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"WITHIN AND ACROSS DEPARTMENT VARIABILITY IN INDIVIDUAL PRODUCTIVITY. THE CASE OF ECONOMICS"

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Abstract

University departments (or research institutes) are the governance units in any scientific field 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 of a population of 2,530 individuals with at least one publication who were working in 81 world top Economics departments in 2007. Individual productivity is measured 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. The academic age of individuals, measured as the number of years since obtaining the PhD until 2007, is used to measure productivity per year. Independently of the two productivity measures, and both before and after age normalization, the main findings of the paper are the following five. 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 across departments is greater than the analogous effect in other contexts. Fourthly, to a large extent, this effect on overall productivity inequality is accounted for by scale factors well captured by departments' mean productivities. Fifthly, 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.

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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 counties. Of course, there is a lot 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, counts 651 publications from that date until 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) where scientists work is not easy to come by. This is important because, in any scientific field, 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 in the world according to the Econphd (2004) university ranking.

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, where peculiar and less flexible public sector hiring and promotion procedures play a dominant role, 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 we will not model explicitly here. Instead, in this paper we raise the following five questions.

1. Do faculty members in a given department have all similar productivities around the department mean, or do they exhibit the productivity inequality and skewness 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 individual productivity distributions across broad scientific fields, see Ruiz-Castillo and Costas, 2014. For citation distributions at different aggregation levels, see Radicci *et al.*, 2008, Albarrán and Ruiz-Castillo, 2011, Albarrán *et al.*, 2011, and Li *et al.*, 2013).

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.*, 2013a, b, Li *et al.*, 2013, Li and Ruiz-Castillo, 2013, Waltman & Van Eck, 2013, and Ruiz-Castillo, 2013. For the analogous effect attributable to differences in citation impact across countries in certain fields, see Albarrán *et al.*, 2013).

4. Finally, 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, up to what point the effect on overall productivity inequality is reduced when we normalize individual productivities using the mean productivity of the department where each individual belongs as normalization factor?

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 to these questions. As a first move in this direction, this paper studies empirically these four issues for our dataset of 81 departments in the field of Economics. For this purpose, 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 measure 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 seen presently, the two productivity measures order individuals and departments quite differently. Consequently, we investigate the above four questions for both measures.

Secondly, since Lotka's (1926) contribution, individual productivity datasets typically consist of a cross-section of researchers of different age in a given moment of time. However, there is evidence concerning the non-linear relationship between researchers' productivity and age (see the references in Section V below). Therefore, it is quite clear that the productivity of two scientists of different age 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 the PhD until 2007. This makes possible investigating how the following features are altered when we consider mean productivity by year: the ranking of Economics departments, the within-department variability in individual productivity, the across department variability in productivity distributions, the effect on overall productivity inequality attributable to productivity differences across departments, the reduction of this effect after using mean department productivities as normalization factors, and the characteristics of the productivity distribution for the population as a whole.

Finally, given that every department belongs to a single country, we can consider an intermediate aggregation level by partitioning the population into seven countries represented in the sample by a sufficiently large number of departments, as well as a residual category including the European Institute, a European institution located in Florence, Italy, plus all remaining countries with only one department in the dataset. This allows us to explore the previous questions before and after age normalization at this intermediate aggregate level.

The remaining of this paper consists of six Sections. Section II motivates the research questions. Section III presents the data, the productivity measures, 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 (or countries). Section IV answers questions 1 to 4 for the two sets of productivity distributions before age normalization, while Sections V and VI answer these questions for departments and countries, respectively, after the normalization of productivity measures by academic age. Finally, Section VII concludes by discussing the main results of the paper, and suggesting some extensions.

II. THE MOTIVATION OF THE RESEARCH QUESTIONS

As indicated in the Introduction, 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 U.S. 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, geographical location, and prestige. In every department, job offers are not tended at random among all recent PhDs. 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 PhD applies to the highest ranked sub-set of departments where she thinks she has a chance of being hired. In this way, search costs for departments are economized: they can focus their attention to a 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 PhDs in all departments every year.

This process reveals a lot 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 pend 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 PhD has been assigned to the "right" department. The tenure process serves to dispel some of these uncertainties. After a careful review, tenured is offered in each department to some of the individuals on tenure-track after a maximum period of, say, six 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 some 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.

As recognized in the Introduction, in other non Anglo-Saxon countries, where less flexible public sector hiring and promotion practices play a dominant role, 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 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 the five basic questions raised in the Introduction for our set of elite Economics departments in the world in 2007.

III. THE DATA, THE TWO PRODUCTIVITY MEASURES, BASIC STATISTICS, AND THE MEASUREMENT OF THE IMPORTANCE OF PRODUCTIVITY DIFFERENCES BETWEEN RESEARCH UNITS

III.1. The data and the two definitions of individual productivity

In this Sub-section, we briefly describe a dataset that was originally constructed to study the elite in Economics (see Albarrán *et al.*, 2014). As indicated in the Introduction, it consists 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).[1]

We found 2,755 economists listed in the 81 departmental web pages in 2007. Among other variables, we obtained information about the publications in the periodical literature,

[1] 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.*, 2014 for further details).

and the university department where these economists were working in 2007. Since people's age is not generally available in departmental or personal web pages, we use the academic age, namely, the number of years 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 sample consists of only 2,705 economists. Out of the 2,705 economists in our dataset, there are 175 faculty members without any publication at all (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 whole.

Because of budgetary restrictions, our information suffers from two serious 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 measure 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 five, 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.*, 2014, for further details concerning the construction of this index). If N is the number of individuals in the population, indexed by $i = 1,\ldots, N$, we denote the productivity distributions by $\boldsymbol{P} = (p_1,\ldots, p_i,\ldots, p_N)$ and $\boldsymbol{Q} = (q_1,\ldots, q_i,\ldots, q_N)$, where p_i and q_i are the number of publications and the number of index points of individual i.

Given the way the data was selected, it is not surprising that we are working with a very productive sample. As we have just seen, 93.5% of the initial number of individuals has at least one publication. On the other hand, individuals in our sample have on average 27 publications per person, and 1.3 publications per year per person. In contrast, only 42.8% of European academic economists published at least once in *EconLit*[2] during 1971-2000 (Combes and Linnemer, 2003), while only 39% of a sample of 1,600 economists graduating in 1969-1988 in the U.S. published at least one article, averaging 0.42 publications per year in 126 journals (Hutchinson and Zivney, 1995).

We should note that our population consists only of economists, while the closest of the 30 fields distinguished in Ruiz-Castillo & Costas (2014) consists of researchers in both Economics & Business. Nevertheless, taking the two sets as broadly comparable, it turns out that 65.8% of the 122,889 scholars in Economics & Business in Ruiz-Castillo & Costas (2014) have only one publication in the period 2003-2011, while their mean productivity is 2.3 publications per person. For the 25,911 individuals with above average productivity in this field, the mean is equal to 6.4 publications per person, or (6.4/9) = 0.7 publications per year during 2003-2011 –still well below what we observe in our sample.[3]

III.2. Basic characteristics of productivity distributions

For any productivity distribution, we are interested in two basic characteristics: the mean, and the individual variability within the distribution in question. Two aspects of the latter are generally investigated: the productivity inequality, measured by the coefficient of variation (*CV* hereafter), and the skewness of the distribution. 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

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[2] *EconLit* is the American Economics Association electronic bibliography that indexes over 120 years of economics literature all over the world.

[3] Furthermore, only 36.9% of the economists in our sample has no publications in the top journal class, while 25% published once or twice, and the remaining 38.1% three or more times in that class. The mean productivity of distribution Q is 307.3 quality points *per capita* (see row II in Table 1.A), equivalent to more than seven articles in the top journal class or about 20 articles in the second class. Alternatively, according to row IV in Table 1.A, the average Q index is 14.9 per year during the academic life (the period from the first year after the Ph.D. to 2007), a quantity approximately equal to the 15 points assigned to one article in the second journal class.

inter alia Ruiz-Castillo & 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 (for a discussion in the context of the financial literature on stock market returns, see Kim and White, 2004). Among the robust measures discussed in the literature, in this paper we use the one suggested by Groeneveld and Meeden (1984). 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 SK, is defined as

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

where $\Theta_2 = \mathrm{F}^{-1}(0.5)$ 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.[5] For the interpretation of results, it should be remembered that the SK index is bounded in the interval [-1, 1].

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, a scale- and size-independent statistical technique 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. Consider the partition of the distribution into three broad classes: (i) individuals with low productivity smaller than or equal to μ_1; (iii) fairly productive individuals, with productivity

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

[5] The Groeneveld and Meeden (1984) measure improves upon the extension of Bowley's (1920) measure due to Hinkley (1975), and has better properties than the well-known measure of Kendall and Stuart (1977).

greater than μ_1 and smaller than or equal to μ_2, and (iii) individuals with remarkable or outstanding productivity greater than μ_2.

III.3. The importance of productivity differences across research units

There are two ways in which we evaluate differences in productivity distributions across research units, be they departments or countries.

Firstly, we are simply interested in the differences exhibited by a number of variables: the size, the mean, the productivity inequality measured by the *CV*, and the skeweness of productivity distributions measured by the *SK* index and the CSS approach. For this purpose, we use the coefficient of variation over research units of the variables in question. To avoid any confusion, in the sequel we reserve the symbol *CV* to denote our measure of productivity inequality. For example, we will refer to the coefficient of variation of the *CV*s over departments (or countries).

Secondly, the effect on overall productivity inequality attributable to productivity differences across research units (departments or countries) will be assessed in the measuring framework introduced in Crespo *et al.* (2013a) for the measurement of the importance of production and citation practices across scientific fields. For this purpose, a double partition of the population into research units and quantiles is used. In turn, for any partition into sub-groups, additively decomposable productivity inequality indices allow us to decompose overall productivity inequality into two terms: a within-group term that captures the weighted sum of productivity inequalities within each sub-group, and a between-group term usually defined as the productivity inequality of the distribution in which each individual is assigned the mean productivity of the sub-group to which she belongs. Under this convention, it is well known that the Generalized Entropy (GE hereafter) family of inequality indices are the only measures of relative inequality that satisfy the usual properties required from any inequality index[6] and, in addition, are decomposable by population sub-group (Bourguignon, 1978, and Shorrocks, 1980, 1984). For reasons explained in Crespo *et al.* (2013a), in Scientometrics the more convenient member of this family is the first Theil index, denoted by I. For any productivity distribution such as $\boldsymbol{Q} = (q_1, \ldots, q_i, \ldots, q_N)$, the productivity inequality index I is defined as:

$$I(\boldsymbol{Q}) = (1/N)\, \boldsymbol{\Sigma}_i\, (q_i/\boldsymbol{\mu})\, \log\, (q_i/\boldsymbol{\mu}),$$

where $\boldsymbol{\mu}$ is the mean of distribution $\boldsymbol{Q}$.[7]

Although the analysis applies equally well to countries, in the sequel we focus on the partition of the population into university departments. For each department k with N^k individuals, indexed by $j = 1, \ldots, N^k$, denote the productivity distribution by $\boldsymbol{Q}^k = (q_1^{\ k}, \ldots, q_j^{\ k}, \ldots, q_{N^k}^{\ k})$, where $q_j^{\ k}$ is the productivity of individual j in department k. Denote the sum of productivities by $\gamma^k = \Sigma_j\, q_j^{\ k}$, and the mean productivity by $\boldsymbol{\mu}^k = \gamma^k / N^k$. The formula for the I index when written in decomposable form for the partition $\boldsymbol{Q} = (\boldsymbol{Q}^1, \ldots, \boldsymbol{Q}^k, \ldots, \boldsymbol{Q}^{81})$ is the following

$$I(\boldsymbol{Q}) = I^W + I^B,$$

where: $I^W = \Sigma_k\, v^k\, I(\boldsymbol{Q}^k)$, with $v^k = \gamma^k/\gamma$, $\gamma = \Sigma_k\, \gamma^k$,

and $I^B = I(\boldsymbol{\mu}^1, \ldots, \boldsymbol{\mu}^{81})$

is the productivity inequality of the distribution in which each individual is assigned the mean productivity of the department to which she belongs, $\boldsymbol{\mu}^k$.

To assess the importance of productivity differences between departments, consider the double partition of productivity distribution $\boldsymbol{Q}$ into the 81 departments and $\boldsymbol{\Pi}$ quantiles,

[6] Namely, continuity; scale invariance; invariance to population replications, or size-invariance, and S-convexity that ensures that transfers from an article with more citations to another with fewer citations without altering their ranking reduces citation inequality.

[7] The measurement procedure summarized in this Sub-section applies equally well to any other productivity distribution, such as $\boldsymbol{P}$ or other alternatives that will be introduced below.

indexed by $\pi = 1,\dots, \Pi$, and let γ_π be the sum of the productivities of the individuals placed in quantile π in all departments. Then, it can be shown that overall productivity inequality can be decomposed into three terms

$$I(\mathbf{Q}) = S + W + IDPD, \tag{2}$$

with
$$IDPD = \Sigma_\pi v_\pi \, I(\boldsymbol{\mu}_\pi^{1},\dots, \boldsymbol{\mu}_\pi^{81}) \tag{3}$$

where $v_\pi = \gamma_\pi / \gamma$ and, for any π, the expression $I(\boldsymbol{\mu}_\pi^{1},\dots, \boldsymbol{\mu}_\pi^{81})$, is the productivity inequality of the distribution where each individual is assigned the mean productivity μ_π^{k} of the quantile π and the department k to which she belongs. The terms S and W in expression (2) need not concern us here. However, for any π, the expression $I(\boldsymbol{\mu}_\pi^{1},\dots, \boldsymbol{\mu}_\pi^{81})$ is the productivity inequality attributable to differences in productivity across departments at that quantile (see Crespo *et al.*, 2013a, for a detailed explanation). Thus, the weighted average that constitutes the third term in expression (3), denoted by *IDPD* (*I*nequality due to *D*ifferences in *P*roductivity across *D*epartments), provides a good measure of the productivity inequality due to such differences. Therefore, a convenient way of assessing the importance of productivity differences between departments is given by the ratio

$$IDPD/I(\mathbf{Q}). \tag{4}$$

Finally, it is useful to study up to what extent differences between department productivity distributions can be accounted for by a scale factor captured by the mean productivity of each department, μ^k, $k = 1,\dots, 81$. For each k, consider the normalized distribution $\mathbf{Q}^{k*} = (q_1^{k*},\dots, q_j^{k*}, \dots, q_{Nk}^{k*})$, where $q_j^{k*} = q_j^{k}/\mu^k$ is the mean normalized productivity of individual j in department k. Denote the sum of productivities by $\gamma^{k*} = \Sigma_j q_j^{k*}$, and $\gamma^* = \Sigma_k \gamma^{k*}$. When we apply the double partition by department and quantile to the normalized productivity distribution for the population as a whole, $\mathcal{Q}* = (\mathcal{Q}^{1*},\ldots, \mathcal{Q}^{k*},\ldots, \mathcal{Q}^{81*})$, we obtain a second decomposition

$$I(\mathcal{Q}*) = S* + W* + IDPD*,$$

with $$IDPD* = \Sigma_{\pi}\, v_{\pi}^{*}\, I(\boldsymbol{\mu}_{\pi}^{1*},\ldots, \boldsymbol{\mu}_{\pi}^{81*}) \qquad (5)$$

where $v_{\pi}^{*} = \gamma_{\pi}^{*}/\gamma*$, γ_{π}^{*} is the sum of the productivities of the individuals placed in quantile π in all departments after normalization and, for any π, the expression $I(\boldsymbol{\mu}_{\pi}^{1*},\ldots, \boldsymbol{\mu}_{\pi}^{81*})$, is the productivity inequality attributable to differences in normalized productivity across departments at that quantile. Thus, the weighted average that constitutes the third term in expression (5), *IDPD**, provides a good measure of the productivity inequality due to such differences after the mean normalization. To assess the impact of this normalization on the effect on overall productivity inequality attributable to differences in productivity distributions across departments, we use the relative change in the *IDCP* term, that is,

$$[IDCP - IDCP*]/IDCP. \qquad (6)$$

IV. CHARACTERISTICS OF PRODUCTIVITY DISTRIBUTIONS *P* AND *Q*

Given the large differences in the weights assigned to journals in the four classes distinguished in the construction of distribution $\mathcal{Q}$, the two productivity notions used in this paper are –in principle– quite different. This Section studies three issue: (i) the main characteristics of productivity distributions $\boldsymbol{P}$ and $\mathcal{Q}$ for the population as a whole, (ii) the answers to the four questions raised in the Introduction concerning the partition of distributions $\boldsymbol{P}$ and $\mathcal{Q}$ at the departmental level, and (iii) the different manner in which both distributions actually order individuals and departments.

IV.1. Basic characteristics

The information about the main characteristics of distributions ***P*** and ***Q*** for the population is in Table 1. The mean, the standard deviation, the *CV*, and the skewness index *SK* are in columns 1 to 4 in Table 1.A., while the results of the CSS approach are in Table 1. B. Two comments are in order.

Table 1 around here

Firstly, the productivity inequality of distributions ***P*** and ***Q*** according to the *CV* is 1.2 and 1.3 (rows I and II in Table 1.A), a very high figure indicating that the standard deviation is 1.2 and 1.3 times greater than the mean. This is comparable to the *CV* of distribution ***P***, equal to 1.38, in the sample of 122,889 scholars in Economics & Business in Ruiz-Castillo & Costas (2014).

Secondly, productivity distribution ***P*** is considerably skewed: its *SK* index is 0.51 (row I in Table 1.A), while the percentage of people with below average productivity is approximately 19 points to the right of the median, and 10.4% of the total population are responsible for 39.5% of all publications (row I in Table 1.B). Orders of magnitude for distribution ***Q*** are very similar indeed (see row II in Table 1). Interestingly, these figures are again comparable to what we find for the population of scholars in Economics & Business in Ruiz-Castillo & Costas (2014). Given the high percentage of people with a single publication in that paper, consider the 21.1% of people with above average productivity. For this subset, the *SK* index is 0.47, while the percentages of people in the corresponding three categories are, approximately, 69/22/9, and the proportion of total publications accounted for by each of them are 43/28/29. This parallelism reflects the fractal nature of productivity distributions in our field.

IV.2. Individual variability within and across departments

The above results indicate that the productivity inequality and the skewness of distributions ***P*** and ***Q*** are of the same order of magnitude, and are broadly comparable with what we find in other closely related but much larger datasets. In this context, it is interesting to turn towards the four questions raised in the Introduction:

1. Do departments consist of individuals with fairly similar productivity?

2. Are department productivity distributions as similar to each other as found in the previous literature?

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 these differences be considered as mere differences in mean productivity across departments?

Table A in the Appendix, where departments are ordered by their mean number of publications in distribution $\boldsymbol{P}$, presents the results for the *CV* and the *SK* index in each department for the two productivity definitions. The average over all departments, and the coefficient of variation of these characteristics for both definitions are in rows I and II in Table 2.A. Given the large variability observed in the size and mean productivity across departments (see columns 1, 3, and 6 in Table A), it is interesting to assess the skewness of productivity distributions using a size- and scale-independent technique such as the CSS approach. To save space, the results for each department concerning the percentages of individuals in the three categories distinguished in the CSS approach, as well as the percentages of total publications (or total *Q* index values) are available on request. The average, the standard deviation, and the coefficient of variation over all departments for these percentages for both productivity definitions are in rows I and II in Table 2.B.

Table 2 around here

Question 1 refers to the individual variability within department productivity distributions, assessed through a measure of productivity inequality and two measures of skeweness. Firstly, judging from their *CV*s, all department distributions exhibit high productivity inequality. The average of the *CV*s over the 81 departments is 1.03 and 1.04 for P and Q. Secondly, recall that, on the one hand, the *SK* index defined in expression (1) in Section III.2 is bounded in the interval [-1, 1], where the absence of skeweness corresponds to a *SK* value equal to 0. According to P, for example, there are 34 and 30 departments with a skewed index between 0.25 and 0.50, and greater than 0.50, respectively, indicating a clear skweness to the right for the majority of departments. The situation for Q is very similar (see columns 5 and 8 in Table A in the Appendix). On the other hand, for a uniform distribution, the percentages of people in the categories 1, 2, and 3 in the CSS approach would be 50/25/25. On average over all departments, these percentages are 64.5/21.5/14.0 and 62.8/22.6/14.6 according to P and Q (see rows I and II in Table 2.B).

The conclusion is that productivity distributions at the department level are far from uniform: there is a high productivity inequality, and the majority of departments are clearly skewed to the right. However, the high coefficients of variation in columns 2 and 3 in Table 2.A and everywhere in rows I and II in Table 2.B indicate that productivity inequality and the skeweness of productivity distributions are very different across departments. As a matter of fact, there are even a handful of departments for which the *SK* index is negative and the mean productivity is to the left of the median, indicating that these departments are skewed to the left. This is a characteristic never found at the level of broad scientific fields (Ruiz-Castillo & Costas, 2014), or indeed for the population as a whole in our dataset (see Table 1). Therefore, the answer to question 2 is that, although we find large within-departmental variability, the productivity inequality and the degree of skeweness of productivity distributions measured by the number of publications per person or by the more elaborate index Q is very different across departments.

Finally, the results concerning questions 3 and 4 are presented in Table 2.C.[8] Two comments are in order. Firstly, the effect on overall productivity inequality of differences in productivity across departments –expression (4) in Section III.3– is considerably greater in distribution Q (29%) than in distribution P (16%). Secondly, the reduction in the IDPD term after using department mean productivities as normalization factors –expression (6) in Section III.3– is also greater in distribution Q (83.9%) than in distribution P (71.6%). This means that scale differences account for more of the total differences in productivity across departments in distribution Q than in distribution P.

It is interesting to compare these figures with what was obtained in two Web of Science (WoS hereafter) datasets in the previous literature. Firstly, 4.4 million articles published in 1998-2003 with a five-year citation window for each year. Articles were classified into 219 WoS journal subject categories (Crespo *et al.*, 2013b). Secondly, 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 WoS journal subject categories (Li *et al.*, 2013). The results can be summarized as follows. Firstly, the effect on overall citation inequality of differences in production and citation practices across sub-fields were, approximately 18% among 219 sub-fields in the first dataset, and from 11.7% to 14.2% across 172 sub-fields in the second dataset. Secondly, scale effects account for percentages of the total effect that are comparable with those obtained in this paper. For example, the reduction of the total effect generated by mean sub-field normalization was 83.2% in the first study, and ranged from 71.3% to 83.3% in the second study.

The conclusion is that the effect on overall productivity inequality due to differences in the 81 productivity distributions in Economics is clearly greater than the corresponding effect attributable to differences in citation distributions across 172 or 219 scientific sub-

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[8] Given the relatively small department sizes, in the double partition into department and quantiles needed for the decomposition of overall productivity inequality into three terms introduced in expressions (3) and (4) in Section II.3, we distinguish between deciles, that is, Π is made equal to 10.

fields. However, the importance of these large differences that can be attributed to scale factors in our dataset is of a comparable order of magnitude to the same phenomenon in the context of sub-field citation distributions.

IV.3. Re-rankings between the two productivity measures

So far, we have seen that both distributions P and Q have similar characteristics, and provide similar answers to the first two questions raised in the Introduction. Only in questions 3 and 4 there is a difference of degree in the answers provided by the two distributions. On the other hand, the correlation coefficient between the distributions P and Q at the individual and department level is 0.79. However, we should probe in more detail into the consequences of adopting each of the two productivity measures for the ordering of individuals and departments. For that purpose, we must take two aspects into account.

Firstly, we should analyze the re-rankings that take place in such a move among individuals, and among departments. The results are summarized in Table 3.A. It is observed that almost 50% of all individuals experience re-rankings of more than 250 positions, while only 11.2 of all re-rankings involve less than 50 positions. Similarly, 39 out of 81 departments, or 48.2% of the total experience re-rankings of more than 10 positions. Four universities (Tilburg University, Iowa University, Stockholm School of Economics, and the University of Nottingham) experience rank loses greater than 45 positions, while one university –the University of Minnesota– experiences a rank gain equal to 43 positions. (For further details, see the left-hand panel in Table B in the Appendix).

Table 3 around here

Secondly, consider the relative productivity of individuals in distribution P, defined by

$$p'_i = p_i / \mu(P),\ i = 1, \ldots, N,$$

where $\mu(P)$ is the mean productivity in that distribution. For each i, the fact that the relative indicator p'_i is greater than, equal to, or smaller than 1 means that this individual has a productivity greater than, equal to, or smaller than the mean of the population. Similarly, consider relative indicators for distribution Q, defined by

$$q'_i = q_i / \mu(Q),\ i = 1, \ldots, N,$$

where $\mu(Q)$ is the mean productivity in that distribution. Then, in the change from P to Q we can compare the differences between the relative positions among individuals (p'_i - q'_i). As pointed out in Waltman *et al.* (2012), since distributions P and Q are rather skewed (see Table 1), an increase in the relative position of an individual by, say, 10 positions is much more significant in the top of the ranking than further down the list. Therefore, the statement "Individual i is performing 20% better in distribution P than in distribution Q" reflects better the situation under comparison than "Individual i is ranked 20 positions higher in distribution P than in distribution Q". Of course, the same analysis can be done for departments rather than individuals (for the skewness of the distribution of department mean productivities, see columns 3 and 6 in Table A in the Appendix). The results are summarized in Table 3.B. It turns out that for 53.4% of all individuals the change in the relative indicator of productivity is greater than 0.20, while only 18% of the total experience a change smaller than or equal to 0.05. The corresponding figures for departments are 44.4% and 18.5%, respectively.

The conclusion is that the ordering of individuals and departments according to the two productivity definitions is very different indeed. The weighting of articles according to the journal class where they have been published represents a dramatically different way of assessing individual and departmental productivity.

V. THE CONSEQUENCES OF AGE NORMALIZATION

V.1. 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 (Diamond, 1984).[9] Consequently, as indicated in the Introduction, the productivity of two scientists of different age 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 age. Table 4 presents the results for ten cohorts.

Table 4 around here

Four points should be emphasized. Firstly, the way mean productivity by cohort evolves as academic age increases according to the two productivity definitions essentially coincides with previous results. Mean productivity increases until it reaches the population average within cohort IV, after 16-19 years since obtaining the Ph.D., and then keeps increasing until the last cohort except for an anomalous reduction in cohort VII (see columns 3 and 7 in Table 4). Secondly, large within-cohort variations give rise to high coefficients of variation ranging from 0.71 to 0.96 for distribution ***P,*** and from 0.78 to 1.17 for distribution ***Q*** (see columns 4 and 8). Thirdly, normalization by age generates a fundamental change: mean productivity becomes essentially the same in each cohort (see columns 5 and 9). According to the first productivity notion, mean productivity for the population as a whole is 1.3 publications per year per person. Mean productivity per cohort smoothly evolves from 1.04 publications per year in cohort I towards 1.50-1.55 in cohorts

[9] This is the pattern found in several studies investigating economists (Kenny and Studley, 1995, Oster and Hamermesch, 1998, and Baser and Pema, 2004); a set of Israeli scientists (Weiss and Lillard, 1982); five of the six areas of physics and earth sciences studied (Levin and Stephan, 1991), and French condensed matter physicists (Turner and Mairesse, 2003). For the dataset used in this paper, this pattern is confirmed in Carrasco and Ruiz-Castillo (2014).

III-VI, and then declines towards 1.30 in cohort IX. The mean productivity in cohort X, which includes very productive individuals, is 1.50. Mean productivity for the population as a whole according to the second definition is 14.9 points, equivalent to a publication in class B per year. The pattern by cohorts is very similar to what we saw for the distribution P/Age. Mean productivity by cohort ranges from 11.8 to 18.1 points per year, very close to the population mean. Fourthly, the within-cohort variation according to both distributions, 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 columns 6 and 10).

The above results explain the reduction of the correlation coefficients 0.57 and 0.50 between distributions P and age and distributions Q and age, respectively, down to essentially cero between distributions P/Age and age and distributions Q/Age and age.

V.2. The re-rankings caused by age normalization

Next, we should ask: what types of changes in the ordering of individuals and departments are generated by age normalization? For reasons of space, we focus on the move from distribution Q to distribution Q/Age (similar results for the move from rom distribution P to distribution P/Age are available upon request). The correlation coefficient between distributions Q and Q/Age at the individual and the department level is positive but relatively small: 0.50 and 0.44, respectively. Table 5, with the structure of Table 3, contains a summary of the results on the consequences of age normalization.

Table 5 around here

We comment separately on the impact of age normalization on individuals and departments. 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 greater than 0.20.

Secondly, although departments are much less affected when they are ordered by mean values of Q or Q/Age, differences are still very large. 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. The Stockholm School of Economics and Hong Kong University experience maximum rank gains of 29 and 27 positions, while the University of Washington and the University of Montreal experience maximum losses of 19 and 17 positions (see the right-hand panel in Table B in the Appendix). Naturally, gainers have relatively low mean ages, while the opposite is the case for losers (see column 2 in Table A in the Appendix). Thus, we must conclude that departments' mean productivities are considerably altered by age normalization.

V.3. Characteristics of productivity distributions after age normalization

As can be observed in Table 1, age normalization does not change very much the characteristics of productivity distributions for the population as a whole. There is simply a moderate decrease in both productivity inequality, measured by the *CV* (see column 3 in Table 1.A), and the skeweness of the distributions, measured by the *SK* index (column 4 in Table 1.A), and the CSS approach (Table 1.B). Therefore, what has been known since Seglen (1992) as the skewness of science is essentially preserved for the population as a whole.

The next issue concerns the answers that the questions raised in the Introduction receive after age normalization.

1. Is the variability within department productivity distributions changed when productivity is normalized by academic age? The answer is: not very much. On average, both productivity inequality (column 2 in Table 2.A), and the skeweness of productivity distributions (column 3 in Table 2.A, and Table 2.B) are somewhat smaller after age normalization. (The detailed information is in Table C in the Appendix).

2. Is within-department variability across departments more or less alike when we consider productivity per year? Differences across departments are now very much

increased. The coefficients of variation in Table 2.A and 2.B indicate that, although mean productivity differences are somewhat reduced (column 1 in Table 2.A), the variation across departments experienced by both productivity inequality (column 2 in Table 2.A), and the skeweness of productivity distributions (column 3 in Table 2.A, and Table 2.B) is clearly greater after age normalization. The large differences across department productivity distributions of the variable Q/Age according to the CSS approach are documented in Table D in the Appendix, and illustrated in Figure 1 –where departments are ordered according to the percentage of researchers in category 1.

Figure 1 around here

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% to 62%.[10] 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 U.S., we should inquire about the degree of variability found among the 51 U.S. departments. As far as the CSS approach is concerned, for example, the results are essentially maintained. On average for the U.S 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 the average percentages for the 81 departments are 59.0 (0.13)/24.7 (0.24)/16.3 (0.31). The situation for the U.S. departments is illustrated in Figure

[10] For example, as can be observed in Table D in the Appendix, at one extreme these percentages range from 8.3% – 9.5% of all economists to 26.6% – 33.5% of all quality points (Rice University, the Hebrew University, and the Free University of Amsterdam). At the other extreme, these percentages range from 23.7% – 35.7% of all economists to 49.6% – 62.1% of all quality points (University of Amsterdam, University College London, University of Wisconsin at Madison, and Johns Hopkins University).

2. (Further results concerning other characteristics of these departments are available on request).

Figure 2 around here

3. How is the effect on productivity inequality attributable to productivity differences across departments affected by the normalization of individual productivity by academic age? Not surprisingly in view of the answer to question 3, differences in productivity distributions across departments have a greater effect on overall productivity inequality when age is taken into account. This effect increases from 16% to 19% in the move from P to P/Age, and from 29% to 36% in the move from Q to Q/Age (column 3 in Table 2.C). However, the importance of scale effects between departments' productivity distributions is of a similar order of magnitude before and after age normalization (column 5 in Table 2.C).

VI. THE PARTITION OF THE POPULATION INTO COUNTRIES

Inn this Section we study the partition of the population described in the Introduction into seven countries represented in the sample by a sufficiently large number of departments, as well as one residual category including the European Institute, a European institution located in Florence, Italy, plus all remaining countries with only one department in the dataset. For reasons of space, we exclusively discuss country characteristics, as well as the consequences of age normalization for the second productivity notion. The results for distributions Q and Q/Age are presented in Table 6 where countries are ordered by mean productivity before normalization.

Table 6 around here

The following three points should be emphasized in relation to distribution Q. Firstly, not surprisingly, the more productive country is the U.S., followed by Canada and the UK.

Secondly, within country productivity inequality, and the skeweness of productivity distributions measured by the *SK* index (columns 4 and 5 in Table 6.A) are generally high. Similarly, the results for the CSS approach (row I in Table 6.B) show that, on average, countries exhibit almost the same skeweness as the population as a whole (see row III in Table 1.B). Thirdly, the size distribution by countries is very unequal, ranging from 1,524 individuals in the U.S. to 32 in Sweden. However, judging from the coefficients of variation over all countries, the mean, the productivity inequality, and the skeweness of productivity distributions are –as expected– more similar across countries than across departments (compare row II in Table 3.A and 3.B with row I in Table 6.A and 6.B). Consequently, as observed in Table 6.D, the effect on overall inequality of differences in productivity across countries is much smaller (9.5%) than across departments (29%). The importance of scale factors is about eight percentage points greater for countries (92.3%) than for departments (83.8%).

The consequences of age normalization can be summarized as follows. Firstly, on average, productivity inequality, and the skeweness of productivity distributions is somewhat smaller than before age normalization (compare columns 4 and 5 with columns 7 and 8 in table 6.A, and row I in Tables 6.B and 6.C). Secondly, judging from the coefficients of variation in Tables 6.A, 6.B, and 6.C, it is seen that, except for mean productivity, the variability across countries is somewhat greater than before age normalization. Nevertheless, the effect on overall inequality of country productivity differences and the importance of scale factors before and after age normalization are very similar 9.5% vs. 9.2%, and 92.3% vs. 88.2%. Thirdly, the results of the CSS approach for country distributions of the variable Q/Age are illustrated in Figure 3. The comparison with Figure 1 clearly illustrates the dramatic consequences of aggregation from departments into countries.

Figure 3 around here

VII. CONCLUSIONS AND EXTENSIONS

VII.1. 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 Section II. 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 until 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. Moreover, the productivity inequality and the skewness of the two productivity distributions for our sample of economists are of the same order of magnitude as the figures for the much larger population of scholars in Economics & Business in Ruiz-Castillo & Costas (2014). However, the ordering of individuals and departments according to the two productivity measures is very different. Therefore, we are advised to conduct our study using both measures. In relation to the partition of the population into the 81 departments, the main findings are the following two.

(i) Independently of how we measure productivity, department productivity distributions are far from uniform. In other words, within each department, individuals have very different productivity.

(ii) 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 –specially according to the second productivity definition– is greater than the effect 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 in 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. 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 main consequences of age normalization are the following two.

(i) On average, department productivity distributions exhibit less productivity inequality, and less skewnes than before age normalization. However, they are still far from uniform, and a relatively low percentage of economists are responsible for a relatively high percentage of all quality points.

(ii) Productivity distributions are practically as different across departments as before age normalization. However, as before, to a large extent the differences between productivity distributions are accounted for by scale factors well captured by 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: 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 when we partition the sample into seven countries and a residual category.

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 among each other than what is the case across department productivity distributions. Together with the fact that there are fewer countries than departments, the greater similarity among countries implies that the effect on overall productivity inequality of differences in productivity distributions across eight country categories is three (four) times smaller than the effect of differences in productivity distributions 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.

VII.2. Shortcomings and extensions

The above results are necessarily provisional in at least three important respects. Firstly, it should be emphasized that information about the department where scientists work is not readily available. As described in Section III.1, this paper has used the listing of faculty members in a selection of top 81 Economics departments in the world 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. At least part of the within- and between-department variability reported in the paper may very well 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, 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 warn 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.

Thirdly, 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 review all of the empirical issues studied in this paper in other scientific fields.

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Table A. Characteristics of productivity distributions for the 81 Departments (Ordered by mean productivity in distribution P)

		Number of people	Mean age	P Mean	P CV	P SK Index	Q Mean	Q CV	Q SK Index
1	MIT	38	24.3	61.9	1.47	0.55	925.6	1.04	0.54
2	Harvard University	55	22.7	53.0	0.95	0.05	909.9	0.90	0.12
3	Yale University	36	23.5	47.8	1.26	0.45	648.5	1.06	0.45
4	U. of Southern California	27	23.7	43.9	1.23	0.59	346.9	1.00	0.29
5	Princeton University	50	22.2	43.0	1.03	0.51	637.0	0.83	0.39
6	University of Bonn	21	23.2	39.2	1.08	0.45	266.0	0.94	0.47
7	Cornell University	31	24.0	38.8	0.94	0.23	441.9	0.96	0.31
8	U. of California, Berkeley	57	22.5	37.9	0.79	0.33	541.9	0.73	0.22
9	Tilburg University	52	18.0	37.6	1.03	0.43	197.3	1.07	0.50
10	Columbia University	45	19.8	37.6	1.32	0.41	561.6	1.39	0.37
11	Stockholm School of Ecs.	14	14.6	35.9	1.45	0.74	190.7	0.78	-0.18
12	New York University	43	22.1	35.6	0.81	0.22	538.4	0.94	0.39
13	University of Montreal	26	26.9	35.3	0.93	0.69	382.9	0.94	0.12
14	Vanderbilt University	33	24.0	34.1	1.21	0.56	297.5	1.08	0.44
15	University of Chicago	29	20.6	32.7	1.01	0.34	585.0	0.95	0.53
16	Arizona State University	25	27.6	32.7	1.08	0.58	295.6	1.16	0.66
17	Iowa State University	44	21.9	32.3	0.87	0.41	173.0	0.86	0.29
18	European Institute	11	19.2	32.1	0.78	0.30	332.3	0.63	0.41
19	Erasmus University	21	12.4	31.9	1.35	0.78	181.7	1.27	0.69
20	Oxford University	43	20.6	31.6	1.22	0.58	319.6	1.07	0.59
21	Queen's University	15	21.1	30.3	0.93	0.57	395.8	0.78	0.13
22	University of Nottingham	47	15.0	29.6	1.09	0.44	167.8	0.93	0.43
23	University of Florida	17	27.6	29.5	0.96	0.54	215.4	1.07	0.50
24	Johns Hopkins	14	24.1	29.2	0.93	0.33	442.4	0.88	0.21
25	Northwestern University	31	21.3	29.1	0.99	0.20	471.2	0.84	0.40
26	University of Pennsylvania	29	18.8	28.4	0.96	0.37	505.7	0.84	0.16
27	Rice University	18	27.3	28.4	0.68	0.19	307.6	0.84	0.60
28	Stanford University	38	19.3	27.6	1.00	0.49	479.4	1.01	0.47
29	Duke University	43	20.8	27.3	1.35	0.67	278.1	1.11	0.56
30	CA Institute of Technology	17	21.0	27.1	1.09	0.53	384.1	1.24	0.58
31	Univ. College London	33	17.1	27.0	1.11	0.49	308.3	1.17	0.75
32	University of Washington	24	25.1	27.0	1.70	0.48	348.6	1.61	0.68
33	U. of Cal., San Diego	37	18.3	26.9	1.17	0.32	379.6	1.04	0.37
34	Washington U., St Louis	29	24.9	26.8	0.68	0.13	354.9	1.01	0.40
35	Catholic Univ. of Louvain	40	17.3	26.6	1.36	0.53	144.8	1.26	0.58
36	U. of Texas, Austin	31	22.5	26.0	1.22	0.43	298.5	1.09	0.35
37	Purdue University	15	22.7	25.7	0.80	0.34	211.0	0.75	0.29
38	Ohio State University	37	24.1	25.5	0.77	0.24	305.5	1.02	0.41
39	University of Maryland	37	21.7	25.3	0.77	0.34	306.3	0.73	0.23
40	University of Warwick	42	19.4	25.2	1.07	0.50	262.2	1.25	0.55
41	Boston College	25	26.4	25.1	0.69	0.21	280.4	0.97	0.22
42	U. of California, Irvine	22	15.1	24.5	1.30	0.71	187.2	1.35	0.56
43	U. of California, LA	43	18.7	23.8	1.04	0.23	319.6	0.89	0.57

		Number of people	Mean age	P Mean	P CV	P SK Index	Q Mean	Q CV	Q SK Index
44	University of Michigan	48	19.4	23.5	0.84	0.27	316.1	0.79	0.29
45	Brown University	25	19.2	23.5	0.81	0.37	351.5	0.84	0.32
46	Cambridge University	30	18.1	23.1	1.21	0.70	222.8	1.45	0.77
47	London Sch. of Economics	51	18.5	22.9	1.24	0.71	294.4	1.12	0.61
48	University of Toronto	23	22.5	22.5	0.95	0.72	249.5	0.93	0.46
49	PA State University	22	24.5	22.5	0.58	0.00	254.8	0.69	0.24
50	Michigan State U.	43	21.5	22.1	0.99	0.41	241.7	1.25	0.57
51	U. of Wisconsin, Madison	25	15.4	22.1	1.08	0.53	304.3	0.97	0.38
52	U. of North Carolina	22	24.1	21.6	1.13	0.44	167.9	1.02	0.38
53	Rutgers University	32	23.5	21.5	0.92	0.18	162.9	0.82	-0.01
54	U. California, Davis	30	18.1	21.4	0.77	0.54	207.9	0.84	0.45
55	Boston University	34	20.5	21.0	0.98	0.43	318.9	1.13	0.64
56	University of Tel Aviv	45	20.1	21.0	0.89	0.40	207.3	0.82	0.32
57	Stockholm University	18	15.2	20.9	2.12	0.82	151.8	2.01	0.81
58	U. of Illinois, Urbana	25	18.2	20.8	1.15	0.41	207.8	1.06	0.52
59	Texas A and M	24	23.1	20.7	1.14	0.66	217.3	1.05	0.54
60	Hebrew University	22	17.0	20.7	1.06	0.44	182.1	1.01	0.48
61	University of Minnesota	23	19.4	20.3	0.86	0.37	361.1	0.83	0.42
62	Toulouse University	78	14.6	20.3	1.23	0.61	171.8	2.09	0.83
63	University of Pittsburgh	20	22.3	20.1	0.57	0.30	202.2	0.84	0.15
64	University of Iowa	15	22.9	20.0	0.50	-0.13	248.0	0.51	-0.26
65	Dartmouth College	27	16.4	19.9	0.84	0.23	178.2	0.80	-0.11
66	Univ. of British Columbia	27	16.0	19.7	1.03	0.26	243.0	1.08	0.29
67	University of Rochester	16	19.0	19.3	1.34	0.71	262.6	1.23	0.30
68	U. Pompeu Fabra	36	13.0	18.7	1.37	0.60	133.8	1.63	0.57
69	University of Indiana	24	19.6	18.2	0.98	0.39	166.9	1.11	0.41
70	U. Autónoma, Barcelona	33	16.6	18.1	1.35	0.62	87.7	1.55	0.73
71	University of Amsterdam	38	15.8	17.9	0.76	0.08	128.2	0.89	0.46
72	University of Virginia	28	18.7	17.6	1.17	0.72	211.9	1.30	0.71
73	Free Univ. of Amsterdam	21	14.1	17.3	0.75	0.25	127.5	1.00	0.15
74	University of Arizona	19	20.4	15.8	0.70	0.55	178.9	0.59	-0.15
75	University of York	41	16.0	15.8	1.23	0.65	96.7	1.63	0.71
76	Georgetown University	23	18.8	15.5	0.59	-0.20	212.0	0.70	-0.06
77	University of Copenhagen	42	15.7	13.7	0.80	0.46	91.1	1.06	0.61
78	Hong Kong University	14	14.2	13.1	0.78	0.02	165.8	0.75	-0.14
79	U. Carlos III, Spain	51	13.5	13.0	1.15	0.34	84.9	1.28	0.62
80	University of Essex	28	14.0	12.4	0.93	0.24	141.2	1.07	0.41
81	Carnegie Mellon U.	22	18.5	12.0	0.91	0.38	185.7	0.86	0.19
	Average	31.2	20.0	26.3	1.03	0.42	294.6	1.0	0.40
	Coefficient of variation	0.40	0.19	0.35	0.26	0.50	0.55	0.27	0.59

Table B. Re-rankings between distributions P and Q, and distributions Q and Q/Age

	Department (Ordered by P)	Number of changed positions when going from P to Q		Department (Ordered by Q)	Number of changed positions when going from Q to Q/Age
1	MIT	0	1	MIT	-1
2	Harvard University	0	2	Harvard University	1
3	Yale University	0	3	Yale University	-5
4	U. of Southern California	-18	4	Princeton University	1
5	Princeton University	1	5	University of Chicago	1
6	University of Bonn	-33	6	Columbia University	0
7	Cornell University	-6	7	U. of California, Berkley	2
8	U. of California, Berkeley	1	8	New York University	-1
9	Tilburg University	-48	9	University of Pennsylvania	2
10	Columbia University	4	10	Stanford University	0
11	Stockholm School of Ecs.	-47	11	Northwestern University	0
12	New York University	4	12	Johns Hopkins	-11
13	University of Montreal	-3	13	Cornell University	-3
14	Vanderbilt University	-20	14	Queen's University	0
15	University of Chicago	10	15	CA Institute of Technology	0
16	Arizona State University	-19	16	University of Montreal	-17
17	Iowa State University	-48	17	U. of Cal., San Diego	5
18	European Institute	-5	18	University of Minnesota	1
19	Erasmus University	-43	19	Washington U., St Louis	-8
20	Oxford University	-5	20	Brown University	2
21	Queen's University	7	21	University of Washington	-19
22	University of Nottingham	-46	22	U. of Southern California	-10
23	University of Florida	-26	23	European Institute	-1
24	Johns Hopkins	12	24	U. of California, LA	11
25	Northwestern University	14	25	Oxford University	-3
26	University of Pennsylvania	17	26	Boston University	0
27	Rice University	-2	27	University of Michigan	7
28	Stanford University	18	28	Univ. College London	9
29	Duke University	-9	29	Rice University	-15
30	CA Institute of Technology	15	30	University of Maryland	8
31	Univ. College London	3	31	Ohio State University	-10
32	University of Washington	11	32	U. of Wisconsin, Madison	11
33	U. of Cal., San Diego	16	33	U. of Texas, Austin	-5
34	Washington U., St Louis	15	34	Vanderbilt University	-5
35	Catholic Univ. of Louvain	-38	35	Arizona State University	-16
36	U. of Texas, Austin	3	36	London Sch. of Economics	11
37	Purdue University	-15	37	Boston College	1
38	Ohio State University	7	38	Duke University	4
39	University of Maryland	9	39	University of Bonn	4
40	University of Warwick	-1	40	University of Rochester	10
41	Boston College	4	41	University of Warwick	-8

	Department (Ordered by P)	Number of changed positions when going from P to Q		Department (Ordered by Q)	Number of changed positions when going from Q to Q/Age
42	U. of California, Irvine	-17	42	PA State University	-14
43	U. of California, LA	19	43	University of Toronto	-12
44	University of Michigan	17	44	University of Iowa	2
45	Brown University	25	45	Univ. of British Columbia	14
46	Cambridge University	-1	46	Michigan State U.	-7
47	London Sch. of Economics	11	47	Cambridge University	-17
48	University of Toronto	5	48	Texas A and M	-14
49	PA State University	7	49	University of Florida	-23
50	Michigan State U.	4	50	Georgetown University	-8
51	U. of Wisconsin, Madison	19	51	University of Virginia	-16
52	U. of North Carolina	-15	52	Purdue University	-9
53	Rutgers University	-18	53	U. California, Davis	5
54	U. California, Davis	1	54	U. of Illinois, Urbana	9
55	Boston University	29	55	University of Tel Aviv	9
56	University of Tel Aviv	1	56	University of Pittsburgh	6
57	Stockholm University	-15	57	Tilburg University	0
58	U. of Illinois, Urbana	4	58	Stockholm School of Ecs.	29
59	Texas A and M	11	59	U. of California, Irvine	-4
60	Hebrew University	-1	60	Carnegie Mellon U.	1
61	University of Minnesota	43	61	Hebrew University	14
62	Toulouse University	-4	62	Erasmus University	25
63	University of Pittsburgh	7	63	University of Arizona	3
64	University of Iowa	20	64	Dartmouth College	10
65	Dartmouth College	1	65	Iowa State University	-4
66	Univ. of British Columbia	21	66	Toulouse University	0
67	University of Rochester	27	67	U. of North Carolina	-11
68	U. Pompeu Fabra	-7	68	University of Nottingham	16
69	University of Indiana	0	69	University of Indiana	-4
70	U. Autónoma, Barcelona	-10	70	Hong Kong University	27
71	University of Amsterdam	-5	71	Rutgers University	-6
72	University of Virginia	21	72	Stockholm University	-2
73	Free Univ. of Amsterdam	-4	73	Catholic Univ. of Louvain	-3
74	University of Arizona	11	74	University of Essex	4
75	University of York	-3	75	U. Pompeu Fabra	10
76	Georgetown University	26	76	University of Amsterdam	8
77	University of Copenhagen	-2	77	Free Univ. of Amsterdam	6
78	Hong Kong University	8	78	University of York	-1
79	U. Carlos III, Spain	-2	79	University of Copenhagen	4
80	University of Essex	6	80	U. Autónoma, Barcelona	-1
81	Carnegie Mellon U.	21	81	U. Carlos III, Spain	1

Table C. Characteristics of productivity distributions for the 81 Departments, ordered by the mean of distribution Q/Age

		N. people (1)	Mean age (2)	Mean (3)	CV (4)	SK Index (5)
1	Harvard University	55	22.7	39.99	0.64	0.32
2	MIT	38	24.3	38.94	0.58	-0.17
3	Princeton University	50	22.2	31.09	0.51	0.32
4	University of Chicago	29	20.6	30.30	0.76	0.28
5	U. of California, Berkeley	57	22.5	27.77	0.52	0.05
6	Columbia University	45	19.8	26.99	0.70	0.41
7	University of Pennsylvania	29	18.8	26.09	0.56	-0.14
8	Yale University	36	23.5	24.96	0.74	0.30
9	New York University	43	22.1	24.30	0.72	0.08
10	Stanford University	38	19.3	23.32	0.62	0.10
11	Northwestern University	31	21.3	21.52	0.51	-0.15
12	U. of Cal., San Diego	37	18.3	18.17	0.65	0.32
13	U. of California, LA	43	18.7	18.11	0.55	0.14
14	Queen's University	15	21.1	18.09	0.50	0.21
15	CA Institute of Technology	17	21.0	18.02	0.90	0.48
16	Cornell University	31	24.0	17.76	0.65	0.20
17	University of Minnesota	23	19.4	17.65	0.65	0.03
18	Brown University	25	19.2	17.62	0.53	0.07
19	Univ. College London	33	17.1	17.37	0.78	0.27
20	University of Michigan	48	19.4	17.34	0.58	0.05
21	U. of Wisconsin, Madison	25	15.4	17.19	0.63	0.33
22	University of Maryland	37	21.7	16.87	0.66	0.25
23	Johns Hopkins	14	24.1	16.53	0.68	-0.15
24	European Institute	11	19.2	16.26	0.39	0.63
25	London Sch. of Economics	51	18.5	16.18	0.79	0.28
26	Boston University	34	20.5	15.66	0.76	0.23
27	Washington U., St Louis	29	24.9	14.24	0.74	0.09
28	Oxford University	43	20.6	13.98	0.82	0.34
29	Stockholm School of Ecs.	14	14.6	13.94	0.89	0.27
30	University of Rochester	16	19.0	13.79	0.68	0.34
31	Univ. of British Columbia	27	16.0	13.65	0.59	0.27
32	U. of Southern California	27	23.7	13.57	0.69	0.19
33	University of Montreal	26	26.9	13.43	0.65	0.14
34	Duke University	43	20.8	13.29	0.71	0.02
35	University of Bonn	21	23.2	13.21	0.87	0.51
36	Boston College	25	26.4	13.03	0.96	0.50
37	Erasmus University	21	12.4	12.58	0.90	0.26
38	U. of Texas, Austin	31	22.5	12.52	0.82	0.22
39	Vanderbilt University	33	24.0	12.11	0.84	0.00
40	University of Washington	24	25.1	11.91	1.12	0.36
41	Ohio State University	37	24.1	11.90	0.80	0.31
42	University of Iowa	15	22.9	11.76	0.61	0.37
43	Hong Kong University	14	14.2	11.57	0.63	0.15
44	Rice University	18	27.3	11.49	0.76	0.51

45	U. of Illinois, Urbana	25	18.2	11.34	0.82	0.19
46	University of Tel Aviv	45	20.1	11.29	0.73	0.48
47	Hebrew University	22	17.0	11.29	0.83	0.34
48	U. California, Davis	30	18.1	11.19	0.56	0.12
49	University of Warwick	42	19.4	11.04	0.88	0.38
50	University of Pittsburgh	20	22.3	10.91	0.77	0.44
51	Arizona State University	25	27.6	10.88	0.91	0.51
52	University of Nottingham	47	15.0	10.72	0.67	0.41
53	Michigan State U.	43	21.5	10.66	0.85	0.50
54	Dartmouth College	27	16.4	10.64	0.73	0.26
55	University of Toronto	23	22.5	10.59	0.63	0.09
56	PA State University	22	24.5	10.48	0.52	0.03
57	Tilburg University	52	18.0	10.29	0.90	0.41
58	Georgetown University	23	18.8	10.21	0.51	-0.20
59	Carnegie Mellon U.	22	18.5	10.16	0.63	0.15
60	University of Arizona	19	20.4	10.06	0.66	-0.04
61	Purdue University	15	22.7	10.01	0.72	-0.22
62	Texas A and M	24	23.1	9.79	0.95	0.54
63	U. of California, Irvine	22	15.1	9.77	0.87	0.58
64	Cambridge University	30	18.1	9.72	1.06	0.65
65	U. Pompeu Fabra	36	13.0	9.39	1.01	0.70
66	Toulouse University	78	14.6	9.35	1.59	0.67
67	University of Virginia	28	18.7	9.32	1.00	0.53
68	University of Amsterdam	38	15.8	9.28	0.75	0.33
69	Iowa State University	44	21.9	9.03	0.88	0.21
70	University of Essex	28	14.0	8.79	0.85	0.38
71	Free Univ. of Amsterdam	21	14.1	8.77	0.81	0.10
72	University of Florida	17	27.6	8.08	1.14	0.54
73	University of Indiana	24	19.6	7.89	0.86	0.06
74	Stockholm University	18	15.2	7.76	0.95	0.65
75	University of Copenhagen	42	15.7	7.70	0.94	0.47
76	Catholic Univ. of Louvain	40	17.3	7.61	0.77	0.27
77	Rutgers University	32	23.5	7.27	0.91	0.48
78	U. of North Carolina	22	24.1	7.08	0.91	0.35
79	University of York	41	16.0	6.03	0.98	0.42
80	U. Carlos III, Spain	51	13.5	5.94	0.98	0.45
81	U. Autónoma, Barcelona	33	16.6	5.32	1.22	0.57
	Average	31.2	20.0	14.2	0.77	0.28
	Coefficient of Variation	0.40	0.19	0.49	0.25	0.79

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

		Percentage of individuals in category:			Percentage of total articles in category:		
	Department	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
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

	Department	Percentage of individuals in category: 1	2	3	Percentage of total articles in category: 1	2	3
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
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

Table 1.A. Characteristics of productivity distributions for the entire population

	Mean	Standard deviation	*CV*	*SK* Index
	(1)	(2)	(3)	(4)
I. *P*	27.0	32.4	1.20	0.51
II. *Q*	307.3	399.2	1.30	0.54
III. *P/Age*	1.30	1.1	0.84	0.44
IV. *Q/Age*	14.9	13.9	0.93	0.38

Table 1.B. Results of the CSS approach for the entire population

	Percentage of individuals in category:			Percentage of total articles in category:		
	1	2	3	1	2	3
I. *P*	69.1	20.5	10.4	27.7	32.8	39.5
II. *Q* **Index**	69.2	20.0	10.8	24.2	32.2	43.6
III. *P/Age*	65.9	23.0	11.1	35.4	32.5	32.1
IV. *Q/Age*	65.0	22.0	13.0	28.5	32.7	38.8

Category 1 = individuals with a low productivity, less than or equal to μ_1
Category 2 = individuals with a fair productivity, greater than μ_1 and less than or equal to μ_2
Category 3 = individuals with a remarkable or outstanding productivity, greater than μ_2

where: μ_1 = mean productivity
μ_2 = mean productivity of individuals with productivity greater than μ_1

Table 2.A. Average (coefficient of variation) over 81 Departments for different characteristics of productivity distributions

	Mean (1)	CV (2)	SK Index (3)
I. P	26.3 (0.35)	1.03 (0.26)	0.42 (0.50)
II. Q	294.6 (0.55)	1.04 (0.27)	0.40 (0.59)
III. P/Age	1.3 (0.30)	0.72 (0.27)	0.29 (0.74)
IV. Q/Age	14.2 (0.49)	0.77 (0.25)	0.28 (0.79)

Table 2.B. The skewness of productivity distributions according to the CSS approach. Average (and coefficient of variation) over 81 Departments of the percentages of individuals, and the percentages of articles (or Q index values) by category

	Percentage of people in category			Percentage of total articles in category		
	1	2	3	1	2	3
I. P	64.5 (0.11)	21.5 (0.26)	14.0 (0.38)	27.4 (0.21)	31.3 (0.25)	41.3 (0.20)
II. Q **Index**	62.8 (0.14)	22.6 (0.29)	14.6 (0.31)	25.3 (0.26)	32.2 (0.25)	43.3 (0.21)
III. P/Age	60.8 (0.14)	23.9 (0.27)	15.4 (0.32)	34.7 (0.21)	30.3 (0.24)	35.0 (0.19)
IV. Q/Age	59.0 (0.13)	24.7 (0.24)	16.3 (0.30)	30.3 (0.24)	32.1 (0.21)	37.9 (0.18)

Category 1 = people with a low productivity, smaller than or equal to m_1
Category 2 = people with a fair productivity, greater than m_1 and smaller than or equal to m_2
Category 3 = people with a remarkable or outstanding productivity, above m_2

Table 2.C. 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]. See expressions (4) and (6) in Section III.3 in the text

	IDPD (1)	$I(C)$ (2)	100 [(1)/(2)] (3)	IDCP* (4)	100 [(1) – (4)] (5)
I. P	0.081	0.50	16.0%	0.023	71.8%
II. Q	0.174	0.59	29.3%	0.028	83.8%
III. P/Age	0.052	0.27	19.2%	0.013	74.0%
IV. Q/Age	0.135	0.37	36.5%	0.021	84.3%

Table 3. Consequences for the ordering of individuals and departments when we move form distribution *P* to distribution *Q*

A. Number of re-rankings among:

	Individuals	%		Departments	%
≤ 10	69	2.7	**≤ 4**	27	33.3
11 - 50	214	8.5	**5 - 10**	15	18.5
51 - 250	1,010	39.9	**11 - 20**	23	28.4
251 - 500	712	28.1	**> 20**	16	19.8
> 500	525	20.8			
Total	2,530	100.0	**Total**	81	100.0

B. Differences in relative productivity indicators

Individuals for whom the ratio of individual productivity to the population mean productivity is in the following interval:	Number	%	Departments for which the ratio of mean department productivity to the population mean productivity is in the following interval:	Number	%
≤ 0.05	457	18.0	**≤ 0.05**	15	18.5
> 0.05 and ≤ 0.10	304	12.0	**> 0.05 and ≤ 0.10**	10	12.4
> 0.10 and ≤ 0.20	419	16.6	**> 0.10 and ≤ 0.20**	20	24.7
> 0.20	1350	53.4	**> 0.20**	36	44.4
Total	2,530	100.0	**Total**	81	100.0

Table 4. Number of individuals, mean age, average productivity, and coefficient of variation (CV) by cohort for productivity distributions P, Q, P/Age, and Q/Age

Academic age *		N. people	Mean age	P Mean	P CV	P/Age Mean	P/Age CV	Q Mean	Q CV	Q/Age Mean	Q/Age CV
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
I.	**1 - 7**	517	4.6	4.2	0.83	1.04	1.05	51.9	1.17	11.8	1.08
II.	**8 - 11**	303	9.4	11.3	0.86	1.20	0.86	130.1	0.80	13.8	0.81
III.	**12 - 15**	260	13.5	17.6	0.71	1.30	0.71	203.1	0.86	15.1	0.87
IV.	**16 - 19**	251	17.3	26.9	0.75	1.56	0.76	300.4	0.78	17.5	0.80
V.	**20 - 23**	255	21.4	32.1	0.73	1.50	0.73	385.5	0.85	18.0	0.85
VI.	**24 - 27**	211	25.5	39.4	0.74	1.55	0.75	461.7	0.91	18.1	0.91
VII.	**28 - 31**	208	29.4	34.4	0.71	1.17	0.71	402.7	0.93	13.7	0.92
VIII.	**32 - 35**	204	33.4	42.7	0.79	1.28	0.79	481.8	0.97	14.4	0.97
IX.	**36 - 39**	163	37.5	48.5	0.81	1.30	0.81	507.1	0.92	13.5	0.91
X.	**> 40**	158	45.3	70.5	0.96	1.53	0.89	776.0	1.03	17.0	1.02
TOTAL		2,530	19.8	27.02	1.20	1.30	0.84	307.32	1.30	14.89	0.93

* Number of years from Ph.D. until 2007

Table 5. Consequences for the ordering of individuals and departments when we measure productivity as Q or as Q/Age

A. Number of re-rankings among:

	Individuals	%		Departments	%
≤ 10	74	2.9	**≤ 4**	36	44.4
11 - 50	265	10.5	**5 - 10**	24	29.6
51 - 250	878	34.7	**11 - 20**	17	21.0
251 - 500	682	27.0	**> 20**	4	5.0
> 500	631	24.9			
Total	2,530	100.0	**Total**	81	100.0

B. Differences in relative productivity indicators

Individuals for whom the ratio of individual productivity to the population mean productivity is in the following interval:	Number	%	Departments for which the ratio of mean department productivity to the population mean productivity is in the following interval:	Number	%
≤ 0.05	344	13.6	**≤ 0.05**	23	28.4
> 0.05 and ≤ 0.10	255	10.1	**> 0.05 and ≤ 0.10**	17	21.0
> 0.10 and ≤ 0.20	433	17.1	**> 0.10 and ≤ 0.20**	26	32.1
> 0.20	1498	59.2	**> 0.20**	15	18.5
Total	2530	100.0	**Total**	81	100.0

Table 6.A. Characteristics of productivity distributions for the different countries

	Country	N. people (1)	Mean age (2)	Distribution Q Mean (3)	CV (4)	SK Index (5)	Distribution Q/Age Mean (6)	CV (7)	SK Index (8)
1	**U.S.**	1,524	21.5	379.2	1.20	0.54	17.7	0.87	0.38
2	**Canada**	91	21.6	309.8	0.96	0.33	13.5	0.61	0.13
3	**UK**	358	17.9	235.7	1.24	0.63	12.1	0.87	0.39
4	**Israel**	67	19.1	199.0	0.87	0.28	11.3	0.76	0.45
5	**Sweden**	32	14.9	168.8	1.46	0.72	10.5	0.98	0.35
6	**Rest of World***	206	16.4	167.9	1.57	0.66	9.6	1.16	0.44
7	**Netherlands**	132	15.9	163.8	1.10	0.54	10.1	0.86	0.34
8	**Spain**	120	14.2	100.3	1.55	0.65	6.8	1.09	0.54
	I. Average	316.3	17.7	215.6	1.25	0.54	11.4	0.90	0.38
	Coeff. Variation	1.58	0.16	0.42	0.21	0.29	0.28	0.19	0.32

Table 6.B. Average, and (coefficient of variation) over countries of the percentages of individuals, and the percentages of Q index values by category

	Countries	Percentage of individuals in category: 1	2	3	Percentage of total articles in category: 1	2	3
1	**U.S.**	66.01	22.44	11.55	25.89	32.79	41.32
2	**Canada**	61.54	21.98	16.48	25.64	28.80	45.56
3	**UK**	67.60	19.55	12.85	22.46	29.99	47.54
4	**Israel**	58.21	25.37	16.42	25.39	33.46	41.14
5	**Sweden**	68.75	28.13	3.13	22.86	52.63	49.02
6	**Rest of World***	68.45	21.36	10.19	20.72	33.53	45.76
7	**Netherlands**	67.42	21.21	11.36	26.55	34.20	39.25
8	**Spain**	70.83	21.67	7.50	25.59	34.81	39.60
	I. Average	66.1	22.7	11.2	24.4	35.0	43.6
	Coeff. Variation	0.06	0.12	0.40	0.09	0.21	0.09

Table 6.C. Average, and (coefficient of variation) over countries of the percentages of individuals, and the percentages of Q/Age index values by category

	Countries	Percentage of individuals in category: 1	2	3	Percentage of total articles in category: 1	2	3
1	**U.S.**	61.22	24.74	14.04	29.00	33.90	37.10
2	**Canada**	53.85	25.27	20.88	30.09	28.77	41.15
3	**UK**	61.45	25.14	13.41	28.01	35.43	36.56
4	**Israel**	67.16	22.39	10.45	41.58	28.29	30.13
5	**Sweden**	65.63	18.75	15.63	31.44	23.00	45.56
6	**Netherlands**	56.82	27.27	15.91	23.65	36.27	40.08
7	**Rest of World***	67.96	21.84	10.19	29.46	33.49	37.05
8	**Spain**	69.17	20.00	10.83	31.59	29.55	38.87
	I. Average	64.0	21.9	14.1	31.9	29.3	38.8
	Coeff. Variation	0.10	0.21	0.22	0.18	0.17	0.17

Table 6.D. The effect on overall productivity inequality of differences in productivity across countries, 100 [$IDPD/I(.)$], and the effect of normalization on productivity inequality attributable to differences in productivity across countries, 100 [IDPD – IDCP*/IDCP]

	100($IDPD$)/$I(.)$	100[$IDPD$ - $IDPD$*]/$IDPD$
I. Q	9.5%	92.3%
II. Q/Age	9.2%	88.2%

* The category "Rest of countries" includes the European Institute, a European institution located in Florence, Italy, plus one department from each of the following countries: Belgium, Denmark, China, France, and Germany

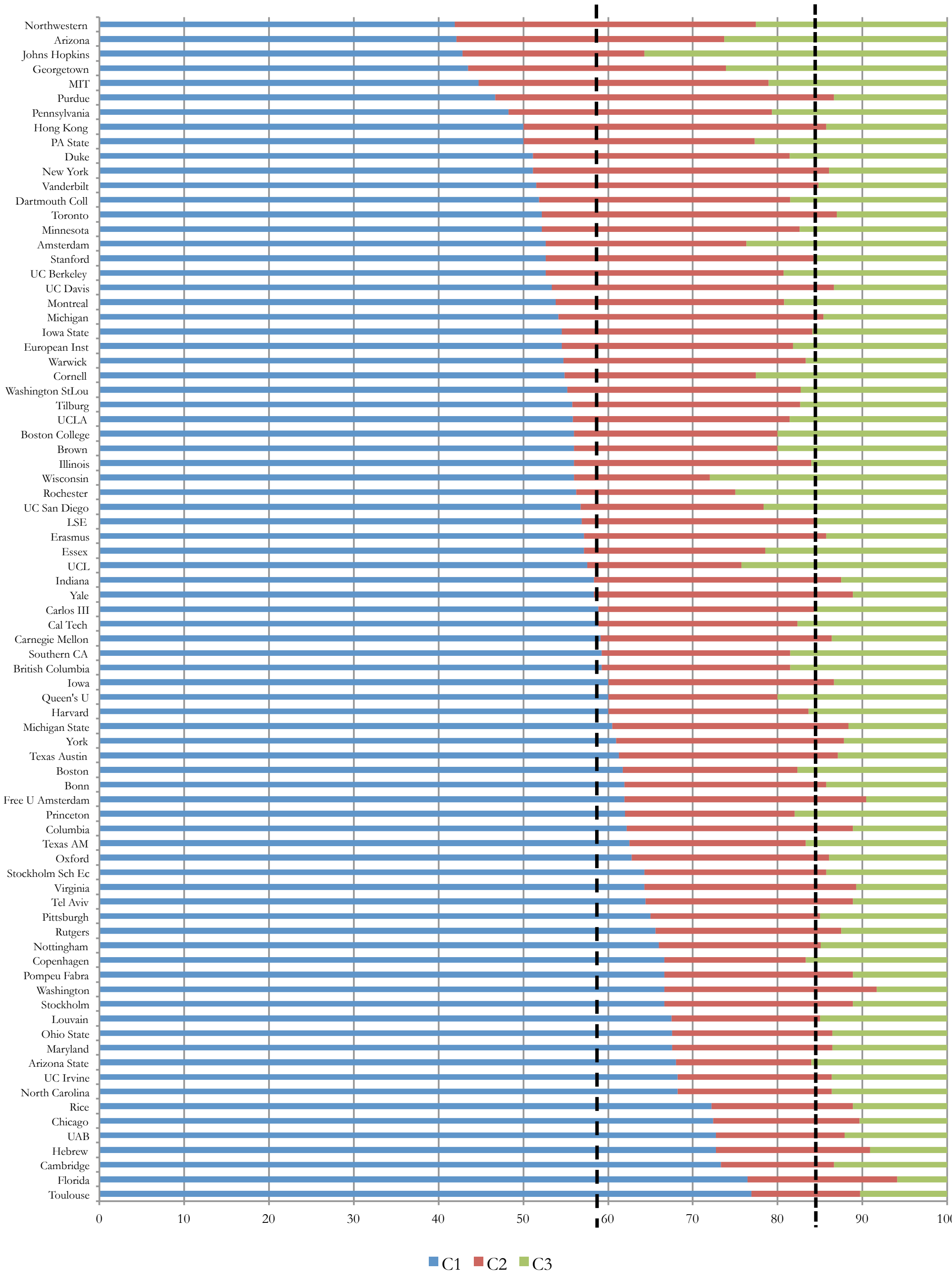

Figure 1. The partition of departments' productivity distributions into three categories according to the CSS technique. Individual productivity = quality index points per year per person (Distribution *Q/Age*). Results for the 81 departments.

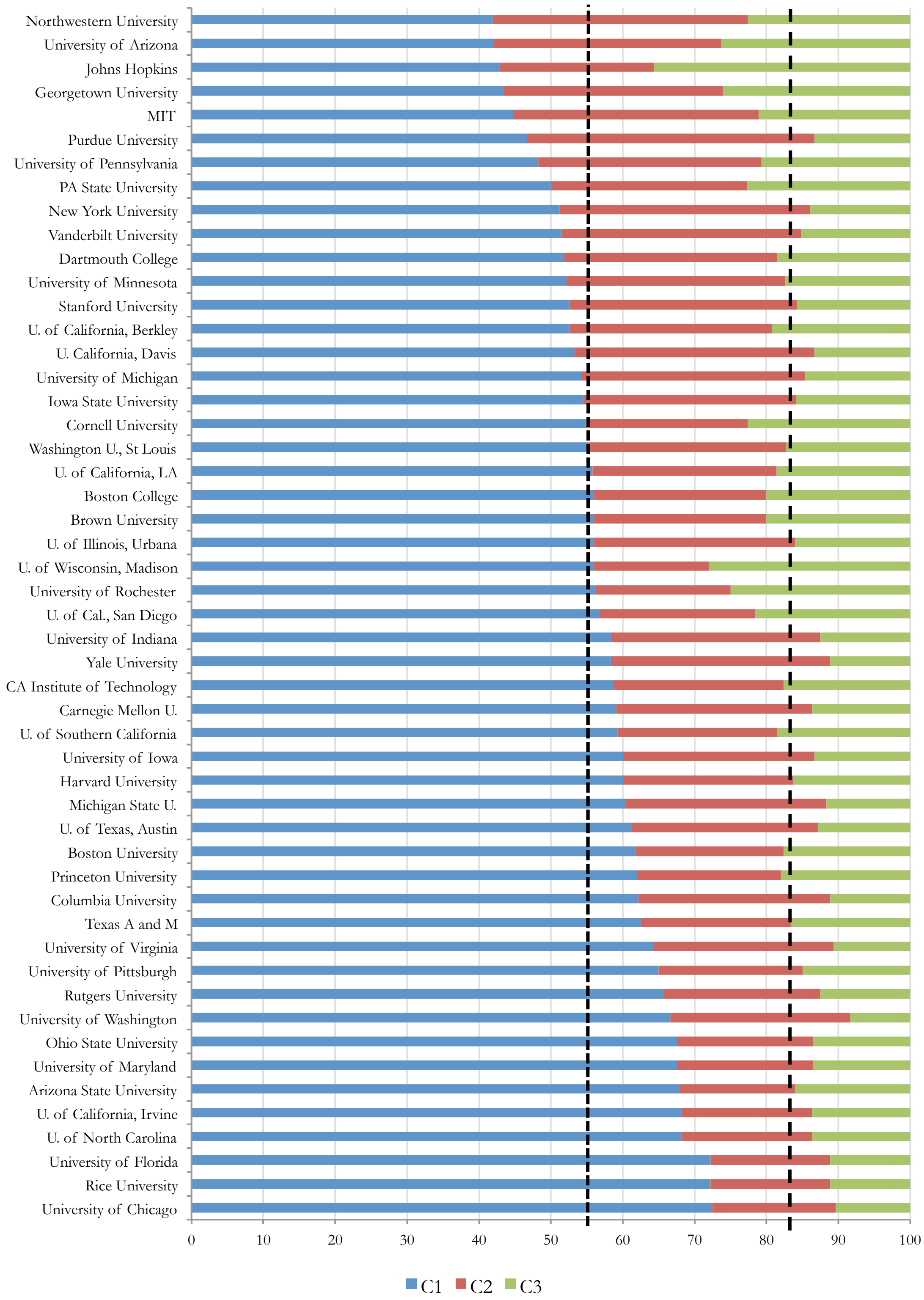

Figure 2. The partition of departments' productivity distributions into three categories according to the CSS technique. Individual productivity = quality index points per year per person (Distribution Q/Age). Results for the 51 U.S. departments

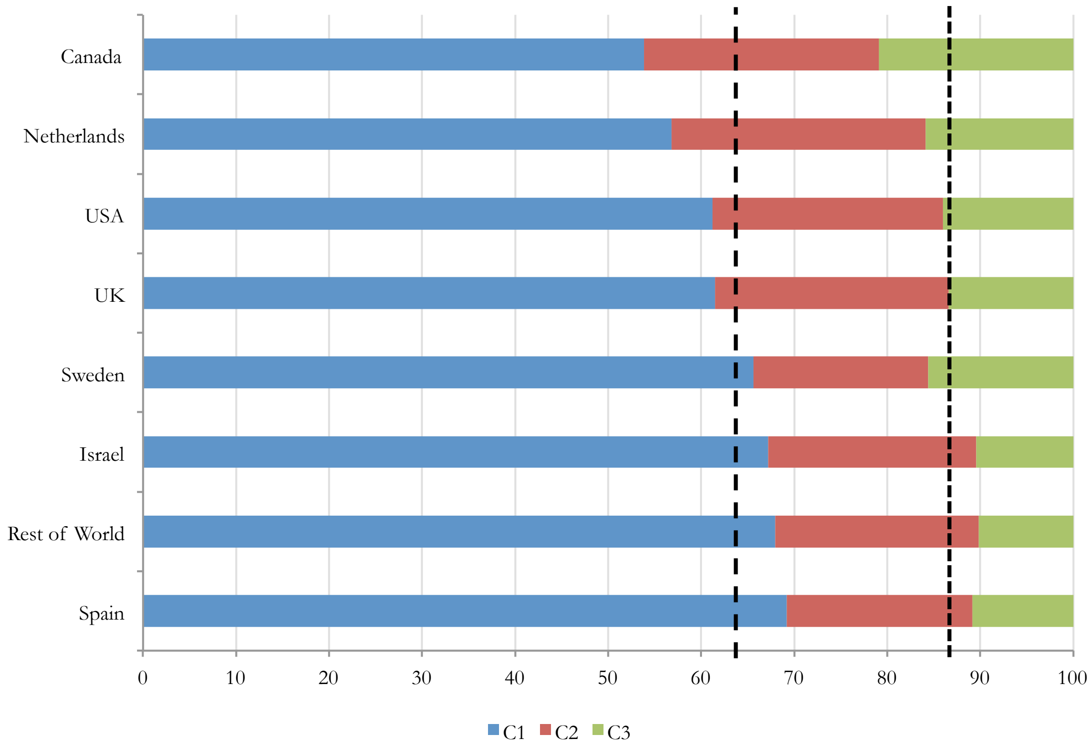

Figure 3. The partition of countries' productivity distributions into three categories according to the CSS technique. Individual productivity = quality index points per year per person (Distribution Q/Age)