“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 publications, weighted by the citation impact of the journals where each article is published in the periodical literature. 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.

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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. Consider the possibility of measuring the productivity of scientists –the subject matter of this paper– 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.² 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.

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*”. For the ‘new’ economics of science, see Dasgupta and David (1994), as well as Stephan (1996, 2010).

² 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.

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 $(1, 3) \rightarrow (1, 5)$ would *disequalize* life cycle productivity relative to the initial period, while a pattern $(1, 3) \rightarrow (5, 1)$ 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.³ 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.

(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*

³ 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.

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 2,485 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 1,147 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 equalizing for five of seven cohorts.

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 $\mathbf{x} = (x_1, \dots, x_n)$ 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 $\mathbf{x}$ has been *transformed* to $\mathbf{y} = (y_1, \dots, y_n)$, and denote this *productivity transformation* by $\mathbf{x} \rightarrow \mathbf{y}$. In what follows, in every transformation $\mathbf{x} \rightarrow \mathbf{y}$, productivity distribution $\mathbf{x}$ will be ordered according to the “less than or equal” relation, so that $x_1 \leq \dots \leq x_n$. 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 $\mathbf{x} + \mathbf{y} = (x_1 + y_1, \dots, x_n + y_n)$ is referred to as the *aggregate productivity distribution*.

An index of mobility is a real valued function defined on the set of productivity transformations $\mathbf{x} \rightarrow \mathbf{y}$. 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

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

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

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 $\mathbf{x}$ and $\mathbf{y}$ once all rank reversals have been removed, denoted by $SM(\mathbf{x}, \mathbf{y})$, and a second one capturing the re-rankings effect, $EM(\mathbf{x}, \mathbf{y})$. Given any distributional transformation $\mathbf{x} \rightarrow \mathbf{y}$, define $\tilde{\mathbf{y}}$ as having the same components as $\mathbf{y}$, but rearranged (if necessary) in the same increasing order as $\mathbf{x}$. Of course, $I(\tilde{\mathbf{y}}) = I(\mathbf{y})$. The following decomposition of the mobility index is now introduced

$$M(\mathbf{x}, \mathbf{y}) = SM(\mathbf{x}, \mathbf{y}) + EM(\mathbf{x}, \mathbf{y}), \quad (2)$$

where

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

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

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

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

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

Thus, whenever $I(\mathbf{x}) > I(\mathbf{y})$ 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 $\tilde{\mathbf{y}} \neq \mathbf{y}$, we always have

$$EM(\mathbf{x}, \mathbf{y}) > 0. \quad (4)$$

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

II. 3. Additive Decomposability

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

It is well known that the GE (Generalized Entropy) family of inequality indices are the only measures

of relative inequality that satisfy the usual properties⁴ required from any inequality index and, in addition, are decomposable by population subgroup (Bourguignon, 1978, and Shorrocks, 1980, 1984). Given the distribution $\mathbf{z} = (z_1, \dots, z_N)$ with mean $\mu(\mathbf{z}) = \mu$, the member of the GE family that will be used in this paper is the first Theil inequality index, denoted by I_I , and defined as:

$$I_I(\mathbf{z}) = (1/N) \sum_i (z_i/\mu) \log(z_i/\mu).$$

For the partition of $\mathbf{x}$ into C cohorts, index I_I 's decomposition formula is the following:

$$I_I(\mathbf{x}) = \sum_c v_c I_I(\mathbf{x}^c) + I_I(\boldsymbol{\mu}^1, \dots, \boldsymbol{\mu}^C), \quad (5)$$

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

$$I_I(\mathbf{x} + \mathbf{y}) = \sum_c w_c I_I(\mathbf{x}^c + \mathbf{y}^c) + I_I(\mathbf{m}^1, \dots, \mathbf{m}^C),$$

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

$$\begin{aligned} M_I(\mathbf{x}, \mathbf{y}) &= \{I_I(\mathbf{x}) - I_I(\mathbf{x} + \mathbf{y})\} / I_I(\mathbf{x}) \\ &= \{[\sum_c v_c I_I(\mathbf{x}^c) + I_I(\boldsymbol{\mu}^1, \dots, \boldsymbol{\mu}^C)] - [\sum_c w_c I_I(\mathbf{x}^c + \mathbf{y}^c) + I_I(\mathbf{m}^1, \dots, \mathbf{m}^C)]\} / I_I(\mathbf{x}) \\ &= \sum_c \beta_c M_I(\mathbf{x}^c, \mathbf{y}^c) + \{\sum_c (v_c - w_c) I_I(\mathbf{x}^c + \mathbf{y}^c)\} / I_I(\mathbf{x}) + \{I_I(\boldsymbol{\mu}^1, \dots, \boldsymbol{\mu}^C) - I_I(\mathbf{m}^1, \dots, \mathbf{m}^C)\} / I_I(\mathbf{x}), \end{aligned} \quad (6)$$

⁴ Namely, continuity, S-convexity, scale invariance, and invariance to population replications.

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

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

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). The high correlation between this university ranking and three other equally acceptable alternatives 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 (for more details, see the Working Paper version of this paper in Carrasco and Ruiz-Castillo, 2012)

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.⁵

III.2. The Measurement of Productivity

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.⁶ The analysis in Carrasco and Ruiz-Castillo (2012) indicates that both indices share similar characteristics and

⁵ 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 in Carrasco and Ruiz-Castillo (2012).

⁶ Oster and Hamermesh (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 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 in Carrasco and Ruiz-Castillo (2012).

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.⁷

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 $\mathbf{x}$ introduced in Section II. The conditions under which academic scholars conduct their research and publication activity change over time.⁸ 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 from 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 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.

⁷ 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.

⁸ For example, as pointed out by a referee, 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 be published there before (for those who seriously tried), than it is today.

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, we end up with a sample of 1,147 individuals classified in the seven cohorts just described. Since there are more females among recent PhDs, the percentage of females goes down from 14.2% in the original dataset to 7.6%, while the average number of years since the PhD increases from 17.8 for the 2,231 individuals with this information in the original dataset 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.⁹

IV. EMPIRICAL RESULTS

IV.1. The Evolution of Average Productivity

We are concerned with productivity transformations $\mathbf{x}^c \rightarrow \mathbf{y}^c$, where the second period distribution, $\mathbf{y}^c$, 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 $\mathbf{x}^c$), denoted by $\mathbf{y}_1^c, \mathbf{y}_2^c, \mathbf{y}_3^c$, and $\mathbf{y}_4^c$, $c = \text{I}, \dots, \text{VII}$. As a matter of fact, CVII is the only cohort

⁹ By way of example, the following 12 are part of the 34 journals in class B: *Economic Journal*, *Games and Economic Behavior*, *International Economic Review*, *Journal of Econometrics*, *Journal of Economic Growth*, *Journal of Economic Theory*, *Journal of Finance*, *Journal of Labor Economics*, *Journal of Monetary Economics*, *Journal of Public Economics*, *Rand Journal of Economics*, *Review of Economics and Statistics*.

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 $y_i^c = Q_{T_i^c}^c - Q_{8i}^c$. If individual i is in cohort IV, for example, then in addition we have: $y_{1i}^{IV} = Q_{16i}^{IV} - Q_{8i}^{IV}$, and $y_{2i}^{IV} = Q_{24i}^{IV} - Q_{16i}^{IV}$, 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 1. To make them comparable across cohorts, rows 6 to 8 include the average productivity per year for the two periods, $\mathbf{x}$ and $\mathbf{y}$, as well as the aggregate $(\mathbf{x} + \mathbf{y})$ distribution, which we denote by $\mu(\mathbf{x}^c/8)$, $\mu[\mathbf{y}^c/(T^c - 8)]$, and $\mu[(\mathbf{x}^c + \mathbf{y}^c)/T^c]$, respectively.

Table 1 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 230 points in CVI, equivalent to four and more than five class A articles, respectively. Secondly, average productivity uniformly decreases with age in all cohorts (according to Diamond, 1986, the quantity and quality of current output for Berkeley mathematicians also declines monotonically with age). With the exception of CV, the difference between the average productivity per year in the first and the second period in the transformation $\mathbf{x}^c \rightarrow \mathbf{y}^c$ (see rows 6 and 7 in Table 1), increases as we proceed from CI to CVII. Such differences, however, are not very large: the average difference for all cohorts is 7.2, comparable with an article in class C. Moreover, this trend is offset by the fact that average productivity in $\mathbf{x}^c$ 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 16.1 to 20.8 points per year for CV and CII, 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, in Carrasco and Ruiz-Castillo (2012) we express these findings in a regression format. The main results are the following four. (i) Not surprisingly, for the entire sample we find that productivity decreases linearly with age.¹⁰ 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).¹¹ Consequently, we also study a partition of the sample into the top 20% of individuals in each cohort and the remaining 80%. We find that productivity of the most prolific economists slightly increases at a declining rate. On the other hand, productivity linearly decreases for the second group, explaining the results for the sample as a whole. Two types of factors might explain this. 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). (ii) 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, 2011, 2012, and Rauber and Ursprung, 2008, as well as the discussion in Stephan, 2010). (iii) Working in better universities increases

¹⁰ 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).

¹¹ 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.

individual productivity. (iv) Except among the top producers where some younger cohorts are less productive, there is no evidence of cohort effects.¹²

IV.2. The Evolution of Productivity Inequality

Table 2 presents the evolution of productivity inequality in all cohorts. The main finding is that, as already discovered in the literature, 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 all periods. In any case, 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 2 around here

The previous evidence in the literature, 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

¹² 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.

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 3 presents mobility matrices between the two periods –that is, between distributions $\mathbf{x}^{\ell}$ and $\mathbf{y}^{\ell}$ – 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 $\mathbf{x}^{\ell}$ during the first eight years of academic life are more likely to reach top status also in distribution $\mathbf{y}^{\ell}$, 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 $\mathbf{x}^{\ell}$ that remain in the same quintile in distribution $\mathbf{y}^{\ell}$ range from 45% to 64% in the first four cohorts. These percentages decrease in the oldest cohorts to 42%-45% in CV and CVI, and to 31-32% in CVII.¹³ Thus, older age cohorts are slightly underrepresented at both the top and the bottom, a pattern not found in Kelchtermans and Veugelers (2012).

Table 3 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 116 individuals, or 10.1% of the sample, belonging to the top quintile in their respective cohorts –a comparable proportion. Note that between 40% and 55% of individuals in the

¹³ 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%.

top 20% in distribution $\mathbf{y}^c$ in cohorts CI to CVI proceed from three –or even all four– of the other quintiles in distribution $\mathbf{x}^c$. This percentage is almost 70% in CVII. 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 26% and 34% in all cohorts. 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 4 includes the most important results of the paper, concerning productivity mobility for all cohorts in selected transformations. Let us begin with the key transformation $\mathbf{x}^c \rightarrow \mathbf{y}^c$ for all cohorts $c = \text{I}, \dots, \text{VII}$. As we saw in Table 2, $I_t(\mathbf{x}^c) < I_t(\mathbf{y}^c)$ for all c . This causes $SM_t(\mathbf{x}^c, \mathbf{y}^c) < 0$ for all c (see Row C in Table 4). However, the re-rankings reported in table 3 cause $EM_t(\mathbf{x}^c, \mathbf{y}^c) > 0$ for all c (see Row B in Table 4). The latter effect is stronger than the SM effect of the opposite sign in all cases except for CV and CVII. For the five cohorts for which mobility is equalizing, i.e. for which $M_t(\mathbf{x}^c, \mathbf{y}^c) > 0$, we can conclude that aggregate productivity inequality is 7% to 16% smaller than productivity inequality in the first eight years of academic life (see Row A in Table 4).

Table 4 around here

Note that in CV the EM effect is stronger than the SM effect of the opposite sign for the transformations $\mathbf{x}^V \rightarrow \mathbf{y}_1^V$ and $\mathbf{x}^V \rightarrow (\mathbf{y}_1^V + \mathbf{y}_2^V)$, so that mobility $M_t(\mathbf{x}^V, \mathbf{y}_1^V)$ and $M_t(\mathbf{x}^V, \mathbf{y}_1^V + \mathbf{y}_2^V)$ turns out to be equalizing. However, the large increase in $I_t(\mathbf{y}_3^V)$ relative to previous eight-year periods (see Table 2) generates a strong $SM_t(\mathbf{x}^V, \mathbf{y}_1^V + \mathbf{y}_2^V + \mathbf{y}_3^V)$ in absolute value that gives rise to a negative overall

mobility $M_I(\mathbf{x}^V, \mathbf{y}_1^V + \mathbf{y}_2^V + \mathbf{y}_3^V) = -0.021$. Similarly, $SM_I(\mathbf{x}^V, \mathbf{y}^V) = -0.324$ is the largest SM term in absolute value among all cohorts (see Row C in Table 4). This offsets the re-ranking effect, so that mobility for the entire cohort becomes disequalizing: $M_I(\mathbf{x}^V, \mathbf{y}^V) = -0.027$. The case of CVII is different. In every transformation a strong SM offsets a large EM of the opposite sign. We conclude that for CV and CVII for which mobility is disequalizing aggregate productivity inequality is 2.7% and 9.8% greater than productivity inequality in the first period.

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 $\mathbf{x}^c \rightarrow \mathbf{y}^c$. Since $M_I(\mathbf{x}^c, \mathbf{y}^c) < 0$ only for $c = V, VII$, it comes as no surprise that the term $\sum_c \beta_c M_I(\mathbf{x}^c, \mathbf{y}^c)$ is positive but small. Since the other two terms in the decomposition are negative, we end up with a small negative value $M_I(\mathbf{x}, \mathbf{y}) = -0.018$. As can be observed in Table 3, rank reversals between distributions $\mathbf{x}$ and $\mathbf{y}$ imply that $EM_I(\mathbf{x}, \mathbf{y}) = 0.051$. 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, $I_I(\mathbf{x})$ is similar to $I_I(\mathbf{x}^c)$ for each c . However, the heterogeneity of distribution $\mathbf{y}$, which is the union of distributions $\mathbf{y}^c$ 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 indicated in the Introduction, productivity distributions are typically highly skewed. We study whether this is the case for two types of distributions: the quality distribution $\mathcal{Q}$ –the analogue of distribution $(\mathbf{x} + \mathbf{y})$ – for the entire, original sample of 2,485 economists, and the distributions $(\mathbf{x}^c + \mathbf{y}^c)$ for $c = I, \dots, VII$ after changes in cross-section productivity inequality and re-rankings between distributions $\mathbf{x}^c$

and y^c have taken place for the cohort sample of 1,147 individuals. 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 feature of productivity distributions. 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 5 includes the percentage of individuals in classes 1 and 4, as well as the percentages of quality points accounted for by these two classes in the two types of distributions.

Table 5 around here

For distribution Q , $\mu_1 = 317$, $\mu_2 = 721$, and $\mu_3 = 1,172$. Note that the mean is 16.8 points above the median, and the top 11.8% of economists in classes 3 and 4 account for 43.7% of all quality points.¹⁴ To understand what type of distribution $(x^c + y^c)$ 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 3 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

¹⁴ 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).

distributions in all sciences, generally). In the latter case, about 88% at the bottom of the distribution 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 23.7% of all quality points. Instead, for cohorts VI and VII, about 60% at the bottom account for only 30% of all quality points, while a large elite with outstanding productivity accounts for half of all quality points.

V. CONCLUSIONS AND EXTENSIONS

This paper has studied the evolution of the research productivity of a sample of 1,147 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 publications weighted by the citation impact of the journals where each article is published in the periodical literature. 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.

1. 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 (2011), 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.

2. As expected, productivity inequality clearly increases with age. It turns out that this makes structural mobility disequalizing for all cohorts.

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

4. The end result is that overall mobility is equalizing for five of the seven cohorts, where aggregate productivity inequality is 7% to 16% smaller than productivity inequality in the first period (in the other two cohorts, aggregate productivity inequality is 2.7% and 9.8% greater than productivity inequality in the first period). 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 1.8% greater than productivity inequality in the first period.

5. 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.¹⁵

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). However, it might be interesting to extend this effort in two directions. Firstly, within this group we may widen the first period 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. We have done this for cohorts V and VII, for which the second period becomes the next 16 to 19 years, or more than 24, respectively. The main result is that doubling the number of years of the first period does not drastically alter the results.¹⁶ Secondly, we may consider a representative sample of

¹⁵ As indicated in note 7, we have replicated Tables 1, 2, 4, and 5 for a less elitist measure of productivity than the one introduced in Section III.2 (see Tables 8, 9, 10, and 11 in Carrasco and Ruiz-Castillo, 2012). With the exception that overall mobility for the sample as a whole is now slightly equalizing (2.1%) rather than the opposite (- 1.8%), the results are strikingly similar to the ones discussed in the paper. 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.

¹⁶ In particular, *EM* slightly decreases and *SM* is slightly increases in both cases, so that overall productivity mobility is greater than before: aggregate productivity inequality increases by 10.8% and 19.5% relative to the first period of 16 years after the PhD,

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 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 subsamples 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

while this increase is equal to 2.7% and 9.8% when the first period included only the first eight years of academic life (for more details, see Carrasco and Ruiz-Castillo, 2012).

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.

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Table 1. Number of Individuals by Cohort, and Average Productivity in Selected Periods After Completion of the PhD

	16-19 CI	20-23 CII	24-27 CIII	28-31 CIV	32-35 CV	36-39 CVI	40-57 CVII	All Cohorts
NUMBER OF INDIVIDUALS	216	200	196	168	169	106	92	1,147
AVERAGE PRODUCTIVITY								
Eight-year Periods								
1. $\mu(\mathbf{x}^{\mathcal{C}})$	158.9	191.8	191.5	185.7	176.9	230.1	210.0	187.5
2. $\mu(y_1^{\mathcal{C}})$	152.1	170.8	157.0	139.8	142.5	183.4	185.5	158.6
3. $\mu(y_2^{\mathcal{C}})$			115.0	108.7	116.7	126.7	155.7	120.8
4. $\mu(y_3^{\mathcal{C}})$					89.7	107.5	118.4	102.0
5. $\mu(y_4^{\mathcal{C}})$							82.8	82.8
PRODUCTIVITY PER YEAR								
6. First Period, $\mu(\mathbf{x}^{\mathcal{C}}/8)$	19.9	24.0	23.9	23.2	22.1	28.8	26.2	23.4
7. Second Period, $\mu[\mathbf{y}^{\mathcal{C}}/(T^{\mathcal{C}} - 8)]$	17.8	18.9	16.3	13.7	14.1	15.5	15.7	16.2
8. Aggregate, $\mu[(\mathbf{x}^{\mathcal{C}} + \mathbf{y}^{\mathcal{C}})/T^{\mathcal{C}}]$	18.7	20.8	18.8	16.3	16.1	18.4	17.6	18.2

$\mathbf{x}^{\mathcal{C}}$ and $\mathbf{y}^{\mathcal{C}}$ = First and Second Period in the Transformation $\mathbf{x}^{\mathcal{C}} \rightarrow \mathbf{y}^{\mathcal{C}}$

$y_1^{\mathcal{C}}, y_2^{\mathcal{C}}, y_3^{\mathcal{C}}$, and $y_4^{\mathcal{C}}$ = Successive Eight-year Periods

$(\mathbf{x}^{\mathcal{C}} + \mathbf{y}^{\mathcal{C}})$ = Aggregate Distribution

$T^{\mathcal{C}}$ = Number of years since PhD in 2007

Table 2. Productivity Inequality in Selected Periods After Completion of the PhD

	16-19 CI	20-23 CII	24-27 CIII	28-31 CIV	32-35 CV	36-39 CVI	40-57 CVII	All Cohorts	
PRODUCTIVITY INEQUALITY									
Eight-year Periods									
$I_1(\mathbf{x}^{\zeta})$	0.263	0.314	0.391	0.355	0.384	0.386	0.332	$I_1(\mathbf{x})$	0.350
$I_1(y_1^{\zeta})$	0.310	0.373	0.396	0.516	0.596	0.552	0.473	$I_1(y_1)$	0.445
$I_1(y_2^{\zeta})$			0.534	0.584	0.685	0.626	0.713	$I_1(y_2)$	0.629
$I_1(y_3^{\zeta})$					1.098	0.887	0.687	$I_1(y_3)$	0.919
$I_1(y_4^{\zeta})$							1.024	$I_1(y_4)$	1.024
Second Period, $I_1(y^{\zeta})$	0.308	0.370	0.394	0.475	0.615	0.509	0.498	$I_1(y)$	0.521
Aggregate, $I_1(\mathbf{x}^{\zeta} + y^{\zeta})$	0.227	0.290	0.329	0.329	0.394	0.338	0.364	$I_1(\mathbf{x} + y)$	0.357

Table 3. Mobility Matrices for All Cohorts

COHORT I							COHORT II						
Quintiles of distribution x	Quintiles of distribution y					Total	Quintiles of distribution y	Quintiles of distribution y					Total
	1.	2.	3.	4.	5.			1.	2.	3.	4.	5.	
1.	20 45.4	10 22.7	9 20.4	3 6.8	2 4.5	44 100.0	1.	24 60.0	8 20.0	4 10.0	4 10.0	0 0.0	40 100.0
2.	10 22.7	15 34.1	8 18.2	7 15.9	4 9.1	44 100.0	2.	6 14.3	14 33.3	8 19.0	8 19.0	6 14.3	42 100.0
3.	9 21.4	12 28.6	10 23.8	6 14.3	5 11.9	42 100.0	3.	8 21.0	11 28.9	10 26.3	6 15.8	3 7.9	38 100.0
4.	5 11.6	5 11.6	9 20.9	18 41.9	6 13.9	43 100.0	4.	5 12.5	4 10.0	13 32.5	8 20.0	10 25.0	40 100.0
5.	0 0.0	1 2.3	8 18.6	8 18.6	26 60.5	43 100.0	5.	0 0.0	2 5.0	3 7.5	14 35.0	21 52.5	40 100.0
Total	44 20.4	43 19.9	44 20.4	42 19.4	43 19.9	216 100.0	Total	44 21.5	43 19.5	44 19.0	42 20.00	43 20.0	200 100.0

COHORT III							COHORT IV						
Quintiles of distribution x	Quintiles of distribution y					Total	Quintiles of distribution y	Quintiles of distribution y					Total
	1.	2.	3.	4.	5.			1.	2.	3.	4.	5.	
1.	23 56.1	13 31.7	3 7.3	1 2.4	1 2.4	41 100.0	1.	18 52.9	9 26.5	4 11.8	3 8.8	0 0.0	34 100.0
2.	11 28.2	11 28.2	11 28.2	4 10.3	2 5.1	39 100.0	2.	7 20.6	13 38.2	8 23.5	5 14.7	1 2.9	34 100.0
3.	3 7.9	9 23.7	13 34.2	8 21.0	5 13.2	38 100.0	3.	3 9.1	6 18.2	11 33.3	6 18.2	7 21.2	33 100.0
4.	2 5.1	5 12.8	11 28.2	15 38.5	6 15.4	39 100.0	4.	1 2.9	5 14.7	7 20.6	14 41.2	7 20.6	34 100.0
5.	1 2.5	1 2.6	1 2.6	11 28.2	25 64.1	39 100.0	5.	5 15.1	1 3.0	3 9.1	6 18.2	18 54.6	33 100.0
Total	40 20.4	39 19.9	39 19.9	39 19.9	39 19.9	196 100.0	Total	34 20.2	34 20.2	33 19.6	34 20.24	33 19.6	168 100.0

COHORT V						
Quintiles of distribution x	Quintiles of distribution y					Total
	1.	2.	3.	4.	5.	
1.	15 44.1	10 29.4	6 17.6	3 8.8	0 0.0	34 100.0
2.	8 23.5	13 38.2	6 17.65	6 17.6	1 2.9	34 100.0
3.	9 11.7	12 20.6	10 26.5	6 17.6	5 23.5	34 100.0
4.	0 0.0	4 11.8	9 26.5	11 32.3	10 29.4	34 100.0
5.	7 21.2	0 0.0	4 12.1	8 24.2	14 42.4	33 100.0
Total	34 20.1	34 20.1	34 20.1	34 20.1	33 19.5	169 100.0

COHORT VI						
Quintiles of distribution x	Quintiles of distribution y					Total
	1.	2.	3.	4.	5.	
1.	10 45.4	7 31.8	3 13.6	2 9.1	0 0.0	22 100.0
2.	4 19.0	8 38.1	5 23.8	3 14.3	1 4.8	21 100.0
3.	4 19.0	2 9.5	5 23.8	6 28.6	4 19.0	21 100.0
4.	1 4.8	3 14.3	5 23.8	5 23.8	7 33.3	21 100.0
5.	3 14.3	1 4.8	4 19.0	4 19.0	9 42.9	21 100.0
Total	22 20.7	21 19.8	22 20.7	20 18.9	21 19.8	106 100.0

COHORT VII						
Quintiles of distribution x	Quintiles of distribution y					Total
	1.	2.	3.	4.	5.	
1.	6 31.6	7 36.8	3 15.8	2 10.5	1 5.3	19 100.0
2.	6 33.3	5 27.8	3 16.7	3 16.7	1 5.6	18 100.0
3.	4 21.0	5 26.3	4 21.0	2 10.5	4 21.0	19 100.0
4.	2 11.1	1 5.6	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 20.6	18 19.6	19 20.6	18 19.6	18 19.6	92 100.0

Table 4. Productivity Mobility in Selected Transformations

PRODUCTIVITY MOBILITY	16-19	20-23	24-27	28-31	32-35	36-39	40-57	ALL COHORTS	
	I	II	III	IV	V	VI	VII		
Eight-year Periods									
$M_I(\mathbf{x}^c, \mathbf{y}_1^c)$	0.135	0.093	0.150	0.087	0.073	0.143	0.081	$M_I(\mathbf{x}, \mathbf{y}_1)$	0.116
$M_I(\mathbf{x}^c, \mathbf{y}_1^c + \mathbf{y}_2^c)$			0.163	0.099	0.060	0.152	- 0.065	$M_I(\mathbf{x}, \mathbf{y}_1 + \mathbf{y}_2)$	0.073
$M_I(\mathbf{x}^c, \mathbf{y}_1^c + \mathbf{y}_2^c + \mathbf{y}_3^c)$					- 0.021	0.115	- 0.081	$M_I(\mathbf{x}, \mathbf{y}_1 + \mathbf{y}_2 + \mathbf{y}_3)$	0.009
$M_I(\mathbf{x}^c, \mathbf{y}_1^c + \mathbf{y}_2^c + \mathbf{y}_3^c + \mathbf{y}_4^c)$							- 0.109	$M_I(\mathbf{x}, \mathbf{y}_1 + \mathbf{y}_2 + \mathbf{y}_3 + \mathbf{y}_4)$	- 0.016
Complete Cohorts									
A. $M_I(\mathbf{x}^c, \mathbf{y}^c)$	0.137	0.076	0.158	0.068	- 0.027	0.125	- 0.098	$M_I(\mathbf{x}, \mathbf{y})$	- 0.018
B. $EM_I(\mathbf{x}^c, \mathbf{y}^c)$	0.201	0.156	0.138	0.235	0.297	0.264	0.222	$EM_I(\mathbf{x}, \mathbf{y})$	0.051
C. $SM_I(\mathbf{x}^c, \mathbf{y}^c)$	- 0.064	- 0.080	0.020	- 0.167	- 0.324	- 0.139	- 0.320	$SM_I(\mathbf{x}, \mathbf{y})$	- 0.069
ALL COHORTS:	$M_I(\mathbf{x}, \mathbf{y}) = \sum_c \beta_c M_I(\mathbf{x}^c, \mathbf{y}^c) + \{ \sum_c (w_c - v_c) I_I(\mathbf{x}^c) + [I_I(\mathbf{m}^I, \dots, \mathbf{m}^C)] - I_I(\mathbf{\mu}^I, \dots, \mathbf{\mu}^C) \} / I_I(\mathbf{x})$								
	- 0.018 = 0.073 - 0.030 - 0.052								

Table 5. The Skewness of Productivity Distributions ($\alpha^f + \gamma^f$) for All Cohorts

	Percentage of Individuals				Percentage of Quality Points Accounted for			
	In Category:				By Category:			
	1	2	3	4	1	2	3	4
QUALITY INDEX, $\mathcal{Q}$	66.8	21.3	7.1	4.7	24.5	31.7	20.0	23.7
(2,485 individuals)								
COHORTS								
CI, 16-19 (216 ind.)	58.3	35.6	4.6	1.4	31.5	51.1	12.0	5.3
CII, 20-23 (200 ind.)	43.5	39.0	12.0	5.6	16.7	42.1	23.1	18.1
CIII, 24-27 (196 ind.)	43.4	36.2	14.3	6.2	14.9	36.6	26.7	21.8
CIV, 28-31 (168 ind.)	44.0	32.1	14.9	8.9	14.1	33.0	27.1	25.8
CV, 32-35 (169 ind.)	43.8	27.8	18.9	9.5	12.4	24.6	32.4	30.5
CVI, 36-39 (106 ind.)	32.1	30.2	17.0	20.7	7.4	21.2	22.3	45.0
CVII, 40-57 (92 ind.)	32.6	27.2	16.3	23.9	8.0	18.9	19.2	53.9
ALL COHORTS	44.5	33.5	13.2	8.8	14.9	32.7	23.8	28.6
(1,147 individuals)								

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 .

	$\mathcal{Q}$	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	317	329	443	476	482	537	686	767	495
μ_2	721	540	653	715	741	837	936	1,047	758
μ_3	1,172	948	1,043	1,132	1,072	1,190	1,297	1,394	1,176