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Within- and between-department variability in individual productivity: the case of economics

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Abstract In the social sciences, university departments are the governance units where the demand for and the supply of researchers interact. As a first step towards a formal model of this process, this paper investigates the characteristics of productivity distributions in a unique dataset consisting of 2,530 faculty members with at least one publication who were working in the 81 top world Economics departments in 2007. Individual productivity is measured in two ways: as the number of publications up to 2007, and as a quality index that weights differently the articles published in four journal equivalent classes. The academic age of individuals, measured as the number of years since obtaining a Ph.D. up to 2007, is used to measure productivity per year. Independently of the two productivity measures, and both before and after age normalization, the five main findings of the paper are the following. Firstly, individuals within each department have very different productivities. Secondly, there is not a single pattern of productivity inequality and skewness at the department level. On the contrary, productivity distributions are very different across departments. Thirdly, the effect on overall productivity inequality of differences in productivity distributions between departments is greater than the analogous effect in other contexts. Fourth, to a large extent, this effect on overall productivity inequality is accounted for by scale factors well captured by departments' mean productivities. Fifth, this high degree of departmental heterogeneity is found to be compatible with greater homogeneity across the members of a partition of the sample into seven countries and a residual category.

Keywords Scientific productivity distributions · Within- and between-group variability · Economics departments · Academic age

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Introduction

Together with citation distributions for individual publications at different levels of aggregation, there are two types of research units whose performance is usually investigated in one or several scientific fields: individuals, and larger units such as universities or entire countries. There is a great deal of information on citation distributions for individual publications in many scientific fields. On the other hand, since Lotka's (1926) seminal contribution, there is a large literature concerning the characteristics of individual productivity distributions (Alvarado 2012, in Spanish, counts 651 publications from that date up to 2010). Similarly, together with the bibliometric literature on international comparisons of citation impact, there are useful world rankings of research institutions at the university or country level (see *inter alia* the *CWTS Leiden Ranking*, www.leidenranking.com, and the *SCImago Institutions Ranking*, www.scimagoir.com).

All of the above is possible because the information about the journal, the scientific field, and the author(s) of individual publications, as well as the university or the country where the authors work is readily available. However, the information about the university departments (or research institutes) to which scientists belong is harder to find (van Raan 2005). Nevertheless, the empirical literature concerning universities' efficiency, productivity, and organizational structure has been largely focused at the departmental level.[1] On our part, we are interested in this organizational level because, in the social sciences, university departments are the governance units where the demand for and the supply of researchers determine an equilibrium allocation of scholars to institutions. This paper uses a unique dataset consisting of all individuals working in 2007 in the top 81 Economics departments worldwide according to the Econphd (2004) university ranking.[2]

The matching of individuals and departments takes place under different institutional scenarios in different countries of the world. There are countries where hiring and promotion procedures are essentially guided by meritocratic practices and competitive market forces. In other countries with a strong public sector that follows peculiar and less flexible hiring and promotion procedures, meritocratic and competitive forces may play a lesser role in determining the final outcomes. We shall assume for the sake of the argument that the allocation of individuals to departments actually observed in our sample approximates an equilibrium outcome of a complex process that we will not model explicitly here. Instead, in this paper we start by raising the following two basic questions.

1. Do faculty members in a given department all have similar productivities around the department mean? Otherwise, are individual productivities normally distributed, or do they exhibit the high skewness (and productivity inequality) found in the previous literature on individual productivity distributions at the field level? (See Ruiz-Castillo and Costas 2014, for a recent investigation concerning the productivity of 17.2 million authors in 30 broad fields).
2. Even if department productivity distributions are not uniform, are they as similar across departments as found in other contexts in the previous literature? (For

[1] See Biglan (1973) for an early contribution to department differences in social structure and output within a single university, as well as Agasisti et al. (2012) and the references cited there for the literature on efficiency differences between departments in a single and several universities.

[2] As pointed our in van Raan (2006a, b, 2008), the *research group*—defined by the internal structure of universities, research institutions, and research and development laboratories of companies—is the more important working floor entity in the natural sciences and the medical research fields. This is not the case in Economics, where the university department is the key organizational unit.

individual productivity distributions across broad scientific fields, see Ruiz-Castillo and Costas 2014. For citation distributions at different aggregation levels, see Radicchi et al. 2008; Albarrán and Ruiz-Castillo 2011; Albarrán et al. 2011; Li et al. 2013).

Naturally, in the absence of a formal model for the labor market in the entire field, it is not easy to come up with sensible conjectures concerning the answers to these questions. As a first move in this direction, this paper studies empirically these two issues for our dataset of 81 departments in the field of Economics. In addition, in order to learn some more about the importance of productivity differences between departments, we ask the following two questions.

3. How does the effect on overall productivity inequality attributable to productivity differences across departments compare with the analogous effects in other contexts? (For the effect on overall citation inequality attributable to differences in production and citation practices across scientific fields, see Crespo et al. 2013, 2014; Li et al. 2013; Li and Ruiz-Castillo 2013; Waltman and Van Eck 2013; Ruiz-Castillo 2014. For the analogous effect attributable to differences in citation impact across countries in certain fields, see Albarrán et al. 2013).
4. Independently of the answer to the previous question, up to what point can the productivity differences between departments be accounted for by a mere scale factor captured by department mean productivities? Or, in other words, to what extent is the effect on overall productivity inequality reduced when we normalize individual productivities in each department using the department mean productivity as the normalization factor?

In order to answer these questions, we must confront two difficulties. Firstly, the characteristics of productivity distributions will typically depend on how we define individual productivity. The information in our dataset restricts us to measuring individual productivity in two ways: as the number of publications until 2007, and as a quality index that weights differently the articles published in four journal equivalent classes. As will be presently seen, the two productivity measures order individuals and departments quite differently. However, since the answers to the above questions are similar for the two measures, in this paper we focus on the quality index, but report on the robustness of the results to the measurement of productivity as the raw number of publications per person.

Secondly, since Lotka's (1926) contribution, individual productivity datasets typically consist of a cross-section of researchers of different ages observed during a given period of time. However, there is evidence concerning the non-linear relationship between researchers' productivity and age (see the references in "The impact of age on productivity" section below). Therefore, it is quite clear that the productivity of two scientists of different ages in a given field is, in principle, non-comparable. Fortunately, our dataset has information on individual researchers' academic age, that is, the number of years since the completion of a Ph.D. up to 2007. This makes it possible to investigate how the following features are altered when we consider individual productivity per year: the ranking of Economics departments, the within-department variability in individual productivity, the between-department variability in productivity distributions, the impact on overall productivity inequality due to productivity differences between departments, the reduction of this effect after using mean department productivities as normalization factors, and the characteristics of the individual productivity distribution for the population as a whole.

The remainder of this paper consists of five Sections. The second section motivates the research questions. The third section presents the data, the productivity measures, the impact of age on productivity, the characteristics of the productivity distributions that will be investigated at all aggregate levels, and a measurement framework for estimating the effect on overall productivity inequality of productivity differences across departments. Using the quality index to measure individual productivity, the fourth section studies the characteristics of the productivity distribution for the population as a whole, and answers questions 1–4 for the partition of the population into departments before and after age normalization. This section also studies the robustness of the results concerning the between-department variability after age normalization when the attention is restricted to the US universities, and the departments with at least 25 faculty members. The fifth section summarizes the evidence on the robustness of our results when individual productivity is measured as the un-weighted number of publications per person. Finally, the sixth section discusses the main results of the paper, including the analysis of country productivity distributions, and suggests some extensions.

The motivation of the research questions

As already indicated, this paper is mainly concerned with the characteristics of university department productivity distributions in the field of Economics. The matching of individuals and departments takes place under different institutional arrangements in different countries of the world. Consider first countries where hiring and promotion procedures are essentially guided by meritocratic practices and competitive market forces. Let us think, for example, of the US and, to a large extent, Canada or the UK. The demand side for first job contracts consists of a set of departments initially ordered in terms of a number of observable variables, such as research performance, wages, research facilities, geographic location, and prestige. In every department, job offers are not tended at random among all recent Ph.Ds. On the contrary, self-selection from the supply side strongly affects the workings of this market. Taking into account a number of personal characteristics, such as the university where she graduates, the adviser and the other faculty members writing her recommendation letters, and the characteristics of her dissertation and job market paper, each recent Ph.D. applies to the highest ranked sub-set of departments where she thinks she has a chance of being hired. In this way, search costs are economized: each department can focus their attention on its set of self-selected candidates. Taking into account department needs, the credentials supplied by each individual in this pool of self-selected candidates, as well as the results of interviews and seminars, each department makes a set of offers among this subset of prospective candidates. Some offers are eventually accepted by some Ph.Ds in all departments every year.

This process reveals a good deal of information to all parties concerned. The self-selection acting from the supply side of the market facilitates an efficient matching between applicants and departments. Nevertheless, strong doses of uncertainty still hang over the outcomes in this annual market. Not even the young participants are at all sure about their long-run “quality”, and hence it is not obvious to anyone whether each recent Ph.D. has been assigned to the “right” department. The tenure process serves to dispel some of these uncertainties. After a careful review, tenure is offered in each department to some of the individuals on tenure-track after a maximum period of, say, 6 years. In parallel, mobility across departments of more senior people in response to meritocratic and competitive market forces provides another adjustment mechanism. Some scholars move towards better departments, and others move in the opposite direction. In the absence of new elements—such as substantial variations in departments' total resources—this complex process can be conjectured to reproduce the initial department ranking.

In other non Anglo-Saxon countries, where less flexible public sector hiring and promotion practices are in place, meritocratic and competitive forces may play a lesser role in determining final outcomes. Nevertheless, in a cross-section of world elite departments in a given field dominated by Anglo-Saxon institutions, as we have in this paper, we can assume for the sake of the argument that our sample does approximately capture some stationary equilibrium allocation of individuals to departments.

Be it as it may, this paper contributes to the formulation of a demand and supply equilibrium model for researchers by investigating two key stylized facts for our set of elite world Economics departments in 2007: the within- and between-department variability of several characteristics of productivity distributions, namely, the empirical questions 1 and 2 raised in the Introduction. Additionally, using a measuring framework already applied in related contexts, we also study the effect on overall productivity inequality that can be attributed to productivity differences between departments before and after the normalization of productivity distributions using mean department productivities as normalization factors.

The data, productivity measures, impact of age on productivity, and measurement issues

The data

In this sub-section, we briefly describe a dataset that was originally constructed to study the elite in Economics (see Albarrán et al. 2014a), consisting of individuals in the top 81 departments in the world according to the Econphd (2004) university ranking. This ranking takes into account the publications in 1993–2003 in the top 63 Economics journals in the Kalaitzidakis et al. (2003) weighted journal ranking, where the weights reflect journal citation counts adjusted for factors such as the annual number of pages and the age of the journal (for further methodological details, see Econphd 2004).[3]

Searching in the 81 departmental web pages in 2007, we found a total of 2,755 economists. The minimum information we require for each individual includes the nationality, the University where the Ph.D. is obtained, the age, and the publications in the periodical literature up to 2007. The information concerning the country of birth is seldom available. Therefore, we generally assign the nationality in terms of the country where each individual obtains a B.A. or an equivalent first College degree. Similarly, since people's age is not generally available we use the academic age, namely, the number of years elapsed from the Ph.D. (or equivalent degree) up to 2007. We could not find information about a person's education and/or publications in 50 cases. Therefore, the initial sample consists of only 2,705 economists.

We take the information available in Internet (personal web pages, *RePEc*, *Publish or Perish*, etc.) concerning the publications until 2007 of these 2,705 people. Out of the 2,705 economists in our dataset, there are 175 faculty members without any publications at all

[3] We have compared this list with the first 81 economics departments listed in three other equally acceptable university rankings. The main conclusion is that, apart from differences in the order in which each institution appears in the various rankings, our list has between 70 and 73 departments in common with each of the three other lists (see Albarrán et al. 2014a for further details).

(typically because they are on tenure track). In line with the previous literature on individual productivity, in the sequel we focus on the remaining 2,530 faculty members with at least one publication that constitute what we call the population as a whole.

The two productivity measures

Because of budgetary restrictions, our information suffers from two limitations. Firstly, the article count in our dataset made no distinction between single and multiple-authorship. Consequently, no correction for co-authorship could be implemented. Secondly, although we know the journal where each article is published, it was impossible to search for the citation impact achieved by every article. Therefore, we are constrained to measuring individual productivity in two ways: by means of the number of publications per person, and by means of a quality index that weights the number of articles published by each author in four journal equivalent classes. The first three classes consist of 5, 34, and 47 journals, respectively, while the fourth consists of all other journals in the periodical literature. The four classes are assigned weights equal to 40, 15, 7, and 1 point, respectively (see Albarrán et al. 2014a, for further details concerning the construction of this index). We denote the two productivity distributions by P and Q, respectively.

Given that we focus on the economists working in 2007 in 81 top world departments, it is not surprising that we are working with a very productive sample (to save space, see the evidence provided in the Working Paper version of this article, Perianes-Rodriguez and Ruiz-Castillo 2014—hereafter PRRC). On the other hand, the correlation coefficient between the distributions P and Q at the individual and department level is 0.79. However, in PRRC we probe into the consequences of adopting each of the two productivity measures for the ordering of individuals and departments. For that purpose, we take into account two aspects: the re-rankings when going from distribution P to distribution Q, and the differences in absolute value between the relative positions of individuals and departments that occur in such a move. The conclusion is that the ordering of individuals and departments according to the two productivity definitions is very different indeed. The weighting of each author's articles according to the journal class where they have been published represents a dramatically different way of assessing individual and departmental productivity (for a summary of results, see Table 3 in PRRC). However, as advanced in the Introduction, in what follows we focus on the quality index, postponing to the fifth section the study of the robustness of the results to the measurement of productivity as the raw number of publications per person.

The impact of age on productivity

Human capital models suggest a humped-shaped progression of individual research productivity with academic age because the stock of human capital needs to be built up at the beginning of the career while, due to the finiteness of life, no new investment offsets depreciation and net investment declines (eventually) over time (see Diamond 1984, as well as the references in note 9 in PRRC). Consequently, the productivity of two scientists of different ages in a given field is, in principle, non-comparable. One convenient way of assessing the impact of age on productivity is by computing mean productivity and productivity variability by cohorts of people with different academic ages. Table 1 presents the results for ten cohorts.

Four points should be emphasized. Firstly, the way mean productivity by cohort evolves as academic age increases essentially coincides with previous results. Mean productivity

Table 1 Number of individuals, mean age, average productivity, and coefficient of variation (CV) by cohort for productivity distributions Q, and Q/Age

Academic age[a]	No. of people	Mean age	Distribution Q		Distribution Q/Age	
			Mean	CV	Mean	CV
	(1)	(2)	(3)	(4)	(5)	(6)
I. 1–7	517	4.6	51.9	1.17	11.8	1.08
II. 8–11	303	9.4	130.1	0.80	13.8	0.81
III. 12–15	260	13.5	203.1	0.86	15.1	0.87
IV. 16–19	251	17.3	300.4	0.78	17.5	0.80
V. 20–23	255	21.4	385.5	0.85	18.0	0.85
VI. 24–27	211	25.5	461.7	0.91	18.1	0.91
VII. 28–31	208	29.4	402.7	0.93	13.7	0.92
VIII. 32–35	204	33.4	481.8	0.97	14.4	0.97
IX. 36–39	163	37.5	507.1	0.92	13.5	0.91
X. >40	158	45.3	776.0	1.03	17.0	1.02
Total	2,530	19.8	307.3	1.30	14.9	0.93

[a] Number of years from Ph.D. until 2007

increases until it reaches the population average within cohort IV, after 16–19 years since obtaining a Ph.D., and then keeps increasing until the last cohort except for an anomalous reduction in cohort VII (see column 3 in Table 1). Secondly, large within-cohort variations give rise to high coefficients of variation ranging from 0.78 to 1.17 (column 4 in Table 1). Thirdly, normalization by age generates a fundamental change: mean productivity becomes very similar in each cohort (see column 5). Mean productivity for the population is 14.9 points, equivalent to a publication in class B per year. Mean productivity by cohort smoothly evolves from 11.8 in cohort I to 17.5–18.1 points per year in cohorts IV–VI, and then declines towards 13.5 in cohort IX. The mean productivity in cohort X, which includes very productive individuals, is 17.0. Fourth, the within-cohort variation, measured by the coefficient of variation, is still very high in all cohorts, and of the same order of magnitude as the within-cohort productivity inequality before age normalization (see column 6).

The above results explain the reduction of the correlation coefficient between distribution Q and age, which is 0.50, down to essentially zero between distribution Q/Age and age. Next, we should ask: what types of changes in the ordering of individuals and departments are generated by age normalization? The correlation coefficient between distributions Q and Q/Age is positive but relatively small: 0.50 and 0.44 at the individual and the department level, respectively. We comment separately on the impact of age normalization on individuals and departments (for more detailed results, see Table 5 in PRRC).

Firstly, it is observed that individuals are very much affected: more than 50 % of all individuals experience re-rankings of more than 250 positions, and almost 60 % of them experience changes in the relative indicators of productivity >0.20.

Secondly, although departments are much less affected, differences are still very large. Although the following tables are constructed for other purposes that will be discussed below, the 81 departments appear ordered by mean productivity of distributions Q and Q/Age in Tables 5 and 6 in the Appendix. Thus, the interested reader can observe on her own the individual re-rankings that take place. However, any attempt to explaining such re-rankings are beyond the scope of this paper. We must limit ourselves to the following descriptive summary: as many as 45 out of the 81 departments experience re-rankings greater than four positions, while 41 departments experience changes in the relative indicator of productivity greater than 0.10 (for further details at the department level, see Table B in the Appendix in PRRC).

The measurement of individual variability within productivity distributions

Departments are expected to be rather different in size, measured by the number of faculty members with at least one publication, as well as in mean productivity, measured by the mean of the quality index before and after age normalization. Therefore, we should focus on the shape of department productivity distributions abstracting from size and scale differences across them.

Two characteristics will be investigated: the inequality and the skewness of productivity distributions. As far as the measurement of productivity inequality is concerned, we use the coefficient of variation (CV hereafter), a well-known size- and scale-independent inequality index. In turn, the skewness of productivity distributions is assessed following two complementary approaches.

In the first place, we summarize the skewness of productivity distributions with a single scalar. The problem, of course, is that extreme observations of individuals with a very large productivity are known to be prevalent in productivity distributions in all fields (see *inter alia* Ruiz-Castillo and Costas 2014). This presents a challenge for conventional measures of skewness that are very sensitive to outliers.[4] Fortunately, robust measures of skewness based on quartiles have been developed in the statistics literature. Among the size- and scale-independent measures that are also robust to extreme observations, in this paper we use the one suggested by Groeneveld and Meeden (1984).[5] Given a process $\{y_t\}$, $t = 1,\ldots, T$, where the y_t's are independent and identically distributed with a cumulative distribution function F, the Groeneveld and Meeden robust measure, denoted GM, is defined as

$$\mathrm{GM} = (\mu - \Theta_2)/E|y_t - \Theta_2|, \tag{1}$$

where $\Theta_2 = F^{-1}(0.5)$ is the second quartile of y_t, or the median of the distribution, and the expectation in the denominator in expression (1) is estimated by the sample mean of the deviations from the median in absolute value. Note that the GM index is bounded in the interval $[-1, 1]$, and whenever the mean is greater (smaller) than the median the GM index takes positive (negative) values.

In the second place, we study the broad features of the skewness phenomenon by simply partitioning productivity distributions into three classes of individuals with low, fair, and very high productivity. For this purpose, we follow the Characteristic Scores and Scale (CSS hereafter) approach, first introduced in Scientometrics by Schubert et al. (1987). In our application of the CSS technique, the following two *characteristic scores* are determined at any aggregation level: μ_1 = mean productivity, and μ_2 = mean productivity for individuals with productivity greater than μ_1. We consider the partition of the distribution into three broad classes: (1) individuals with low productivity smaller than or equal to μ_1;

[4] Naturally, extreme observations can also affect any measure of productivity inequality, such as the CV.

[5] For a discussion of robust measures of skewness in the context of the financial literature on stock market returns, see Kim and White (2004), and for the properties of the Groeneveld and Meeden's measure, see the references in note 5 in PRRC.

(2) fairly productive individuals, with productivity greater than μ_1 and smaller than or equal to μ_2, and (3) individuals with remarkable or outstanding productivity greater than μ_2.

For the interpretation of results, the following two properties should be taken into account. Firstly, both the GM index and the CSS approach are scale- and size-independent indicators. Secondly, note that both the uniform and the normal distributions are characterized by a GM index equal to zero, and a partition of individual authors in the CSS approach equal to 50 %/25 %/25 %. Distributions different from the uniform and the normal might be, for example, skewed to the right, in which case the mean is greater than the median, the GM index is positive, and the partition into three classes in the CSS approach is equal to *X* %/*Y* %/*Z* % with *X* greater than 50 %, and *Z* typically small.

The measurement of between-department variability for a number of productivity distributions' characteristics

Consider the following characteristics of any productivity distribution: the size, the mean, the productivity inequality measured by the CV, as well as the skewness of productivity distributions measured by the GM index and the CSS approach. We are interested in two characteristics of the distribution of the values taken by any of the above variables in the partition of the population into departments or countries: the average, and the between-group variability. The latter is measured by the coefficient of variation over the research units in question.

To avoid any confusion, in the sequel we reserve the symbol CV to denote the index of productivity inequality for a single distribution, and we use the term "coefficient of variation" to denote the measure of the variability of the above characteristics in a given partition. Thus, for example, to assess the variability of productivity inequality values in the partition of the population into departments, we use the coefficient of variation of the CVs in this partition.

The measurement of the importance of productivity differences between research units

Independently of the assessment of between-group variability concerning the distribution characteristics studied above, we are interested in measuring how important are the productivity differences between departments or countries. Formally, this problem is analogous to the measurement of the importance of differences in production and citation practices between scientific fields. For the latter, Crespo et al. (2013) suggested to measure the impact of such differences on the overall citation inequality for the entire set of field citation distributions. Similarly, in our case we suggest to measure how much of the individual productivity inequality exhibited by our sample as a whole can be attributed to the productivity differences between departments or countries.

For that purpose, we begin with the partition of, say, each department productivity distribution into Π quantiles, indexed by $\pi = 1,\ldots, \Pi$. Assume for a moment that, in any department *d*, we disregard the citation inequality within every quantile by assigning to every individual in that quantile the mean productivity of the quantile itself, μ_d^π. The interpretation of the fact that, for example, $\mu_d^\pi = 2\mu_e^\pi$ is that, on average, the index *Q* for department *d* is twice as large as the index *Q* for department *e* in spite of the fact that both quantities represent a common underlying phenomenon, namely, the same *degree of productivity* in both departments. In other words, for any π, the distance between μ_{d}^π and μ_{e}^π is entirely attributable to the difference in the performance that prevails in the two departments for individuals with the same degree of productivity. Thus, the productivity inequality between departments at each quantile, denoted by $I(\pi)$, is entirely attributable to the productivity differences between the 81 departments holding constant the degree of productivity in all departments at quantile π. Hence, any weighted average of these quantities, denoted by IDPD (Inequality due to Differences in Productivity across Departments), provides a good measure of the total impact on overall productivity inequality that can be attributed to such differences. We use the ratio

$$\mathrm{IDPD}/I(Q) \tag{2}$$

to assess the relative effect on overall productivity inequality, $I(Q)$, attributed to productivity differences between departments (for details, see PRRC and Crespo et al. 2013).

Finally, we are interested in estimating how important scale differences between department productivity distributions are in accounting for the effect measured by expression (2). Following the experience in other contexts, we choose the department mean productivities as normalization factors. To assess the importance of such scale factors, we use the relative change in the IDPD term, that is, the ratio

$$[\mathrm{IDPD}-\mathrm{IDPD}^{*}]/\mathrm{IDPD}, \tag{3}$$

where IDPD* is the term that measures the effect on overall productivity inequality attributed to the differences in productivity distributions after the normalization of individual productivity using department mean productivities as normalization factors (for details, see again PRRC and Crespo et al. 2013).

Characteristics of productivity distributions before and after age normalization

Results for the population as a whole

Before answering the questions raised in the Introduction, we should review the characteristics of the population as a whole. The information about distributions Q and Q/Age in this case is in Tables 2, 3. The mean, the CV, and the skewness index GM are in row I in Table 2, whereas the percentages of individuals in the three categories distinguished in the CSS approach, as well as the percentages of the total Q and Q/Age index values in the three categories, are in row I in Table 3. The information before and after age normalization is in the left- and the right-hand side in Tables 2 and 3. Beginning with distribution Q, three comments are in order.

Firstly, the productivity inequality of distribution Q according to the CV is 1.3, a very high figure indicating that the standard deviation is 1.3 times greater than the mean.

Secondly, recall that the absence of skewness in a uniform or a normal distribution corresponds to a value of the GM index equal to zero, and to a partition of the population into three classes in the CSS approach equal to 50 %/25 %/25 %. Thus, productivity distribution Q is neither uniform nor normal. Instead, it is considerably skewed: its GM index is 0.54, while the percentage of people with below average productivity is approximately 19 points to the right of the median, and 10.8 % of the total population is responsible for 43.6 % of all quality points.

Thirdly, interestingly enough age normalization does not change very much the characteristics of the productivity distribution for the population as a whole (row I in the right-hand side of Table 2). There is simply a moderate decrease in both productivity inequality, measured by the CV (columns 2 and 5 in row I in Table 2), and the skewness of the

Table 2 Characteristics of productivity distributions before and after age normalization: mean productivity, productivity inequality (CV), and GM skewness index

	Distribution *Q* (before age normalization)			Distribution *Q/Age* (after age normalization)		
	Mean (1)	*CV* (2)	*GM* index (3)	Mean (4)	*CV* (5)	*GM* index (6)
I. Population as a whole	307.3	1.30	0.54	14.9	0.93	0.38
II. Departments						
Average	294.6	1.04	0.40	14.2	0.77	0.28
Coeff. of variation	(0.55)	(0.27)	(0.59)	(0.49)	(0.25)	(0.79)

Characteristics for the population as a whole, as well as the average (and coefficient of variation) of these characteristics for the 81 departments

distributions, measured by the GM index (columns 3 and 6 in Table 2), and the CSS approach (Table 3). Therefore, after age normalization, what has been known since Seglen (1992) as the skewness of science is essentially preserved for the population as a whole.

Individual variability within- and between-departments before age normalization

Of the 81 departments, 52 belong to the US, 29 are European, and the remaining 8 are in Canada, Israel, and China. Results on the characteristics of productivity distributions at the department level are relegated to the Appendix. In particular, the information on the number of people and the mean age by department, where the departments are ordered by the mean of distribution *Q*, is in columns 1 and 2 in Table 5 in the Appendix. Likewise, the information about mean productivity, the CV, and the GM index for distributions *Q* and *Q/Age* for the 81 departments, is in columns 3–8 in Table 5. As far as the results of the CSS approach, to save space only the results for the *Q/Age* distribution in each department, where the departments are ordered by the mean of distribution *Q/Age*, are presented in Table 6 in the Appendix (the results for the *Q* distribution for each department are available on request). On the other hand, the results on the average and the coefficient of variation of mean productivity, CV, and GM index over all departments are in row II in Table 2, while the corresponding information for the CSS approach is in row II in Table 3. As before, the results in Tables 2, 3 before and after age normalization appear in the left- and the right-hand sides, respectively.

We shall now turn towards the first two questions raised in the Introduction for the situation before age normalization:

1. Do departments consist of individuals with fairly similar productivity? Otherwise, do individual productivities follow the normal distribution?
2. Are department productivity distributions as similar to each other as found in the previous literature?

Question 1 refers to the individual variability within department productivity distributions, assessed through a measure of productivity inequality and two measures of skewness. Firstly, judging from their CVs (column 4 in Table 5 in the Appendix), all department distributions exhibit high productivity inequality. The average of these values is 1.04 (row II in Table 2). Secondly, there are 32 and 28 departments with a GM index between 0.25 and 0.50, and greater than 0.50, respectively, indicating a clear skewness to the right for the majority of departments (column 5 in Table 5 in the Appendix). On the other hand, on average over all departments, the

Table 3 The skewness of productivity distributions according to the CSS approach before and after age normalization

	Distribution Q (before age normalization)						Distribution Q/Age (after age normalization)					
	% people in category:			% index values in category:			% people in category:			% index values in category:		
	1	2	3	1	2	3	1	2	3	1	2	3
I. Population as a whole	69.2	20.0	10.8	24.2	32.2	43.6	65.0	22.0	13.0	28.5	32.7	38.8
II. Departments												
Average	62.8	22.6	14.6	25.3	32.2	43.3	59.0	24.7	16.3	30.3	32.1	37.9
Coeff. of variation	(0.14)	(0.29)	(0.31)	(0.26)	(0.25)	(0.21)	(0.13)	(0.24)	(0.30)	(0.24)	(0.21)	(0.18)

Percentages of individuals and percentages of Q index values by category for the population as a whole, as well as the average (and coefficient of variation) of these percentages for the 81 departments

Category 1 = people with a low productivity, smaller than or equal to μ_1

Category 2 = people with a fair productivity, greater than μ_1 and smaller than or equal to μ_2

Category 3 = people with a remarkable or outstanding productivity, above μ_2

percentages of people in the categories 1, 2, and 3 in the CSS approach are 62.8/22.6/14.6 (row II in Table 3). The conclusion is that individual productivities at the department level are far from being uniformly or normally distributed. Productivity distributions are highly unequal, and for the majority of departments are clearly skewed to the right.

However, the high coefficients of variation in row II in both Tables 2 and 3 indicate that productivity inequality and the skewness of productivity distributions are very different across departments. As a matter of fact, there are even a handful of departments for which the *GM* index is negative and the mean productivity is to the left of the median, indicating that more than 50 % of their members have productivities above the department's mean.[6] This is a characteristic never found in productivity distributions at the level of broad scientific fields (Ruiz-Castillo and Costas 2014), or indeed for the population as a whole in our dataset. Therefore, the answer to question 2 is that, although we find large within-departmental variability, the productivity inequality and the degree of skewness of productivity distributions are very different across departments.

Next, we shall discuss the answers to questions 3 and 4 raised in the Introduction:

3. How does the effect on overall productivity inequality attributable to productivity differences across departments compare with the analogous effects in the context of citation distributions?
4. Up to what point can this effect be accounted for by scale factors captured by the differences in mean productivity across departments?

The results concerning these questions before age normalization are presented in the left-hand side in Table 4.[7] It is interesting to compare these figures with what was obtained in two Web of Science datasets in the previous literature.[8] Two comments are in order. Firstly, the effect on overall productivity inequality due to productivity differences across the 81 departments in Economics (29.3 %) is clearly greater than the corresponding effect on overall citation inequality attributable to differences in production and citation practices across 172 sub-fields (from 11.7 to 14.2 %) in the first study, or 219 sub-fields (approximately 18 %) in the second dataset. Secondly, the percentage of these large differences that can be attributed to scale factors in our dataset (83.8 % of the total effect) is of a comparable order of magnitude to the same phenomenon in the context of sub-field citation distributions. The reduction of the total effect generated by mean sub-field normalization ranged from 71.3 to 83.3 % in the first study, and was 83.2 % in the second study.

The consequences of age normalization in the partition into departments

The final issue in this sub-section concerns the consequences of age normalization for the above four questions. The relevant information appears in the right-hand side of Tables 2–4.

[6] In any case, the GM index is not strongly associated to mean productivity: the coefficient of correlation between these two variables is 0.10.

[7] Given the relatively small department sizes, in the double partition mentioned in "The measurement of the importance of productivity differences between research units" section, we distinguish between deciles, that is, Π is made equal to 10.

[8] The first study entails 2.9 million articles published in several years in the 1980–2004 period with a variable citation year from the publication year up to May 2011. Articles were classified into 172 journal subject categories (Li et al. 2013). The second study encompasses 4.4 million articles published in 1998–2003 with a 5-year citation window for each year. Articles were classified into 219 journal subject categories (Crespo et al. 2014).

1. Is the within-department variability changed when productivity is normalized by academic age? The answer is: not very much. On average, both productivity inequality (row II and column 2 in Table 2), and the skewness of productivity distributions (row II and column 3 in Table 2, as well as in Table 3) are somewhat smaller after age normalization.[9]
2. Is between-department variability altered when we consider productivity per year? Differences between departments are generally decreased. Except for the GM index, the coefficients of variation in row II in both Tables 2 and 3 are somewhat smaller than before age normalization. Nevertheless, it should be emphasized that department productivity distributions are still very large. Observe, for example, the partition of department productivity distributions into three categories in the CSS approach after age normalization in Table 6 in the Appendix. The percentage of people in the three categories in all departments is illustrated in Fig. 1, where departments are ordered according to the percentage of researchers in category 1.

However, it is important to note that, in spite of these differences, all department productivity distributions share a basic feature: a relatively low percentage of economists, ranging from less than 10 % to more than 35 %, are responsible for a relatively high percentage of all quality points, ranging from more than 25–62 %.[10] On average, 16.3 % of scholars account for 37.9 % of all quality points per year (row II in Table 3). This is the limited but interesting sense in which we can conclude that the skewness of science is preserved at the department level.

Since, as opposed to the rest of the world, hiring and promotion procedures are distinctively competitive in the US, we should inquire about the degree of variability found between the 51 US departments. As far as the CSS approach is concerned, for example, the results are essentially maintained. On average for the US departments, the percentages of individuals in the three categories (with the coefficient of variation in brackets) are 57.6 (0.14)/25.5 (0.22)/16.9 (0.31), while according to row I in Table 3 the average percentages for the 81 departments are 59.0 (0.13)/24.7 (0.24)/16.3 (0.31) (For a graphical illustration of the situation for the US departments, see Figure 2 in PRRC).

We have also studied the robustness of the results to the restriction of the exercise to departments with a minimum size. Consider, for example, the 53 departments with at least 25 faculty members, and the results for the CSS approach (results for other characteristics are available on request). On average, the percentages of individuals in the three categories (with the coefficient of variation in brackets) are 63.5 (0.12)/22.6 (0.26)/14.0 (0.32). The average results are comparable to the results for the 81 departments. Unfortunately, the coefficients of variation are only slightly smaller (see row II in Table 3). Therefore, the large between-department variability cannot be attributed to the contribution by the small departments.

3. How is the effect on productivity inequality attributable to between-department productivity differences affected by the normalization of individual productivity by

[9] In this case there is a weak negative correlation between the GM index and mean *Q/Age*: the coefficient of correlation between these two variables is −0.34. Therefore, the higher is the ranking according to *Q/Age*, the smaller tends to be the skewness measured by the GM index.

[10] As can be observed in Table 6 in the Appendix, at one extreme, a very small percentage of economists, ranging from 8.3 to 9.5 %, are responsible for 26.6–33.5 % of all quality points (Rice University, the Hebrew University, and the Free University of Amsterdam). At the other extreme, 23.7–35.7 % of all economists account for 49.6–62.1 % of quality points (University of Amsterdam, University College London, University of Wisconsin at Madison, and Johns Hopkins University).

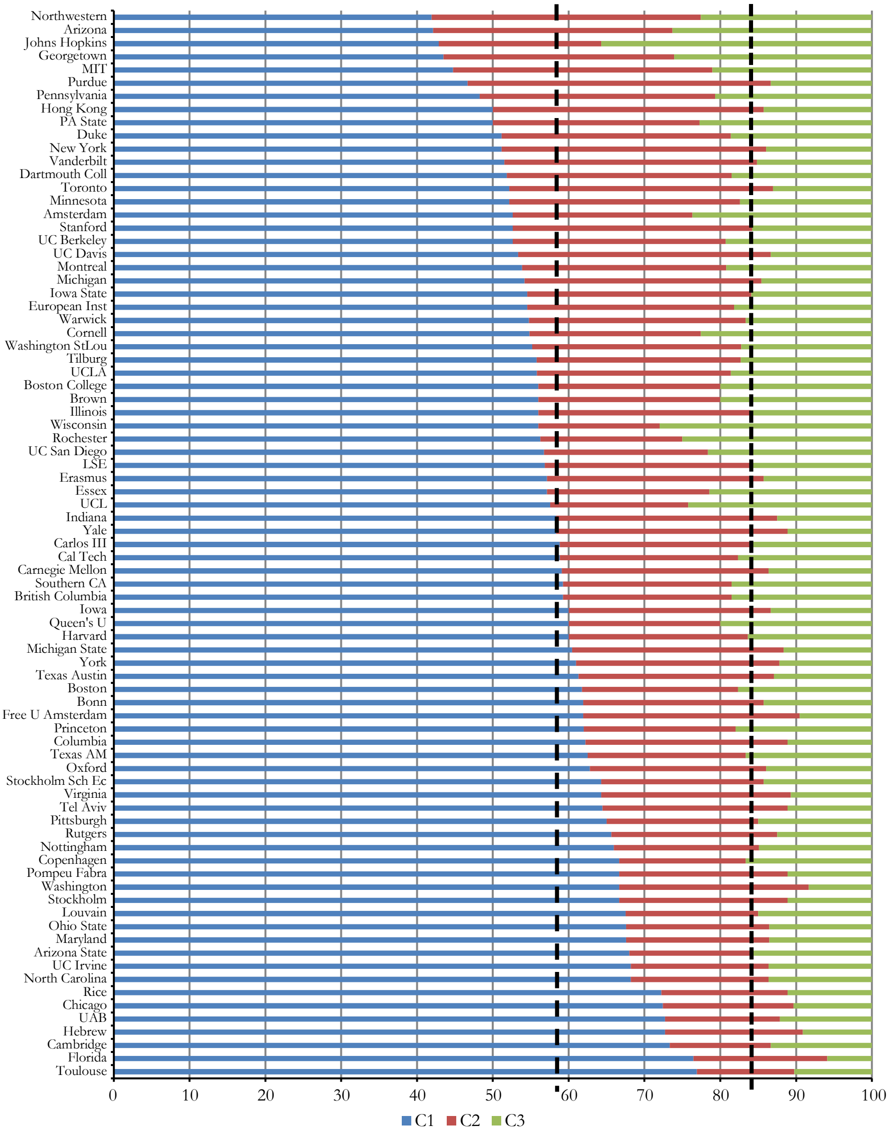

Fig. 1 The partition of departments' productivity distributions into three categories according to the CSS technique. Individual productivity = quality index points per year per person (Distribution *Q*/*Age*). Results for the 81 departments

academic age? Differences in between-department productivity distributions have a greater effect on overall productivity inequality when age is taken into account. This effect increases from 29 % to 36 % in the move from *Q* to *Q*/*Age* (Table 4).

4. However, the importance of scale effects between departments' productivity distributions is of a similar order of magnitude before and after age normalization.

Table 4 The effect on overall productivity inequality, $I(.)$, of differences in productivity distributions across departments, 100 [IDPD/$I(.)$], and the impact of normalization on this effect, [IDPD − IDCP*/IDCP], before and after age normalization

	100 [IDPD/$I(.)$] (%)	[IDPD − IDCP*/IDCP] (%)
Before age normalization	29.3	83.8
After age normalization	36.5	84.3

The robustness of results

As indicated in "The impact of age on productivity" section, the ordering of individuals and departments according to the two productivity distributions by P and Q is very different indeed. Therefore, it is important to review the robustness of our results using distributions Q and Q/Age to the measurement of individual productivity as the number of publications independently of the journal where they have appeared. For reasons of space, we will simply present the main conclusions of the analysis carried on in PRRC.

Firstly, the characteristics of the distributions for the population as a whole using both productivity definitions are essentially the same. Interestingly, the results from the CSS approach are comparable to what we find for the closely related population of scholars in Economics and Business in Ruiz-Castillo and Costas (2014) when productivity is measured as the number of publications. Secondly, the results on the individual variability within and across departments for distributions P and P/Age essentially coincide with the corresponding results for distributions Q and Q/Age. Thirdly, the effect on overall productivity inequality of productivity differences across departments, however, is considerably greater in distribution Q (29 %) than in distribution P (16 %). Nevertheless, the latter figure is still greater than the corresponding one for differences in production and citation practices across 172 or 219 scientific sub-fields. Similarly, the reduction in the IDPD term after using department mean productivities as normalization factors is also greater in distribution Q (83.9 %) than in distribution P (71.6 %). Finally, as with the previous definition of individual productivity, age normalization leads to an increase in the effect on overall productivity inequality of productivity differences across countries.

Conclusions and extensions

Summary and discussion of main results

The matching of individuals and university departments in any scientific field results from the interaction between the demand for and the supply of researchers at different stages in their career. Some of the basic elements of this process have been informally described in "The motivation of the research questions" section. As a first step towards the development of a formal model of this process, this paper has investigated some of the characteristics of productivity distributions of a population of 2,530 individuals with at least one publication who were working in 81 top Economics departments in 2007.

Individual productivity has been measured in two ways: as the number of publications up to 2007, and as a quality index that weights differently the articles published in four journal equivalent classes. For the population as a whole, the corresponding distributions

P and Q have very similar characteristics. Nevertheless, we are advised to conduct our study using both measures. In relation to the partition of the population into the 81 departments, the two main findings are the following.

1. Independently of how we measure productivity, department productivity distributions are not uniform or normal. In other words, within each department, individuals have very different productivity, and the skewness of department distributions is significantly different from zero in a majority of cases.
2. There is not a single pattern of productivity inequality and skewness at the department level. On the contrary, productivity distributions are very different across departments. In particular, although most distributions are skewed to the right, approximately 20 % of all departments exhibit a very low skewness or even skewness to the left. Consequently, the effect on overall productivity inequality of differences in productivity distributions across the 81 departments—especially according to the quality index Q—is greater than the effect on citation inequality attributable to differences in production and citation practices across 172 or 219 sub-field citation distributions. Interestingly enough, to a large extent these differences—however important—are accounted for by scale factors well captured by departments' mean productivities.

As usual in productivity studies, our data includes a mixture of heterogeneous individuals at a different stage in the academic career. Therefore, it is important to verify if the above results are robust to the normalization of productivity by age. For reasons of space, in this paper we have focused on the consequences of the move from distribution Q to distribution Q/Age. It should be said at the outset that distributions Q and Q/Age order individuals and departments very differently. In this sense, age normalization makes a fundamental difference whose study is beyond the scope of this paper. On the other hand, for the population as a whole age normalization somewhat diminishes both productivity inequality, and the skewness of the distribution. For the partition of the population into the 81 departments, the two main consequences of age normalization are the following.

1. On average, department productivity distributions exhibit less productivity inequality, and less skewness than before age normalization. However, individual productivity distributions are still far from being uniformly or normally distributed and, as before age normalization, a relatively low percentage of economists are responsible for a relatively high percentage of all quality points.
2. Although productivity distributions are practically as different across departments as before age normalization, the effect on overall productivity inequality of productivity differences across departments increases to some extent after age normalization. However, as before, to a large extent this effect is accounted for by differences between departments' mean productivities.

The conclusion is that, both before and after age normalization, any theory about the interaction between demand and supply forces for researchers must cope with the following two features: large within-department individual productivity variability, and strong differences between department productivity distributions.

Productivity heterogeneity at the department level goes against the considerable similarity found in three other contexts: (a) productivity distributions across broad scientific fields, (b) citation distributions across scientific fields at different aggregation levels, and (c) country citation distributions within certain broad scientific fields. Therefore, a natural question to ask is whether the aggregation of departments into countries in our dataset leads us to recover this similarity. This is partially what we find in PCRC when we partition the sample into seven countries and a residual category. The analysis can be summarized as follows.

On average, country productivity distributions are characterized by a somewhat higher productivity inequality, and higher skewness to the right than department productivity distributions. More importantly for our purposes, although country productivity distributions are still rather different, they are found to be more similar to each other than what is the case across departments. Together with the fact that there are only eight country categories versus 81 departments, the greater similarity among countries implies that the effect on overall productivity inequality of productivity differences across country categories is three (four) times smaller than the effect of productivity differences across 81 departments before (after) age normalization. The conclusion is that a high degree of departmental heterogeneity is compatible—as expected—with greater country homogeneity.

Shortcomings and further research

The above results are necessarily provisional in at least four important respects. Firstly, it should be emphasized that the information in the publications in the periodical literature concerning the department where the authors work is not always available and, when it exists, is not always accurate or easy to record. As described in "The data" section, this paper has used the listing of faculty members in a selection of top 81 Economics departments worldwide according to the department web pages in 2007. The information about researchers' publications and academic age has been taken from this source, as well as the individuals' web pages or the available information in Internet about researchers characteristics. We conjecture that, at least part of the within- and between-department variability reported in the paper, may very well be due to the fact that the quality of the institutional and personal information provided by our Internet sources is admittedly very uneven and subject to error.

Secondly, it should be recalled that the nexus between productivity and age is highly non-linear. Furthermore, Carrasco and Ruiz-Castillo (2014) and Albarrán et al. (2014b) have shown that this relationship is much weaker for remarkably high productive scholars than for the rest of the elite included in our sample. Under these conditions, the simple age normalization used in this paper leaves much to be desired. The residuals of a regression of productivity on age and other control variables might provide a promising avenue for a tailor-made individual adjustment for every individual in the sample.

Thirdly, given the skewness of the citation distribution of articles in any journal, including an important percentage with zero citations, Seglen's (1992, 1997) seminal contributions caution us about the wisdom of judging the quality of individual publications—as we have done in this paper—by the citation impact of the journal where they have been published. Similarly, for the field of Economics, Oswald (2007) has shown that "It is better to write the best article published in an issue of a medium quality journal such as the Oxford Bulletin of Economics and Statistics than all four of the worst four articles published in an issue of an elite journal like the American Economic Review." Therefore, one way to improve upon the results presented in this paper is to introduce productivity measures based on the citation impact directly achieved by each individual publication. On the other hand, information on citations at the department level would make possible to carry on the research program pioneered by van Raan (2006a) for 157 research groups in Chemistry in the Netherlands.

Finally, our results only refer to the field of Economics. Before formally modeling the interplay of demand and supply of researchers at the department level, it is advisable to extend the coverage of the issues studied in this paper to other scientific fields.

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Appendix

See Tables 5 and 6.

Table 5 Characteristics of productivity distributions for the 81 departments, ordered by mean productivity in distribution *Q*

	Number of people	Distribution *Q*				Distribution *Q/Age*		
		Mean age	Mean	CV	GM index	Mean	CV	GM Index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1. MIT	38	24.3	925.6	1.04	0.54	38.9	0.58	−0.17
2. Harvard University	55	22.7	909.9	0.90	0.12	40.0	0.64	0.32
3. Yale University	36	23.5	648.5	1.06	0.45	25.0	0.74	0.30
4. Princeton University	50	22.2	637.0	0.83	0.39	31.1	0.51	0.32
5. University of Chicago	29	20.6	585.0	0.95	0.53	30.3	0.76	0.28
6. Columbia University	45	19.8	561.6	1.39	0.37	27.0	0.70	0.41
7. U. of California, Berkeley	57	22.5	541.9	0.73	0.22	27.8	0.52	0.05
8. New York University	43	22.1	538.4	0.94	0.39	24.3	0.72	0.08
9. University of Pennsylvania	29	18.8	505.7	0.84	0.16	26.1	0.56	−0.14
10. Stanford University	38	19.3	479.4	1.01	0.47	23.3	0.62	0.10
11. Northwestern University	31	21.3	471.2	0.84	0.40	21.5	0.51	−0.15
12. Johns Hopkins	14	24.1	442.4	0.88	0.21	16.5	0.68	−0.15
13. Cornell University	31	24.0	441.9	0.96	0.31	17.8	0.65	0.20
14. Queen's University	15	21.1	395.8	0.78	0.13	18.1	0.50	0.21
15. CA Institute of Technology	17	21.0	384.1	1.24	0.58	18.0	0.90	0.48
16. University of Montreal	26	26.9	382.9	0.94	0.12	13.4	0.65	0.14
17. U. of Cal., San Diego	37	18.3	379.6	1.04	0.37	18.2	0.65	0.32
18. University of Minnesota	23	19.4	361.1	0.83	0.42	17.6	0.65	0.03
19. Washington U., St Louis	29	24.9	354.9	1.01	0.40	14.2	0.74	0.09
20. Brown University	25	19.2	351.5	0.84	0.32	17.6	0.53	0.07
21. University of Washington	24	25.1	348.6	1.61	0.68	11.9	1.12	0.36
22. U. of Southern California	27	23.7	346.9	1.00	0.29	13.6	0.69	0.19
23. European Institute	11	19.2	332.3	0.63	0.41	16.3	0.39	0.63
24. U. of California, LA	43	18.7	319.6	0.89	0.57	18.1	0.55	0.14
25. Oxford University	43	20.6	319.6	1.07	0.59	14.0	0.82	0.34
26. Boston University	34	20.5	318.9	1.13	0.64	15.7	0.76	0.23
27. University of Michigan	48	19.4	316.1	0.79	0.29	17.3	0.58	0.05

Table 5 continued

	Number of people	Distribution Q				Distribution Q/Age		
		Mean age	Mean	CV	GM index	Mean	CV	GM Index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
28. Univ. College London	33	17.1	308.3	1.17	0.75	17.4	0.78	0.27
29. Rice University	18	27.3	307.6	0.84	0.60	11.5	0.76	0.51
30. University of Maryland	37	21.7	306.3	0.73	0.23	16.9	0.66	0.25
31. Ohio State University	37	24.1	305.5	1.02	0.41	11.9	0.80	0.31
32. U. of Wisconsin, Madison	25	15.4	304.3	0.97	0.38	17.2	0.63	0.33
33. U. of Texas, Austin	31	22.5	298.5	1.09	0.35	12.5	0.82	0.22
34. Vanderbilt University	33	24.0	297.5	1.08	0.44	12.1	0.84	0.00
35. Arizona State University	25	27.6	295.6	1.16	0.66	10.9	0.91	0.51
36. London Sch. of Economics	51	18.5	294.4	1.12	0.61	16.2	0.79	0.28
37. Boston College	25	26.4	280.4	0.97	0.22	13.0	0.96	0.50
38. Duke University	43	20.8	278.1	1.11	0.56	13.3	0.71	0.02
39. University of Bonn	21	23.2	266.0	0.94	0.47	13.2	0.87	0.51
40. University of Rochester	16	19.0	262.6	1.23	0.30	13.8	0.68	0.34
41. University of Warwick	42	19.4	262.2	1.25	0.55	11.0	0.88	0.38
42. PA State University	22	24.5	254.8	0.69	0.24	10.5	0.52	0.03
43. University of Toronto	23	22.5	249.5	0.93	0.46	10.6	0.63	0.09
44. University of Iowa	15	22.9	248.0	0.51	-0.26	11.8	0.61	0.37
45. Univ. of British Columbia	27	16.0	243.0	1.08	0.29	13.6	0.59	0.27
46. Michigan State U.	43	21.5	241.7	1.25	0.57	10.7	0.85	0.50
47. Cambridge University	30	18.1	222.8	1.45	0.77	9.7	1.06	0.65
48. Texas A and M	24	23.1	217.3	1.05	0.54	9.8	0.95	0.54
49. University of Florida	17	27.6	215.4	1.07	0.50	8.1	1.14	0.54
50. Georgetown University	23	18.8	212.0	0.70	-0.06	10.2	0.51	−0.20
51. University of Virginia	28	18.7	211.9	1.30	0.71	9.3	1.00	0.53
52. Purdue University	15	22.7	211.0	0.75	0.29	10.0	0.72	−0.22
53. U. California, Davis	30	18.1	207.9	0.84	0.45	11.2	0.56	0.12
54. U. of Illinois, Urbana	25	18.2	207.8	1.06	0.52	11.3	0.82	0.19
55. University of Tel Aviv	45	20.1	207.3	0.82	0.32	11.3	0.73	0.48
56. University of Pittsburgh	20	22.3	202.2	0.84	0.15	10.9	0.77	0.44
57. Tilburg University	52	18.0	197.3	1.07	0.50	10.3	0.90	0.41
58. Stockholm School of Ecs.	14	14.6	190.7	0.78	-0.18	13.9	0.89	0.27
59. U. of California, Irvine	22	15.1	187.2	1.35	0.56	9.8	0.87	0.58
60. Carnegie Mellon U.	22	18.5	185.7	0.86	0.19	10.2	0.63	0.15
61. Hebrew University	22	17.0	182.1	1.01	0.48	11.3	0.83	0.34
62. Erasmus University	21	12.4	181.7	1.27	0.69	12.6	0.90	0.26
63. University of Arizona	19	20.4	178.9	0.59	-0.15	10.1	0.66	−0.04
64. Dartmouth College	27	16.4	178.2	0.80	-0.11	10.6	0.73	0.26
65. Iowa State University	44	21.9	173.0	0.86	0.29	9.0	0.88	0.21
66. Toulouse University	78	14.6	171.8	2.09	0.83	9.4	1.59	0.67
67. U. of North Carolina	22	24.1	167.9	1.02	0.38	7.1	0.91	0.35

Table 5 continued

	Number of people (1)	Distribution Q				Distribution Q/Age		
		Mean age (2)	Mean (3)	CV (4)	GM index (5)	Mean (6)	CV (7)	GM Index (8)
68. University of Nottingham	47	15.0	167.8	0.93	0.43	10.7	0.67	0.41
69. University of Indiana	24	19.6	166.9	1.11	0.41	7.9	0.86	0.06
70. Hong Kong University	14	14.2	165.8	0.75	-0.14	11.6	0.63	0.15
71. Rutgers University	32	23.5	162.9	0.82	-0.01	7.3	0.91	0.48
72. Stockholm University	18	15.2	151.8	2.01	0.81	7.8	0.95	0.65
73. Catholic Univ. of Louvain	40	17.3	144.8	1.26	0.58	7.6	0.77	0.27
74. University of Essex	28	14.0	141.2	1.07	0.41	8.8	0.85	0.38
75. U. Pompeu Fabra	36	13.0	133.8	1.63	0.57	9.4	1.01	0.70
76. University of Amsterdam	38	15.8	128.2	0.89	0.46	9.3	0.75	0.33
77. Free Univ. of Amsterdam	21	14.1	127.5	1.00	0.15	8.8	0.81	0.10
78. University of York	41	16.0	96.7	1.63	0.71	6.0	0.98	0.42
79. University of Copenhagen	42	15.7	91.1	1.06	0.61	7.7	0.94	0.47
80. U. Autónoma, Barcelona	33	16.6	87.7	1.55	0.73	5.3	1.22	0.57
81. U. Carlos III, Spain	51	13.5	84.9	1.28	0.62	5.9	0.98	0.45
Average	31.2	20.0	294.6	1.04	0.40	14.2	0.77	0.28
Coefficient of Variation	0.40	0.19	0.55	0.27	0.59	0.49	0.25	0.79

Table 6 Results of the CSS approach for productivity distribution Q/Age at the departmental level (Departments are ordered by mean productivity according to Q/Age)

Department	Percentage of individuals in category:			Percentage of total articles in category:		
	1	2	3	1	2	3
1. Harvard University	60.0	23.6	16.4	34.0	31.9	34.0
2. MIT	44.7	34.2	21.1	20.6	42.3	37.1
3. Princeton University	62.0	20.0	18.0	42.5	23.6	34.0
4. University of Chicago	72.4	17.2	10.3	49.7	21.1	29.2
5. U. of California, Berkley	52.6	28.1	19.3	31.4	34.7	33.8
6. Columbia University	62.2	26.7	11.1	39.9	33.7	26.4
7. University of Pennsylvania	48.3	31.0	20.7	26.3	36.2	37.5
8. Yale University	58.3	30.6	11.1	32.6	37.2	30.1
9. New York University	51.2	34.9	14.0	25.1	44.0	30.8
10. Stanford University	52.6	31.6	15.8	28.6	39.7	31.7
11. Northwestern University	41.9	35.5	22.6	21.0	42.1	36.9
12. U. of Cal., San Diego	56.8	21.6	21.6	28.9	29.2	41.8
13. U. of California, LA	55.8	25.6	18.6	34.0	31.7	34.3
14. Queen's University	60.0	20.0	20.0	39.1	27.1	33.8
15. CA Institute of Technology	58.8	23.5	17.6	19.0	39.4	41.6
16. Cornell University	54.8	22.6	22.6	30.0	25.6	44.4
17. University of Minnesota	52.2	30.4	17.4	28.9	35.9	35.1

Table 6 continued

Department	Percentage of individuals in category:			Percentage of total articles in category:		
	1	2	3	1	2	3
18. Brown University	56.0	24.0	20.0	35.2	28.7	36.1
19. Univ. College London	57.6	18.2	24.2	26.0	22.4	51.6
20. University of Michigan	54.2	31.3	14.6	31.4	38.9	29.7
21. U. of Wisconsin, Madison	56.0	16.0	28.0	29.1	20.1	50.8
22. University of Maryland	67.6	18.9	13.5	44.4	23.8	31.8
23. Johns Hopkins	42.9	21.4	35.7	13.9	24.0	62.1
24. European Institute	54.5	27.3	18.2	38.8	30.9	30.3
25. London Sch. of Economics	56.9	27.5	15.7	28.0	34.2	37.9
26. Boston University	61.8	20.6	17.6	31.7	27.8	40.4
27. Washington U., St Louis	55.2	27.6	17.2	27.5	33.9	38.5
28. Oxford University	62.8	23.3	14.0	32.6	32.1	35.3
29. Stockholm School of Ecs.	64.3	21.4	14.3	33.6	27.9	38.5
30. University of Rochester	56.3	18.8	25.0	25.5	28.3	46.3
31. Univ. of British Columbia	59.3	22.2	18.5	36.7	26.1	37.2
32. U. of Southern California	59.3	22.2	18.5	32.5	28.5	39.0
33. University of Montreal	53.8	26.9	19.2	30.0	31.4	38.6
34. Duke University	51.2	30.2	18.6	22.9	37.4	39.6
35. University of Bonn	61.9	23.8	14.3	29.3	30.7	39.9
36. Boston College	56.0	24.0	20.0	17.7	31.7	50.6
37. Erasmus University	57.1	28.6	14.3	23.7	36.9	39.4
38. U. of Texas, Austin	61.3	25.8	12.9	30.4	36.2	33.4
39. Vanderbilt University	51.5	33.3	15.2	19.1	44.7	36.2
40. University of Washington	66.7	25.0	8.3	36.3	30.2	33.6
41. Ohio State University	67.6	18.9	13.5	37.3	27.0	35.7
42. University of Iowa	60.0	26.7	13.3	37.1	34.8	28.1
43. Hong Kong University	50.0	35.7	14.3	28.3	42.6	29.1
44. Rice University	72.2	16.7	11.1	45.5	22.4	32.1
45. U. of Illinois, Urbana	56.0	28.0	16.0	24.6	37.5	37.9
46. University of Tel Aviv	64.4	24.4	11.1	39.9	30.2	29.9
47. Hebrew University	72.7	18.2	9.1	45.0	25.5	29.5
48. U. California, Davis	53.3	33.3	13.3	33.2	39.9	26.9
49. University of Warwick	54.8	28.6	16.7	20.3	36.5	43.1
50. University of Pittsburgh	65.0	20.0	15.0	32.5	33.1	34.5
51. Arizona State University	68.0	16.0	16.0	34.7	19.7	45.6
52. University of Nottingham	66.0	19.1	14.9	41.3	24.5	34.2
53. Michigan State U.	60.5	27.9	11.6	29.5	37.4	33.1
54. Dartmouth College	51.9	29.6	18.5	22.4	39.1	38.5
55. University of Toronto	52.2	34.8	13.0	27.2	45.1	27.7
56. PA State University	50.0	27.3	22.7	30.0	31.9	38.2
57. Tilburg University	55.8	26.9	17.3	20.2	35.9	43.9
58. Georgetown University	43.5	30.4	26.1	23.6	35.0	41.4

Table 6 continued

Department	Percentage of individuals in category:			Percentage of total articles in category:		
	1	2	3	1	2	3
59. Carnegie Mellon U.	59.1	27.3	13.6	35.6	34.8	29.6
60. University of Arizona	42.1	31.6	26.3	16.7	34.9	48.4
61. Purdue University	46.7	40.0	13.3	17.9	52.8	29.3
62. Texas A and M	62.5	20.8	16.7	30.1	24.7	45.2
63. U. of California, Irvine	68.2	18.2	13.6	35.9	27.2	36.9
64. Cambridge University	73.3	13.3	13.3	33.3	22.3	44.4
65. U. Pompeu Fabra	66.7	22.2	11.1	29.7	31.9	38.4
66. Toulouse University	76.9	12.8	10.3	27.1	24.3	48.6
67. University of Virginia	64.3	25.0	10.7	24.8	41.3	33.9
68. University of Amsterdam	52.6	23.7	23.7	21.2	29.2	49.6
69. Iowa State University	54.5	29.5	15.9	22.0	37.8	40.2
70. University of Essex	57.1	21.4	21.4	22.2	27.3	50.4
71. Free Univ. of Amsterdam	61.9	28.6	9.5	35.4	38.0	26.6
72. University of Florida	72.2	16.7	11.1	38.6	37.1	24.3
73. University of Indiana	58.3	29.2	12.5	25.6	41.2	33.2
74. Stockholm University	66.7	22.2	11.1	35.2	26.9	37.9
75. University of Copenhagen	66.7	16.7	16.7	30.7	24.0	45.2
76. Catholic Univ. of Louvain	67.5	17.5	15.0	39.1	23.3	37.5
77. Rutgers University	65.6	21.9	12.5	34.7	28.2	37.1
78. U. of North Carolina	68.2	18.2	13.6	39.5	23.3	37.2
79. University of York	61.0	26.8	12.2	24.4	36.7	38.9
80. U. Carlos III, Spain	58.8	25.5	15.7	24.5	31.8	43.7
81. U. Autónoma, Barcelona	72.7	15.2	12.1	30.5	22.6	46.9
Average	60.8	23.9	15.4	34.8	30.4	35.3
Coefficient of variation	0.14	0.27	0.32	0.21	0.23	0.19

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