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"THE EVOLUTION OF THE SCIENTIFIC PRODUCTIVITY OF HIGHLY PRODUCTIVE ECONOMISTS"

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Abstract. This paper studies the evolution of research productivity of a sample of economists working in the best 81 departments in the world in 2007. The main novelty is that, in so far as a productivity distribution can be identified with an income distribution, we measure productivity mobility in a dynamic context using an indicator inspired in an income mobility index suggested by Fields (2010) for a two-period world. Productivity is measured in terms of the number of publications in each of four classes, weighted according to a rather elitist scheme. We study the evolution of average productivity, productivity inequality, the extent of rank reversals, and productivity mobility for seven cohorts, as well as the population as a whole. We offer new evidence confirming previous results about the heterogeneity of the evolution of productivity for top and other researchers. However, the major result is that –contrary to what was expected– for our sample of very highly productive scholars the effect of rank reversals between the two periods on overall productivity mobility offsets the effect of an increase in productivity inequality from the first to the second period in the youngest five out of seven cohorts.

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I. INTRODUCTION

The public nature of basic scientific knowledge had been emphasized in the seminal contributions of Nelson (1959) and Arrow (1962) to what has been described as the 'old' economics of basic research. We owe to Robert Merton (1957, 1961, 1973, 1988), the founder of the modern sociology of science, the recognition at about the same time of crucial non-market aspects in the reward structure in science around the *priority of discovery* as a form of property right. The genius of Merton is that he stood the public-private distinction on its head, proposing that the search for priority functioned to make a public good private (Stephan, 2004).[1]

Linking rewards to priority sets up a contest, a race, for scientific discoveries. The allocation of rewards takes many forms, depending upon the importance that the scientific community attaches to the discovery in question. Publication –a necessary step in establishing priority– is a lesser form of recognition within the reach of most scientists. In Merton's (1957, p. 237) words, "*For most of us artisans of research, getting things into print becomes a symbolic equivalent to making a scientific discovery*." Formal and informal procedures to grant academic tenure, promotions, resources for research, and entrance to professional societies are increasingly connected to publication and citation counts that are readily observable. There is also a large literature on the roles of the quantity and the citation impact of publications in salary determination.[2] Finally, it has been argued that the advantage of taking scientists as an object of study in labor economics is that information about research productivity –the subject matter of this paper– is available through bibliographic databases (Coupé *et al.*, 2006).

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[1] Specifically, Merton (1988, p.620) wrote: "*I propose the seeming paradox that in science, private property is established by having its substance freely given to others that may want to make use of it.*" In the words of David (1994, p.70), *"Recognition of one's contributions and consequent collegiate reputation, or esteem in the eyes of one's scientific colleagues, is the key currency of the open science reputation system"*. The 'new' economics of science arises as the synthesis between two sets of ideas: (i) the insights from the early sociology of science and the old economics of science; and (ii) the modern literature on behavior under incomplete and asymmetric information, as well as the dynamics of waiting and winner-takes-all or tournament games. See the excellent survey by Dasgupta and David (1994), as well as Stephan (2010), which builds upon Stephan (1996).

[2] For economics, see *inter alia* Hamermesch *et al.* (1982), Diamond (1986), Hamermesch (1989), Kenny and Studley (1995), Hamermesch and Schmidt (2003), Moore *et al.* (1998, 2001), and Ragan *et al.* (1998). Even the reputation of academic economists has been separately linked to these observables in Hamermesch and Pfann (2012).

Consider the possibility of measuring the productivity of scientists in terms of publications, weighted by the citation impact of the journals where each article is published in the periodical literature. The distribution of individual researchers' productivities has been known for some time to be extremely unequal, being characterized –in each of many different research areas– by a long upper tail in the frequency distribution of the number of papers published in a specified time interval.[3] This paper is a contribution to the measurement of the evolution of scientific productivity. Its distinctive feature is that, since a productivity distribution can be identified with an income distribution, in a dynamic context it is useful to measure productivity mobility using an income mobility index.

There are many ways of measuring income mobility. More than 20 measures have been used in the literature and, as emphasized in the recent survey by Fields (2008), there are six different mobility concepts. In this paper, we choose the concept of mobility as an equalizer of long-term productivities. Also, as in the seminal papers by Miranda (1982, 1984) and King (1983), we restrict ourselves to a two-period world. In a two persons world, this mobility notion would judge that a pattern of productivity change in the two periods (1, 3) → (1, 5) would *disequalize* life cycle productivity relative to the initial period, while a pattern (1, 3) → (5, 1) would *equalize* life cycle productivity relative to the initial period.

In particular, we choose the mobility index suggested by Fields (2010) for a two period world, according to which if aggregate productivity inequality decreases (increases) relative to the initial situation, then productivity mobility takes a positive (negative) sign.[4] This index choice is motivated by the following two stylized facts that, according to David (1994, p.72), appear to characterize the evolution of scientists' productivity over time.

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[3] See the landmark paper by Alfred Lotka (1926), as well as the book by Derek deSolla Price (1963) that starts the modern quantitative study of science. "Lotka's law" states that if k is the number of scientists that publish one paper, then the number publishing n papers is k/n^2. In many disciplines, approximately 6% of publishing scientists produce half of all papers. "Price's Law" indicates that one half of the total output of papers published by a population of P scientists will be the work of $P^{1/2}$ most productive members.

[4] From a positive point of view, the Fields index is essentially equivalent to the income mobility index first suggested by Chakravarty *et al.* (1985). See Fields (2010) for a discussion and the precise relationship between the two indices.

(1) "*The arresting observation … is not simply that there are unusually marked inequalities in 'publication attainments' among scientists during a given time interval, but, rather, that the pronounced productivity stratification in science existing at any moment reflects the persistence of a particular hierarchical ordering throughout most of the life of a cohort*."

(2) In both true and synthetic cohort data, "*the dispersion of current period rates is found to increase over the professional life of the cohort*".

The interest of the Fields framework is that it perfectly accommodates these two facts. In a dynamic context, there are different types of productivity changes taking place simultaneously. For our purposes, it is convenient to distinguish between rank reversals, or changes in the individuals' relative positions in the productivity scale, and changes in cross-section productivity inequality in different time periods. Applying the arguments in Ruiz-Castillo (2004), it will be seen that the Fields index can be conveniently decomposed into two terms that reflect these two types of productivity change. The first term captures so-called *exchange mobility* (*EM* hereafter), namely, the effect of rank reversals, or re-rankings between the first- and second-period productivity distributions. It can be shown that the re-rankings equalizing effect causes *EM* to be positive. David's fact (1) indicates that there is a lot of persistence in researchers' productivity over time or, in other words, few re-rankings. Similarly, Kelchtermans and Veugelers (2011, p. 296) state "*There is remarkable little turbulence, with top researchers more likely to repeat top performances, and similarly at the bottom of the distribution*." Hence, we should expect a positive but small contribution to overall mobility from *EM*. The second term in the decomposition captures so-called *structural mobility* (*SM* hereafter), namely, the effect of changes in productivity inequality between the aggregate and the initial productivity once all re-rankings have been eliminated. It can be shown that a decrease in productivity inequality from the first to the second period causes *SM* to be positive. However, there are counterexamples to the opposite statement even in the absence of rank reversals. Nevertheless, we expect that an increase in productivity inequality from the first to the second period as indicated in fact (2) might generally cause *SM* to be negative. As a matter of fact, we interpret the quotation from Davis (1972) as indicating that, because the second effect may dominate the first one, we should expect overall mobility to be disequalizing.

We begin with a dataset consisting of the publications of 2,474 economists working in 81 of the best university economics departments in the world at the end of 2007. Therefore, this paper contributes to the literature on Economics of Economics recently surveyed by Coupé (2004). This dataset contains productivity information for every eight-year period after obtaining the PhD. For the study of productivity mobility in a two period world, we distinguish between several cohorts. For all cohorts, the first period always consists of the first eight years after the PhD. The second period varies in length, from the youngest cohort, for which it lasts only eight more years, to the oldest cohort, for which it lasts 32 or 49 more years. Thus, we focus on the sub-set of 1,136 economists that, counting from 2007, have spent at least 16 years in academic life since their PhD.

We study the evolution of average productivity, productivity inequality, the extent of re-rankings, and productivity mobility for seven cohorts and the sample as a whole. The main findings are the following four. 1. Although average productivity decreases with the time elapsed since the PhD for the entire cohorts sample, top performers and the remaining individuals present very different patterns. 2. In agreement with fact 2 above, productivity inequality increases with time. 3. Although there is some hierarchical persistence, contrary to fact 1 above we find that among this sub-set of highly productive scholars there are a lot of rank reversals. 4. Thus, contrary to what we expected, productivity mobility is clearly equalizing in the youngest three cohorts, and it is clearly disequalizing only in the oldest cohort.

The remaining part of the paper is organized in four Sections. Section II presents the Fields mobility index used in the paper. Section III describes the data and its organization into seven cohorts. Section IV is devoted to two types of empirical results: the evolution of average productivity and productivity inequality, two topics that have been quite extensively investigated in the past, and our results on productivity mobility that, as far as we know, appear here for the first time in the literature. Section IV concludes.

II. THE MEASUREMENT OF PRODUCTIVITY MOBILITY

II.1. Notations and Definitions

In a two-period world, let $\boldsymbol{x} = (x_1,\ldots, x_n)$ represent the productivity distribution of an n-person scientific community where individual i's productivity level is the non-negative quantity $x_i \geq 0$. Assume that individual i's productivity changes to $y_i \geq 0$ over a given time interval. We say that $\boldsymbol{x}$ has been *transformed* to $\boldsymbol{y} = (y_1,\ldots, y_n)$, and denote this *productivity transformation* by $\boldsymbol{x} \rightarrow \boldsymbol{y}$. In what follows, in every transformation $\boldsymbol{x} \rightarrow \boldsymbol{y}$, productivity distribution $\boldsymbol{x}$ will be ordered according to the "less than or equal" relation, so that $x_1 \leq \ldots \leq x_n$. Each individual i is characterized by a productivity stream (x_i, y_i). Over the two periods, individual i produces the quantity $x_i + y_i$. The distribution $\boldsymbol{x} + \boldsymbol{y} = (x_1 + y_1,\ldots , x_n + y_n)$ is referred to as the *aggregate productivity distribution*.

An index of mobility is a real valued function defined on the set of productivity transformations $\boldsymbol{x} \rightarrow \boldsymbol{y}$. As indicated in the Introduction, the mobility concept actually explored is the extent to which the mobility that takes place works to equalize longer-term productivities relative to the base, disequalizes longer-term productivities relative to the base, or has no effect. Given this context, we choose Fisher's (2010) mobility measure defined by

$$M(\boldsymbol{x},\boldsymbol{y}) = \{I(\boldsymbol{x}) - I(\boldsymbol{x} + \boldsymbol{y})\}/I(\boldsymbol{x}), \qquad (1)$$

where I(.) is a Lorenz-consistent inequality measure. Therefore, whenever aggregate productivity inequality decreases (increases) relative to the productivity inequality in the first period, productivity mobility is positive (negative). An immobile income structure where aggregate productivity inequality coincides with productivity inequality in the first period is assigned a mobility value of zero (see Fields, 2010, for the properties satisfied by this measure).

Note that a distributional transformation $\boldsymbol{x} \rightarrow \boldsymbol{y}$ that involves only a change in scale causes no mobility, i. e., whenever $\boldsymbol{y} = \lambda\boldsymbol{x}$ for some $\lambda > 0$, $M(\boldsymbol{x}, \lambda\boldsymbol{x}) = 0$. In other words, in this approach productivity growth *per se* has no mobility consequences. For $M(\boldsymbol{x}, \boldsymbol{y}) \neq 0$, it is necessary that either $I(\boldsymbol{x}) \neq I(\boldsymbol{y})$ or that there is some re-ranking, so that $I(\boldsymbol{x})$ can be different from $I(\boldsymbol{x} + \boldsymbol{y})$. Note that when $M(\boldsymbol{x}, \boldsymbol{y}) \neq 0$, differences in mean productivity do affect productivity mobility, but only through their impact on $I(\boldsymbol{x} + \boldsymbol{y})$.

II. 2. Structural and Exchange Mobility

Following the argument in Ruiz-Castillo (2004) for the Chakravarty *et al.* (1985) mobility index, the Fields mobility index can be decomposed into two terms: one capturing the change in inequality between the cross-section distributions $\boldsymbol{x}$ and $\boldsymbol{y}$ once all rank reversals have been removed, denoted by $SM(\boldsymbol{x}, \boldsymbol{y})$, and a second one capturing the re-rankings effect, $EM(\boldsymbol{x}, \boldsymbol{y})$. Given any distributional transformation $\boldsymbol{x} \rightarrow \boldsymbol{y}$, define $\tilde{\boldsymbol{y}}$ as having the same components as $\boldsymbol{y}$, but rearranged (if necessary) in the same increasing order as $\boldsymbol{x}$. Of course, $I(\tilde{\boldsymbol{y}}) = I(\boldsymbol{y})$. The following decomposition of the mobility index is now introduced

$$M(\boldsymbol{x}, \boldsymbol{y}) = SM(\boldsymbol{x}, \boldsymbol{y}) + EM(\boldsymbol{x}, \boldsymbol{y}), \tag{2}$$

where

$$SM(\boldsymbol{x}, \boldsymbol{y}) = \{I(\boldsymbol{x}) - I(\boldsymbol{x} + \tilde{\boldsymbol{y}})\}/I(\boldsymbol{x})$$

$$EM(\boldsymbol{x}, \boldsymbol{y}) = \{I(\boldsymbol{x} + \tilde{\boldsymbol{y}}) - I(\boldsymbol{x} + \boldsymbol{y})\}/I(\boldsymbol{x}).$$

The term $SM(\boldsymbol{x}, \boldsymbol{y})$ can be viewed as the productivity mobility associated with the distributional transformation $\boldsymbol{x} \rightarrow \tilde{\boldsymbol{y}}$ in which all the re-rankings between $\boldsymbol{x}$ and $\boldsymbol{y}$ have been eliminated, i. e. $SM(\boldsymbol{x}, \boldsymbol{y}) = M(\boldsymbol{x}, \tilde{\boldsymbol{y}})$. Then, exchange mobility is defined as a residual, i. e. $EM(\boldsymbol{x}, \boldsymbol{y}) = M(\boldsymbol{x}, \boldsymbol{y}) - M(\boldsymbol{x}, \tilde{\boldsymbol{y}})$.

As indicated in Ruiz-Castillo (2004), we have the following two properties:

$$I(\boldsymbol{x}) \geq I(\boldsymbol{y}) \Rightarrow SM(\boldsymbol{x}, \boldsymbol{y}) \geq 0. \tag{3}$$

Thus, whenever $I(\boldsymbol{x}) > I(\boldsymbol{y})$ the SM index captures the equalizing effect due to a decrease in cross-section or snapshot inequality. The opposite, even in the absence of rank reversals, need not be necessarily the case.

On the other hand, in the presence of some re-rankings, so that $\tilde{\boldsymbol{y}} \neq \boldsymbol{y}$, we always have

$$EM(\boldsymbol{x}, \boldsymbol{y}) > 0. \tag{4}$$

In view of (3) and (4), for productivity mobility to be disequalizing we must have $I(\boldsymbol{x}) < I(\boldsymbol{y})$ causing a $SM(\boldsymbol{x}, \boldsymbol{y}) < 0$ that in absolute value dominates $EM(\boldsymbol{x}, \boldsymbol{y})$.

II. 3. Additive Decomposability

In our context, it is always desirable to partition distribution $\boldsymbol{x}$ into, say, C cohorts, indexed by $c = 1,\ldots, C$, with $\boldsymbol{x}^c = (x_1^c,\ldots, x_{nc}^c)$, and $\Sigma_c\, n^c = n$. Note that, in this case, for each c productivity distribution $\boldsymbol{x}^c$ is ordered according to the "less than or equal" relation, so that $x_1^c \leq \ldots \leq x_{nc}^c$. In this way, we can study the dynamics involved in the C productivity transformations $\boldsymbol{x}^C \rightarrow \boldsymbol{y}^C$, $c = 1,\ldots, C$, where $\boldsymbol{y}^C$ will typically cover periods of different length. In order to be able to express the productivity mobility for the entire population, $M(\boldsymbol{x}, \boldsymbol{y})$, in terms of the productivity mobility of each cohort, $M(\boldsymbol{x}^c, \boldsymbol{y}^c)$, we must use an additively decomposable inequality index I in definitions (1) and (2).

For any population partition we are interested in expressing the overall productivity inequality as the sum of two terms: a weighted sum of *within-group* inequalities, plus a *between-group* inequality component. An inequality index is said to be decomposable by population subgroup, if the decomposition procedure of overall inequality into a within-group and a between-group term is valid for any arbitrary population partition. In the relative case, it is customary to calculate the between-group component by applying the inequality index to a productivity vector in which each person in a given subgroup is assigned the subgroup's mean productivity. Under this convention, it is well known that the GE (Generalized Entropy) family of inequality indices are the only measures of relative inequality that satisfy the usual properties[5] required from any inequality index and, in addition, are decomposable by population subgroup (Bourguignon, 1978, and Shorrocks, 1980, 1984). Given the

[5] Namely, continuity, S-convexity, scale invariance, and invariance to population replications.

distribution $z = (z_1, \ldots, z_N)$ with mean $\mu(z) = \mu$, the GE family can be described by means of the following convenient cardinalization:

$$I_\alpha(z) = (1/N)\,(1/\alpha^2 - \alpha)\,\Sigma_i\,(z_i/\mu^\alpha - 1),\ \alpha \neq 0,1;$$

$$I_0(z) = (1/N)\,\Sigma_i\,log\,(\mu/z_i);$$

$$I_1(z) = (1/N)\,\Sigma_i\,(z_i/\mu)\,log\,(z_i/\mu).$$

The parameter α summarizes the sensitivity of I_α in different parts of the productivity distribution: the more positive (negative) α is, the more sensitive I_α is to differences at the top (bottom) of the distribution (Cowell and Kuga, 1881)). I_1 is the original Theil index, while I_0 is the mean logarithmic deviation.

The weights in the within-group term add up to one only for I_0 and I_1. In the partition by cohorts, for example, in I_0 and I_1 these weights are the demographic and the productivity shares, respectively. In this paper we will use the I_1 index, whose decomposition formula for the partition of x into C cohorts is the following:

$$I_1(x) = \Sigma_c\, v_c\, I_1(x^c) + I_1(\mu^1, \ldots, \mu^C), \tag{5}$$

where v_c is the share of total productivity in distribution x held by individuals in cohort c, and $I_1(\mu^1, \ldots, \mu^C)$ is the between-group inequality calculated as if each individual in cohort c received that cohort's mean productivity μ^c in distribution x. Similarly, for distribution $(x + y)$ we write:

$$I_1(x + y) = \Sigma_c\, w_c\, I_1(x^c + y^c) + I_1(m^1, \ldots, m^C),$$

where w_c is the share of total productivity per year in distribution $(x + y)$ held by individuals in cohort c, and $I_1(m^1, \ldots, m^C)$ is the between-group inequality calculated as if each individual in cohort c received that cohort's mean productivity m^c in distribution $(\boldsymbol{x} + \boldsymbol{y})$. Consequently, the overall productivity mobility using index I_1, $M_1(\boldsymbol{x},\boldsymbol{y})$, can be expressed as follows:

$$M_1(\boldsymbol{x},\boldsymbol{y}) = \{I_1(\boldsymbol{x}) - I_1(\boldsymbol{x} + \boldsymbol{y})\}/I_1(\boldsymbol{x})$$

$$= \{[\Sigma_c\, v_c\, I_1(\boldsymbol{x}^c) + I_1(\boldsymbol{\mu}^1,..., \boldsymbol{\mu}^C)] - [\Sigma_c\, w_c\, I_1(\boldsymbol{x}^c + \boldsymbol{y}^c) + I_1(\boldsymbol{m}^1,..., \boldsymbol{m}^C)]\}/I_1(\boldsymbol{x})$$

$$= \Sigma_c\, \beta_c\, M_1(\boldsymbol{x}^c,\boldsymbol{y}^c) + \{\Sigma_c\, (v_c - w_c)\, I_1(\boldsymbol{x}^c+\boldsymbol{y}^c)\}/I_1(\boldsymbol{x}) + \{I_1(\boldsymbol{\mu}^1,..., \boldsymbol{\mu}^C) - I_1(\boldsymbol{m}^1,..., \boldsymbol{m}^C)\}/I_1(\boldsymbol{x}), \qquad (6)$$

where $\beta_c = v_c\, [I_1(\boldsymbol{x}^c)/I_1(\boldsymbol{x})]$. Thus, overall productivity mobility is the sum of three terms: (i) the weighted sum of productivity mobility in each cohort, $M_1(\boldsymbol{x}^c, \boldsymbol{y}^c)$, where cohorts with greater share of total productivity in distribution $\boldsymbol{x}$, v_c, and greater productivity inequality in the first period, $I_1(\boldsymbol{x}^c)$, will carry a greater weight in that sum; (ii) the weighted sum of changes in the share of total productivity between distributions $\boldsymbol{x}$ and $(\boldsymbol{x} + \boldsymbol{y})$, $\{\Sigma_c(v_c - w_c)\, I_1(\boldsymbol{x}^c + \boldsymbol{y}^c)\}/I_1(\boldsymbol{x})$, and (iii) the difference in between-cohort productivity inequality from distributions $\boldsymbol{x}$ and $(\boldsymbol{x} + \boldsymbol{y})$, $\{I_1(\boldsymbol{\mu}^1,..., \boldsymbol{\mu}^C) - I_1(\boldsymbol{m}^1,..., \boldsymbol{m}^C)\}/I_1(\boldsymbol{x})$.

Finally, overall productivity mobility, $M_1(\boldsymbol{x}, \boldsymbol{y})$, can be expressed as the sum of two terms $SM(\boldsymbol{x}, \boldsymbol{y})$ and $EM(\boldsymbol{x}, \boldsymbol{y})$ by using expression (2), where $\tilde{\boldsymbol{y}} = (\tilde{\boldsymbol{y}}^1,\dots, \tilde{\boldsymbol{y}}^C)$, and $\tilde{\boldsymbol{y}}^c$ is defined as having the same components as $\boldsymbol{y}^c$, but rearranged (if necessary) in the same increasing order as $\boldsymbol{x}^c$. Of course, $I(\tilde{\boldsymbol{y}}) = I(\boldsymbol{y})$.

III. DESCRIPTION AND ORGANIZATION OF THE DATA

III.1. The Original Dataset

Our dataset has been constructed in two steps. Firstly, we select the top 81 Economics Departments in the world according to the Econphd (2004) university ranking that takes into account the publications in 1993-2003 in the top 63 journals in the Kalaitzidakis *et al.* (2003) journal ranking, where the journal quality weighting reflects citation counts, adjusted for factors such as the annual number of pages and the age of a journal (for further methodological details, see Econphd, 2004).

Typically, university rankings tend to coincide in the top 10 or 20 departments, but differences tend to increase as we proceed to larger sets. We have compared the Econphd ranking adopted in this paper with three other equally acceptable university rankings.[6] The correlation coefficients are 0.73, 0.78, and 0.81, which indicate that we are really dealing with a sensible selection of the best departments in the world circa 2007 –an interesting sample of the academic community for the study of productivity dynamics.

Secondly, we visited the 81 departmental web pages to list the tenured and tenure-track faculty members at the end of 2007. We were able to find a total of 2,485 economists. Using the departmental and/or personal web pages we register information on (i) the number of years since the PhD was obtained, and (ii) the number of articles in four journal classes published each period of eight years, plus a residual period of a variable number of years until 2007 whenever necessary. The article count in our dataset made no distinction between single and multiple-authorship. Consequently, no correction for co-authorship could be implemented. Classes A, B and C consist of five, 34, and 47 journals, respectively, while class D consists of all other journals.[7] Universities have been classified into five groups: two within the U.S.; two within the European Union (EU), namely, the 15 member countries before the 2004 accession, and the Rest of the World (RW), consisting of four Canadian, two Israeli, and one Chinese university. Of the 2,485 individuals, 62.3% belong to U.S. universities, 30.9% to European universities, and the remaining 6.8% to the RW. The percentage of females is 14.2, while the average number of years since the PhD for the 2,231 individuals with this information is 17.8.

III.2. The Measurement of Productivity

[6] The first two are based on the publications during 1990-2000 in the 71 journals in Laband and Piette (1994), and in the journals ordered by the mean rank according to 12 different criteria (for both of them, see Coupé, 2003). The third ranking is based on the publications in 1995-1999 in the top 30 journals in the Kalaitzidakis *et al.* (2003) journal ranking. For a discussion of these and other alternative rankings, see Ruiz-Castillo (2008).

[7] In brief, starting from the top 63 journals in the Kalaitzidakis *et al.* (2003) journal ranking, the different classes have been constructed taking also into account the rankings in Lubrano *et al.* (2003), and Kodrzycki and Yu (2006). The details, as well as a listing of all journals are in Appendix A.

We work with two possible productivity indices: one based on the number of publications, *P*, and another quality index based on a particular weighting of the different publication classes already described. After some experimentation, a quality index *Q* for each researcher has been constructed by applying the following weighting system (very close to the one in use at our own department in 2007): class A (five journals), 40 points; class B (34 journals), 15 points, class C (48 journals), 7 points, and class D, 1 point.[8]

The university listing, together with information on the number of faculty members, the total of publications in each class, and the two productivity indices we use can be found in Appendix B. The following four features should be noted. Firstly, the average productivity for the entire sample is 25.2 publications per capita, and 298.3 quality points per capita, equivalent to 7.5 articles of class A or almost 20 articles of class B. Both measures clearly indicate that we are indeed working with a very productive sample. Secondly, the coefficient of correlation between the two productivity measures is 0.80. On the other hand, columns 9 and 10 in Appendix B include the university rankings according to *P* and *Q*. Not surprisingly, the coefficient of correlation between the rankings is 0.86. Furthermore, the correlation coefficients between the Econphd ranking (column 1 in Appendix B) and columns 9 and 10 are 0.84 and 0.70, respectively. These figures indicate that the two measures are capturing approximately the same phenomenon. Thirdly, since the weighting system introduces strong differences among journals in the four classes, we expect the index *Q* to exhibit more productivity inequality than index *P*. Indeed, the coefficients of variation of the two indices are 1.108 and 1.259, respectively. Finally, as indicated in the Introduction, productivity distributions are typically highly skewed. We use the Characteristic Scores and Scales (CSS hereafter) technique, introduced by Schubert *et al.* (1987) in the analysis of citation distributions, to describe this characteristic.

[8] Oster and Hamermesch (1998) use the Laband and Piette (1994) weights that, as in our case, distinguish strongly between journals. Rauber and Ursprung (2008) use the Combes and Linneman (2003) weights that lie between unity for five top journals, 2/3 for sixteen journals, down to 1/12 for the lowest quality journals –a more egalitarian scheme than our own. Coupé *et al.* (2006) use the average of the rankings based on 12 different weighting schemes computed in Coupé (2003). In order to assess the different degree of elitism involved, Henrekson and Waldenström (2011) display the cumulative distribution of the weights attributed in three important measures of journal quality.

The CCS permits the partition of any productivity distribution into a number of classes as a function of their members' citation characteristics. The following *characteristic scores* are determined: μ_1 = mean of a productivity distribution; μ_2 = mean productivity of individuals with productivity above μ_1, and μ_3 = mean productivity of the individuals with productivity above μ_2. Consider the partition of the distribution into four broad classes: individuals with low productivity, smaller than or equal to μ_1; individuals with an intermediate productivity, above μ_1 and smaller or equal to μ_2; individuals with a remarkable productivity, above μ_2 and smaller or equal to μ_3, and individuals with an outstanding productivity above μ_3. Table 1 includes the percentage of individuals in classes 1 and 4 in the two distributions, as well as the percentages of publications or quality points accounted for by these two classes when productivity is measured by *P* or *Q*. For distribution *P*, μ_1 = 25.2, μ_2 = 54.4, and μ_3 = 86.8. Note that μ_1 is 15.6 percentage points above the median. On the other hand, the top 12.1% of economists with a remarkable or outstanding productivity in classes 3 and 4 account for 40.2% of all publications. For distribution *Q*, μ_1 = 319, μ_2 = 719, and μ_3 = 1,170. Interestingly enough, distribution *Q* is only slightly more skewed than distribution *P*: the mean is 16.4 points above the median, and the top 11.9% of economists in classes 3 and 4 account for 43.4% of all quality points.[9]

Table 1 around here

[9] It is worth while pointing out that the skewness of these productivity distributions for economists is extremely similar to the one found for the citation distributions in 219 scientific sub-fields with the same technique: on average, the mean is 18.6 points above the median, and the top 10% of most cited articles accounts for 44.9% of all citations (see Albarrán *et al.*, 2011).

The conclusion from this discussion is that both indices share similar characteristics and provide a similar picture of productivity in our sample. Therefore, in the sequel we will restrict ourselves to measuring productivity according to the quality index.[10]

III.3. Cohorts' Definitions

We assume that, in universities where the system is in place, the tenure-track period lasts, at a maximum, approximately six years. Since in Economics there are large publication lags, we have recorded the publications that actually appeared in the periodical literature in the first eight years after completion of the PhD. For universities where tenure is differently regulated, we still think that eight is a reasonable number of years for our first period, namely, for the productivity distribution x introduced in Section II. The conditions under which academic scholars conduct their research and publication activity change over time.[11] This is the reason why it is advisable to partition the sample into cohorts that include individuals with comparable research and publication opportunities. In our case, since we have information about publications every eight years, we choose seven cohorts. The first six cohorts consist of individuals who finished their PhD four years apart in 1991-88, 1987-84, 1983-80, 1979-76, 1975-72, and 1971-68, or individuals that finished their PhD form 16-19 to 36-39 years since 2007. There are only 55 economists that finished their PhD 40-43 years before 2007. Therefore, to increase the last cohort size we include people who received their PhD in 1967 or before, that is, who finished their PhD 40 or more years before 2007. The problem, of course, is that cohort members become less comparable. On the other hand, the extra 37 oldest people with more than 43 years after their PhD may be expected to increase cohort variability, a feature we find interesting to monitor. At any rate, assuming that economists obtain their PhD at age 25 (at

[10] Admittedly, the quality index used is rather elitist –as it should be, in our opinion. Nevertheless, we have also considered a quite different alternative: instead of assigning weights 40, 20, 7, and 1 to classes A, B, C, and D, the second index assigns weights 20, 10, 5, and 1 to these classes. As we will see below, all our results are robust to this change.

[11] For example, the number of articles in top-5 journals is largely unchanged, while the number of economists vying for a slot in these journals has dramatically increased since the 1970s. Thus, it was much easier to publish there before (for those who seriously tried), than it is today.

the earliest), this cohort consists of 65-years-olds (at a minimum) in 2007, while the youngest cohort consists of 41-44-years-olds at that date.

As we have seen, there are good *a priori* reasons to conduct the analysis by cohort. Nevertheless, independently of the empirical importance of cohort effects, we also find interesting to analyze results for the sample as a whole. After eliminating 1,084 recent PhDs who finished their studies in 1992 or afterwards, plus the 254 economists for which the variable "years since PhD" was missing and 11 for which the second period productivity was in doubt, we end up with a sample of 1,136 individuals classified in the seven cohorts just described. Since there are more females among recent PhDs, the percentage of females goes down to 7.6%, while the average number of years since the PhD increases to 26.6. Finally, the following two features should be enough to illustrate that this is indeed a subset of very productive economists. Firstly, only 42.8% of European academic economists published at least once in *EconLit* 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). In comparison, all economists in the cohort sample have produced at least one article, and the average is 1.52 publications per year. Secondly, only 18.2% of the sample has no class A publication, while 23.5% published once or twice, and the remaining 58.3% three or more times in the top class. The average quality index is 18.2 per year that can be compared with the 15 points assigned to one article in class B.[12]

IV. EMPIRICAL RESULTS

IV.1. The Evolution of Average Productivity

[12] Even in the original dataset, only 28 faculty members –all of them in the first eight or fewer years since graduating– did not publish at all. The 2,183 economists that had finished their PhD in 2006 or before had published on average 1.44 publications and 17.25 quality points per year.

We are concerned with productivity transformations $x^c \rightarrow y^c$, where the second period distribution, y^c, refers to academic lives of different lengths for different cohorts CI,…, CVII. Since we have information about publications every eight years, we can compute the productivity over complete eight-year periods (after period x^c), denoted by $y_1{}^c$, $y_2{}^c$, $y_3{}^c$, and $y_4{}^c$, c = I,…, VII. As a matter of fact, CVII is the only cohort with four complete eight-year periods; CVI and CV have three complete eight-periods; CIV and CIII have two, while the youngest CII and CI have only one. It is important to establish the relationship between this notation and the available data on the quality index. Let T_i^c be the number of years in 2007 since the i-th individual in cohort c finished her PhD, and let $Q_{ti}{}^c$ be the quality index for this individual at time $t \leq T_i^c$. Then, for each i in cohort c we have: $x_i^c = Q_{8i}{}^c$, and $y_i^c = Q_{Ti}{}^c - Q_{8i}{}^c$. If individual i is in cohort IV, for example, then in addition we have: $y_{1i}{}^{IV} = Q_{16i}{}^{IV} - Q_{8i}{}^{IV}$, and $y_{2i}{}^{IV} = Q_{24}{}^{IV} - Q_{16i}{}^{IV}$, and so on for individuals in other cohorts. The information on the number of individuals, as well as average productivity for all cohorts in all possible periods is in Table 2. To make them comparable across cohorts, rows 6 to 8 include the average productivity *per year* for the two periods, x and y, as well as the aggregate $(x + y)$ distribution, which we denote by $\mu(x^c/8)$, $\mu[y^c/(T^c - 8)]$, and $\mu[(x^c + y^c)/T^c]$, respectively.

Table 2 around here

Two points should be emphasized. Firstly, as expected, average productivity is very high indeed. In the first eight-year period, for example, it ranges from 159 in CI to 200 points in CVI, equivalent to four and more than five class A articles, respectively. Secondly, average productivity uniformly decreases with age in all cohorts. With the exception of CV, the difference between the average productivity per year in the first and the second period in the transformation $x^c \rightarrow y^c$ (see rows 6 and 7 in Table 2), increases as we proceed from cohort I to CVII. Such differences, however, are not very large: the average difference for all cohorts is six points, one point less than an article in class C. Moreover, this trend is offset by the fact that average productivity in x^c tends to be higher in older cohorts. As a result, average productivity in the aggregate distribution is not very different across cohorts: it ranges from 16.5 to 21.1 points per year for CV and VII, respectively. We must conclude that no strong cohort effects are observed.

In spite of having relatively little information on a few exogenous and institutional explanatory variables, it is illustrative to express these findings in a regression format. Table 3 includes the results of several regressions of productivity in terms of years since the PhD, this variable squared, six dummies for the first six cohorts, and a gender dummy as exogenous factors, and three dummies for university types –with type I to type IV representing the first 20 to the last 21 institutions in our listing of 81 university departments as institutional factors (only variables with a significant effect are shown in Table 3). The regression in Panel A pools five equations

$$v_{ki} = a + b_1 t_{ki} + b_2 (t_{ki})^2,$$

for $k = 1,.., 5$, where:

$$v_{1i} = x_i^c,\ i = 1,.., n^c,\ c = \mathrm{I}, \ldots, \mathrm{VII}, \text{ and } t_{1i} = 8,$$

$$v_{2i} = y_{1i}^c,\ i = 1,.., n^c,\ c = \mathrm{I}, \ldots, \mathrm{VII}, \text{ and } t_{2i} = 16,$$

$$v_{3i} = y_{2i}^c,\ i = 1,.., n^c,\ c = \mathrm{III}, \ldots, \mathrm{VII}, \text{ and } t_{3i} = 24,$$

$$v_{4i} = y_{3i}^c,\ i = 1,.., n^c,\ c = \mathrm{V}, \ldots, \mathrm{VII}, \text{ and } t_{4i} = 32,$$

$$v_{5i} = y_{4i}^c,\ i = 1,.., n^c,\ c = \mathrm{VII}, \text{ and } t_{5i} = 40.$$

Human capital models suggest a humped-shaped progression of individual research productivity 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). 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). In agreement with this model, we should have $b_1 > 0$ and $b_2 < 0$. However, in Panel A we find that $b_1 < 0$ and b_2 is not significantly different from 0, that is, productivity decreases linearly with age (according to Diamond, 1986, the quantity and quality of current output for Berkeley mathematicians also declines monotonically with age). Nevertheless, it should be noted that since our data refers to publications every eight years, we cannot test whether productivity raises sharply in an initial stage inside the first eight year period, as found in Bell and Seater (1978), Goodwin and Sauer (1995), and Hutchinson and Zivney (1995).

Table 3 around here

The literature abounds with cases of heterogeneity in patterns of productivity over time (Goodwin and Sauer, 1995, Grimes and Register, 1997, Oster and Hamermesch, 1998, Kelchtermans and Veugelers, 2011, 2012, and Rauber and Ursprung, 2008).[13] Consequently, Table 3 also reports results for a partition of the sample into the top 20% of individuals in each cohort (Panel B), and the remaining 80% (panel C). A test shows that b_1 and b_2 are jointly significant in Panel B. However, now we have that $b_1 > 0$ and $b_2 < 0$, indicating that productivity of the most prolific economists slightly increases at a declining rate. On the other hand, $b_1 < 0$ and b_2 is not significantly different from 0 in Panel C, explaining these results for the sample as a whole in panel A. This might be explained by two

[13] Other studies, it should be said, find a very small age effect or no significant decline in productivity as experience increases (Hutchinson and Zivney, 1995, Hartley *et al.* 2001, and Gonzalez-Brambila and Veloso, 2007, among the most productive researchers in all areas of knowledge in Mexico). The most careful contribution to the identification issue, Hall *et al.* (2007) also concludes that the independent effect of the researcher age above and beyond that due to the cohort in which she entered and the year of publication is at most slight.

types of factors. Firstly, a stronger taste for "puzzle solving" for top researchers, a factor that when added to the objective function produces a flattening of the productivity profile (Levin and Stephan, 1991), or a stronger taste for peer recognition and monetary rewards. Secondly, because institutional explanatory variables –such as research funding and promotion policies operate differentially across the distribution of scientific performance– as found by Kelchtermans and Veugelers (2011).

In line with the literature, we find clear evidence that productivity of males is greater than the productivity of females (see *inter alia* Cole and Cole, 1973, Weiss and Lillard, 1982, Cole and Zuckerman, 1984, Long, 1992, Xie and Shauman, 1998, Turner and Mairesse, 2003, Gonzalez-Brambila and Veloso, 2007, Kelchtermans and Veugelers, 2007, 2011, and Rauber and Ursprung, 2008, as well as the discussion in Stephan, 2010). We also find that working in better universities increases individual productivity. However, except among the top producers where some younger cohorts are less productive, there is no evidence of cohort effects.[14]

IV.2. The Evolution of Productivity Inequality

Table 4 presents the evolution of productivity inequality in all cohorts. The main finding is that, as already discovered in the literature, except in two instances in CIII and CVII, productivity inequality tends to increase with age. Note that, as expected, the presence of a contingent of older people in the asymmetric construction of CVII manifests itself in greater variability in most periods. In any case, except in CIII, productivity inequality in y^c is always greater than in distribution x^c for all c. This is also fact 2 in Davis (1994), quoted in the Introduction.

Table 4 around here

[14] This is also the case in studies of the economic profession such as Goodwin and Sauer (1995), and Baser and Pema (2004). Vintage matters in Levin and Stephan (1991) but, with the possible exception of geology, more recent vintages are never found to be significantly more productive than earlier vintages. Cohort dummies increase over time in Rauber and Ursprung (2008), not because members of younger cohorts are more productive researchers than their older peers, but possibly because the German economics profession has increasingly been exposed to the Anglo-Saxon research tradition that stresses publication on a continuous basis.

The previous evidence, however, is rather weak. The classical contribution by Allison and Stewart (1974) uses low quality data: self-reported number of research publications through mailed questionnaires and telephone interviews in the last five years before 1966, and total citations in 1966 to works published at any previous time. Moreover, they have cross-section data for 1,922 researchers, broken down into eight age strata by the number of years since the PhD. Except for the 507 biologists in the sample, productivity inequality measured by the Gini index increases with age for 361 mathematicians, 499 physicists, and 555 chemists. Using true cohort data for 239 chemists who had spent up to eight years since the PhD, and two cohorts of 271 and 286 biochemists after eight and 14 career years, Allison *et al.* (1982) report increasing inequality for publication counts, but not for citations to all previous publications, grouped into three-year intervals. Similarly, Weiss and Lillard (1982) report that, along with mean, the variance of publications increases markedly over the first ten or 12 years in their pooled dataset for 1,000 Israeli scientists.

IV.3. The Extent of Re-rankings

Table 5 presents mobility matrices between the two periods –that is, between distributions $\boldsymbol{x}^c$ and $\boldsymbol{y}^c$– for all cohorts. The following three points should be stressed. Firstly, if we define top productivity as belonging to the last quintile, then it is true that top productivity generally is persistent over time: top performers in distribution $\boldsymbol{x}^c$ during the first eight years of academic life are more likely to reach top status also in distribution $\boldsymbol{y}^c$, 16, 24, 32, or 40 years after receiving the PhD. Using a panel dataset comprising the publications of biomedical and exact scientists at the KU Leuven in the period 1992-2001, Kelchtermans and Veugelers (2012) find a similar phenomenon. Secondly, in our case the pattern can be summarized as follows. The percentage of individuals in the top and bottom 20% of distribution $\boldsymbol{x}^c$ that remain in the same quintile in distribution $\boldsymbol{y}^c$ range from 49% to 64% in the first four cohorts. These percentages decrease in the oldest cohorts to 45%-57% in CV and CVI, and to 33-47% in CVII.[15] Thus, older age cohorts are slightly underrepresented at both the top and the bottom, a pattern not found in Kelchtermans and Veugelers (2012).

Table 5 around here

Finally, we should ask: is this persistence, particularly at the top, large or small? A researcher is considered in Kelchtermans and Veugelers (2012) as 'persistent top' if she belongs to the top performance category in every two-year window in 1992-2001. Only 61 individuals, about 6% of the sample are part of that category. In our case, we find 124 individuals, or 10.9% of the sample, belonging to the top quintile in their respective cohorts –a comparable proportion. Note that between 46% and 63% of individuals in the top 20% in distribution $\boldsymbol{y}^c$ in all cohorts except CIV (where this figure is 38%) proceed from three –or even all four– of the other quintiles in distribution $\boldsymbol{x}^c$. Moreover, the degree of persistence in the intermediate quintiles representing 60% of the sample is even lower. For example, the diagonal element for the third quintile is between 24% and 31% in all cohorts, except CIII in which it is 19%. Thus, perhaps the main finding is that, contrary to fact (1) in Davis (1994) and the statement by Kelchtermans and Veugelers (2011) quoted in the Introduction, in our two-period world there are a lot of re-rankings. The consequence of such a high number of rank reversals is an important contribution of exchange mobility to overall productivity mobility with a positive sign.

IV.4. Productivity Mobility

Table 6 includes the most important results of the paper, concerning productivity mobility for all cohorts in selected transformations. Let us begin with the key transformation $\boldsymbol{x}^c \rightarrow \boldsymbol{y}^c$ for all cohorts c = I,…, VII. As we saw in Table 2, $I_1(\boldsymbol{x}^c) < I_1(\boldsymbol{y}^c)$ for all c (except CIII). This causes $SM_1(\boldsymbol{x}^c, \boldsymbol{y}^c) < 0$ in all these

[15] For the entire sample, the percentage of individuals in the top and bottom 20% of their respective cohorts in the first period that remain in the same quintile in the second period is 48.9% and 52.4%.

six cases (see Row C in Table 4). However, the re-rankings reported in Table 3 cause $EM_1(\boldsymbol{x}^c, \boldsymbol{y}^c) > 0$ for all c (see Row B in Table 4). The latter effect is clearly stronger than the *SM* effect of the opposite sign in the three youngest cohorts, of very similar strength in CIV to CVI, and clearly weaker in CVII. For the three cohorts for which mobility is clearly equalizing, we can conclude that aggregate productivity inequality is 8.7% to 18.8% smaller than productivity inequality in the first eight years of academic life, while in CVII aggregate productivity inequality is 5.6% greater than productivity inequality at the beginning of academic life (see Row A in Table 4).

Table 6 around here

For the sample as a whole, the first term in the decomposition presented in equation (6) in Section II.3 is the weighted sum of productivity mobility in all transformations $\boldsymbol{x}^c \to \boldsymbol{y}^c$. Since $M_1(\boldsymbol{x}^c, \boldsymbol{y}^c) < 0$ only for c = VI, and VII, it comes as no surprise that the term $\Sigma_c\, \beta_c\, M_1(\boldsymbol{x}^c, \boldsymbol{y}^c)$ is positive but small. Since the other two terms in the decomposition are negative, we end up with a small negative value $M_1(\boldsymbol{x}, \boldsymbol{y}) = -\ 0.030$. As can be observed in Table 4, rank reversals between distributions $\boldsymbol{x}$ and $\boldsymbol{y}$ imply that $EM_1(\boldsymbol{x}, \boldsymbol{y}) = 0.190$. On the other hand, productivity inequality during the first period for the sample as a whole is not that different from productivity inequality in any cohort, that is, $I_1(\boldsymbol{x})$ is similar to $I_1(\boldsymbol{x}^c)$ for each c. However, the heterogeneity of distribution $\boldsymbol{y}$, which is the union of distributions $\boldsymbol{y}^c$ of different length for each cohort, manifests itself in a high productivity inequality. Therefore, contrary to most cohorts, for the cohort sample as a whole the increase in productivity inequality slightly offsets the effect of rank reversals, so that overall productivity mobility, although small, is disequalizing.

IV.5. The Skewness of Productivity Distributions

As we saw in Table 1, the quality distribution Q –the analogue of distribution ($\boldsymbol{x} + \boldsymbol{y}$)– for the entire, original sample was highly skewed. The last question we investigate is the skewness of distribution ($\boldsymbol{x}^c + \boldsymbol{y}^c$) when we restrict ourselves to those individuals with at least 16 years since the PhD in 2007, and after changes in cross-section productivity inequality and re-rankings between distributions $\boldsymbol{x}^c$ and $\boldsymbol{y}^c$ have taken place. The relevant information is in Table 7.

Table 7 around here

To understand what type of distribution ($\boldsymbol{x}^c + \boldsymbol{y}^c$) we have after the dynamic processes we have analyzed in this paper, it is best to focus on the oldest cohorts CVI and CVII. After the intense re-ranking process –particularly among the intermediate quintiles– documented in Table 5 and manifested in a large exchange mobility component, the type of skewness characterizing the productivity distribution of individuals at the end of their life cycle, after 36 or more years of academic life, is quite different from the skewness that characterizes the productivity distribution Q of all individuals in the original dataset (as well as citation distributions in all sciences, generally). In the latter case, about 88% at the bottom of the distribution (in classes 1 and 2) account for 55% of all quality points, while a small minority of 4.7% with outstanding productivity (above the characteristic score μ_3) accounts for 23.4% of all quality points (see Table 1). Instead, for cohorts VI and VII, about 60% at the bottom account for only 30% of all quality points, while a large elite of about 20% of all economists with outstanding productivity accounts for half of all quality points.

IV.6. Changing the Cohort Definition

We believe that fixing the first period equal to the first eight years of academic life after the PhD, as we have done in this paper, is an acceptable choice worth investigating. However, one may wonder about the consequences of widening this length. Given the structure of our dataset, where productivity information comes in eight-year slots, our only opportunity is to define the first period as the first 16 years after the PhD. It seems natural to consider a second period of the same or greater length. We will consider two cohorts, say A and B, in which the second period consists of the next 16 to 19 years, or more than 24, respectively. These coincide with the previous cohort V (167 individuals), and cohort VII (91 individuals), precisely the only cohorts for which overall productivity mobility was positive.

It turns out that overall productivity mobility is negative and greater than before: aggregate productivity inequality increases by 4.9% and 16.4% relative to the first period of 16 years after the PhD, while this increase was equal to 5.6% for cohort VII and overall mobility was slightly equalizing for CV when the first period included only the first eight years of academic life. The conclusion is that doubling the number of years of the first period does not drastically alter the results.

V. CONCLUSIONS AND EXTENSIONS

This paper has studied the evolution of the research productivity of a sample of 1,136 economists who, counting from 2007, have spent at least 16 years since their PhD in (some of) the best 81 economics departments in the world. Individual productivity is measured in terms of the number of publications in each of four classes, weighted according to a rather elitist scheme. The main novelty is the measurement of productivity mobility using an indicator inspired in the index of income mobility suggested by Fields (2010) for a two-period world in which the first period coincides with the first eight years after the PhD, and the second period varies in length for seven cohorts. Productivity mobility is equalizing (disequalizing) if the actual productivity inequality at the end of the life cycle is smaller (greater) than the productivity inequality that obtains in the initial situation, in which case the mobility index takes positive (negative) values. The Fields index can be conveniently decomposed into two terms: the exchange mobility term that captures the effect of rank reversals between the first and the second period and cause overall mobility to increase, and the structural mobility term that captures the effect of changes in productivity inequality between the aggregate and the initial productivity once all re-rankings have been eliminated. Productivity inequality is measured with the first Theil inequality index. The main findings are the following five.

(i) For the top 20% of researchers in each cohort productivity slightly increases with time at a declining rate. For the remaining 80%, individual productivity linearly decreases with the number of years since the PhD. As indicated in Oster and Hamermesch (1998), without direct observation on how scholars' use of time changes as they age, it is impossible to distinguish whether this relationship is due to natural declines in capacity or decreased incentives to produce. However, in their rich model, Kelchtermans and Veugelers (20011), for example, find no effects from teaching to research, so that a reduced teaching load for less productive researchers may not lead to an increase in publications. Productivity is also significantly larger for males, and for scholars working at the top 40 universities.

(ii) As expected, productivity inequality tends to increase with age. It turns out that this makes structural mobility disequalizing for all cohorts except one.

(iii). Exchange mobility is always equalizing. Moreover, since in this subset of highly productive scholars there is less persistence than expected, the exchange mobility effect is relatively large in all cohorts.

(iv). In the first place, the end result is that overall mobility is clearly equalizing for the youngest three cohorts, where aggregate productivity inequality is 9% to 19% smaller than productivity inequality in the first period. In the oldest cohort, aggregate productivity inequality is 5.6% greater than productivity inequality in the first period, while in the remaining three cohorts total productivity mobility is close to zero. This makes the within-group term in the decomposition of the overall productivity mobility for the sample as a whole to be positive. However, overall mobility for the sample as a whole is slightly disequalizing: aggregate productivity inequality is 3% greater than productivity inequality in the first period.

(v) Consider the partition into individuals with low, intermediate, remarkable or outstanding productivity. The usual productivity distribution is highly skewed: the first two groups represent about 88% of the total and account for 55% of all quality points, and the last category –representing less than 5% of the total– accounts for more than 23% of the quality points. However, after the dynamics studied in this paper take place, individuals at the end of their life cycle in the first two groups are about 60% of the total with less than 30% of all quality points, while there is a relatively large group of 20/25% researchers with outstanding productivity, accounting for 45/50% of all quality points.[16]

Given the skewness of the citation distribution of articles in any journal, including an important percentage with zero citations, Seglen (1992, 1997) warns 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, 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.

Quite independently of the productivity metric, this paper has studied a very peculiar sample of very productive scholars. We agree with Goodwin and Sauer (1995) that, given the skewness of publishing productivity, including the important percentage of individuals with zero publications, to study life cycle productivity in research it makes sense to focus on scholars at research-oriented institutions (see also Levin and Stephan, 1991). In any case, it might be interesting to extend this effort towards a representative sample of economists. It can be conjectured that, in a two-period world analogous to the one studied here, the presence of economists with an intermediate or low productivity would increase productivity inequality during the first period and, perhaps, during the second period. This may increase the structural mobility component. On the other hand, a more inclusive sample will push the highly productive to the top of the distribution. Some of the rank reversals observed in this paper within this elite will surely disappear, but it is impossible to conjecture the extent of re-rankings

[16] As indicated in note 9, we have replicated Tables 2, 4, 6, and 7 for a less elitist measure of productivity than the one introduced in Section III.2 (see Tables 8, 9, 10, and 11). Regression results and mobility matrices presented in Tables 3 and 5, respectively, are available on request. With the exception that overall mobility for the sample as a whole is now slightly equalizing (2.1%) rather than the opposite (- 1.8%), all results are strikingly similar to the ones obtained with the first quality index. This contrasts with the main finding in Henrekson and Waldenström (2011) suggesting large discrepancies between seven measures of productivity in terms of both the rank order of Economics professors in Sweden and the absolute differences between their performances.

in the larger sample, and hence, the sign of overall productivity mobility.

More importantly, since the evidence already quoted indicates that the age/productivity profile varies in different disciplines, it would be interesting to extend this paper to other scientific fields. In particular, it remains to be seen whether rank reversals –that have been seen to strongly qualify persistence in economics –also play a major role in other fields.

Beyond the measurement exercise presented in this paper, scientific policy requires explanatory models of productivity dynamics. As David (1994, p. 74) notes: "*the phenomena (of persistent scientific hierarchies) may be understood as arising from the interplay between a heterogeneous population of researchers, and an environment whose reward system acts to reinforce and amplify the effects of initially limited differences in productivity potential*". In our view, such interplay and possibly other factors should also account for the phenomenon unveiled here: the extent of rank reversals over time among the researchers' elite in a world with a relatively short first period.

Finally, consider all articles published in the same year in a scientific field, and allow for a flow of citations to arrive year by year. For those in charge of the evaluation of research units responsible for sub-samples of these citation distributions, it is important to know how long does it take for these distributions to stabilize and adopt the characteristic skewed shape we are familiar with. The shorter it takes, the easier the job of evaluation would be. By identifying a citation distribution with an income distribution, income mobility indexes can be profitably used to study the dynamics of citation distributions, exactly as we have done in this paper with productivity distributions. In particular, we may learn how long it takes for citation distributions to acquire their typical shape by observing when citation mobility indices become stabilized.

APPENDIX A

A CLASSIFICATION OF JOURNALS INTO FOUR GROUPS

The following three references, whose merits will not be discussed here, have been taken into account.

1. Kalaitzidakis *et al.* (2003) rank 159 journals from the Economics section of the SSCI (*Social Science Citation Index*) on the basis of the citations received during 1998 by the papers published during 1994-1998. The procedure takes into account the relative importance of the journal making each citation, and does not include self-citations, namely, citations made by one journal to papers published in that same journal.

2. Lubrano *et al.* (2003) follow a mixed strategy: they start by entrusting to one of their members, Alan Kirman, the ranking of 505 journals that come from the 680 journals in *EconLit* after eliminating those with fewer than ten articles in ten years. In a second phase, they gathered information on the number of citations which 307 journals receive. Finally, they asked Professor Kirman to modify his original ranking in light of this information. The result is a grouping of all the journals in six classes that contain six journals with ten points, 17 with eight (except for one with seven), 45 with six, and the remaining 437 with four, two, or one point. For certain purposes, these authors select the 68 journals with six or more points.

3. Kodrzycki and Yu (2006) are the first to apply the method axiomatized by Palacios-Huerta and Volij (2004) to a large set of journals.

We are interested in classifying relevant international journals into three groups, classes A, B, and C, including all remaining journals in class D. Hopefully the first 60 or 70 journals in each of the 4 rankings already introduced are sufficiently overlapping.

• We start from the first 30 journals in Kalaitzidakis *et al.* (2003). Class A, consisting of 5 journals, needs little justification.

• There remain 25 journals from the initial list. To these, we add 4 top journals in non-Economics areas that are assigned eight (or seven) points in Lubrano *et al.* (2003): *American Political Science*, *JASA*, *Michigan Law Review*, and *Yale Law Journal*. Then we bring in four journals highly classified in Kodrzycki and Yu (2006), namely, those journals whose average rank goes from 3.5 to 23 according to these authors: *Journal of Finance*, *Journal of Money Credit and Banking*, *Brookings Papers*, and *Journal of Economic Growth*. Class B is formed with these 25 + 4 + 4 = 33 journals.

• Next, we consider the 34 journals ranked 31 to 64 in Kalaitzidakis *et al.* (2003). First, we add three journals with six points in Lubrano *et al.* (2003), clearly within the first 80 in Kodrzycki and Yu (2006), and within ranks 71-73 in Kalaitzidakis *et al.* (2003): *Journal of Economics and Management Strategy*, *Journal of Health Economics*, and *Regional Science and Urban Economics*. Two more journals with six points in Lubrano *et al.* (2003) are included: *Macroeconomic Dynamics* and *Industrial and Labor Relations Review*. Second, we include eight journals whose average rank in Kodrzycki and Yu (2006) is within the 7-37 range: 2 Macro journals - *NBER Macroeconomic Annual* and *Review of Economic Dynamics*- five Business and Financial Economics journals - *Journal of Business*, *Journal of Accounting Economics*, *Review of Financial Studies*, *Journal of Financial Intermediaries*- and *Economic Policy*. Therefore, class C is formed by 47 = 34 + 5 + 8 journals.

• In brief, as indicated in the text, starting from the top 64 Kalaitzidakis *et al.* (2003) journals we have reached a total of 5 + 34 + 47 = 86 journals in classes A, B, and C, respectively, paying attention to the other rankings.

We exclude six journals with six points in Lubrano *et al.* (2003) -that do not appear at all in the other classifications- and five journals with average rank between 60 and 70 in Kodrzycki and Yu (2006).

Class A
American Economic Review
Econometrica
Journal of Political Economy
Quarterly Journal of Economics
Review of Economic Studies.

Class B
American Political Science Review

Brookings Papers on Economic Activity
Econometric Theory
Economic Journal
Economic Theory
Economics Letters
European Economic Review
Games and Economic Behavior
International Economic Review
Journal of Applied Econometrics
Journal of Business and Economic Statistics
Journal of Econometrics
Journal of Economic Dynamics and Control
Journal of Economic Growth
Journal of Economic Literature
Journal of Economic Perspectives
Journal of Economic Theory
Journal of Environmental Economics and Management
Journal of the European Economic Association
Journal of Finance
Journal of Financial Economics
Journal of Human Resources
Journal of International Economics
Journal of Labor Economics
Journal of Monetary Economics
Journal of Money, Credit and Banking
Journal of Public Economics
Journal of the American Statistical Association
Michigan Law Review
Oxford Bulletin of Economics and Statistics,
Rand Journal of Economics
Review of Economics and Statistics
Scandinavian Journal of Economics
Yale Law Journal

Class C
American Journal of Agricultural Economics
Applied Economics
Canadian Journal of Economics
Contemporary Economic Policy
Economic Inquiry
Economic Policy
Economic Record
Economica
Explorations in Economic History
IMF Staff Papers
Industrial and Labor Relations Review
International Journal of Game Theory
International Journal of Industrial Organization
Journal of Accounting Economics
Journal of Banking and Finance
Journal of Business
Journal of Comparative Economics
Journal of Development Economics
Journal of Economic Behavior and Organization
Journal of Economic History
Journal of Economics and Management Strategies
Journal of Financial and Quantitative Analysis
Journal of Financial Intermediaries

Journal of Health Economics
Journal of Industrial Economics
Journal of Institutional and Theoretical Economics
Journal of International Money and Finance
Journal of Law, Economics and Organization
Journal of Law and Economics
Journal of Mathematical Economics
Journal of Population Economics
Journal of Risk and Uncertainty
Journal of Urban Economics
Land Economics
Macroeconomic Dynamics
National Tax Journal
NBER Macroeconomics Annual
Oxford Economic Papers
Public Choice
Regional Science and Urban Economics
Review of Economic Dynamics
Review of Financial Studies
Social Choice and Welfare
Southern Economic Journal
Theory and Decision
World Bank Economic Review
World Development.

APPENDIX B

Econphd University Ranking (1)		N = Number of Faculty (2)	Number of Publications A (3)	B (4)	C (5)	D (6)	P = Total (7)	Q = Quality Index (8)	University Rankings According to: P (9)	Q (10)
	U.S.1	614	4,895	6,575	2,284	6,088	19,842	314,217		
1	Harvard University	55	838	905	294	779	2,816	49,638	1	1
2	University of Chicago	29	290	281	112	212	895	16,699	28	8
3	MIT	37	425	446	168	390	1,429	25,088	8	4
4	U. of California, Berkeley	56	450	623	273	662	2,008	29,645	2	2
5	Princeton University	53	470	607	165	693	1,935	29,588	3	3
6	Stanford University	38	272	291	90	264	917	16,049	24	9
7	Northwestern University	35	230	307	87	280	904	14,607	26	11
8	University of Pennsylvania	29	203	340	84	113	740	13,837	36	12
9	Yale University	39	326	479	118	398	1,321	21,331	10	7
10	New York University	44	351	535	129	439	1,454	23,278	7	6
11	U. of California, LA	39	198	230	160	322	910	12,652	25	16
13	Columbia University	44	381	533	199	463	1,576	24,892	5	5
14	U. of Wisconsin, Madison	29	86	238	74	154	552	7,608	45	37
15	Cornell University	32	156	391	182	472	1,201	13,669	12	13
16	University of Michigan	55	219	369	149	447	1,184	15,636	13	10
	U.S.2	935	2,680	7,005	4,365	8,275	22,325	246,740		
17	University of Maryland	36	144	246	219	283	892	11,047	29	22
19	U. of Texas, Austin	31	114	243	120	328	805	9,253	32	29
21	U. of Cal., San Diego	35	174	385	97	264	920	13,581	23	14
22	University of Rochester	14	56	100	51	100	307	4,146	76	61
23	Ohio State University	36	143	295	163	324	925	11,447	22	20
25	U. of Illinois, Urbana	20	37	166	89	204	496	4,708	55	58
26	Boston University	35	156	235	131	201	723	10,752	37	23

27	Brown University	27	128	184	119	119	550	8,713	46	32
28	U. California, Davis	31	54	185	159	243	641	6,132	41	46
29	University of Minnesota	23	127	193	50	100	470	8,375	61	33
32	U. of Southern California	22	62	263	110	355	790	7,440	33	38
33	Michigan State U.	43	100	325	181	328	934	10,289	19	26
35	Duke University	46	141	305	189	568	1,203	11,917	11	19
38	PA State University	21	64	142	76	171	453	5,317	63	51
40	Carnegie Mellon U.	21	46	92	26	61	225	3,437	79	71
41	U. of North Carolina	22	20	142	62	182	406	3,484	67	70
42	Boston College	22	69	221	113	209	612	6,962	43	40
43	Georgetown University	18	84	161	74	132	451	6,351	64	45
44	Texas A and M	22	47	161	103	163	474	5,076	60	53
49	University of Indiana	25	28	153	130	170	481	4,365	58	60
51	Johns Hopkins	12	59	147	46	67	319	4,908	75	56
52	Rutgers University	34	42	161	163	342	708	5,415	38	50
53	University of Virginia	28	67	157	126	142	492	5,933	57	47
54	Vanderbilt University	32	98	296	240	541	1,175	10,341	14	25
55	Georgetown University	23	42	170	63	73	348	4,681	73	59
56	Arizona State University	24	59	243	171	333	806	7,364	31	39
57	University of Arizona	17	30	80	65	77	252	2,867	77	76
58	Dartmouth College	27	47	141	131	226	545	5,007	49	54
60	University of Washington	24	80	257	132	152	621	7,999	42	34
62	Iowa State University	40	31	191	324	567	1,113	6,616	15	42
63	Washington U., St. Louis	29	130	243	163	217	753	10,040	35	27
67	Purdue University	15	30	91	87	191	399	3,278	70	72
70	University of Pittsburgh	20	36	142	50	174	402	4,044	68	62
72	University of Iowa	13	26	124	41	57	248	3,203	78	73
75	Rice University	18	63	152	88	205	508	5,533	53	49
77	U. of California, Irvine	18	23	116	135	202	476	3,672	59	65
78	University of Florida	11	23	97	78	204	402	3,047	69	75

	EU1	329	630	2,326	1,050	3,595	7,601	69,985		
12	London Sch. of Ecomics	49	162	345	90	270	867	12,465	30	18
18	Toulouse University	76	124	406	193	791	1,514	12,999	6	15
24	Tilburg University	47	35	353	222	1,131	1,741	9,158	4	30
31	Oxford University	43	119	338	152	386	995	11,128	17	21
34	University of Warwick	43	85	371	184	286	926	10,355	21	24
37	University of Amsterdam	37	19	194	125	322	660	4,742	40	57
39	Cambridge University	34	86	319	84	409	898	9,138	27	31
	EU2	438	488	2,487	1,286	4,939	9,200	69,480		
45	European Institute	11	23	152	49	161	385	3,655	71	66
46	U. Carlos III	46	14	171	74	352	611	3,921	44	64
47	Univ. College London	35	164	329	111	324	928	12,485	20	17
48	University of Essex	25	23	148	72	81	324	3,653	74	67
59	Stockholm University	17	7	57	45	93	202	1,498	80	81
65	University of York	42	56	222	81	419	778	6,475	34	44
66	U. Pompeu Fabra	36	49	151	56	433	689	4,994	39	55
68	University of Nottingham	48	28	300	210	833	1,371	7,713	9	36
71	Stockholm School of Ecs.	17	16	106	80	347	549	3,057	47	74
73	Erasmus University	18	5	123	60	282	470	2,687	62	79
74	University of Copenhagen	39	11	161	67	259	498	3,516	54	68
76	Catholic Univ. of Louvain	38	32	258	191	575	1,056	6,871	16	41
79	U. Autónoma, Barcelona	30	15	95	63	375	548	2,778	48	77
80	Free Univ. of Amsterdam	22	11	116	55	183	365	2,693	72	78
81	University of Bonn	14	34	98	72	222	426	3,484	66	69
	RW	169	399	1,295	725	1,216	3,635	40,951		
20	Univ. of British Columbia	27	73	188	110	160	531	6,560	50	43

36	University of Toronto	45	99	255	190	401	945	9,326	18	28
61	Queen's University,	23	34	203	122	165	524	5,302	52	52
64	University of Montreal	21	18	162	113	141	434	3,969	65	63
30	University of Tel Aviv	17	90	240	68	130	528	7,738	51	35
50	Hebrew University	22	69	152	91	181	493	5,767	56	48
69	Hong Kong University	14	16	95	31	38	180	2,289	81	80
TOTAL		**2,485**	**9,092**	**19,688**	**9,710**	**24,113**	**62,603**	**741,373**		

REFERENCES

Albarrán, P., J. Crespo, I. Ortuño, and J. Ruiz-Castillo (2011), "The Skewness of Science In 219 Sub-fields and A Number of Aggregates", *Scientometrics*, **88**: 385-397.

Allison, P. and Stewart, J. (1974), "Productivity Differences Among Scientists: Evidence for Accumulative Advantage", *American Sociological Review*, **39**: 596-606.

Allison, P. , long, J.S., and Krauze, T. (1982), "Cumulative Advantage and Inequality in Science", *American Sociological Review*, **47**: 615-625.

Arrow, K. (1962), "Economic Welfare and the Allocation of Resources for Invention", in *The Rate and Direction of Scientific Activity: Economic and Societal Factors*, Princeton University Press, 609-625.

Baser, O. and Pema, E. (2004), "Publications Over the Academic Life-Cycle: Evidence for Academic Economists", *Economics Bulletin*, **1**: 1-8.

Bell, J. and Seater, J. (1978), "Publishing Performance: Departmental and Individual", *Economic Inquiry*, **16**: 599-615.

Bourguignon, F. (1979), "Decomposable income inequality measures", *Econometrica*, **47**: 901-920.

Chakravarty, S., B. Dutta and J. Weymark (1985), "Ethical Indices of Income Mobility," *Social Choice and Welfare*, **2**: 1-21.

Cole, J. and Cole, S. (1973), *Social Stratification in Science*, Chicago: University of Chicago Press.

Cole, J. and Zuckerman, H. (1984), "The Productivity Puzzle: Persistence and Change in Patterns of Publications of Men and Women Scientists," *Advances in Motivation and Achievement*, **2**: 217-258.

Combes, P. and L. Linnemer (2003), "Where Are the Economists Who Publish? Publication Concentration and Rankings in Europe Based on Cumulative Publications", *Journal of the European Economic Association*, **1**: 1250-1308.

Coupé, T. (2003), "Revealed Performances: Worldwide Ranking of Economists and Economic Departments", *Journal of the European Economic Association*, **1**: 1309-1345.

Coupé, T. (2004), "What Do We Know about Ourselves? On the Economics of Economics", *Kyklos*, **57**: 197-216.

Coupé, T., Smeets, V., and Warzynski, F. (2006), "Incentives, Sorting and Productivity along the Career: Evidence from a Sample of Top Economists", *Journal of Law, Economics, & Organization*, **22**: 137-167.

Cowell, F. A. and K. Kuga (1981), "Inequality Measurement: An Axiomatic Approach," *European Economic Review,* **15**: 287-305.

Dasgupta, P., and David, P.A. (1994), "Toward a New Economics of Science", *Research Policy*, **23**: 487-521.

David, P.A. (1994), "Positive Feedbacks and Research productivity in Science: Reopening Another Black Box", Chapter 3 in Granstrand (ed.), *Economics of Technology*, Elsevier Science.

Diamond, A.M. (1984), "An Economic Model of the Life-Cycle Research Productivity of Scientists", *Scientometrics*, **6**: 189-196.

Diamond, A.M. (1986), "The Life-Cycle Research Productivity of Mathematicians and Scientists", *Journal of Gerontology*, **41**: 520-525.

Econphd.net rankings (2004), http://econphd.econwiki.com/rank/rallec.htm.

Fields, G. S. (2008), "Income mobility", in L. Blume & S. Durlauf (Eds.) *The new Palgrave dictionary of economics*. New York, NY: Palgrave Macmillan.

Fields, G. S. (2010), "Does Income Mobility Equalize Longer–term Incomes? New Measures of an Old Concept", *Journal of Economic Inequality*, **8**: 409-427.

Gonzalez-Brambila, C., and Veloso, F. (2007), "The Determinants of Research Productivity: A Study of Mexican Researchers", *Department of Engineering and Public Policy*, Paper 133 (http://repository.cmu.edu/epp/133).

Goodwin, T. and Sauer, R. (1995), "Life Cycle Productivity in Academic Research: Evidence from Cumulative Publication Histories of Academic Economists", *Southern Economic Journal*, **62**: 728-743.

Grimes, P., and Register, C. (1997), "Career Publication and Academic Job rank: Evidence from the Class of 1968", *Journal of Economic Education*, **28**: 82-92.

Hall, B, Mairesse, J., and Turner, L. (2007), "Identifying Age, Cohort, and Period Effects in Scientific Research Productivity: Discussion and Illustration Using Simulated and Actual Data on French Physicists", *Economics of Innovation and New Technology*, **16**: 159-177.

Hamermesch, D. (1989), "Why Do Individual-Effects Models Perform So Poorly? The Case of Academic Salaries", *Southern Economic Journal*, **56**: 39-45.

Hamermesch, D., Johnson, G.E., and Weisbrod, B.A. (1982), "Scholarships, Citations and salaries: Economic Rewards in Economics", *Southern Economic Journal*, **49**: 472-481.

Hamermesch, D., and Schmidt, P.J. (2003), "The Determinants of Econometric Society Fellows Elections", *Econometrica*, **71**: 399-407.

Hamermesch, D., and Pfann, G. (2012), "Reputation and Earnings: The Roles of Quality and Quantity in Academe", *Economic Inquiry*, **50**: 1-16.

Hartley, J., Monks, J., and Robinson, M. (2001), "Economists' Publication Patterns", *American Economist*, **45**: 80-85.

Henrekson, M. and Waldenström, D. (2011), "How Should Research Performance Be Measured? A Study of Swedish Economists", *The Manchester School*, **79**: 1139-1156.

Hutchinson, E., and Zivney, T. (1995), "The Publication Profile of Economists", *Journal of Economic Education*, **26**: 59-79.

Kalaitzidakis, P., T. Mamuneas and T. Stengos (2003), "Rankings of Academic Journals and Institutions in Economics", *Journal of the European Economic Association*, **1**: 1346-1366.

Kelchtermans, S. and Veugelers, R. (2011), "The Great Divide in scientific Productivity: Why the Average Scientist Does Not Exist", *Industrial and Corporate Change*, **20**: 295-336.

Kelchtermans, S. and Veugelers, R. (2012), "Top Research Productivity and Its Persistence", in press *Review of Economics and Statistics* (doi:10.1162/REST_a_00275).

Kenny, L. and Studley, R. (1995), "Economists' Salaries and Lifetime Productivity", *Southern Economic Journal*, **65**: 382-393.

King, M. (1983), "An Index of Inequality: With Applications to Horizontal Equity and Social Mobility," *Econometrica*, **51**: 99-115.

Kodrzycki and Yu (2006), "New Approaches to Ranking Economics Journals", *Contributions to Economic Analysis and Policy*, 5, 1, Article 24, The Berkeley Electronic Press.

Laband, D. and M. Piette (1994), "The Relative Impact of Economics Journals", *Journal of Economic Literature*, **32**: 640-666.

Levin, S. and Stephan, P. (1991), "Research Productivity Over the Life-Cycle: Evidence for Academic Scientists", *The American Economic Review*, **81**: 114-132.

Long, S. (1992), "Measures of Sex Differences in Scientific Productivity", *Social Forces*, **71**: 159-178.

Lotka, A. (1926), "The Frequency Distribution of Scientific productivity", *Journal of the Washington Academy of Sciences*, **16**: 317-323.

Lubrano, M., L. Bauwens, A. Kirman and C. Protopopescu (2003), "Ranking Economics Departments in Europe: A Statistical Approach", *Journal of the European Economic Association*, 1: 1367-1401.

Markandya, A. (1982), "Intergenerational Exchange Mobility and Economic Welfare," *European Economic Review*, **17**: 307-324.

Markandya, A. (1984), "The Welfare Measurement of Changes in Economic Mobility," *Economica*, **51**: 457-471.

Merton, R. (1957), "Priorities in Scientific Discovery: A Chapter in the Sociology of Science", *American Sociological Review*, **39**: 663-671.

Merton, R. (1961), "Singletons and Multiples in Scientific Discovery", reprinted in R. Merton (1973).

Merton, R. K. (1973), *The Sociology of Science: Theoretical and Empirical Investigations*, Chicago: University of Chicago Press.

Merton, R. (1988), "The Mathew Effect in Science, II: Cumulative Advantage and the Symbolism of Intellectual Property", *Isis*, **79**: 606-623.

Moore, W., Newman, R., and Turnbull, G. (1998), "Do Academic Salaries Decline with Seniority?", *Journal of Labor Economics*, **16**: 352-366.

Moore, W., Newman, R., and Turnbull, G. (2001), "Reputational Capital and Academic Pay", *Economic Inquiry*, **39**: 663-671.

Nelson, R. (1959), "The Simple Economics of Basic Scientific Research", *Journal of Political Economy*, **67**: 297-306.

Oster, S., and Hammermesch, D. (1998), "Aging and Productivity Among Economists", *The Review of Economics and Statistics*, **80**: 154-156.

Oswald, A. (2007), "An Examination of the Reliability of Prestigious Scholarly Journals: Evidence and Implications for Decision-Makers", *Economica*, **74**: 21-31.

Price, D. deSolla (1963), *Little Science, Big Science*, Columbia University Press.

Ragan, J., Warren, J., and Bratsberg, B. (1999), "How Similar Are Pay Structures In 'Similar' Departments of Economics?", *Economics of Education Review*, **18**: 347-360.

Rauber, M. and H. W. Ursprung (2008), "Life Cycle and Cohort Productivity in Economic Research: The Case of Germany", *German Economic Review*, **9**: 431-456.

Ruiz-Castillo, J. (2004), "The Measurement of Structural and Exchange Income Mobility", *The Journal of Economic Inequality*, **2**: 219-228.

Ruiz-Castillo, J. (2008), "Economics Research in Spain during the 1990s: A Literature Review", *Spanish Economic Review*, **10**: 221-249.

Schubert, A., W. Glänzel and T. Braun (1987), "A New Methodology for Ranking Scientific Institutions", *Scientometrics*, **12**: 267-292.

Seglen, P. (1992), "The Skewness of Science", *Journal of the American Society for Information Science*, **43**: 628-638.

Seglen, P. (1997), "Why the Impact Factor of Journals Should Not Be Used for Evaluating Research", *British Medical Journal*, **314**: 498-502.

Shorrocks, A. F. (1980), "The Class of Additively Decomposable Inequality Measures," *Econometrica,* **48**: 613-625.

Shorrocks, A. F. (1984), "Inequality Decomposition by Population Subgroups," *Econometrica,* **52**: 1369-1388.

Stephan, P. E. (1996), "The Economics of Science", *Journal of Economic Literature,* XXXIV: 1199-1235.

Stephan, P. E. (2004), "Robert K. Merton' Perspective on Priority and the provision of the Public Good Knowledge", *Scientometrics,* **60**: 81-87.

Stephan, P. E. (2010), "The Economics of Science", Chapter 5 in B. Hall and N. Rosenberg (eds), *Handbook of The Economics of Innovation,* Vol 1: 217-273.

Turner, L. and Mairesse, J. (2003), "Explaining Individual productivity Differnces in Scientific Research Productivity: How Important Are Institutional and Individual Determinants?",

Weiss, Y. and Lillard, L. (1982), "Output Variability, Academic labor Contracts, and Waiting Times for Promotion", *Research in Labor Economics*, **5**: 157-188.

Xie, Y. and Shauman, K. (1998), "Sex Differences in Research Productivity: New Evidence about an Old Puzzle", *American Sociological review*, **63**: 847-870.

Table 1. The Skewness of Productivity Distributions in the Original Sample

	Percentage of Individuals In Category:				Percentage of Publications or Quality Points Accounted for By Category:			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Number of Publications, *P*	65.6	22.3	7.9	4.1	27.2	32.6	20.8	19.4
Quality Index, *Q*	66.2	21.5	7.7	4.6	25.7	31.4	20.8	22.2

Category 1 = individuals with low productivity, smaller than or equal to μ_1;
Category 2 = individuals with an intermediate productivity, above μ_1 and smaller or equal to μ_2;
Category 3 = individuals with a remarkable productivity, above μ_2 and smaller or equal to μ_3;
Category 4 = individuals with an outstanding productivity above μ_3,

where: μ_1 = mean of the productivity distribution;
μ_2 = mean productivity of individuals with productivity above μ_1,
μ_3 = mean productivity of individuals with productivity above μ_2.

	Productivity Distributions *P*	*Q*
μ_1	25.2	319
μ_2	54.4	719
μ_3	86.8	1,170

Table 2. Number of Individuals by Cohort, and Average Productivity in Selected Periods After Completion of the PhD

	16-19 I	20-23 II	24-27 III	28-31 IV	32-35 V	36-39 VI	40-57 VII	All Cohorts
NUMBER OF INDIVIDUALS	216	198	195	164	167	105	91	1,136
AVERAGE PRODUCTIVITY								
Eight-year Periods								
1. $\mu(x^c)$	158.5	194.2	191.8	179.7	165.2	199.8	206.2	182.1
2. $\mu(y_1^c)$	153.4	174.1	160.6	147.5	152.2	188.9	189.0	163.3
3. $\mu(y_2^c)$			116.5	113.4	125.6	134.6	158.4	125.8
4. $\mu(y_3^c)$					96.2	114.1	121.5	107.7
5. $\mu(y_4^c)$							84.7	84.7
PRODUCTIVITY PER YEAR								
6. First Period, $\mu(x^c/8)$	19.8	24.3	24.0	22.5	20.6	25.0	25.8	22.8
7. Second Period, $\mu[y^c/(T^c - 8)]$	18.1	19.2	16.7	14.4	15.2	16.3	16.0	16.8
8. Aggregate, $\mu[(x^c + y^c)/T^c]$	18.8	21.1	19.0	16.6	16.5	18.2	17.7	18.4

x^c and y^c = First and Second Period in the Transformation $x^c \rightarrow y^c$

y_1^c, y_2^c, y_3^c, and y_4^c = Successive Eight-year Periods

$(x^c + y^c)$ = Aggregate Distribution

T^c = Number of years since PhD in 2007

Table 3.A. Age/Productivity Profiles. Entire Cohorts' Sample

Variables*:	Coefficients	Std. Error
Period	-4.13	1.21
(Period)^2	0.00	0.03
Gender	69.80	10.31
University Type I	123.88	7.38
University Type II	31.60	7.85
University Type III	14.11	8.21
Constant	100.52	17.45

*** Six cohort dummies are insignificant**

N = 3,498

Adjusted R^2 = 0.158

Table 3.B. Age/Productivity Profiles. Highly Productive Individuals

Variables*:	Coefficients	Std. Error
Period	1.12	3.57
(Period)^2	-0.18	0.08
Gender	70.98	55.66
Cohort I	-101.94	33.91
Cohort IV	-73.37	31.78
Cohort V	-58.74	28.65
Constant	376.96	75.25

*** Remaining cohort dummies, as well as University Type variables are insignificant**

N = 690

Adjusted R^2 = 0.082

Table 3.C. Age/Productivity Profiles. Rest of the Cohorts Sample

	Coefficients	Std. Error
Variables*:		
Period	-5.32	0.79
(Period)^2	0.042	0.019
Gender	33.18	6.25
University Type I	-8.49	7.21
University Type II	23.73	4.82
Cohort V	-12.88	6.16
Constant	376.96	75.25

*** Remaining cohort dummies, as well as the University Type III variable are insignificant**

N = 2,808

Adjusted R^2 = 0.164

Table 4. Productivity Inequality in Selected Periods After Completion of the PhD

	16-19 I	20-23 II	24-27 III	28-31 IV	32-35 V	36-39 VI	40-57 VII	All Cohorts	
PRODUCTIVITY INEQUALITY									
Eight-year Periods									
$I_1(x^c)$	0.264	0.306	0.389	0.311	0.380	0.331	0.341	$I_1(x)$	0.334
$I_1(y_1^c)$	0.287	0.344	0.352	0.425	0.474	0.470	0.426	$I_1(y_1)$	0.388
$I_1(y_2^c)$			0.495	0.493	0.535	0.511	0.659	$I_1(y_2)$	0.539
$I_1(y_3^c)$					0.894	0.747	0.622	$I_1(y_3)$	0.776
$I_1(y_4^c)$							0.946	$I_1(y_4)$	0.946
Second Period, $I_1(y^c)$	0.285	0.343	0.352	0.393	0.477	0.416	0.449	$I_1(y)$	0.456
Aggregate, $I_1(x^c + y^c)$	0.223	0.280	0.316	0.307	0.370	0.339	0.359	$I_1(x+y)$	0.344

Table 5. Mobility Matrices for All Cohorts

COHORT I

x/y	1.	2.	3.	4.	5.	Total
1.	22	10	7	3	3	45
	48.9	22.2	15.6	6.7	6.7	100.0
2.	10	16	7	7	4	44
	22.7	36.4	15.9	15.9	9.1	100.0
3.	8	12	10	7	4	41
	19.5	29.3	24.4	17.1	9.8	100.0
4.	4	6	9	18	6	43
	9.3	13.9	20.9	41.9	13.9	100.0
5.	0	1	8	8	26	43
	0.0	2.3	18.6	18.6	60.5	100.0
Total	44	45	41	43	43	216
	20.4	20.8	19.0	19.9	19.9	100.0

COHORT II

x/y	1.	2.	3.	4.	5.	Total
1.	22	9	6	2	1	40
	55.0	22.5	15.0	5.0	2.5	100.0
2.	6	13	8	9	4	40
	15.0	32.5	20.0	22.5	10.0	100.0
3.	8	11	10	6	4	39
	20.5	28.1	25.6	15.4	10.3	100.0
4.	4	6	13	8	9	40
	10.0	15.0	32.5	20.0	22.5	100.0
5.	0	2	2	14	21	39
	0.0	5.1	5.1	35.9	53.8	100.0
Total	40	41	39	39	39	198
	20.2	20.7	19.7	19.7	19.7	100.0

COHORT III

x/y	1.	2.	3.	4.	5.	Total
1.	21	13	3	1	1	39
	53.8	33.3	7.7	2.6	2.6	100.0
2.	12	9	12	4	2	39
	30.8	23.1	30.8	10.3	5.1	100.0
3.	3	10	2	9	5	39
	7.7	25.6	30.8	23.1	12.8	100.0
4.	3	6	11	13	6	39
	7.7	5.4	28.2	33.3	15.4	100.0
5.	0	1	1	12	25	39
	0.0	2.6	2.6	30.8	64.1	100.0
Total	39	39	39	39	39	195
	20.0	20.0	20.0	20.0	20.0	100.0

COHORT IV

x/y	1.	2.	3.	4.	5.	Total
1.	21	7	4	2	0	34
	61.8	20.6	11.8	5.9	0.0	100.0
2.	6	11	9	5	1	32
	18.7	34.4	28.1	15.6	3.1	100.0
3.	4	7	8	7	7	33
	12.1	21.2	24.2	21.2	21.2	100.0
4.	2	5	9	11	7	34
	5.9	14.7	26.5	32.3	20.6	100.0
5.	1	2	3	8	17	31
	3.2	6.4	9.7	25.8	54.8	100.0
Total	34	32	33	33	32	164
	20.7	219.5	20.1	20.1	19.5	100.0

COHORT V

x/y	**1.**	**2.**	**3.**	**4.**	**5.**	**Total**
1.	17 50.0	7 20.6	5 14.7	5 14.7	0 0.0	34 100.0
2.	10 30.3	12 36.4	5 15.1	5 15.1	1 3.0	33 100.0
3.	6 17.6	6 17.6	9 26.5	6 17.6	7 20.6	34 100.0
4.	0 0.0	7 21.2	9 27.3	7 21.2	10 30.3	34 100.0
5.	1 3.0	1 3.0	6 18.2	10 30.3	15 45.4	33 100.0
Total	34 20.4	33 19.8	34 20.4	33 19.8	33 19.8	167 100.0

COHORT VI

x/y	**1.**	**2.**	**3.**	**4.**	**5.**	**Total**
1.	12 57.1	6 28.6	1 4.8	2 9.5	0 0.0	21 100.0
2.	4 19.0	7 33.3	6 28.6	3 14.3	1 4.8	21 100.0
3.	4 19.0	4 19.0	4 19.0	7 33.3	2 9.5	21 100.0
4.	1 4.8	3 14.3	6 28.6	3 14.3	8 38.1	21 100.0
5.	0 0.0	1 4.8	4 19.0	6 28.6	10 47.6	21 100.0
Total	22 20.0	21 20.0	21 20.0	21 20.0	21 20.0	105 100.0

COHORT VII

x/y	**1.**	**2.**	**3.**	**4.**	**5.**	**Total**
1.	9 47.4	5 26.3	2 10.5	2 10.5	1 5.3	19 100.0
2.	6 33.3	6 33.3	2 11.1	3 16.7	1 5.6	18 100.0
3.	3 16.7	4 22.2	5 27.8	2 11.1	4 22.2	18 100.0
4.	0 0.0	3 16.7	7 38.9	2 11.1	6 33.3	18 100.0
5.	1 5.6	0 0.0	2 11.1	9 50.0	6 33.3	18 100.0
Total	19 20.9	18 19.8	18 19.8	18 19.8	18 19.8	91 100.0

Table 6. Productivity Mobility in Selected Transformations

	16-19 I	20-23 II	24-27 III	28-31 IV	32-35 V	36-39 VI	40-57 VII	ALL COHORTS	
PRODUCTIVITY MOBILITY									
Eight-year Periods									
$M_1(x^c, y_1^c)$	0.151	0.104	0.172	0.033	0.075	- 0.014	0.092	$M_1(x,y_1)$	0.099
$M_1(x^c, y_1^c+y_2^c)$			0.192	0.041	0.098	0.005	-0.038	$M_1(x,y_1+y_2)$	0.062
$M_1(x^c, y_1^c+y_2^c+y_3^c)$					0.028	- 0.037	-0.041	$M_1(x\ y_1+y_2+y_3)$	- 0.001
$M_1(x^c, y_1^c+y_2^c+y_3^c+y_4^c)$							-0.062	$M_1(x,y_1+y_2+y_3+y_4)$	- 0.027
Entire Cohorts									
A. $M_1(x^c, y^c)$	0.158	0.087	0.188	0.012	0.022	-0.027	-0.056	$M_1(x, y)$	- 0.030
B. $EM_1(x^c, y^c)$	0.193	0.151	0.125	0.173	0.184	0.151	0.161	$EM_1(x, y)$	0.190
C. $SM_1(x^c, y^c)$	-0.035	-0.064	0.062	-0.161	-0.162	-0.178	-0.217	$SM_1(x, y)$	- 0.220

ALL COHORTS: $M_1(x, y) = \Sigma_c \beta_c M_1(x^c, y^c) + \{\Sigma_c (w_c - v_c)\, I_1(x^c) + [I_1(\boldsymbol{m}^1,..., \boldsymbol{m}^C)] - I_1(\boldsymbol{\mu}^1,..., \boldsymbol{\mu}^C)]\} / I_1(x)$

- 0.030 = 0.059 - 0.036 - 0.053

Table 7. **The Skewness of Productivity Distributions ($x^c + y^c$) for All Cohorts**

($x^c + y^c$)		Percentage of Individuals In Category:				Percentage of Publications Accounted for By Category:			
		1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
CI, 16-19	(216 ind.)	57.9	36.1	4.6	1.4	31.4	51.3	12.0	5.3
CII, 20-23	(198 ind.)	42.9	38.9	12.6	5.5	16.7	41.5	23.8	18.0
CIII, 24-27	(195 ind.)	42.6	36.9	14.4	6.2	15.0	36.9	26.5	21.6
CIV, 28-31	(164 ind.)	42.7	33.5	14.6	9.1	14.0	34.4	25.8	25.8
CV, 32-35	(167 ind.)	40.7	30.5	19.2	9.6	11.4	26.6	32.0	30.1
CVI, 36-39	(105 ind.)	32.4	30.5	18.1	19.0	7.6	21.7	24.2	46.4
CVII, 40-57	(91 ind.)	29.7	29.7	16.5	24.2	6.8	20.0	19.3	53.9
ALL COHORTS (1,136 individuals)		43.3	34.5	13.5	8.7	14.6	33.4	23.5	28.1

Category 1 = individuals with low productivity, smaller than or equal to μ_1;
Category 2 = individuals with an intermediate productivity, above μ_1 and smaller or equal to μ_2; **Category 3** = individuals with a remarkable productivity, above μ_2 and smaller or equal to μ_3;
Category 4 = individuals with an outstanding productivity above μ_3,

where: μ_1 = mean of the productivity distribution;
μ_2 = mean productivity of individuals with productivity above μ_1,
μ_3 = mean productivity of individuals with productivity above μ_2.

	Q	**16-19 I**	**20-23 II**	**24-27 III**	**28-31 IV**	**32-35 V**	**36-39 VI**	**40-57 VII**	**All Cohorts**
μ_1.	319	331	451	482	492	552	680	775	501
μ_2	719	538	658	713	738	825	929	1,026	755
μ_3	1,170	948	1,037	1,132	1,068	1,191	1,295	1,395	1,174

Table 8. Number of Individuals by Cohort, and Average Productivity in Selected Periods After Completion of the PhD With a Less Elitist Quality Index

	16-19 I	20-23 II	24-27 III	28-31 IV	32-35 V	36-39 VI	40-57 VII	All Cohorts
NUMBER OF INDIVIDUALS	216	198	195	164	167	105	91	1,136
AVERAGE PRODUCTIVITY								
Eight-year Periods								
1. $\mu(x^c)$	98.4	116.7	114.6	105.8	96.5	115.4	113.5	107.9
2. $\mu(y_1^c)$	95.3	106.2	97.3	89.3	92.0	110.8	107.6	98.6
3. $\mu(y_2^c)$			72.0	71.4	79.3	83.2	93.6	77.9
4. $\mu(y_3^c)$					61.0	72.4	73.7	67.5
5. $\mu(y_4^c)$							52.7	52.7
PRODUCTIVITY PER YEAR								
6. First Period, $\mu(x^c/8)$	12.3	14.6	14.3	13.2	12.1	14.4	14.2	13.5
7. Second Period, $\mu[y^c/(T^c - 8)]$	11.3	11.8	10.2	8.9	9.4	10.0	9.5	10.3
8. Aggregate, $\mu[(x^c + y^c)/T^c]$	11.7	12.8	11.5	10.1	10.1	11.0	10.3	11.2

x^c and y^c = First and Second Period in the Transformation $x^c \rightarrow y^c$

y_1^c, y_2^c, y_3^c, and y_4^c = Successive Eight-year Periods

$(x^c + y^c)$ = Aggregate Distribution

T^c = Number of years since PhD in 2007

Table 9. Productivity Inequality in Selected Periods After Completion of the PhD With a Less Elitist Quality Index

	16-19 I	20-23 II	24-27 III	28-31 IV	32-35 V	36-39 VI	40-57 VII	All Cohorts	
PRODUCTIVITY INEQUALITY									
Eight-year Periods									
$I_1(x^c)$	0.225	0.272	0.343	0.276	0.335	0.305	0.317	$I_1(x)$	0.295
$I_1(y_1^c)$	0.294	0.310	0.302	0.383	0.419	0.437	0.398	$I_1(y_1)$	0.345
$I_1(y_2^c)$			0.433	0.445	0.481	0.467	0.593	$I_1(y_2)$	0.481
$I_1(y_3^c)$					0.813	0.681	0.553	$I_1(y_3)$	0.703
$I_1(y_4^c)$							0.841	$I_1(y_4)$	0.841
Second Period, $I_1(y^c)$	0.251	0.310	0.302	0.357	0.429	0.386	0.407	$I_1(y)$	0.413
Aggregate, $I_1(x^c + y^c)$	0.193	0.250	0.272	0.278	0.330	0.317	0.330	$I_1(x+y)$	0.307

Table 10. Productivity Mobility in Selected Transformations With a Less Elitist Quality Index

	16-19 I	20-23 II	24-27 III	28-31 IV	32-35 V	36-39 VI	40-57 VII		ALL COHORTS
PRODUCTIVITY MOBILITY									
Eight-year Periods									
$M_1(x^c, y_1^c)$	0.142	0.102	0.187	0.026	0.079	- 0.028	0.083	$M_1(x,y_1)$	0.098
$M_1(x^c, y_1^c+y_2^c)$			0.210	0.024	0.100	-0.010	-0.043	$M_1(x,y_1+y_2)$	0.060
$M_1(x^c, y_1^c+y_2^c+y_3^c)$					0.022	- 0.052	-0.039	$M_1(x\ y_1+y_2+y_3)$	- 0.009
$M_1(x^c, y_1^c+y_2^c+y_3^c+y_4^c)$							-0.056	$M_1(x,y_1+y_2+y_3+y_4)$	- 0.039
Entire Cohorts									
A. $M_1(x^c, y^c)$	0.143	0.083	0.207	-0.008	0.012	-0.043	-0.047	$M_1(x, y)$	- 0.041
B. $EM_1(x^c, y^c)$	0.198	0.158	0.129	0.176	0.191	0.146	0.155	$EM_1(x, y)$	0.203
C. $SM_1(x^c, y^c)$	-0.054	-0.075	0.078	-0.184	-0.179	-0.189	-0.202	$SM_1(x, y)$	- 0.244

ALL COHORTS: $M_1(x, y) = \Sigma_c\, \beta_c\, M_1(x^c, y^c) + \{\Sigma_c\,(w_c - v_c)\, I_1(x^c) + [I_1(m^1,..., m^C)] - I_1(\mu^1,..., \mu^C)]\} / I_1(x)$

$- 0.041 = 0.055 - 0.043 - 0.053$

Table 11. The Skewness of Productivity Distributions ($x^c + y^c$) for All Cohorts With a Less Elitist Quality Index

	Percentage of Individuals In Category:				Percentage of Publications Accounted for By Category:			
	1	2	3	4	1	2	3	4
QUALITY INDEX, *Q* (2,485 individuals)	66.2	21.5	7.7	4.6	25.7	31.4	20.8	22.2
COHORTS								
CI, 16-19 (216 ind.)	56.5	36.6	6.0	0.9	31.9	49.8	15.0	3.2
CII, 20-23 (198 ind.)	42.9	37.4	15.1	4.5	17.9	39.2	28.4	14.5
CIII, 24-27 (195 ind.)	40.0	39.5	13.8	6.7	15.2	38.6	24.9	21.3
CIV, 28-31 (164 ind.)	42.7	32.3	16.5	8.5	15.0	33.3	28.5	23.2
CV, 32-35 (167 ind.)	37.7	32.3	19.2	10.8	11.2	27.3	30.3	31.2
CVI, 36-39 (105 ind.)	32.4	29.5	19.0	19.0	8.3	21.1	25.2	45.4
CVII, 40-57 (91 ind.)	29.7	28.6	16.5	25.3	7.6	19.3	18.7	54.2
ALL COHORTS (1,136 individuals)	42.2	34.7	14.4	8.7	15.3	33.1	24.9	26.7

Category 1 = individuals with low productivity, smaller than or equal to μ_1;
Category 2 = individuals with an intermediate productivity, above μ_1 and smaller or equal to μ_2;
Category 3 = individuals with a remarkable productivity, above μ_2 and smaller or equal to μ_3;
Category 4 = individuals with an outstanding productivity above μ_3,

where: μ_1 = mean of the productivity distribution;
μ_2 = mean productivity of individuals with productivity above μ_1,
μ_3 = mean productivity of individuals with productivity above μ_2.

	Q	16-19 I	20-23 II	24-27 III	28-31 IV	32-35 V	36-39 VI	40-57 VII	All Cohorts
μ_1.	194	206	274	292	299	337	410	450	304
μ_2	426	119	193	233	198	301	330	592	445
μ_3	675	542	598	657	619	693	761	788	677