) also HERD expenditures will be higher in that specific field. However, while this is true for the component of HERD that is due to personnel wages, this must not be necessarily true for other types of expenditures, such as investments in laboratories and scientific instruments. For these types of investments it is likely that hard sciences and medical sciences will display a higher share of investments with respect to social sciences and humanities.

In this section we relax the assumption of similar costs for each discipline and we take advantage of the limited availability of data on the distribution of HERD by academic discipline provided by the OECD. As we said previously we have information on HERD data distinguished by academic field only for a subset of the countries in our database.[7]

We therefore implement the following imputation strategy: we build the share of expenditures in HERD for each of the four scientific disciplines only for the countries and years for which we have data:

$$HS\_sh_{it} = HS\_HERD_{it} / HERD_{it} \tag{8}$$

Where *HS_HERD* is the amount of expenditures of *HERD* in hard sciences and HERD is the total amount of HERD; as usual *i* and *t* denote country and year. We replicate the procedure displayed for hard sciences for all the four academic fields (social sciences, medical sciences and humanities) and obtain the yearly share of HERD expenditures in each discipline for the countries for which we have data.

The imputation strategy

We apply a standard imputation strategy in which we regress the shares of HERD expenditures in each discipline, as computed in equation (8), on a rich set of variables that are likely to be related with these shares. This set of variables include: capital intensity, patent intensity, share of manufacturing on employment, openness to trade, the share of employment in high tech sectors, the

[7] The countries for which we have data on HERD distinguished by scientific field are: Australia, Belgium, Czech Republic, Hungary, Japan, Spain.

share of Knowledge Intensive Business Services on total GDP, the ratio of Business R&D over total employment and the share of international students among the total number of students enrolled in the tertiary education system. We estimate the model only on the subset of countries for which we have data and obtain the estimated coefficients for each of the independent variables used. Then we use these estimated coefficients to predict the HERD shares in each discipline also for the other countries in our sample for which we lack HERD data by discipline In this way we are able to generate the predicted shares of HERD in each of the discipline also for the whole set of countries in our sample.

The correction measure

We use the predicted shares of HERD to build a "correction" measure for the share of graduates in each discipline as follows:

$$HS\_corr_{it} = pred\_HS\_sh_{it} / (hs\_grad_{it} / total\_grad_{it}) \tag{9}$$

Where *pred_HS_sh* is the predicted share of HERD expenditures in Hard Sciences, while between parentheses is the share of graduates in hard sciences over the total number of graduates. *HS_corr* will be higher than 1 when the share of predicted HERD in hard sciences is higher than the observed share of graduates in hard sciences. Viceversa when the share of predicted HERD is lower than the share of graduates *HS_corr* will be lower than 1. We apply this time-varying country-specific correction to our previous measure of HERD expenditure in Hard Sciences (*HS*), based on the share of graduates. The correction formula is as follows:

$$HERD\_HS\_corr = HS * HS\_corr_{it} \tag{10}$$

Then we replicate the procedure for each of the four disciplines and obtain four new variables in which the shares of graduate students are "corrected" by the use of the predicted shares of HERD expenditures by academic fields.

We then re-estimate equations (4) and (7) using these new variables and adopting the usual fixed effects specification. The results are displayed in Table (2). As we can see both in the TFP and in the labor productivity specification the signs of the coefficients do not change with respect to Table (1): furthermore we notice that the coefficients of Hard Sciences and Social Sciences are now significant respectively at the 5% and 1% level. The coefficients of Medical Sciences and Humanities are instead always not significantly different from zero. The coefficients of the other control variables are also left largely unaffected.

3.6 CAUSALITY

While so far we have focused mainly on the proper measurement of the HERD expenditures in the different discipline, we did not account for the possible endogeneity problems related with the estimation of our models. Our independent variables of interest are obtained by multiplying two different variables: the shares of graduates in each specific discipline and the HERD expenditures. We have no particular reasons to believe that the share of graduate can be correlated with the error term ε_{it}: the graduation of students in fact is the final outcome of a choice generally undertook 3-5 years before, so it is not correlated with contemporaneous economic conditions. Things would have been different, had we used the number of enrolled students, in that case exogenous economic shocks might affect the contemporaneous decision of students to enroll into the university (and in which discipline) or enter the labor market.

It is indeed likely that the overall level of wealth in a country will influence the choices of students towards specific disciplines: for example in richer countries the greater availability of (expensive) research infrastructure might increase the propensity to enroll in hard and medical sciences. However these country differences, which are rather stable in the 11 years time period chosen, are already accounted for by the fixed effects specification.

On the contrary the other component of the disciplinary variable in our model, the total sum of HERD expenditures, is likely to be endogenous, since both contemporaneous and past shocks in labor productivity and TFP will necessarily have also an effect on the amount of public resources devoted to research in the academia. Therefore HERD is likely to be endogenous in our specification.

The best way to take into account of this endogeneity problem is to resort to an instrumental variable strategy and build a new measure of HERD that is not related with the productivity shocks and use that as an instrument for the real HERD. We hence need to identify some variables that are strongly correlated with the amount of HERD in a country but that are not correlated with productivity shocks. We use the number of articles in scientific journals and the share of foreign students in tertiary education. In other words we exploit the fact that scientific journals will be strongly correlated with the levels of HERD; however the publication of a paper in a scientific journal is usually a long process that is strongly related with idiosyncratic features of individual researchers and the length of the publication time is often subject to a certain degree of randomness, due to many factors that might influence the peer-review process of publication. Therefore while on average the number of publications and the expenditures in HERD will be highly correlated, on the contrary a shock in productivity at the country level will not necessarily influence the number of publications. On the basis of these considerations we believe that the number of scientific publications should be a good instrument for the level of HERD. As a second exogenous variable we use the number of foreign students enrolled in the universities of a country: the presence of foreign students can be considered as a good proxy of the attractiveness of the university system of that country, therefore of its intrinsic quality. Again this quality will be highly correlated with the amount of resources invested in HERD, however there are no particular reasons to believe that a shock in productivity in a country might have an effect on the share of international students in that same country.

In Table (5) we regress the ratio of total HERD expenditures over employment on the number of scientific articles and on the share of international students: we use fixed effects and include country dummies. The results show that indeed there is a positive and significant correlation between the two exogenous regressors and HERD. We then compute the predicted values of the dependent variables: intuitively this new variable will correspond to the portion of HERD that is only explained by the two exogenous variables that are not correlated with productivity shocks. We hence use this new variable to create the instruments for the estimation of equations (4) and (7) as follows:

$$HS_{it}^{IV} = \hat{HERD}_{it} * (hs\_grad_{it} / total\_grad_{it}) \tag{11}$$

Where $\hat{HERD}_{it}$ is the predicted ratio of HERD over employment from the estimation performed in Table (5). The new HS^{IV} variable can be used as an instrumental variable since it will be highly correlated with the HS variable, but it will not be correlated with the error term. We replicate the same procedure used for Hard Sciences for all of the four types of disciplines and obtain 4 instrumental variables that we can use to control for the possible endogeneity of HERD.

Since in our specifications the all four academic variables are likely to be endogenous we need to instrument all of them. However with such a limited sample instrumenting the four variables contemporaneously is not a suitable methodology, since external instruments that have a strong predictive power for a specific variable will not necessarily be correlated with the other endogenous variables: this fact would typically lead to a problem of weak instruments which might affect our estimates (Angrist and Pischke, 2009). Therefore we preferred to run 4 different Two Stage Least Squares estimations (2SLS) and in each regression we will instrument only one of the endogenous variable with its respective instrument. Tables (3) and (4) present the IV-2SLS estimates in the specification of TFP and labor productivity. In all the specifications the F-statistics for the first stage indicate that our chosen instruments are not weak, since the statistics are well above the threshold identified in the literature (Bound et al., 1995)

In column (1) of both tables Hard Sciences are instrumented with the HS^{IV} variable built using the predicted levels of HERD: both in Table (3) and (4) the results are consistent with our hypotheses, since hard sciences remain positive and significant. In column (2) Social Sciences are instrumented with the SS^{IV} variable used as instrument and they remain positive and significant. When in column (3) we instrument humanities with HU^{IV}, instead, we find that the coefficient remains non significantly different from zero. Similarly in column (4) we instrument medical sciences with the external instrument MS^{IV} and find that these are not significantly different from zero. In all cases we find that only hard sciences and social sciences have positive and significant coefficients, thus providing further evidence that supports our research hypotheses.

4. CONCLUSIONS

The fading role of the corporation as the exclusive institutional locus for the generation and exploitation of technological knowledge has brought the academic system back to the center stage of the analysis of the determinants of economic growth. Needless to say, the intrinsic value of Science goes well beyond its specific contribution to economic growth, as advances in all scientific fields generally fosters the development of human society. However in recent years the academic system has been also increasingly considered as a generator of new knowledge able to foster the technological performances of firms and, ultimately, the economic growth of countries. The vast literature on National Innovation Systems (Freeman, 1987; Lundvall, 1992; Nelson, 1993) has provided wide evidence about the important role of the formal institutions of science and education as upstream suppliers of valuable knowledge that, once made accessible to firms, is able to increase their technological competences and their economic performances. The National Systems of Innovation literature also suggests that it is the fruitful interaction between several different actors and institutions (among which the academic system) that eventually leads to better economic performances. The wide consensus on the centrality of the academic system in such system, as a crucial engine for the generation of knowledge -the basic engine of the growth of total factor productivity and hence output- has called increased attention on its accountability. The centrality of the academic system calls for the allocation of increasing resources into the academic system to foster the generation of knowledge and hence TFP and economic growth. This in turn calls for a closer scrutiny of the actual benefits stemming from their allocation. The allocation of more resources calls for more attention and feeds the increasing need to better assess their efficiency.

Much attention has been paid to increase the accountability of the academic system. Two distinct notions of efficiency apply in this context. Internal efficiency accounts for the relationship between inputs and outputs at the academic system level. Output here is measured in terms of standardized units of knowledge. External efficiency accounts for the relationship between the resources transferred to the academic system and their effects on the output of the economic system at large.

Much attention has been directed to assess the levels of internal efficiency with the elaboration and application of new tools to better measure the output of the academic systems in the effort to measure the amount and the quality of knowledge actually generated and transferred to the economic system. Lesser attention has been paid to assess the actual levels of external efficiency i.e. to measure the relationship between the amount of resources allocated to generate new knowledge and its eventual effects in terms of output growth in the system at large. The two notions of efficiency would coincide only if knowledge were a homogenous good. As soon as we appreciate that knowledge is a composite bundle of a variety of different kinds of knowledge, the problem of the composition of the bundle becomes crucial.

The risks of a mismatch between supply and demand are high. Some types of knowledge may engender lower levels of knowledge externalities than others. The economic system may demand more intensively some kinds of knowledge as an intermediary input than others.

The distribution of public resources across scientific fields has received little attention and poor empirical investigation. Recent advances of the economics of knowledge enable to investigate more directly the intra-allocation of resources within the academic system. The new economics of knowledge has made it possible to understand that knowledge is not a homogenous basket of an undifferentiated good. Knowledge differs on many counts. A crucial difference concerns the capability of the different types of knowledge to contribute economic growth according to their differentiated support to the introduction of innovations. Some kinds of scientific knowledge and more specifically some disciplinary fields are likely to generate types of knowledge that as intangible capital and intermediary inputs foster technological change and ultimately might increase the levels of TFP. Other kinds of knowledge with much a narrower scope of application and lower levels of appropriability enter directly the utility function of final consumers and share the characteristics of final goods. Building upon this distinction we have articulated the hypothesis that the former type of academic knowledge is more effective with respect to the actual support of the rates of TFP growth, than the other.

Our approach enables to make an original use of the information on the composition by disciplinary fields of the R&D expenses of the higher education system. The statistics on graduate students, a rich and detailed source of empirical evidence, widely available and little used so far, has made possible to improve the quality of the original statistics on the disciplinary composition of higher education R&D expenses.

In order to provide a first possible measurement of the impact of each type of academic knowledge on the economic performances of a country, i.e. the degree of their external efficiency, we propose a very simple econometric approach in which we identify the output elasticity of four main academic fields, proxied by their shares of R&D expenses in the higher education system of 13 OECD countries in the years 1998-2008.

The results show that there are important differences in the contribution of these fields to economic growth: specifically hard sciences and social sciences, contribute more to TFP growth, than, respectively, medical sciences and human sciences. The lack of reliable statistics based on hedonic prices does not make possible to appreciate the improvements in the utility of consumers in their ability to appreciate aesthetic experiences or simply to live more years in better health conditions.

Both the approach and the results seem important. The proposed approach implements the exploration of the actual impact of the knowledge output of the academic system and the assessment of its external efficiency. The approach elaborated in this paper provides an integrated frame of analysis where the emphasis on the external efficiency of the academic system is focused and contribution of the different types of knowledge on economic growth is directly assessed.

The results shed some light on the crucial issue of the intra-academic allocation of the growing amount of resources devoted to the academic system as a whole. It seems more and more important to call attention on the differences among academic fields in terms of their actual capability to contribute economic growth. It seems no longer appropriate to call for more support to the academic system as an undifferentiated whole. The results of our empirical analysis, that might be considered as a first attempt to discriminate among different "knowledge(s)" based upon the type of academic disciplines, call for future research directed to a finer grained and more rigorous assessment of the impact of the stocks of academic knowledge on the national or regional economic performances. It seems worth to explore and carefully assess which fields deserve more funding than others, if the support to economic growth is the aim of public funding. More generally it is clear that there is an emerging need to better direct the resources invested into the academic system, not only in terms of internal efficiency but also and mainly in terms of their actual of application and appropriation and hence actual effects on economic growth. It is no longer sufficient to claim that all kinds of knowledge yield knowledge externalities: as a matter of fact some types of knowledge yield knowledge externalities that can be better exploited by the business sector than others. Public support aimed at fostering the rate of growth of the economy should be directed towards the most productive types of knowledge rather than across the board of all disciplines. The appreciation of knowledge as a final good as distinct from an intangible capital and intermediary input is important as it finally enables to reduce ambiguities and confusions about the economic role of knowledge.

The undersupply of knowledge items that are closer to capital goods is likely to reduce the dynamic efficiency of the economic system. Undersupply of knowledge items that are closer to final goods is likely to have smaller effects in terms of static efficiency. The undersupply of the former in fact inhibits the introduction of upstream innovations that have positive effects on a large set of downstream industries. The undersupply of the latter affects only its final consumers. This distinction enabled to articulate and test the hypothesis that the academic supply of knowledge items that are closer to capital goods is likely to have stronger positive effects in terms of both output elasticity and hence output and total factor productivity than the academic supply of knowledge items that are closer to final goods.

Before discussing the implications of our results there are some important limitations of our empirical work that should be kept in mind and that call for future research in this field. It must be stressed that our method does not take into account other sources of public R&D funding such as specific R&D subsidies, public procurement or investments in infrastructures by field of research, even if these are likely to affect the overall productivity levels of economies. Moreover in our empirical strategy we did not account thoroughly for the effects of knowledge indivisibility and hence for the existence of possible complementarities between the different fields of research. Finally our specification does not investigate carefully the lag structure of each of the different disciplines analyzed. It seems most plausible to expect differentiated time-lags among disciplines in their impact on productivity growth. Our assumption of homogeneous time-lags was motivated by the lack of long time-series for our analysis. This seems an important limit of our analysis and an element that should be investigated in future research.

Notwithstanding these important limitations the policy implications of this study are important: public policy can chose to subsidize academic research for several reasons that might have little to do with economic growth. Indeed economic growth is only one of the possible measures of external efficiency of the university system. An academic system might display very high levels of non-economic external efficiency that could be measured by other indicators, such as diseases incidence, life expectancy, achievements in human rights, relation between leisure and work time. However if and when the subsidies to the university system are advocated as a mean to enhance economic growth, then our results suggest that public support to the academic system should focus the academic fields that are better able to contribute economic growth. Policy guidelines should be fine-tuned to this necessity and, on the demand-side, might introduce incentives for students to enroll in specific academic fields, for example through differentiated fees.

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Figure 2. Average ratio of HERD per worker (1998-2008)

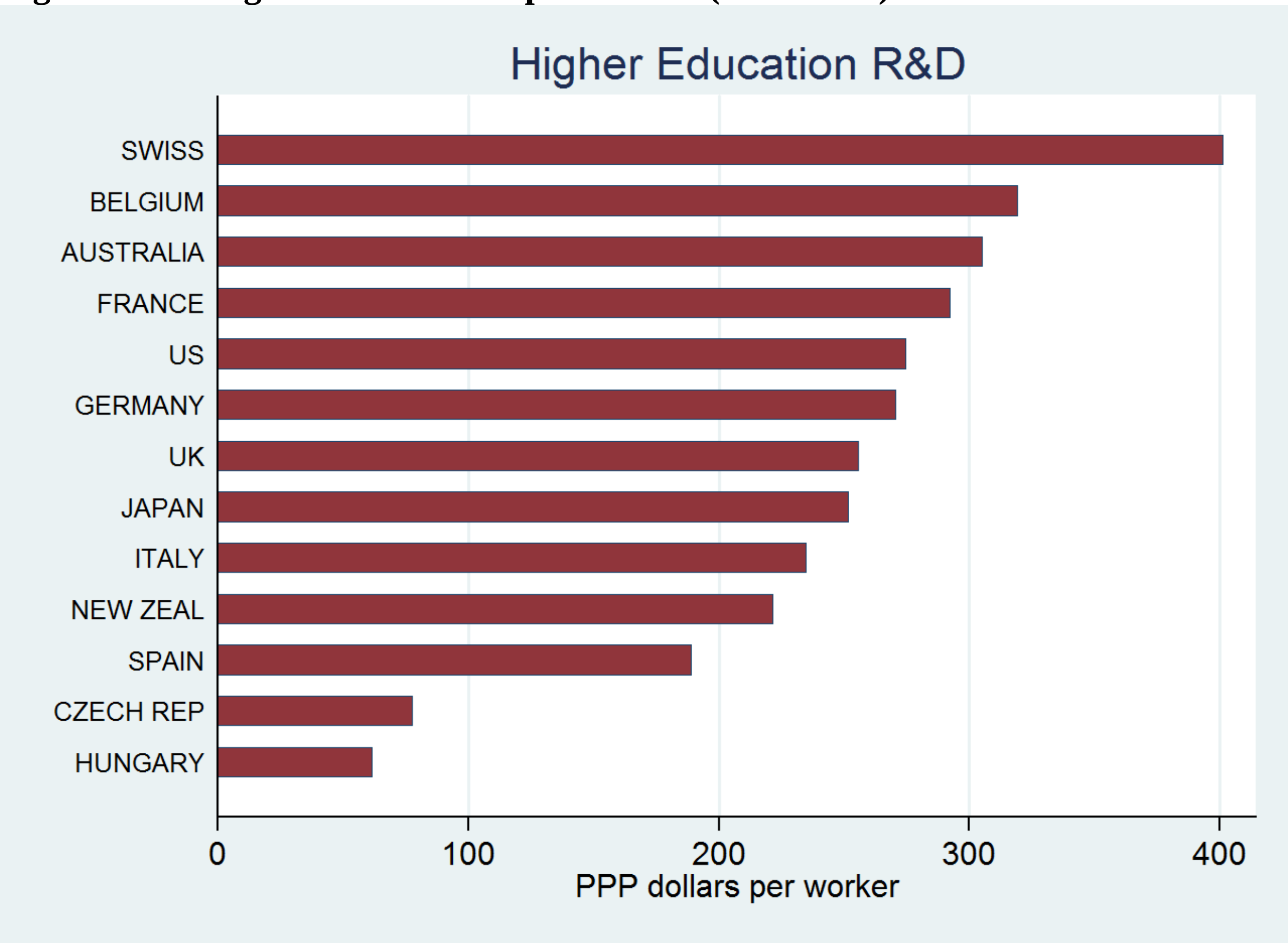

Figure 3. Average share of graduates by discipline (1998-2008)

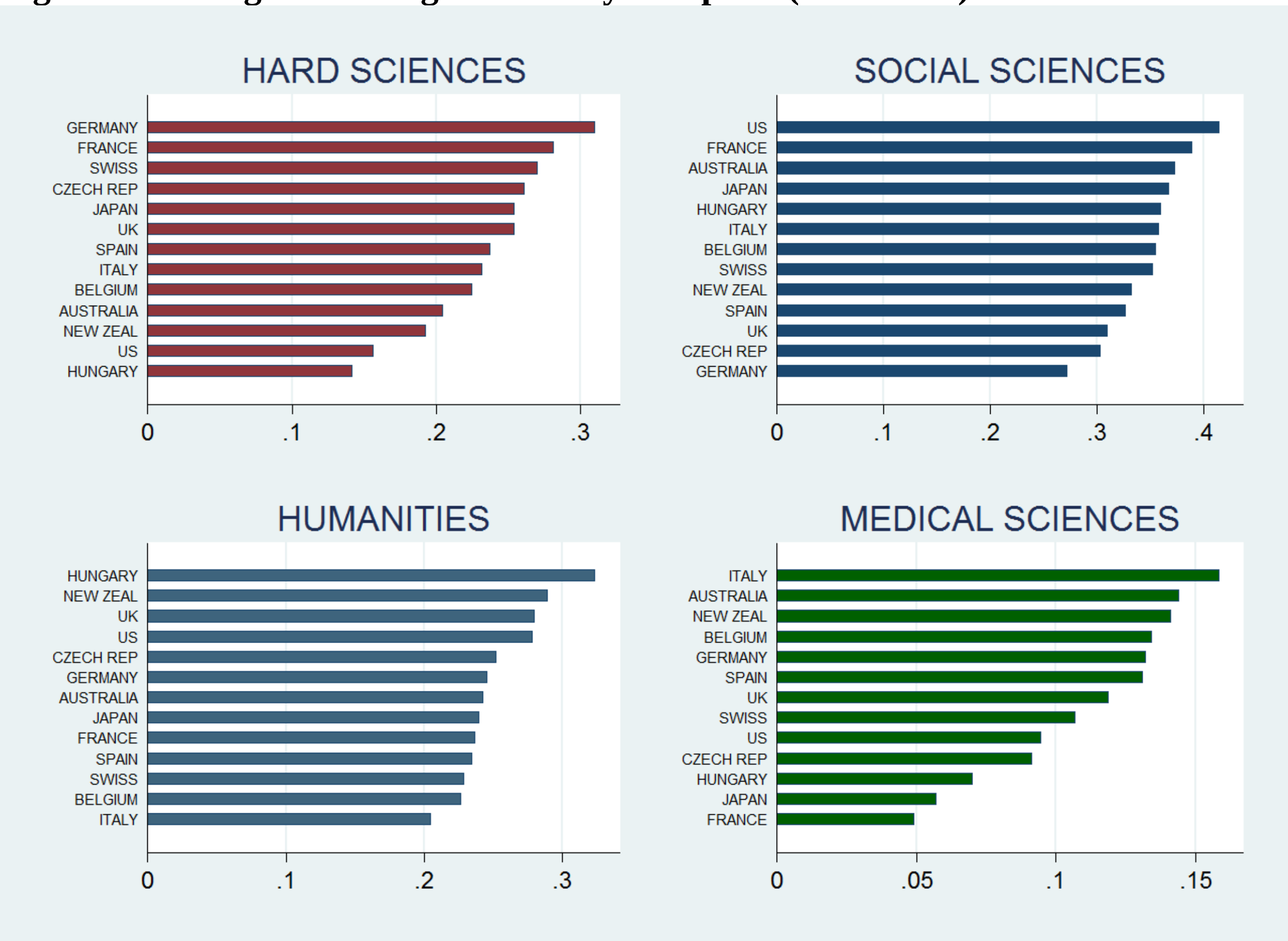

Table 1. Baseline specification

	(1)	(2)	(3)	(4)	(5)	(6)
	Total Factor Productivity			*Labor Productivity*		
			NO US			NO US
ln(HERD/L)	0.192***			0.177***		
	(0.030)			(0.037)		
ln(HERD_HS/L)		0.082*	0.082*		0.081*	0.082*
		(0.039)	(0.038)		(0.039)	(0.040)
ln(HERD_SS/L)		0.114**	0.114**		0.111***	0.113***
		(0.042)	(0.041)		(0.036)	(0.035)
ln(HERD_HU/L)		-0.003	-0.008		-0.012	-0.012
		(0.022)	(0.021)		(0.022)	(0.023)
ln(HERD_MS/L)		0.001	0.001		-0.007	-0.010
		(0.013)	(0.013)		(0.013)	(0.014)
ln(K/L)				0.471***	0.542***	0.604***
				(0.151)	(0.110)	(0.129)
ln(PAT/L)	0.013	0.021**	0.021**	0.010	0.017*	0.018*
	(0.009)	(0.008)	(0.009)	(0.010)	(0.009)	(0.009)
MANU_sh	0.316	-0.031	-0.046	0.672	0.424	0.404
	(0.956)	(0.621)	(0.687)	(1.080)	(0.796)	(0.779)
OPENNESS	0.002**	0.002***	0.002***	0.002**	0.002***	0.002***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Constant	6.128***	9.159***	9.062***	4.074**	5.943***	5.192***
	(0.214)	(0.288)	(0.337)	(1.794)	(1.521)	(1.626)
Observations	123	123	114	123	123	114
Number of id	13	13	12	13	13	12
R-squared	0.822	0.862	0.860	0.888	0.919	0.912

The dependent variable in columns (1) to (3) is Total factor Productivity, the dependent variable in columns (4) to (6) is Labor Productivity. All models are estimated with fixed effects and they include time dummies. In Columns (3) and (6) the observations for United States are excluded from the regression. Standard errors are clustered at the country level, *** p<0.01, ** p<0.05, * p<0.1

Table 2. Correcting for cost differences by discipline

VARIABLES	(1) *Total Factor Productivity*	(2) NO US	(3) *Labor Productivity*	(4) NO US
ln(HERD_HS_corr/L)	0.059**	0.057**	0.052**	0.052**
	(0.025)	(0.023)	(0.023)	(0.023)
ln(HERD_SS_corr/L)	0.065***	0.067***	0.066***	0.068***
	(0.016)	(0.017)	(0.012)	(0.012)
ln(HERD_HU_corr/L)	0.023	0.018	0.019	0.019
	(0.016)	(0.016)	(0.011)	(0.012)
ln(HERD_MS_corr/L)	0.007	0.008	0.001	0.000
	(0.005)	(0.005)	(0.004)	(0.004)
ln(K/L)			0.691***	0.720***
			(0.097)	(0.138)
ln(PAT/L)	0.016*	0.013	0.010	0.010
	(0.008)	(0.009)	(0.009)	(0.009)
MANU_sh	-0.215	-0.209	0.413	0.312
	(0.795)	(0.893)	(0.939)	(0.900)
OPENNESS	0.003***	0.003***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	8.597***	8.486***	3.628**	3.271*
	(0.303)	(0.321)	(1.336)	(1.729)
Observations	122	113	122	113
Number of id	13	12	13	12
R-squared	0.819	0.827	0.905	0.897

The dependent variable in columns (1) and (2) is Total factor Productivity, the dependent variable in columns (3) and (4) is Labor Productivity. All models are estimated with fixed effects and they include time dummies. In Columns (2) and (4) the observations for United States are excluded from the regression. Standard errors are clustered at the country level, *** p<0.01, ** p<0.05, * p<0.1

Table 3. IV Total Factor Productivity

	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
	hard sciences	*social sciences*	*humanities*	*medical sciences*
ln(HERD_HS/L)	0.138***	0.068***	0.060**	0.076***
	(0.022)	(0.023)	(0.026)	(0.024)
ln(HERD_SS/L)	0.097***	0.148***	0.112***	0.110***
	(0.019)	(0.019)	(0.020)	(0.019)
ln(HERD_HU/L)	-0.029	-0.005	0.033	0.004
	(0.019)	(0.018)	(0.020)	(0.017)
ln(HERD_MS/L)	-0.007	-0.003	0.009	0.008
	(0.008)	(0.009)	(0.008)	(0.008)
ln(PAT/L)	0.021***	0.025***	0.021**	0.021**
	(0.008)	(0.009)	(0.009)	(0.009)
MANU_sh	-0.186	-0.092	0.109	0.028
	(0.407)	(0.406)	(0.425)	(0.420)
OPENNESS	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.001)	(0.001)	(0.000)
First stage				
ln(HERD_HS/L)_predicted	1.105***			
	(0.068)			
ln(HERD_SS/L)_predicted		1.145***		
		(0.061)		
ln(HERD_HU/L)_predicted			1.110***	
			(0.056)	
ln(HERD_MS/L)_predicted				1.054***
				(0.019)
Observations	123	123	123	123
Number of id	13	13	13	13
Angrist and Pischke F-statistics	263.72	351.43	382.13	287.4
p-value	0.000	0.000	0.000	0.000

The dependent variable is Total Factor Productivity. All models are estimated with fixed effects and they include time dummies. In Column (1) hard sciences are instrumented with the predicted values of hard sciences, in Column (2) social sciences are instrumented with the predicted values of social sciences, in Column (3) humanities are instrumented with the predicted values of humanities, In Column (4) medical sciences are instrumented with the predicted values of medical sciences.Standard errors are clustered at the country level, *** p<0.01, ** p<0.05, * p<0.1

Table 4. IV Labor Productivity

	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
	hard sciences	*social sciences*	*humanities*	*medical sciences*
ln(HERD_HS/L)	0.125***	0.070***	0.063***	0.076***
	(0.023)	(0.023)	(0.024)	(0.024)
ln(HERD_SS/L)	0.099***	0.138***	0.110***	0.109***
	(0.016)	(0.017)	(0.018)	(0.018)
ln(HERD_HU/L)	-0.032*	-0.013	0.017	-0.006
	(0.019)	(0.018)	(0.018)	(0.017)
ln(HERD_MS/L)	-0.014	-0.010	0.000	-0.001
	(0.009)	(0.009)	(0.008)	(0.007)
ln(K/L)	0.538***	0.533***	0.524***	0.519***
	(0.065)	(0.065)	(0.063)	(0.066)
ln(PAT/L)	0.017**	0.020**	0.017*	0.017*
	(0.008)	(0.009)	(0.010)	(0.010)
MANU_sh	0.298	0.365	0.494	0.439
	(0.431)	(0.452)	(0.468)	(0.464)
OPENNESS	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.001)	(0.000)	(0.000)
First stage				
ln(HERD_HS/L)_predicted	1.140***			
	(0.078)			
ln(HERD_SS/L)_predicted		1.172***		
		(0.053)		
ln(HERD_HU/L)_predicted			1.137***	
			(0.051)	
ln(HERD_MS/L)_predicted				1.075***
				(0.018)
Observations	123	123	123	123
Number of id	13	13	13	13
Angrist and Pischke F-statistics	212.7	489.54	500.4	329.8
p-value	0.000	0.000	0.000	0.000

The dependent variable is Labor Productivity. All models are estimated with fixed effects and they include time dummies. In Column (1) hard sciences are instrumented with the predicted values of hard sciences, in Column (2) social sciences are instrumented with the predicted values of social sciences, in Column (3) humanities are instrumented with the predicted values of humanities, In Column (4) medical sciences are instrumented with the predicted values of medical sciences Standard errors are clustered at the country level, *** p<0.01, ** p<0.05, * p<0.1

Table 5. The HERD equation

	HE R&D
ln(Num. of scientific journals/L)	1.192**
	(0.427)
share of international students over total students	0.105*
	(0.054)
time-dummy 1998	-0.179***
	(0.042)
time-dummy 1999	-0.168***
	(0.032)
time-dummy 2000	-0.102***
	(0.023)
time-dummy 2001	-0.015
	(0.025)
time-dummy 2002	0.019
	(0.017)
time-dummy 2003	-0.048
	(0.042)
time-dummy 2004	-0.016
	(0.036)
time-dummy 2005	-0.010
	(0.039)
time-dummy 2006	0.031
	(0.040)
time-dummy 2007	0.039
	(0.055)
Constant	13.435***
	(2.871)
Observations	122
Number of id	13
R-squared	0.746

The dependent variable is the level of expenditures in Higher Education R&D. All models are estimated with fixed effects. Standard errors are clustered at the country level, *** p<0.01, ** p<0.05, * p<0.1

APPENDIX

The source of data for the number of graduates students is: “Graduates by field of Education”, UNESCO-OECD-Eurostat (UOE) data collection on education statistics, compiled on the basis of national administrative sources, reported by Ministries of Education or National Statistical Offices. In the following tables are listed the distinct disciplines and the criteria of aggregation used in order to obtain the variables included in the regression analysis.

TABLE A.1. Disciplines and categories included in the data

Broad categories	Disciplines	Courses
HUMANITIES (HU)	*140: Education*	141: Teacher training (ISC 141)
		142: Education science (ISC 142)
	200: Humanities and Arts	210: Arts (ISC 21)
		220: Humanities (ISC 22)
SOCIAL SCIENCES (SS)	*300: Social sciences, business and law*	310: Social and behavioural science (ISC 31)
		320: Journalism and information (ISC 32)
		340: Business and administration (ISC 34)
		380: Law (ISC 38)
HARD SCIENCES (HS)	*400: Science*	420: Life sciences (ISC 42)
		440: Physical sciences (ISC 44)
		460: Mathematics and statistics (ISC 46)
		480: Computing (ISC 48)
	500: Engineering, manufacturing and construction	520: Engineering and engineering trades (ISC 52)
		540: Manufacturing and processing (ISC 54)
		580: Architecture and building (ISC 58)
MEDICAL SCIENCES (MS)	*700: Health and welfare*	720: Health (ISC 72)
		760: Social services (ISC 76)
not included	*600: Agriculture*	
	800: Services	
TOTAL	*900000: Total over all fields of study*	

Source: UNESCO-OECD-Eurostat (UOE), “Graduates by field of Education”

Description of the variable “graduates”

“Graduates are those who successfully complete an educational programme during the reference year of the data collection. One condition of a successful completion is that students should have enrolled in, and successfully completed, the final year of the corresponding educational programme, although not necessarily in the year of reference. Students who do not complete the final year of an educational programme, but later successfully complete a recognised "equivalency" examination based on knowledge learned outside of the education system, should not be counted as graduates. Successful completion is defined according to the graduation requirements established by each country: in some countries, completion occurs as a result of passing a final, curriculum-based examination or series of examinations. In other countries, completion occurs after a specific number of teaching hours has been accumulated (although completion of some or all of the course hours may also involve examinations).” (Source: UNESCO-OECD-Eurostat UOE).

TABLE A2.

List of countries included in the database

Australia	Italy
Hungary	Japan
Belgium	Spain
Czech Republic	Switzerland
France	United Kingdom
Germany	United States