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Abstract

This paper investigates the properties of knowledge production in academic research using a panel of 17 OECD countries reaching from 1989 to 1996. The production process is modelled using capital and labour as inputs and the number of published international journal articles and/or the number of graduates as outputs. First, we test for the existence of *economies of scale* in academic research. Our results give indication for decreasing returns to scale in the production of new academic knowledge. This empirical result might contribute to the recent controversy on the properties of the innovation technology used in endogenous growth models. Second, we determine efficiency scores for each individual country. For the estimation of efficiencies we apply parametric and non-parametric methods. Although results differ slightly with the method used, a stable efficiency ranking is found.

Keywords
Academic research, education, knowledge production, efficiency, endogenous growth

JEL Classifications
A1, A2

Comments

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1 Introduction

Today, economies and societies are increasingly becoming science- and knowledge-based. The continuous production of new knowledge is a precondition for the development of new products and efficiency improvement of economic processes. A major part of the total stock of knowledge in advanced economies is generated by academic research. New academic knowledge is at the interface with industrial R&D determining the rate of technological change. Academic knowledge is diffused through publishing and academic training augmenting the human capital stock. Thus, academic performance clearly constitutes a major driving force behind competitiveness and economic growth. Although there is no doubt that the contribution of knowledge to economic growth is substantial, the economic profession is still far from fully understanding the mode of production, its structure and the use of knowledge. Kirman and Dahl (1994, 1996) argue that the debate on the state and adequacy of academic research has been conducted on the basis of very few facts. While inputs to academic research are vividly discussed, little attention has yet been devoted to monitoring output patterns and assessing efficiency in science. In many countries there is an ongoing debate on the needs, role and configuration of academic science. Throughout the community of industrially advanced nations, a sense of urgency is now surrounding discussions and debates about the funding and conduct of academic science. Decision-making concerned with major public expenditure commitments in many different areas has been held in the tightening grip of fiscal restrictions. At the same time industry emerged to increasingly support and influence OECD Member countries' science systems (OECD 1996).

The goal of this paper is to empirically determine the key factors of aggregate academic knowledge production by studying the properties of the production process of national academic science systems. In this paper we shall develop answers to two questions. The first question to be examined is related to the properties of the production function of scientific knowledge. More specifically, we will test for the existence of economies of scale in academic knowledge production. Second, we will try to illustrate to what extent OECD countries differ with respect to their academic performance by empirically comparing productivity and efficiency levels.

Recent endogenous growth models have emphasised the importance of the production of knowledge and R&D for understanding long run economic growth. A key issue is the question, whether an economy undertakes too little or too much knowledge production and R&D. The assumption of constant returns to scale of the R&D technology is among the central growth generating factors in most standard endogenous growth models. In fact, the most prominent policy advice from the new growth theory is to promote growth via subsidised R&D. It should be noted, however, that this advice is subject to several qualifications (Arnold 1998). Endogenous growth models implicitly state, assuming *constant-returns-to-scale*, that doubling the input factors engaged in R&D will lead, at least in the steady state, to a doubled per capita growth rate of output (Jones 1995). Romer (1990), for example, believed that "linearity in H_A (labour input for R&D) is not important for the dynamic properties of the model, but weakening this assumption would require a more detailed specification of how income in the research sector is allocated to the participants". Later research revealed that the equilibrium analysis is analogous to Romer's believe. However, in the welfare analysis significant deviations can be observed: With diminishing returns it is no longer clear that the equilibrium growth is too slow. Young (1998) concludes that "... while the subject has yet to be analysed exhaustively, the existing empirical evidence in favour of scale effects might best be described as inconsistent".

Under such conditions in quality upgrading models (e.g. Grossman and Helpman (1991, Ch. 4) and Aghion and Howitt (1992)) a profit destruction effect dominates in equilibrium. Empirical studies testing for the decreasing returns hypothesis are still far from abundant. For example, Aghion and Howitt (1998) cite only Arroyo et al. (1994) and Kortum (1993) as empirical studies finding decreasing returns of the innovation function. They assume that this finding results from research congestion within a product. Stockey (1995), basing her results on numerical simulations, suggests that diminishing returns in the innovation technology is the most important potential source for excessive R&D in a competitive economy. In addition, decreasing returns to R&D are consistent with the Jones (1995) critique, which centres on the empirical fact that the post-war growth rate of scientists and capital engaged in R&D of almost all industrialised countries is far larger than the per capita growth rate of GNP.

Kortum (1993) reports empirical point estimates for the elasticity of the number of inventions with respect to R&D input to lie between 0.1 and 0.6, supporting the assumption of decreasing returns in R&D. Among the possible explanations for diminishing returns in industrial R&D are the "crowding" effect and exhaustion of technological opportunities as advocated by Evenson (1991). The "crowding" effect has been well studied in the patent race literature and arises by duplication of efforts in trying to exploit a limited stock of innovative ideas. We believe that similar effects are likely to take place in academic research. The standard policy conclusion to subsidise innovation must then be scrutinised. It is possible that research efforts in academia center around competition for a larger share of a relatively slower growing pie of knowledge. The attraction of additional resources by subsidised research efforts would, thus, turn out to be inefficient if the pool of new ideas cannot sufficiently be enlarged.

Let us return to our second question of efficiency and productivity levels. Although there are considerable differences in research culture and the design of science systems across OECD countries, we are able to find common patterns in both efficiency and productivity measures. Our results suggest that it is the Anglo-American countries and small open European countries with a tradition of international publications, e. g. Sweden, the Netherlands and Switzerland, that are leading. This pattern is independent of the econometric method used.

Finally, academic research is closely related to higher education. Academia not only produces new knowledge, but also through academic education contributes to rising human capital for the research sector and for the economy as a whole by increasing the ability to adopt and produce new inventions. This argument that teaching and research should not be treated separately leads us to add the education outcome, measured by the number of higher education graduates, to our analysis. OECD countries differ widely with respect to their productivities in the higher education sector, which explains relative changes in the efficiency ranking compared to the single output (publications) model.

2 Data and Models

The production of new academic knowledge is modelled by using the number of journal articles entering the SCI and the SSCI as the proxy for the academic output, and labour and capital as the respective inputs. At the outset, we assume a single equation translog production function, which is the most flexible functional production relation. Due to the nature of the data at hand (panel data) we estimate the two-way fixed effects error component model (Fix2), the two-way random effects error component model (Rdm2), and the Battese and Coelli (1992) frontier model (BC92). Efficiency estimates are computed using both non-parametric and parametric methods. Data Envelopment Analysis (DEA), the non-parametric approach, is a nonlinear ratio model, of multiple inputs and outputs, that can be converted to a linear programming problem according to Ali and Seiford (1993). The computed enveloping hull, in another terminology the 'efficient frontier', can either take the form of constant returns to scale (CRS) or variable returns to scale (VRS). The parametric models employed are stochastic frontier models due to Aigner, Lovell, and Schmidt (1977), Battese and Corra

(1977), Meeusen and van den Broeck (1977), Battese and Coelli (1992), Battese and Coelli (1995). In the fixed effects model efficiencies are treated as fixed effects, whereas in the BC92 model efficiencies are modelled to be truncated normally distributed. Both, the parametric and the non-parametric approach are capable to compute technological change. However, the continuous expansion of the analysed journal basket, which not necessarily reflects the genuine nature of the growth of new knowledge fields, would directly be interpreted as technological progress. Due to this measurement problem we decided not to further pursue this interesting feature of knowledge production. The two input factors, labour and capital, enter as averages of the past four years. This is the conjectured average time to conduct an experiment, and the time needed for analysis and publishing. The size of the country basket was determined by the availability of input data. The panel covers 17 OECD countries for the years 1989 to 1996.

The input data stem from the Main Science and Technology Indicators published by the OECD (1997). Labour and capital serve as input factors. For the academic labour input we refer to the definition in the Frascati Manual (OECD 1994) of the total number of full time equivalent researchers of government research institutes, higher education facilities, and private non-profit organisations (see OECD 1995a). To calculate the capital proxy we add 'other current' expenditures to the defined capital expenditures. 'Other current' expenditures mainly include important capital components such as computer services, administrative and other overhead, materials for laboratories (chemicals, animals ...), books and journals, purchased software, and rent for research facilities (for further details see OECD (1994)). Expenditures are in constant US$ (1990 prices and purchasing power parities (PPPs)) and refer to the same set of research organisations as discussed for the labour data. Since we average expenditures over the past four years this average can be interpreted as a capital stock proxy that is associated with the publication output.

For the calculation of efficiencies presented in table 3, where we include the education outcome as additional output, labour and capital inputs are constituted by the sum of academic research and academic education inputs. Additional labour for academic education is measured by the number of higher education teachers in full-time equivalent of public and private institutions (ISCED 5,6,7 [1]). Capital inputs for academic education were computed by combining data from the OECD

[1]Note that according to the International Standard Classification of Education level 5 is defined as education at the tertiary level, first stage, of the type that leads to an award not equivalent to a first university degree. Germany reported data for the West German education sector only.

(1995a,b) and data published by the OECD on the internet.[2] Capital inputs for academic education refer to the OECD definition of total expenditures excluding teacher compensation.

Publication data for all sciences,[3] were compiled by Felderer and Campbell (1995) for the years 1989 to 1993 and were updated to the year 1996 by own calculation using the source index of the SCI and SSCI. Publications were not weighted by their citation frequency. The geographic location of the first author of a journal article was taken as reference for the country assignment. The sample covers all major scientific journals in the world according to the SCI and SSCI. In 1989, the total number of journals covered was 5,662 and thereafter increased to 7,844 journals in 1996. In 1996, 3,674 journals were fully covered by the SCI, 2,352 journals were fully covered by the SSCI and 1,818 journals were selectively covered by the SSCI. In 1996, we counted a total number of 490,858 journal articles for the respective 17 OECD countries. The ratio of publications (published articles) in science and the social sciences can roughly be estimated to be 9:1. In English-speaking countries the share of publications in the social sciences is slightly higher.

The education outcome, as presented in table 3, measured by the number of university graduates (ISCED 6,7) graduating from public and private institutions was taken from the education statistics (OECD 1995) and the above mentioned internet site of the OECD.

Dusansky and Vernon (1998) argue that a selective yet objective measurement criterion of academic performance of economists is impact-adjusted equal apportioned pages in core journals. In our analysis, however, publications and graduates were not weighted by any impact factor such as citation frequency or university ranking. We believe that in this respect the science of sciences is still far from a consensus to provide a fair weighting method across all science fields on an international scale.

[2]The respective internet location of the data made available through the OECD education database is http:*www.oecd.org**els**stats**edu_db**edu_db.htm*.

[3]We had to consider the aggregate of all sciences to match with the aggregate inputs. This is the only level of aggregation where we can consistantly relate inputs to outputs. Although, there are input statistics on individual science fields it is currently not possible to compute the relevant outputs.

3 Empirical Findings

Economies of Scale

The probably most interesting result is the empirical finding that the international science system, represented by 17 OECD countries, exhibits decreasing returns-to-scale. Estimates of the Cobb-Douglas technology (table 2) show that the sum of the labour and capital coefficients is well below unity. This holds true for all three models (Fix2, Rdm2, BC92) used. The F-statistics of the restricted model indicate that the sum of the coefficients of the Cobb-Douglas production function is different from unity at a 1 % level of significance. The corresponding F-statistic for the two-way fixed effects model for the restriction that the sum of the labour and capital coefficients equals unity is $F(1, 109) = 48.4818$. Individual coefficients are significantly different from zero on a 1% significance level. The Cobb-Douglas specification was tested against the more flexible translog specification. The null-restrictions for the simpler Cobb-Douglas specification were accepted with the resulting F-value $F(3,106) = 1.4199$. The R^2 was over 0.99 for all three models, which is not uncommon for panel data estimations.

There are two reasons to assume the two way error component to be the adequate model. First, the hypothesis that the time-specific intercepts are different from zero, were tested by the likelihood ratio test and the F-test, which argue in favour of the two way error component model. The χ^2-statistics with 4 degrees of freedom was 141.085 (Probability value: 0.00000) and the corresponding F-statistic was $F(7,109) = 5.539$ with probability of 0.00002. Second, the journal basket was increasing and changing over time, which speaks clearly in favour of the two-way error component model. We do not believe that the change in the journal basket exhibits any systematic pattern reflecting real output change of the science systems studied. Thus, the difference in the coverage of measuring publications is captured by a time-specific intercept.

Table 2 presents the results for both the fixed and the random effects model. The Hausman test would favour the random effects model against the fixed effects model. The Hausman test value is 5.74 with a probability value of 0.0166. However, due to the asymptotic properties the Hausmann test appears not to be very informative for testing misspecification with respect to fixed and random effects model given a panel reaching over only eight periods. We therefore decided to present the result for both the fixed and the random effects error component model.

The analysis of our panel data set also involves the question of homogeneity of the coefficients of the production function across different country groups. Analysis of covariance, based on the residual sum of squares, revealed homogeneity of the Cobb-Douglas coefficients across country groups. The respective F-ratios were not significant for testing the partitioned models of English / non-English, Romance / non-Romance and Germanic / non-Germanic country groups against the non-partitioned model. This is true for the two way error component fixed and random effects model with the only exemption of the partitioned model of Romance / non-Romance using the two way error component fixed effects model. In this case the null hypothesis of parameter homogeneity was rejected at a 5% significance level, but not at a 10% level. We conclude that it is justified to use the non-partitioned model.

The estimation results of the production frontier technology using the BC92 model (table 2) confirm the results of diseconomies of scale in academic research. It is important to note that it is not only the 'average production technology' that displays decreasing returns-to-scale, but also the 'best practice' or benchmark production frontier.

Average Productivities

There are considerable differences in the productivity ranking between OECD countries. This can be seen from the average capital and labour productivities in table 1. In terms of labour productivity the United States lead before the United Kingdom and Switzerland, whereas Ireland and Switzerland show the highest capital productivities. Large continental European countries like France, Italy and Germany are placed in the lower third. Interestingly, due to their large per capita capital expenditures, the United States show a rather low capital productivity. Japan and Portugal can consistently be ranked lowest for both labour and capital productivity. Differences in capital productivity are, however, also driven by differences in the structure of expenditures. For instance, in Austria 17% of the total expenditures are due to expenditures for buildings and houses, whereas in Italy the respective reading only amounts to 3% in 1989.

There is a positive relationship between labour productivity and the capital-labour ratio. When we regress the capital-labour ratio in a two-way error component model on labour productivity the resulting coefficient is strictly positive on a 1 % significance level with a $R^2 > .99$. This suggests that high labour productivity can only be sustained by increasing capital inputs per researcher.

Efficiencies

The notion of efficiency used here can briefly be described as the difference between the benchmark input-output relation defined by the computed production frontier surface and the actual input-output relation of each individual country. Efficiency in this case can equally be interpreted as total factor productivity with a non-constant returns to scale potential technology. Comparing estimates of efficiency across different methods indicates relatively small changes in efficiency rankings (figure 1). The correlation among computed efficiency scores is high suggesting that the different models construct similar benchmark technologies and, thus, efficiencies are comparable across methods. From figure 1 we also see that the United States, United Kingdom, Sweden and Switzerland are consistently above average efficiency. Within the Romance countries Spain is leading whereas France and Italy seem to be almost equally less efficient. Within Scandinavian countries, Sweden is above the OECD average, whereas Finland is on the average, and Norway below the average in the efficiency ranking. Portugal, across all models used, is the least efficient of all OECD countries. Japan, the second largest academic R&D country in our sample, is consistently the second most inefficient science country in our sample.

Changes in the efficiency ranking, among the different models used, are due to differences in the construction of the production frontier. The fact that efficiency scores of the parametric and the non-parametric estimation are highly correlated, suggests that the efficient hull constructed by DEA must be similar to the production frontier estimated by the Battese and Coelli (1992) (BC92) model and the two-way error component fixed effects model. Efficiency estimates from the DEA are on average higher than those of the parametric models. This is due to the fact that the efficient frontier constructed by the DEA more closely envelops the input-output data. France, Germany, Japan, Italy and Portugal show, on a relative scale, smaller DEA efficiencies than the remaining countries. This is related to the fact that capital productivity played a greater role in the DEA estimation. In the CRS case, for example, 75% of all countries were compared to a linear combination of Ireland and Switzerland, which are leading in terms of capital productivity as can be seen from table 1.

Table 3 shows the results of the efficiency model where two outputs and two inputs were used.[4] The introduction of university education – by including the number of university teachers and capital devoted to the higher education sector as ad-

[4]Due to data limitations we only performed the analysis of the education sector for the year 1992 and did not estimate a separate education production function.

ditional inputs and the number of university graduates as the additional output – changes the relative positions of the countries analysed only to a small extent. Spain and Japan, due to their high capital productivity in the higher education sector, become relatively more efficient using the model with two outputs. Productivities in education measured in graduates per capital unit or graduates per teachers widely differ across OECD countries. The United Kingdom is the most capital and labour productive country in the higher education sector. German speaking countries and Nordic countries rank lowest in terms of capital productivities. However, within this country group Denmark and Switzerland are highly productive in terms of labour productivity in academic education.

4 Comments

Our research goals have been to compile consistent data in order to assess the efficiency of academic research and study the properties of academic knowledge production across OECD countries. Estimation results can only be validated by a comparison of the results gained from different methods. Kumbhakar et al. (1997) note that issues of model specification and selection of various specification forms are rarely emphasised in the empirical literature on the estimation of production frontiers using panel data. This critique is taken into account and different approaches are compared, in order to derive estimates of the production technology and efficiency scores.

Although there seems to be a common production function for the countries analysed, countries do differ remarkably in their scientific performance as measured by their efficiency. The geography and cultural pattern of academic activities are anything but homogenous. The variance in scientific performance across developed countries reflects profound differences in national innovation systems (Archibugi and Pianta 1992). Thus, what we label as inefficiency might to some extent also incorporate other elements than just technical inefficiency.

Such "other" elements of efficiency might be related to the way the production process of academic science is modelled. We decided to model the academic research system as a production process, where R&D factor inputs are converted into new scientific knowledge and graduates from the higher education sector. The selection of input and output variables defining this particular production process is crucial for the analysis. While input factors can clearly be identified, the measurement of new scientific knowledge on the other hand has been discussed for a long time. Scientific and technical knowledge has traditionally been validated and distributed through publishing. Happily, from the point of view of developing indicators, publishing leaves a long-lived paper trail that can be used as a proxy for the stock of knowledge (Hicks and Katz 1996). Plausible and generally accepted methods of measuring the production, circulation, and utilisation of scientific knowledge became available only thirty years ago with the invention by Eugene Garfield of the so-called citation indices (Leontief 1993). The authors of this article came to the conclusion that given the underlying research goal, new knowledge can best be captured by the number of publications in major international journals. It is this international journal market where competition of scientific ideas at a global scale becomes apparent. We are aware that the number of journal articles entering the SCI and SSCI (Science Citation Index and Social Sciences Citation Index) is not an exact mapping of the research output at the national level, however, it seems to be a fair measure for transnational comparison. So for example the European Commission (1994) comes to the conclusion that "indicators based on the SCI and SSCI database are likely to provide a well-balanced macro indication of the international performance of a country's scientific community".

A number of features of a nation's science system may account for differences in efficiencies. Some are related to the functioning of the science system *per se* and others are related to inevitable biases due to the way the production process is organised. The following we find worth mentioning:

- The reward system.
- Goal functions of research funds.
- Language barriers.
- The structure of the research system.
- Scientific clubs.
- The presentation of new scientific knowledge in other media.
- Higher education systems.

Taking reference to the first point, we have to consider that scientific performance of research in Anglo-American countries is mainly measured by the number of journal articles in prominent journals. Salary, reputation and career possibilities depend heavily on this measure. In many Continental European countries criteria are somewhat different and generally more soft. It can be argued that in the latter country group international scientific output of a researcher is not as important, which leads to inefficiencies in the sense used above. Parallel to the question of the publication maximising behaviour of researchers we also have to ask whether research managers do compete for cost leadership i. e. configure research such that publications are produced at lowest input levels, as implicitly assumed by the model. Clearly, since early delivery of results and creation of new ideas are the most important determinants for success in academia, the most modern and capital intensive equipment will most readily yield scientific breakthrough, which implies a tendency to an excessive increase in costs. Input minimisation is in many cases not rewarded at the individual laboratory level. However, balanced cost-benefit considerations seem to be important for the aggregate academic science system.

There are large differences between OECD countries' views and goals on how academic science should be conducted and how results should be disseminated. Funds financing academic research not always intend to maximise the number of journal articles, which finally enter the SCI and SSCI. Japan, which in its publication behaviour followed more an isolationist strategy, is the first country to ask this question. Another question related to the funding of the research system is that in English-speaking countries the share of academic research financed by business is larger. Industry inputs contributing to publication output were, however, not included in our analysis. In the US for example, 8% of all scientific and technical articles stem from industry in 1993 (NSF 1996). It is almost impossible to correct for these measurement errors, nor can we proof that they are of the same magnitude across countries.

Language and the composition of the journal basket might favour certain countries. Most international journals are issued in English, which could still give a comparative advantage to the English speaking researchers. Top researchers as a rule will place their articles in journals where the visibility is highest. As the number of journals an academic researcher can survey or read is limited to a small fraction of all relevant journals and articles, (s)he will tend to read articles of the most prominent and influential scientists first. Today, a large fraction of the articles of the most prominent researchers appear in the Anglo-American journal market, which favours native speakers. However, the scientific journals sampled for our investigation were not only issued in English and were selected upon criteria of their international impact measured by their citation frequency. The English language has been and is still increasingly becoming the dominant medium for the exchange of academic knowledge. Thus, poor knowledge of English can directly result in inefficiency.

In our analysis we implicitly assume that the aggregate science systems are comparable. This is also justified by our test for homogeneity of the aggregate science systems. However, research systems of OECD countries differ according to their composition of science fields.[5] Thus, efficiency as measured by our models might also capture the effect of different compositions of the science fields in each country, which results in *a priory* differences in the productivity levels. The Anglo-American dominance is much weaker in science fields, which are generally more input-intensive, than in the social sciences. Taking into account the rather small share of the social sciences, one-tenth of all publications, this effect is, however, of minor importance. Interestingly, the composition of science fields seems to have an influence on economic growth. Murphy et al. (1991) provide evidence that countries with a higher proportion of engineering college majors grow faster; whereas countries with a higher proportion of law concentrators grow more slowly. If we were to relate efficiency in academia to a country's economic performance, we would have to take this factor into account. However, without formally testing we assume, that mismeasurement due to differences in the composition of science fields even out in the aggregation.

The study of citation networks of both articles and journals has become routine (Hummon and Dorleian 1989). The existence of informal scientific clubs facilitate the acceptance of journal articles for club members. Certain research topics or strategies are more acceptable to certain clubs publishing in certain journals. In the case of economics, Elliot et al. (1998) show that North American and affiliated authors clearly dominate North-American journals, whereas European journals are less dominated by European economists. We consider networking capabilities as vital ingredients of a country's competitiveness in academia, although there is still room to make the international science market more open and transparent to give equal opportunities to all participants.

Article counts are one indication of the sheer volume of scientific output on a country level. As already mentioned, these counts can only to a limited extent be interpreted as a comparative indicator of scientific output. Indirectly, they might also illustrate specific publishing conventions and national differences in scientific publishing practices. A good example for this are the German-speaking countries, where the scientific output traditionally and on a relative scale more often is reported in form of books, monographs and *Festschriften* and not in the form of less comprehensive journal articles. However, in many disciplines publishing conventions are similar across countries (e. g. historians rather tend to write books), which might allow for the conclusion that this bias is of minor importance. In addition, there is a clear tendency across all sciences to use articles

[5]For a detailed description of compositional differences see European Commission (1994) and the NSF (1996).

as the major means to publish and distribute *new* scientific knowledge.

When we include teaching in our analysis, we unintentionally model the effects of different university education systems. OECD countries are still very different with regard to their higher education systems (see e. g. OECD (1992)). Inefficiencies with respect to the education system mainly arise due to differences in the intensity of education (teachers per student), to general differences in the set-up of university curricula and to the drop-out rate. The latter is especially high in German-speaking countries, which show the lowest productivities in education. In this case, what we measure is the true inefficiency of the education system.

5 Conclusion

Taking reference to recent theories of economic growth, this study brings forth empirical evidence for decreasing returns to scale in academic science. There are a number of ways to interpret the finding of decreasing returns to scale in the production of scientific publications. The first line of reasoning to explain decreasing returns to scale refers to networking capabilities of academia in different countries. It might be that a relatively important share of academic researchers of large science countries concentrate more on the domestic market and thus do not benefit from international networking externalities and of a potential size (scale) effect of an international journal market. This can be due to the peculiarities of the incentive system of a more closed cultural market of large science systems. Contrarily, science systems of small countries seem to be more open towards international exchange and competition in the science market, as they can be shown to behave in other markets. Durden and Perri (1995) show that co-authorship in economics enhances productivity in total and per-capita article production supporting the argument that the degree of openness in research leads to productivity improvement.

The second way of reasoning, which is input-oriented, might explain the inefficient functioning of the science apparatus by arguing that fewer talented people are attracted to science with increasing size of the science apparatus. However, we did not find strong correlations between efficiency or labour productivity and the share of researchers in the working force of the OECD countries analysed.

It appears more reasonable to assume that an increasingly complex configuration of large science systems explains diseconomies of scale. This might on the one hand be due to inefficiencies in the interaction of factors of production, including knowledge spillovers within and between science fields, of large science systems caused by organisational deficiencies. Such organisational deficiencies might be rooted in the more centralised research systems of large science countries. According to John Goddard (SCIENCE 1998), a more decentralised research landscape might bolster industry in outlying regions and a more even distribution might provide bigger benefits to the economy as a whole. Large science systems, of countries such as Japan, France and Germany, are governed by less adaptive centralised institutions. Strong institutional inertia of such large research systems and outdated incentive schemes, featured in part by a low level of creative destruction of unsustainable scientific paradigms and a lower rate of adoption of new ideas and methods, might explain decreasing returns. Unfortunately, our data structure does not allow for the estimation of features such as a rate of creative destruction in academic research, as Caballero and Jaffe (1993) computed for industrial R&D.

Third, as already mentioned, diminishing returns can arise due to congestion and invention exhaustion in academic research. The interesting implication here is that under such conditions the aggregate probability of success is a strictly concave function of the aggregate resources in knowledge production in a competitive environment, so the average effectiveness exceeds the marginal, and the market is biased toward excessive input levels (Stockey 1995). However, it is this competitive environment that spurs inventions and innovation, which justifies the existence of several independent research programs working at the same problem at a time. The existence of several independent programs can, however, also be interpreted as using an increased variety of technologies (e.g. increase in number and types of AIDS therapies), which increases the utility of the consumers of scientific outcomes. Young (1998), shows that continued improvement of increased variety of technologies requires increased research input, a rise in the scale of the market could raise the equilibrium quantity of R&D without increasing the economy's growth rate.

There is one final conclusion still to be made that more empirical research will have to be conducted with richer and more disaggregated data to further examine the validity of our results and with the aim to give more informed judgement on the patterns and processes of academic R&D and its contribution to economic growth.

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Table 1: **Publication productivities and capital labour ratio***

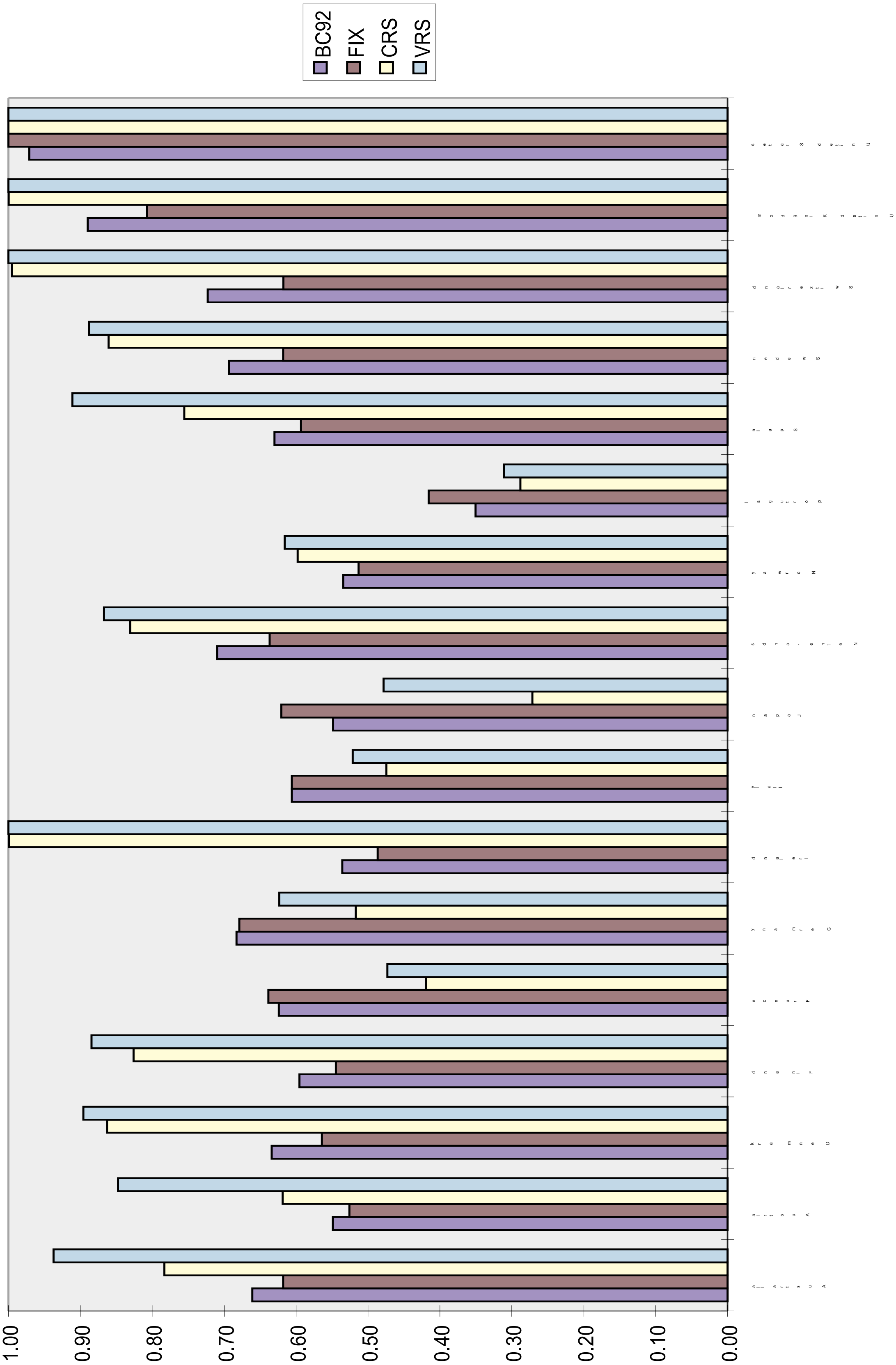
	P/L	P/K	K/L
Australia	0.39	14.35	27.26
Austria	0.64	6.57	96.94
Denmark	0.62	14.29	43.50
Finland	0.46	14.86	30.67
France	0.39	6.07	64.44
Germany	0.43	8.10	52.87
Ireland	0.37	20.44	18.13
Italy	0.36	7.96	45.58
Japan	0.17	4.66	37.33
Netherlands	0.68	13.28	51.43
Norway	0.42	9.97	41.95
Portugal	0.13	5.45	24.24
Spain	0.37	14.51	25.25
Sweden	0.70	13.36	52.27
Switzerland	0.93	16.00	57.83
United Kingdom	0.96	14.74	64.93
United States	1.12	8.03	139.55

* Productivities are defined as the ratio of the number of publications per researcher (P/L), and number of publications per '000.000' US $ PPP capital expenditure (P/K) respectively. The capital-labour ratio, K/L, is defined as '000' US $ PPP capital expenditure per researcher. Source: Felderer and Campbell (1995), Source Index of SCI and SSCI Index and own calculation (1998), OECD (1997).

Table 2: **Cobb-Douglas parameter estimates of the Fix2, Rdm2, and the BC92 model. Values in parenthesis are standard deviations**

	Fix2	Rdm2	BC92
Labor	0.3138	0.4367	0.3976
	(0.0726)	(0.0641)	(0.3541)
Capital	0.2419	0.3443	0.3571
	(0.0602)	(0.0557)	(0.2638)
Constant	1.9184	1.0826	1.6774
	(0.2621)	(1.0826)	(0.8728)

Figure 1: **Efficiency scores computed by the BC92, Fix2, CRS, and the VRS model**



Source: Felderer and Campbell (1995), Source Index of SCI and SSCI Index and own calculation (1998), OECD (1997).

Table 3: **CRS and VRS efficiency scores with number of publications and the number of university graduates as output variables for the year 1992 (Peer groups are indicated by P1, P2, and P3)**

	ID	Graduates	Publications	Labor	Capital	CRS	P1	P2	VRS	P1	P2	P3
Australia	1	110414	12690	83994.5	4928.8	0.698628062	13	16	0.699131783	7	13	16
Austria	2	11912	3279	19754.3	1315.2	0.507636245	16	0	0.651291328	7	16	0
Denmark	3	22909	4251	11993.3	1218.4	0.807503256	16	0	1	3	0	0
Finland	4	14648	3626	58640	1146.9	0.643732246	16	0	0.867370544	7	16	0
France	5	167000	27675	171217	14802.6	0.429829109	13	16	0.531668233	16	17	0
Germany	6	171941	36892	229154	17524.8	0.428629594	16	0	0.596733837	16	17	0
Ireland	7	12870	1047	8483.8	529.5	0.775980667	13	16	1	7	0	0
Italy	8	111702	16376	88558.7	8401	0.533220177	16	0	0.535890431	3	16	0
Japan	9	477519	45159	522090.3	28142.1	0.496077884	13	16	0.98245956	16	17	0
Netherlands	10	71159	11674	48277	4236.4	0.64473909	13	16	0.657652184	7	13	16
Norway	11	11765	2773	13650	1008.5	0.559856842	16	0	0.797288517	7	16	0
Portugal	12	12726	756	20570	814.5	0.420771007	13	0	0.528712834	7	13	0
Spain	13	136154	10189	77448.8	3666.7	1	13	0	1	13	0	0
Sweden	14	18460	8673	32393	2182.8	0.80901842	16	0	0.918955563	7	16	0
Switzerland	15	12211	6988	14336.5	2087.3	1	15	0	1	15	0	0
United Kingdom	16	252284	49144	106651.4	10006.3	1	16	0	1	16	0	0
United States	17	1508385	213487	843026	107458.2	0.756394007	16	0	1	17	0	0

Source: Felderer and Campbell (1995), Source Index of SCI and SSCI Index and own calculation (1998), OECD (1997), OECD (1995b,c).

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