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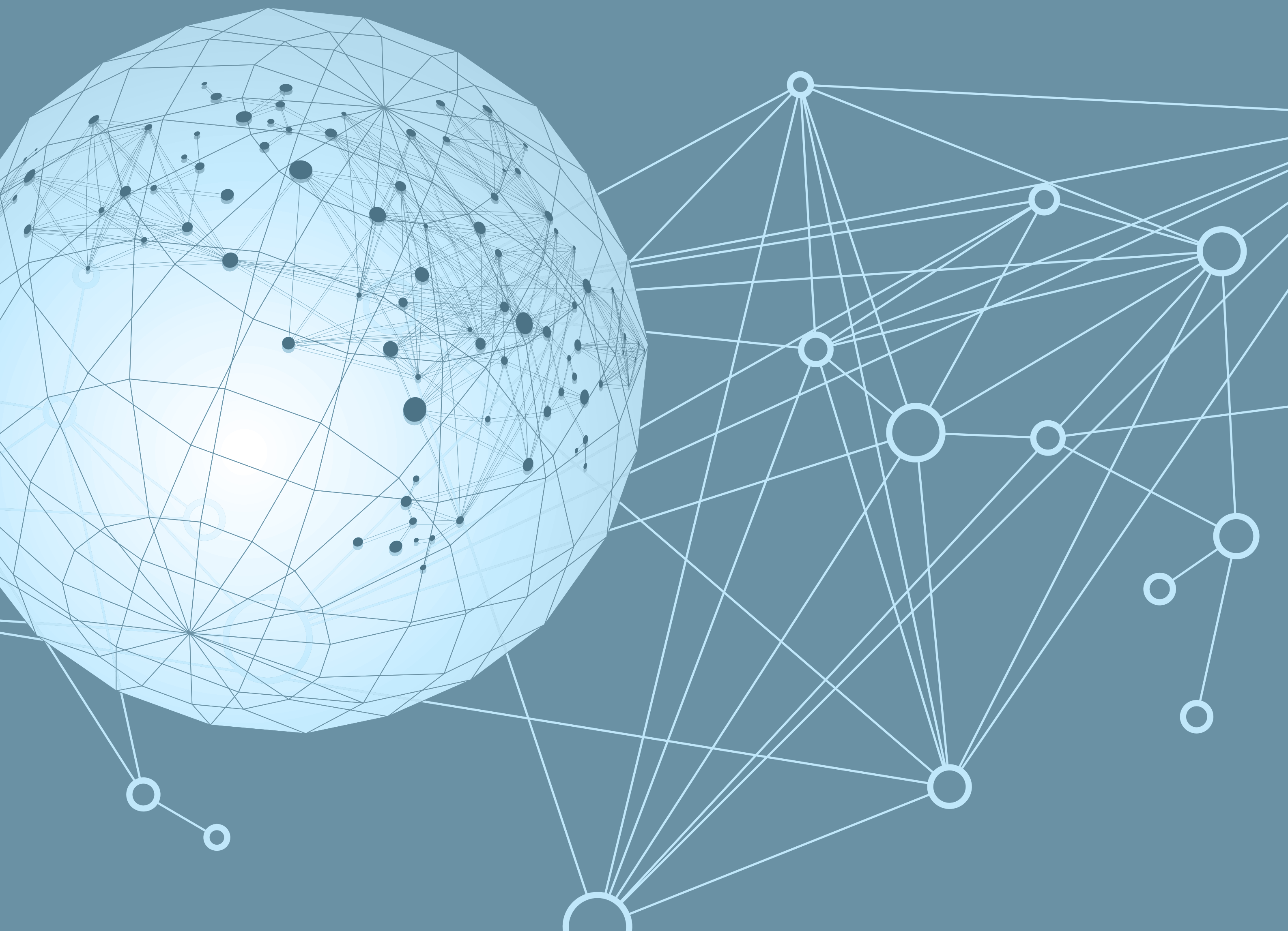

Within- and between-department variability in individual productivity. The case of Economics

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Introduction

There are two types of research units whose performance is usually investigated in one or several scientific fields: individuals (or publications), or larger units such as universities or entire countries. In contrast, the information about the university departments (or research institutes) is not easy to come by (Van Raan, 2005). This is important because, in the social sciences, university departments are the governance units where the demand for and the supply of researchers determine an equilibrium allocation of scholars to institutions. This paper uses a unique dataset consisting of all individuals working in 2007 in the top 81 Economics departments in the world according to the Econphd university ranking (2004).

The allocation of researchers to departments takes place under different institutional scenarios 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, research facilities, geographical location, and prestige. Job offers are not tended at random among recent PhDs. On the other hand, 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: each department can focus their attention on its set of self-selected candidates. Taking into account department needs, the credentials supplied by each candidate, as well as the results of interviews and seminars, each department makes a set of offers among the pool of its prospective candidates. Some offers are eventually accepted by some PhDs in all departments every year.

This process reveals a good deal of information to all parties concerned. The self-selection acting from the supply side of the market facilitates an efficient matching between applicants and departments. Nevertheless, strong doses of uncertainty still 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, tenure 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 in response to meritocratic and competitive market forces provides another adjustment mechanism. Some people 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.

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 countries, as we have in this paper, we can assume for the sake of the argument that the equilibrium allocation of individuals to departments captured in our sample does approximately reproduce some initial department ranking.

Be it as it may, this paper contributes to the formulation of a demand and supply equilibrium model for researchers by investigating two key stylized facts for our set of elite world Economics departments in 2007: the within- and between-department variability of several characteristics of productivity distributions or, in other words, the following two empirical questions:

1. Do we expect faculty members in a given department to have all similar productivities around the department mean?

2. If department productivity distributions are not uniform, do we expect these distributions to be similar across departments?

Naturally, in the absence of a formal model for the labor market as a whole 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 issues for 81 top Economics departments. We obtained information about the publications in the periodical literature for the 2,705 economists working in these departments in 2007. We could not find information about a person's education and/or publications in 50 cases, and there are 175 faculty members without any publication at all. Therefore, we focus on the remaining 2,530 faculty members with at least one publication that constitute what we call the population as whole.

Let the individuals be indexed by i, where $i = 1, 2,.., 2,530$. For every i, we measure individual productivity as a quality index, Q_i, that weights differently the articles published in four journal equivalent classes, where 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, as well as the comparison of our sample with the field of Economics as a whole). Given the way the data was selected, it is not surprising that we are working with a very productive sample.[1]

[1] We also measure individual productivity as the number of publications until 2007. The robustness of our results using both measures can be seen in the Working Paper version of this paper, Perianes-Rodriguez & Ruiz-Castillo (2014), hereafter PRRC.

Characteristics of the productivity distribution for the population as a whole

Basic characteristics

For the productivity distribution $\boldsymbol{Q} = (Q_1, \dots, Q_i, \dots, Q_{2,530})$, we are interested in two basic characteristics: the mean, and the individual variability within the distribution in question. Two aspects of the latter are investigated: the productivity inequality, measured by the coefficient of variation (*CV* hereafter), and the skewness of the distribution for which we follow the Characteristic Scores and Scale (CSS hereafter) approach (see PRRC for a second skewness measure using an index robust to extreme observations). 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 greater than μ_1 and smaller than or equal to μ_2, and (iii) individuals with remarkable or outstanding productivity greater than μ_2. The information about the main characteristics of distribution $\boldsymbol{Q}$ for the population as a whole is in Table 1.

Table 1. Characteristics of productivity distribution *Q*. Results of the CSS approach for the entire population

		Percentage of individuals in category:			Percentage of total articles in category:		
Mean	***CV***	**1**	**2**	**3**	**1**	**2**	**3**
307.3	1.30	69.2	20.0	10.8	24.2	32.2	43.6

Two comments are in order. Firstly, the productivity inequality according to the *CV* is 1.3, a very high figure indicating that the standard deviation is 1.3 times greater than the mean. Secondly, distribution $\boldsymbol{Q}$ is considerably skewed: the percentage of people with below average productivity is approximately 19 points to the right of the median, and 10.8% of the total population are responsible for 43.6% of all index points. These figures are comparable to what we find for the population of scholars in Economics & Business in Ruiz-Castillo & Costas (2014) for a much larger population. This parallelism reflects the fractal nature of productivity distributions in our field.

Individual variability within- and between- departments

We now turn towards the two questions raised in the Introduction for the partition of distribution $\boldsymbol{Q}$ into the 81 departments. Table A in the Appendix of PRRC presents the results for the mean productivity and the *CV* in each department, while Table B presents the results of the CSS approach for all departments. The average over all departments, and the coefficient of variation of these characteristics are in in Table 2.

Table 2. Average (coefficient of variation) over 81 Departments for different characteristics of productivity distributions. Results of the CSS approach (*Q*)

		Percentage of people in category			Percentage of total articles in category		
Mean	***CV***	**1**	**2**	**3**	**1**	**2**	**3**
294.6 (0.55)	1.04 (0.27)	62.8 (0.14)	22.6 (0.29)	14.7 (0.31)	25.3 (0.25)	32.2 (0.25)	43.3 (0.21)

The first 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. Moreover, the high coefficients of variation in Table 2 indicate that productivity inequality and the skeweness of productivity distributions are very different across departments. Therefore, although we find large within-departmental variability, the productivity inequality and the degree of skeweness of productivity distributions is very different across departments.

Finally, in PRRC we investigate in detail the importance of differences between department productivity distributions in the measuring framework introduced in Crespo *et al.* (2013a) with the purpose of analyzing the effect on overall citation inequality of differences in production and citation practices across scientific fields. The conclusion is that the effect on overall productivity inequality that can be attributed to differences in the 81 productivity distributions in Economics (29%) is clearly greater than the corresponding effect attributable to differences in citation distributions across a large number of Web of Science subject categories (Crespo *et al.*, 2013a, b, Li *et al.*, 2013, and Waltman & Van Eck, 2013). However, the part of these differences that can be attributed to scale factors in our dataset is of a comparable order of magnitude (84%) to the same phenomenon in the context of sub-field citation distributions.

Characteristics of productivity distributions after age normalization

Since Lotka (1926), individual productivity datasets typically consist of a cross-section of researchers of different age in a given moment of time. However, 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). Consequently, the productivity of two scientists of different age in a given field is, in principle, non-comparable. Fortunately, our dataset has information on both individual researchers publications and their academic age, Age_i, $i = 1, \dots, 2{,}530$, where Age_i is the number of years since the completion of their Ph.D. and 2007.

Denote by $\boldsymbol{Q/Age} = (Q_1/Age_1, \dots, Q_i/Age_i, \dots, Q_{2,530}/Age_{2,530})$ the distribution of individual productivity after age normalization. We begin by asking: what types of changes in the ordering of individuals and departments are generated by age normalization? 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, the ranking of departments is also greatly altered (see PRRC for details). However, as can be observed in Table 3, age normalization does not change very much the characteristics of the productivity distribution for the population as a whole. Comparing with Table 1, there is simply a moderate decrease in both productivity inequality, measured by the *CV* and the skeweness of the distributions.

Table 3. Characteristics of productivity distribution *Q/age*. Results of the CSS approach for the entire population

		Percentage of individuals in category:			Percentage of total articles in category:		
Mean	***CV***	**1**	**2**	**3**	**1**	**2**	**3**
14.9	0.93	65.0	22.0	13.0	28.5	32.7	38.8

Next, we should answer the two questions raised in the Introduction. Firstly, does the variability within department productivity distributions change when productivity is normalized by academic age? Taking into account the information summarized in Table 4, the answer is: not very much. On average, both productivity inequality, and the skeweness of productivity distributions are somewhat smaller after age normalization.

Table 4. Average (coefficient of variation) over 81 Departments for different characteristics of productivity distributions. Results of the CSS approach (*Q/age*)

		Percentage of people in category			Percentage of total articles in category		
Mean	***CV***	**1**	**2**	**3**	**1**	**2**	**3**
14.2 (0.49)	0.77 (0.25)	59.0 (0.13)	24.7 (0.24)	16.3 (0.29)	30.3 (0.24)	32.1 (0.21)	37.9 (0.18)

Secondly, does between-department variability change when we consider productivity per year? Differences across departments are now considerably increased. In comparison with Table 3, the coefficients of variation in Table 4 indicate that, although mean productivity differences are somewhat reduced, the between-department variability experienced by both productivity inequality, and the skeweness of productivity distributions is clearly greater after age normalization. The large differences across department productivity distributions according to the CSS approach are illustrated in Figure 1 (see also Table D in the Appendix in PRRC).

Finally, how is the effect on overall productivity inequality attributable to productivity differences across departments affected by the normalization of individual productivity by academic age? As reported in detail in PRRC, this effect increases from 29% to 36%. However, the part of these differences that can be attributed to scale factors is of a similar order of magnitude before and after age normalization.

Conclusions

The matching of individuals and university departments in any scientific field results from a complex equilibrium between the demand for and the supply of researchers at different stages in their career. 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 for a population of 2,530 individuals with at least one publication who were working in 81 top Economics departments in 2007.

For the population as a whole, the productivity inequality and the skewness of distribution ***Q*** before and after age normalization 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). In relation to the partition of the population into the 81 departments, the main findings are the following two.

(i) 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. Consequently, the effect on overall productivity inequality of differences in productivity distributions across the 81 departments 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.

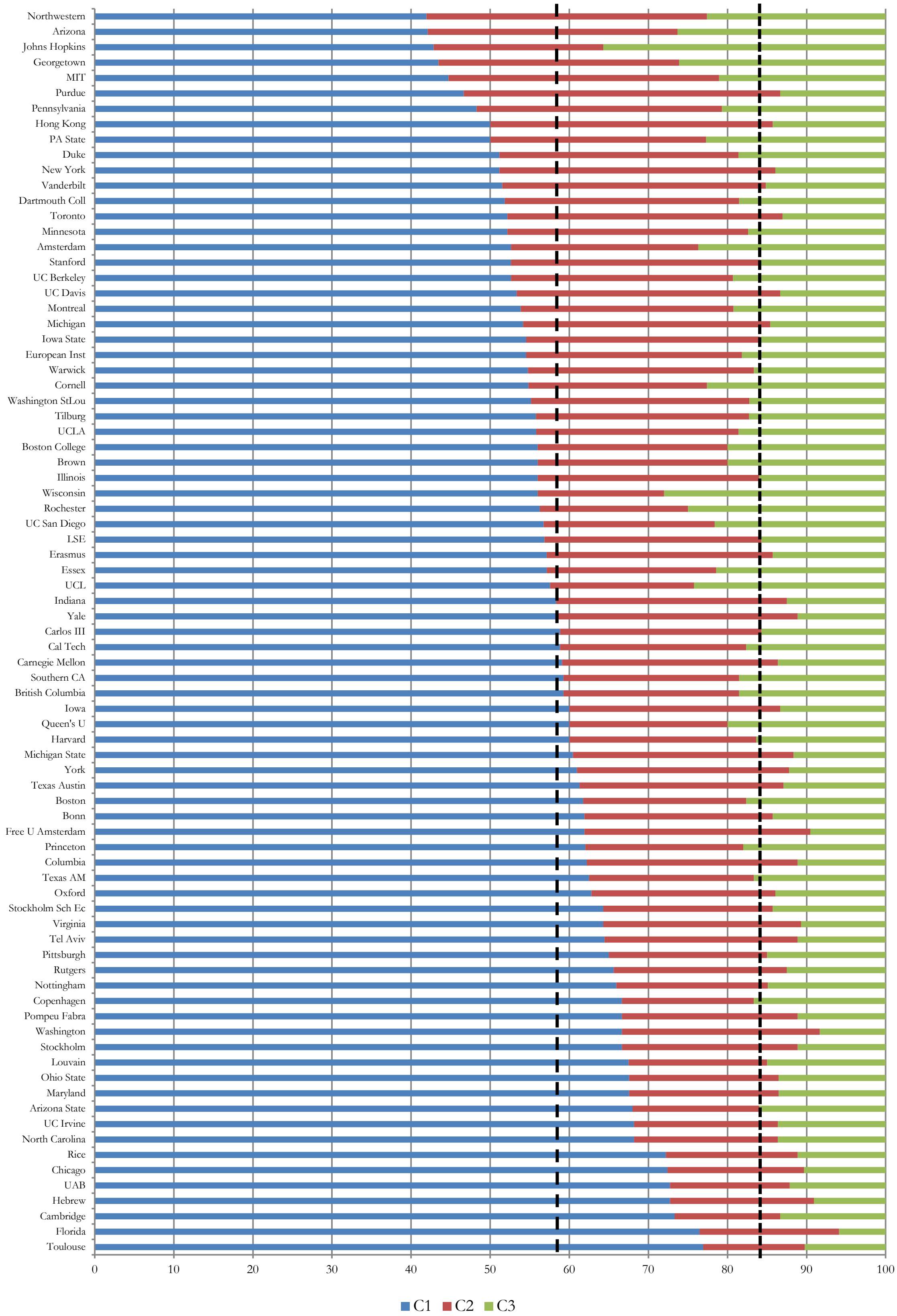

Figure 1. The partition of departments' productivity distributions into three categories according to the CSS technique. Individual productivity = quality index points per year per person (Distribution *Q/Age*)

The conclusion is that, both before and after age normalization, any theory about the interaction between demand and supply forces for researchers must cope with the following two features: large within-department individual productivity variability, and strong differences between department productivity distributions.
Between-department productivity heterogeneity goes against the considerable similarity between: (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. As pointed out by a referee, the large doses of between-department heterogeneity may be due in part to statistical fluctuations combined with the relatively small number of researchers by department (see the evidence in this respect in PRRC). Therefore, a natural question to ask is whether the aggregation of departments into countries in our dataset leads us to recover some similarity. As documented in PRRC, this is essentially what we find when we partition the sample into seven countries and a residual category. The conclusion is that a high degree of departmental heterogeneity is compatible with considerably greater country homogeneity.

The above results are necessarily provisional in at least four important respects. Firstly, we conjecture that, at least part of the within- and between-department variability reported in the paper, may very well be due to the fact that the quality of the institutional and personal information provided by our Internet sources is admittedly very uneven and subject to error. Secondly, it should be recalled that the nexus between productivity and age is highly non-linear. Furthermore, Albarrán *et al.* (2014) have shown that this relationship is much weaker for remarkably productive scholars than for the rest of the elite included in our sample. Under these conditions, the simple age normalization used in this paper leaves much to be desired. The residuals of a regression of productivity on age and other control variables might provide a promising avenue for a tailor-made individual adjustment for every individual in the sample. Thirdly, given the skewness of the citation distribution of articles in any journal, including an important percentage with zero citations, Seglen's (1992, 1997) seminal contributions caution us about the wisdom of judging the quality of individual publications –as we have done in this paper– by the citation impact of the journal where they have been published. 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. Finally, our results only refer to the field of Economics. Before formally modeling the interplay of demand and supply of researchers at the department level, it is advisable to extend the coverage of the issues studied in this paper to other scientific fields.

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