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ABSTRACT

We investigate how increases in publication delays have affected the life-cycle of publications of recent Ph.D. graduates in economics. We construct a panel dataset of 14,271 individuals who were awarded Ph.D.s between 1986 and 2000 in US and Canadian economics departments. For this population of scholars, we amass complete records of publications in peer reviewed journals listed in the JEL (a total of 368,672 observations). We find evidence of significantly diminished productivity in recent relative to earlier cohorts when productivity of an individual is measured by the number of AER equivalent publications. Diminished productivity is less evident when number of AER equivalent pages is used instead. Our findings are consistent with earlier empirical findings of increasing editorial delays, decreasing acceptance rates at journals, and a trend toward longer manuscripts. This decline in productivity is evident in both graduates of top thirty and non-top thirty ranked economics departments and may have important implications for what should constitute a tenurable record. We also find that the research rankings of the faculty do not line up with the research quality of their students in many cases.

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1 Introduction

Ellison (2002) documents that the time an economics paper spends at one journal between submission and publication has more than doubled over the last thirty or so years. As Ellison notes, this has important implications:

> "The change in the publication process affects the economics profession in a number of ways: it affects the timeliness of journals, the readability and completeness of papers, the evaluation of junior faculty, and so forth." (Ellison 2002 p. 948)

In this paper we investigate how this change has affected the research productivity across consecutive cohorts of economics Ph.D. graduates as measured by publications in Journal of Economic Literature (JEL) indexed journals over the life cycle. Conversations with colleagues suggest that the concerns outlined by Ellison about how changes in the publication process might affect the evaluation of junior faculty are widespread. Intuitively, one would expect that, *ceteris paribus*, increased publication lags would make it more difficult for members of recent cohorts to produce as long a curriculum vitae in six years as earlier cohorts. We construct a simple model that captures this intuition and then explore how well theory and data support or refute this intuition.

We combine data from various sources to reconstruct the JEL-listed journal-publication record of almost every graduate of a U.S. and Canadian Ph.D.-granting economics department from 1986 to 2000. In addition to the evidence of cohort effects on publication productivity, this dataset also allows us to make a number of general observations about the patterns of journal-publication productivity in the economics profession.

Our major findings are as follows:

First, there is remarkable consistency in some aspects of journal-publication productivity across cohorts. We find that approximately half of the graduates never publish at all, at least in those journals found in EconLit.[1] Of those graduates who do publish, the proportion of journal publications produced by each productivity-percentile of a cohort is remarkably stable: the publication "Lorenz curve" for each cohort is practically identical. Roughly speaking, among the publishing members of each cohort, 80 per cent of the output is produced by the top 20 per cent of the researchers while the top one percent of researchers produces approximately 14 percent of all publications.

Second, there is a consistent time-profile of journal publication across all cohorts: publications per year rise until the fifth or sixth year after receiving the Ph.D. and then slowly decline to around sixty percent of the peak.

Third, the longer "time to build" production process for published manuscripts, documented by Ellison (2002), has a measurable, but not uniformly dramatic, effect on productivity of all cohorts in terms of AER equivalent *pages* published at the end of the sixth year (the approximate time that tenure decisions are made). By this measure for graduates of the top thirty programs, older cohorts are on average more productive than mid cohorts, and mid cohorts are on average more productive than the youngest cohorts. However, there is no such pattern of declining productivity for the non-top thirty departments using this productivity measure.

Fourth, when we look at the number of AER equivalent *publications* instead of pages published at the end of six years, we find large and statistically significant declines in productivity over time for graduates of both

[1] This percentage is also found for a small sample of graduates from 1997 by Stock and Siegfried (2006), for a sample of graduates from 1969-1988 by Hutchinson and Zivney (1995), and for a sample of European economists by Combes and Linnermer (2003).

the top and non-top thirty departments. By this measure for graduates of the top thirty programs, the oldest cohort is 48% more productive than the middle cohorts and 68% more productive than the youngest. The middle cohorts in turn, are 12% more productive than the youngest cohorts. For non-top thirty departments, the oldest cohort is 19% more productive than the middle and 58% more productive than the youngest, while the middle cohorts are 33% more productive than the youngest cohorts.

This, in conjunction with the finding that publication pages are similar across cohorts (at least for the top thirty departments), is consistent with Ellison's (2002) documentation of the increasing length and decreasing number of published papers, and is the central finding of the current paper. It suggests two things. First, this exposes a significant methodological question about the best way to measure productivity of departments, graduate programs and individual scholars. Productivity patterns over time look different depending on whether papers or pages is chosen as a basis of comparison. We argue that what the profession values when granting tenure, giving raises, or making senior hires is the number of lines on a CV and the quality of the research papers on those lines. It is much harder to distill this into the number of AER-quality weighted pages, and we suspect that this is seldom attempted in practice. If this speculation is true, then it is important to look at AER equivalent papers rather than AER equivalent pages. Second, when AER equivalent papers are used as the productivity metric, there is a significant drop-off in the weighted quality of the CVs of Ph.D. graduates over time. Thus, unless we believe that recent graduates are fundamentally of poorer quality, the same quality of tenure candidate is significantly less productive today than 10 or 15 years ago. We will explore the robustness of this finding and its implications below.

Fifth, the institution from which students receive their Ph.D.s has a significant impact on the quality and quantity of their published research. Publishing graduates of top thirty departments produce more than three times as many AER equivalent pages and papers than do their counterparts from non-top thirty departments.[2] The average quality of each published paper and page is about three times better for graduates of the top programs compared to the non-top programs and this holds for all cohorts. However, we do not see much change in average quality over time for either top or non-top programs.

Finally, these data allow us to investigate the relative performance of graduate programs in terms of the research output of their Ph.D.s. This allows us to construct a new type of departmental ranking system that can be compared with other, more traditional systems which focus on the publications of faculty members at a particular department. We find that MIT, Princeton, Harvard and Rochester do best by this quality measure and more generally that the rankings of other departments does not entirely agree with more traditional measures that use faculty output.

In the remainder of the paper we develop a dynamic model of an individual's publication production in which the time between submission and publication is allowed to vary. A simple example using specific, plausible parameter values shows how the change in "time to build" documented by Ellison (2002) affects the time-profile of an individual's vita. We then describe our data and report the empirical findings.

2 An Illustrative Model

Our purpose here is not to develop a general model of lifetime production and consumption, but rather to focus on a simple partial-equilibrium model that highlights the effects of a change in the time between submission and acceptance of a manuscript. The focus is on the period of time between entry into the

[2] We use the ranking from Coupe (2003) to determine the top thirty U.S. and Canadian economics departments. His ranking appears highly correlated with other popular rankings.

academic workforce and the time of decision on tenure, namely six years. It is undoubtedly consistent with a more general model such as found in Levin and Stephan (1991), in which individuals optimize over their lifetimes by choosing their allocation of time between labor and leisure.

2.1 Model Parameters and Solutions

We construct a model in which there are five exogenous parameters:

- s: the length of a manuscript[3];
- P_0: an individual's stock of unpublished papers at the time he receives a Ph.D. (thus P_0 is the number of manuscripts initially submitted to journals);
- m: the individual's production of manuscript pages (per-year);
- Δ : the "time to build" lag between when an individual's stock of unpublished manuscripts is submitted and when a decision on acceptance is received;
- a_t: the percentage of the stock of an individual's unpublished manuscripts that were newly-submitted at $t-\Delta$, that are accepted for publication at time t.

Of course, in a more complete model, these exogenous variables would be endogenous and would reflect optimal choices of individual producers and the supply of journal pages available.

An individual's number of newly-submitted manuscripts at any time t is denoted by P_t, and the number of newly-submitted pages is denoted by p_t. Thus, given that manuscripts have s pages, $(p_t/s) = P_t$.

To summarize, we assume that an individual arrives in the profession with a stock $P_0 = (p_0/s)$ of manuscripts. Each year after that, the individual writes $M = m/s$ manuscripts, where m and s are exogenous constants. Each year, all individuals submit every one of their existing unpublished manuscripts that are not in the evaluation process. Then, after a specified period of time, a percentage a of these newly-submitted manuscripts are accepted.

To capture the change in the time between submission and publication emphasized by Ellison (2002), we consider two scenarios. In the first scenario, the exogenous percentage a of newly-submitted manuscripts are accepted for publication the year following submission. Thus, the time to build is one period ($\Delta = 1$). In the second scenario, the exogenous percentage a of newly-submitted manuscripts are accepted for publication two periods after submission. Thus, the time to build is two periods ($\Delta = 2$).To distinguish between these two cases, we denote parameters and variables associated with the one-period lag between submissions and acceptances by putting a "tilde" over the symbol. That is, in the first scenario the number of newly-submitted manuscripts at time t is denoted as $\widetilde{P}_t$ and so forth.

With a one-period submission-acceptance lag, the number of newly-submitted manuscripts at time t evolves according to the following first-order difference equation:

$$\widetilde{P}_t = \tilde{M} + \widetilde{P}_{t-1} - a\widetilde{P}_{t-1} = \tilde{M} + (1-a)\widetilde{P}_{t-1} \tag{1}$$

This says that the number of newly-submitted papers at time t equals the previous period's submissions plus new additions $\widetilde{M}$ minus accepted submissions from the previous period $a\widetilde{P}_{t-1}$. With the exogenously

[3] Ellison (2002) documents that s has increased over time at a greater rate than the number of high-quality journal pages published. While he speculates on the causes of this change, he does not offer conclusive evidence of a particular cause. Thus, we treat this as exogenous.

given original stock of unpublished papers P_0, the solution to this difference equation is found by well-known methods to be:

$$\widetilde{P}_t = \sum_{i=0}^{t-1} \tilde{M}\left(1-\tilde{a}\right)^i + \left(1-\tilde{a}\right)^t \widetilde{P}_0 = \left(\frac{\tilde{M}}{\tilde{a}}\right) + \left(\widetilde{P}_0 - \left(\frac{\tilde{M}}{\tilde{a}}\right)\right)\left(1-\tilde{a}\right)^t \tag{2}$$

The number of acceptances per year, denoted by $\tilde{A}_t$, is the

$$\tilde{A}_t = a\widetilde{P}_{t-1} \tag{3}$$

The length of an individual's vita at any time t, denoted by $\tilde{V}_t$, is thus given as

$$\tilde{V}_t = \tilde{V}_{t-1} + \tilde{A}_t \tag{4}$$

Now consider our second scenario, in which the time between acceptance and publication is two periods. In this case, the number of newly-submitted manuscripts evolves according to the following second-order difference equation:

$$P_t = M + P_{t-2} - aP_{t-2} = M + \left(1-a\right)P_{t-2} \tag{5}$$

The key difference here from the first scenario is that newly-submitted manuscripts have to wait for two periods for a decision. As a result, submitted manuscripts at time t will still be waiting for a decision at time $t+1$; hence those manuscripts will be contained neither among new journal submissions at time $t+1$, nor among accepted manuscripts at time $t+1$, denoted by A_{t+1}.

There are two initial conditions that apply to this problem: P_0 is given and $P_1 = M$. Thus, the solution to (5) will be

$$P_t = \frac{M}{a} + B_1\theta_1^t + B_2\theta_2^t, \tag{6}$$

where B_1 and B_2 satisfy the two boundary conditions

$$\begin{aligned} B_1 + B_2 + \frac{M}{a} &= P_0, \\ \frac{M}{a} + B_1\theta_1 + B_2\theta_2 &= M, \end{aligned} \tag{7}$$

and

$$\theta_i = \pm\sqrt{1-a}\ ,\ i \in \{1,2\} \tag{8}$$

Alternatively, we can write the solution as

$$P_t = \sum_{i=0}^{\frac{t}{2}-1} M\left(1-a\right)^i + \left(1-a\right)^{\frac{t}{2}} P_0 = \left(\frac{M}{a}\right) + \left(P_0 - \left(\frac{M}{a}\right)\right)\left(1-a\right)^{\frac{t}{2}} \tag{9}$$

when t is even, and

$$P_t = \sum_{i=0}^{\frac{t-3}{2}} M\left(1-a\right)^i + \left(1-a\right)^{\frac{t-1}{2}} P_1 = \left(\frac{M}{a}\right)\left(1 - \left(1-a\right)^{\frac{t+1}{2}}\right) \tag{10}$$

when t is odd.

The number of acceptances per year, denoted in this scenario as A_t, are

$$A_t = aP_{t-2} \tag{11}$$

Thus, the length of an individual's vita in this scenario, denoted as V_t, is

$$V_t = V_{t-1} + A_t \tag{12}$$

2.2 Calibrated examples

To give some sense of the quantitative implications of the model, we calibrate the model based on plausible values of the parameters from the work of Ellison (2002). We explore three separate changes to the publishing environment that Ellison discusses: an increase in publication lags, a decrease in acceptance rates, and increase in the length of manuscripts.

First, we consider a base case meant to represent the historical publishing environment. We take a benchmark of a 20% acceptance rate, one new paper per year as flow of production, an initial stock of three papers at graduation and a one year "Time to Build":

$$(1)\ \tilde{a} = 0.20,\ \tilde{M} = 1 \text{ and } \tilde{P}_0 = 3$$

Second, we consider the effects of increased delays. We change the time to build to two years, but keep the same set of parameter values otherwise:

$$(2)\ a = 0.20,\ M = 1 \text{ and } P_0 = 3$$

Third, we go back to a one period lag, but we consider the effect of increasing manuscript length by one third so that both initial stock and flow of new manuscripts decreases to 75% of the two cases above:[4]

$$(3)\ \tilde{a} = 0.20,\ \tilde{M} = 0.75 \text{ and } \tilde{P}_0 = 2.25$$

Finally, we consider a one period lag and no increase in manuscript length, but decrease the acceptance rate to 12%:[5]

$$(4)\ \tilde{a} = 0.12,\ \tilde{M} = 1 \text{ and } \tilde{P}_0 = 3$$

The results are shown in Table 1, and they reveal that new Ph.D.s trying to publish in the historical regime (case 1) are significantly more productive than new Ph.D.s facing any one of the three changes considered above. Agents publishing under the historical regime were 75% more productive than agents facing a two period time to build, 33% more productive than agents who must publish longer manuscripts, and 42% more productive than agents facing lower acceptance rates.

[4] Ellison finds that articles increased in page length about 33%, from about 18 pages to 24.

[5] Note that the increase in manuscript length that Ellison documents implies that if the annual page budgets of journals has not increased (which is substantially the case at least with the top journals) then the acceptance rate, a, should fall. Add to this the number of submissions seems to be going up each year, and that for the few journals that actually report acceptance rates, the rates have gone down, and there is strong reason to believe that we see lower acceptance rates in general at economics journals in more recent periods.

Table 1. The Effect of Lags, Acceptance Rate and Manuscript Length on CVs

	Length of Vitae			
	(1)	(2)	(3)	(4)
Year	One year delay	Two year delay	Longer Manuscript	Low Acceptance Rate
1	0.60	0	0.45	0.36
2	1.28	0.60	0.96	0.80
3	2.03	0.80	1.52	1.30
4	2.18	1.48	2.11	1.87
5	3.65	1.84	2.74	2.50
6	4.52	2.58	3.40	3.18

These drops are substantial, and would be even more so if we subjected new Ph.D.s to all three changes at once as we do in the real world. Of course, new Ph.D.s may be aware of the current publication environment and may be responding. For example, they may submit more papers while a graduate student or stay in graduate school longer in order to have a better chance at tenure.

3 Data

The panel dataset we construct consists of two parts: a census of Ph.D. recipients from academic institutions in the US and Canada who received their economics Ph.D.s between 1986 and 2000 and a complete record of the journal publications of these individuals for the years 1985 to 2006 in EconLit listed journals.

3.1 Economics Ph.D. Holders

The record of economics Ph.D. recipients was constructed from two sources. The definitive source is the list provided by the American Economic Association (AEA), based upon an annual survey of economic departments. We use the Economics Ph.D. list of the AEA that records economics Ph.D. recipients beginning in 1985, and we supplement the data with information from the "2003-2004 Prentice Hall Guide to Economics Faculty by Hasselback". This directory contains information about current faculty members of all economics departments in the US, and of well-known Canadian and European research universities. Using the information about faculty members' graduation year and Ph.D. granting institution found in the Hasselback, a more comprehensive dataset of records of economics Ph.D. recipients from 1986 to 2000 was created. The number of Ph.D. recipients listed in both the AEA economics Ph.D. list, and in Hasselback is shown in Table A.1 in the appendix. The total number of Ph.D. recipients in a given year is not simply the sum of the entries from each source as there is considerable overlap between them. From 1988 to 2000 the number of Ph.D.s granted is fairly stable at about 1,000 per year. The significant growth from 1986 to 1988 may be due to less comprehensive coverage of Ph.D.s early in the AEA survey. Pooling all years, the panel contains 14,271 economics Ph.D.s.

3.2 Journal Publications

The record of journal publications is obtained from two different sources. Our main source is the EconLit Publication Database. The number of publications for the years 1985 to 2006 recorded in EconLit is listed in Table A.2 in the appendix. The number of papers has grown from about 9,500 in 1984 to almost 26,000 in 2005. Pooling all years, the panel of publications contains 368,672 peer-review papers. Of course, only a fraction of these are coauthored by Ph.D.s in our sample.

The International Bibliography of Social Sciences (IBSS) database was used to obtain additional information on journal publications that have more than three authors. The reason for this is that EconLit reports only the first author's name, if a journal publication has more than three authors. There were 1,125 such occurrences in the EconLit journal publication database, and 558 of those were in top 25 journals.

3.3 Supplemental data

Raw counts of publications are imperfect measures of the research productivity of individual scholars because of the variation in the quality of those publications. The journal rankings and journal quality indexes from Kalaitzidakis, Mamuenas and Stengos (2003) are used to account for this variation. We convert their journal quality indexes into American Economic Review (AER) equivalence, meaning that we express quality of each journal as a fraction of AER quality and use these weights in calculating numbers of AER equivalent publications and AER equivalent pages in our analysis. Ph.D.s in our database published in 992 different journals that are indexed in EconLit. The top 65 of these journals carry weights for AER equivalence as listed in Table A.3 in the appendix. We assign each of the remaining journals a weight of 0.012. That is, according to the impact-adjusted ranking of peer-reviewed journals in economics, 12 pages in the AER (a relatively short paper) are equivalent to 1000 pages in the 66th ranked journal.

One might worry that our results might be highly dependent on the specific quality index employed here. As a robustness check we use a discrete ranking for journal quality provided by Combes and Linnemer (2010), where journals are not assigned a unique quality index but grouped into quality categories. Top 5 journals form the top quality group, denoted by AAA in Combes and Linnemer (2010), and we assign these journals a conversion rate of 1 to the AER. The next 15 journals form the second quality group (denoted by AA), and we assign these journals a conversion rate of $\frac{2}{3}$ to the AER. The next 82 journals form the third quality group (denoted by A), and we assign these journals a conversion rate of $\frac{1}{3}$ to the AER.[6] Fortunately, the qualitative results obtained are similar regardless of which approach is used to ranking journals.[7].

By matching manuscripts by authors in our Ph.D. panel with the indices of journal quality, we calculate the number of AER equivalent pages for article i in journal j as:

$$\text{AER Pages}_{ij} = \frac{(\text{raw pages})_i \, (\text{journal index})_j}{(\text{authors})_i} \tag{13}$$

where "raw pages" is the length of the manuscript, "journal index" is the quality weight converting the number of pages in journal j into an equivalent number of pages of the AER, and "authors" is the number of authors of the manuscript. Dividing by number of authors we assign each author an equal share of credit for the research output. We also analyze how productivity measures change when we give each author full

[6] Combes and Linnemer (2010) group journals into six quality groups: AAA, AA, A, B, C, and D. We use the AER conversion rate of 0.12 for all journals in categories B, C, and D.

[7] Whenever we refer to AER equivalent pages or AER equivalent publications in this paper, the AER equivalence is obtained by employing indices provided by Kalaitzidakis et al. (2003) unless otherwise noted.

credit for the research output, and in this case we don't divide by the number of authors. Taking the sum of this index over all publications by an individual Ph.D. recipient in a specific year, gives the publication quality index for this individual in that year.

Similarly, the number of AER equivalent publications for article i in journal j is calculated as:

$$\text{AER Publications}_{ij} = \frac{(\text{journal index})_j}{(\text{authors})_i} \tag{14}$$

The focus of our analysis is the impact of the ongoing slowdown in the publication process on the productivity of vintages of Ph.D.s indexed by their year of graduation. Since the variation in productivity across individuals at a point in time is immense, we also examine subsets of the panel for evidence of a slowdown. This entails controlling for life cycle patterns of productivity as well as conditioning on the ranking of the institution the Ph.D. received her degree and the ranking of the department where a Ph.D. is first hired.

4 Empirical Results

The main goal of our empirical study is to evaluate the consequences of the slowdown in the publication process across cohorts of new Ph.D.s. As one might expect, there is considerable variation in the publication records of the approximately 1,000 individuals who receive Ph.D. in U.S. and Canada each year. For example, in most cohorts and in most departments, about 40 to 60 percent of graduates fail to publish a single paper in an EconLit listed journal in their first six years after graduation. These graduates are eliminated from the sample on the grounds that we wish to focus attention on graduates with scholarly research ambitions. Thus, when we use the term "graduates" in what follows it should be taken to mean "graduates who have published at least one paper in an EconLit listed journal within their first six year of graduation." Ph.D.s are organized into five cohorts, each pooling three consecutive years of Ph.D. graduates. For example, the 1987 cohort consists of individuals who had their Ph.D. conferred in either 1986, 1987 or 1988.[8]

4.1 Productivity Distribution within Cohorts

An interesting way to characterize within cohort heterogeneity is to use an "intellectual Lorenz curve" to quantify the inequity of contributions in each cohort to the aggregate flow of peer-review publications. Table 2 shows the cumulative distribution of all AER equivalent pages and publications in our panel of peer-review publications as a function of the productivity ranking of Ph.D.s at their sixth year after graduation.

Table 2. Intellectual Lorenz Curve

	Percent AER Pages					Percent AER Publications				
Productivity Percentile	1987	1990	1993	1996	1999	1987	1990	1993	1996	1999
99%	86.7	83.5	83.7	87.0	84.3	87.5	86.1	85.6	88.2	87.1
95%	57.9	54.0	54.5	57.9	54.6	61.6	59.3	59.4	62.5	60.0
90%	37.7	35.1	37.2	37.8	36.5	42.9	41.0	41.9	43.4	42.1
80%	19.0	17.2	18.1	17.8	17.6	23.0	21.0	21.7	21.8	21.4

[8] Ph.D. cohorts defined in this way are also used in subsequent parts of the paper, except for the regression analysis.

The top 1% of producers generates about 14% of all AER equivalent pages. The top 10% produces more than 60% of all published pages and the top 20% produces about 80% of the output. These proportions are robust across all cohorts and does not change significantly when AER equivalent publications are used in place of AER equivalent pages, especially when top 1% and top 5% of Ph.D.s are considered.

We take a closer look at productivity variation within cohorts across various percentiles. We rank Ph.D.s in each cohort based on their cumulative productivity at their sixth year after graduation. For each cohort, total number of AER equivalent pages and papers produced by Ph.D.s at 99th, 95th, 90th, 85th, 80th, 75th and 50th (median) percentiles are reported in Table 3.

Table 3. Performance of Various Percentiles

	AER Equivalent Pages					AER Equivalent Publications				
Percentiles	1987	1990	1993	1996	1999	1987	1990	1993	1996	1999
99th	70.0	57.2	69.6	57.3	65.1	3.87	3.06	3.23	2.45	2.48
95th	33.9	28.0	27.1	26.7	24.3	2.00	1.48	1.33	1.28	1.22
90th	20.5	14.5	15.9	15.0	15.0	1.34	0.98	0.85	0.76	0.73
85th	13.6	9.4	10.6	9.4	9.7	0.99	0.62	0.61	0.52	0.51
80th	8.4	6.2	7.3	6.2	6.3	0.62	0.43	0.44	0.37	0.37
75th	6.2	4.0	5.3	4.0	4.3	0.45	0.31	0.30	0.26	0.26
Median	1.1	0.9	1.0	0.9	0.9	0.08	0.06	0.06	0.06	0.05

Comparing different percentiles of productivity distribution within any cohort reveals that productivity is very skewed. Based on AER equivalent pages, a Ph.D. ranked at 99th percentile is more than twice as productive as a Ph.D. ranked at 95th percentile and a remarkable 60 to 70 times more productive than the median Ph.D.. One obtains similar results if one looks at AER equivalent publications instead of pages.

Comparing, on the other hand, a given percentile across cohorts, AER equivalent pages don't show a clear pattern, whereas AER equivalent publications do. Especially when we aggregate cohorts 1990 and 1993 into one large cohort, and cohorts 1996 and 1999 into another, the downward trend as measured in AER equivalent publications becomes evident at all percentiles reported here. These findings may have crucial implications for the tenure evaluation process of younger cohorts. Two Ph.D.s in different cohorts may be ranked at exactly the same percentile within their respective cohorts and yet the younger cohort member has fewer AER equivalent publications than the member of older cohort.

4.2 Graduates from Top Thirty and Non-Top Thirty Institutions

As documented in the prior section, approximately half of Ph.D.s never publish, and even restricting attention to those Ph.D.s who publish, we observe a very skewed productivity distribution. Thus, our data confirms the conventional wisdom that a very small but highly productive group of Ph.D.s create a disproportionately large share of total publications. Although there are always exceptions and outliers, the best performers are mostly graduates of top research universities. We therefore separate all the Ph.D.s in our dataset into two groups: graduates of top thirty economics departments and graduates of non-top thirty economics departments. We use economics departments' ranking of Coupe (2003)[9] for our analysis.

[9] Coupe (2003) ranks economics departments worldwide by the productivity of their faculty. There are only two economics departments within Coupe's top thirty that are outside U.S. and Canada: the London School of Economics and the University

Which departments are "top thirty" is open to question, of course, and could be calculated in several different ways. Given the length of time covered by this study (fourteen years) it is doubtless the case that departments have moved in and out of this group. It is not our purpose to make any definitive judgment on which departments deserve this recognition. In our view, it would be better to view our division of departments into two groups as an effort to study how a representative set of "top departments" performs against "non-top" departments.

Table A.4 in the appendix provides two rankings of the top thirty departments in U.S. and Canada. In the left column in Table A.4 department ranking of Coupe (2003) is reproduced, where departments are ranked by the productivity of their faculty members. Alternatively, one can argue that a department's true quality is measured by its graduates' productivity[10]. Following this idea, department ranking presented in the right column in Table A4 is based on our own calculations. We rank departments according to their Ph.D.s' productivity, which is measured as the average number of AER equivalent publications accumulated at the sixth year after graduation. Figure 1 shows the distribution of AER equivalent publications per graduate of each of the top thirty departments aggregated across all cohorts.

It is interesting to see that the Coupe ranking that focuses on faculty research quality does not line up particularly well with this measure which instead focuses on the research quality of graduates of these programs. Potential graduate students might do well to consider the implied ranking of departments given here when deciding where to apply for graduate training.

4.3 Life Cycle Productivity Measured by Flows of Publications

We begin by exploring the annual productivity of graduates of the top thirty departments and non-top thirty departments by various measures. The first measure of productivity is the annual number of raw pages published by graduates of the top thirty economics department and the remaining departments in our dataset. Young scholars at top and non-top thirty departments share a very similar career-cycle pattern of productivity. Annual productivity steadily rises from the year before the Ph.D is granted to a peak at about the fifth year. Productivity then drops off at a decreasing rate for the remaining years in our sample to about 60% of the peak value. This qualitative pattern also holds for all cohorts in both top and non-top thirty departments. It is certainly possible that productivity rises while new Ph.D.s are "eating their yolk". As they exhaust the stock of research questions they studied in graduate school, they become less productive. However, it is at least a little suspicious that this capital stock happens to start declining exactly at the point that tenure decisions are made. Also note that the gradual decline from the fifth year on is consistent with the presence of an overhang of completed and submitted work done before the tenure decision that only is accepted in subsequent years. Thus, we find evidence that is at least broadly consistent with the remarkable hypothesis that incentives seem to work in the economics profession.

Figures 2 and 3 show life cycle productivity of graduates of top thirty and non-top thirty departments, respectively, in terms of number of published pages. Graduates of the top thirty departments peak at about 11 raw pages published in their fifth years, and then slowly decline to about 7 pages. Graduates of the non-top thirty departments, in contrast, peak at about 6-7 pages published per year and then decline to about 4 pages per year. There seems to be no obvious chronological ranking of the productivity graphs by cohorts based on annual number of published pages.

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of Oxford. Since our dataset consists of U.S. and Canadian economics departments' Ph.D.s, we drop the London School of Economics and the University of Oxford and include Coupe's numbers 31 and 32 (both in the U.S.) instead.

[10] See for example Collins et al. (2000).

Although published pages seems to be the standard way of measuring productivity in similar studies[11] our view is that it does not capture the true productivity incentives faced by new members of the profession. Our experience is that lines on a CV (as opposed to pages published) is more valued by the profession for tenure, promotion, raises, and so on. There are at least two reasons to use manuscripts as the unit of account. First, each paper contains a self-contained research idea and some require more pages to fully articulate than others even when their inherent scientific value is quite similar. Second, there are significant variances in the length of research manuscripts across sub-fields of economics having to do with the content of the topic and the norms of exposition. This renders the page metric a somewhat dubious unit of account. We therefore consider the annual number of raw publications (that is, papers) published by members of our sample.

When we measure productivity in terms of number of published papers, we see a similar pattern as above for all cohorts with productivity peaking at about year five and then declining. Graduates of the top thirty departments peak at about 0.5 to 0.7 papers per year (see Figure 4), while non-top thirty peak at about 0.3 to 0.5 papers per year. Chronological ranking of the productivity across cohorts that was not apparent in published pages becomes now apparent revealing a ranking of cohorts with the oldest cohorts publishing the most and the youngest the least.

These first two measures are still limited in that they take no account of where graduates publish their papers. We therefore produce comparable figures but weight publications according to journal quality to get AER equivalent pages and papers published annually. As mentioned above, our journal quality index is based on Kalaitzidakis et al (2003). Considering AER equivalent pages, we continue to see the familiar productivity peak at about five years. Graduates of the top thirty departments peak at about 1.5 to 2 AER pages per year, and this is shown in Figure 5, while non-top thirty peak at about 0.4 to 0.5 pages. Thus, we see that top thirty graduates are more than 3 times as productive as non-top thirty graduates compared at their peak annual productivity levels.

Figure 6 shows an alternative version of Figure 5, where number of AER equivalent pages is based on the discrete quality index provided by Combes and Linnemer (2010). Graduates of the top thirty departments peak at about 4 to 4.5 AER pages per year, while non-top thirty graduates peak at about 1.4 to 1.7 pages. Comparing peak levels of their annual productivities, we see that top thirty graduates are about 3 times more productive than non-top thirty graduates.

Moving to AER equivalent publications (again using Kalaitzidakis et al (2003) as this is our default quality index), graduates of the top thirty departments peak at about 0.08 to 0.13 AER publications per year compared to 0.02 to 0.03 for non-top thirty departments. Again we see that top thirty graduates are more than three times as productive as non-top thirty graduates compared at their peak annual productivity levels.

As a final robustness check on these findings, we look at the annual number of AER equivalent pages published by graduates who got first jobs in the top thirty and non-top thirty departments. This is an interesting way to slice the data as "first placement in top thirty" may be a better filter of quality than "graduated from top thirty". Broadly, the story is the same with productivity peaking at five years and a somewhat muddled picture about which cohorts were more productive. What is notable is that graduates with placement in top thirty departments peak at about 3.7 to 5 AER pages per year while those with placement in non-top thirty peak at about 1.4 to 1.5 AER pages. Thus, the productivity gap is about the same (on the order of three) as for graduates of top and non-top thirty departments. Note that all the productivity numbers are more than twice as high as the figures for graduates of the top and non-top thirty

[11] See for example Combes and Linnemer (2003) and Rauber (2008).

departments. This is because not all research active Ph.D.s are placed in even a non-top thirty department and so this part of the sample (most likely employed in business and government) are not counted in the table above.

4.4 Life Cycle Productivity and Coauthorship

It is typical to divide the credit evenly over the authors of a paper, as we have done in the data reported above. Thus, if there are two authors on a ten page AER paper, they are each credited with producing five AER pages. It is debatable whether or not this is fair. It surely takes more than half the time to write a coauthored paper than an equivalent single authored paper (as all the authors of the current paper will surely attest). Again, our experience suggests that the profession tends to look at lines on a CV and only make some smaller discount for coauthorship. Thus, one might wonder what would happen if we gave all authors full credit for a paper.

We find the same pattern of productivity peaking at five years and the same slight tendency of the older cohorts to be more productive than the younger cohorts when we do not discount for coauthorship. However, it seems that the drop off after five years is not as steep. This might reflect increased coauthorship with graduate students or more opportunities for collaboration as a scholar becomes better known. The overall effect is to raise the peak productivity in terms of AER equivalent pages to a range from 2.4 to 3.2 for top thirty graduates and to a range from .6 to .8 for non-top thirty graduates. This compares to 1.5 to 2 AER pages per year for top thirty graduates, and .4 to .5 for non-top thirty graduates with coauthor discounts.

An independent question is whether there have been secular changes in the pattern of coauthorship over the years. Based on our extensive panel, coauthorship does appear to be on the rise. This may be due to the increasing importance of the Internet and email which lowers the transactions cost of working with authors outside one's department. We find that the average number of authors per publication in all EconLit journals rises from 1.35 authors in 1984 to 1.6 authors 2001, while for the top twenty journals, it goes from about 1.5 to 1.8 (see Figure 7).

This secular trend of increased coauthorship is in line with the observation that younger cohorts have on average more coauthors in their publications. We see a very interesting life-cycle pattern in coauthorship as well. Figure 8 shows the average number of authors of publications that are affiliated with at least one member of the respective cohort.

We observe a U-shaped life cycle for coauthorship across cohorts. This is a similar observation to that presented by Rauber and Ursprung (2008) about German academic economists. Coauthorship tends to be much less frequent between 1st and 4th years after graduation. This pattern remains consistent over all cohorts. As we move from older to younger cohorts, we observe that the U-shape is preserved and gradually shifted upwards. This indicates that although the coauthorship pattern for younger cohorts is similar to that for older cohorts, younger cohorts collaborate with larger numbers of coauthors compared to older cohorts.

4.5 Life Cycle Productivity Measured by Stocks of Publications

We now turn to cumulative productivity measures to investigate how different cohorts compare to each other at the same point in time, namely at the end of the sixth year after graduation. We decide to focus on the sixth year for cumulative productivity analysis since tenure or promotion decisions are mostly based on the evaluation of cumulative productivity around this time.

Table 4 provides an overview of various productivity measures attained by an average member of each respective cohort at the end of their sixth year after graduation. We provide two measures for the number of total publications: one which splits credit for a publication equally between coauthors, and one which gives full credit to each of the coauthors. Similarly we provide two versions of AER equivalent publications and AER equivalent pages: The first one is calculated as explained above, splitting credit equally between coauthors and using a continuous journal quality index. The second one is calculated by giving full credit to each of the coauthors.

Table 4. Per capita output at the end of the sixth year after Ph.D.

	Ph.D.s from Top Thirty				
Equal Credit to each coauthor	1987	1990	1993	1996	1999
Total Pages	58.0	52.8	56.7	54.2	51.7
Total Publications	3.58	3.04	2.99	2.76	2.47
Pages per publication	16.2	17.4	19.0	19.6	20.9
AER Pages	9.95	7.56	8.14	7.32	8.04
AER Publications	0.61	0.43	0.41	0.36	0.37
Full credit to each coauthor					
Total Pages	82.0	76.5	82.9	81.5	82.3
Total Publications	4.94	4.33	4.27	4.07	3.84
Pages per publication	16.6	17.7	19.4	20.0	21.4
AER Pages	14.9	10.9	12.2	11.4	13.6
AER Publications	0.89	0.62	0.6	0.56	0.61
Ratio of 'Full' to 'Equal' Credit					
AER Pages	1.50	1.44	1.50	1.56	1.69
AER Publications	1.46	1.44	1.46	1.56	1.65

	Ph.D.s from Non-Top Thirty				
Equal Credit to each coauthor	1987	1990	1993	1996	1999
Total Pages	33.8	34.2	36.3	33.2	38.8
Total Publications	2.57	2.38	2.36	2.0	2.16
Pages per publication	13.2	14.4	15.4	16.6	18.0
AER Pages	2.42	2.29	2.33	1.88	2.07
AER Publications	0.19	0.17	0.14	0.11	0.12
Full credit to each coauthor					
Total Pages	51.0	51.2	55.3	51.4	63.6
Total Publications	3.83	3.57	3.54	3.09	3.49
Pages per publication	13.3	14.3	15.6	16.6	18.2
AER Pages	4.04	3.7	3.9	3.04	3.55
AER Publications	0.3	0.26	0.23	0.18	0.2
Ratio of 'Full' to 'Equal' Credit					
AER Pages	1.67	1.62	1.67	1.62	1.71
AER Publications	1.58	1.53	1.64	1.64	1.67

At the end of six years, cumulative productivity of graduates of the top thirty departments is consistent with the hypothesis that productivity is decreasing for younger cohorts. Based on total number of raw publications (see second row in Table 4 as well as Figure 9), the 1987 cohort is 45% more productive than the 1999 cohort. This ratio drops to 29% when we assign full credit for coauthored publications, however this is still quite substantial, and would certainly affect a tenure committee's view of a tenure candidate. To be more precise, at the end of six years, we test for each cohort pair the null hypothesis that cohort means are equal against the alternative hypothesis that older cohort outperforms the younger one. Comparing 1987 cohort to 1990 cohort, 1990 cohort to 1993 cohort, 1993 cohort to 1996 cohort, and 1996 cohort to 1999 cohort, we obtain p-values of 0.0004, 0.35, 0.035, and 0.0039, respectively. For non-top thirty graduates, the story is less clear, because cohorts' productivity ranking does not follow a strictly decreasing trend, and cohorts do not line up as hypothesized from the old to the young, when compared at six years after graduation.

We get more definitive results for productivity when we look at AER equivalent publications for graduates of top thirty as well as non-top thirty departments. One can see that the 1990 and 1993 cohorts and the 1996 and 1999 cohorts, respectively have very similar productivity patterns (see Figure 10). Thus, we will aggregate these for both the top and non-top thirty departments. At the end of six years, the top thirty 1987, 1990+1993, and 1996+1999 cohorts published 0.61, 0.42, 0.37 AER equivalent publications over all, respectively. We see a very striking decline in productivity over time: the middle cohorts are 12% more productive than the youngest cohorts while the oldest cohort is 48% more productive than the middle and 68% more productive than the youngest. We test the null hypothesis that cohort means are equal against the alternative hypothesis that the older cohort outperforms the younger one. We obtain the following p-values: 0 for 1987 and 1990+1993, 0 for 1987 and 1996+1999, 0.0089 for 1990+1993 and 1996+1999.

For non-top thirty schools we find at the end of six years, the 1987, 1990+1993, and 1996+1999 cohorts published 0.19, 0.16, 0.12 AER equivalent publications, respectively. We see an overall trend in which the middle cohorts are 33% more productive than youngest cohorts while the oldest cohort is 19% more productive than the middle and 58% more productive than the youngest. We test the null hypothesis that cohort means are equal against the alternative hypothesis that older cohorts outperforms the younger one. We obtain the following p-values: 0.079 for 1987 and 1990+1993, 0.0003 for 1987 and 1996+1999, 0.0003 for 1990+1993 and 1996+1999.

The strong trend of individual cohorts lining up chronologically in decreasing productivity (with 1999 cohort being only slightly more productive than the 1996 cohort) does not hold, however, if we switch our productivity measure from AER equivalent publications to AER equivalent pages. As shown in Table 4, 1987 cohort is the most productive cohort, however other cohorts do not line up chronologically: 1993 cohort achieves higher productivity than 1990 cohort, and 1999 cohort outperforms 1996 cohort. Considering Ph.D.s from top thirty departments, although 1990 and 1993 cohorts together have higher average productivity than 1996 and 1999 cohorts together, this is not the case anymore when we assign full credit to each coauthor. Moreover, comparing different cohorts of top thirty departments using different policies to discount for coauthortship (namely equal credit and full credit), we see that the ratio of coauthor-not-discounted to coauthor-discounted AER equivalence measures, which is denoted as the "ratio of full to equal credit" in Table 4, decreases from 1987 cohort to 1990 cohort, but then increases from older to younger cohorts. Thus we find quality discounted rates of coauthorship increasing as cohorts get younger. This is in line with our discussion of coauthorship patterns over the life cycle of cohorts in the previous subsection.

This suggests a very important methodological and policy question about what is the right measure of productivity: AER equivalent publications or AER equivalent pages? Moreover, should coauthors share the credit or should they be assigned full credit? Our position is that tenure committees look at lines on a CV, first and page counts second, if at all. If this is true, then younger scholars look significantly less productive than their older colleagues. In part, this is because papers seem to have gotten longer on average over the years. This leads to a potential double whammy for assistant professors seeking tenure. First, by counting publications instead of pages, more recent tenure candidates will appear unfairly less productive than their colleagues who got tenure in the past. Second, a department that set a standard that could be met by say the top twenty percent of new tenure candidates who graduated in 1987 will find that it can be met perhaps by only eleven percent of those who graduated in 1999. This may be good or bad, but at least tenure committees should be aware of the implications of not adjusting tenure standards that reflect the current publishing environment of longer papers, lower acceptance rates and longer delays.

Another interesting way to think about how publishing patterns have changed is to look at the ratio of AER equivalent publications to total publications. This is a measure of average publication quality across cohorts. One can think of this as a "signal to noise ratio" as it indicates what fraction of an AER-quality publication is contained in a given publication. As publication quality of a cohort decreases, the ratio of AER equivalent publications to total publications will decrease. Table 5 shows total number of publications within six years after obtaining Ph.D., number of AER equivalent publications, and the percentage of AER equivalent publications in total publications (hence the signal to noise ratio) across cohorts. We calculate AER equivalent publications using indices provided by Kalaitzidakis et al. (2003) as well as by Combes and Linnemer (2010). AER equivalent publications obtained by two different indices are very highly correlated, thus yielding very similar trends.

Table 5. Aggregate cohort output

	Total publication output					'Signal to noise' ratio				
	1987	1990	1993	1996	1999	1987	1990	1993	1996	1999
Top 30 Ph.D.s										
Total Publications	1988	2531	2792	2468	2075					
AER (Combes)	772	877	964	843	756	0.388	0.347	0.345	0.342	0.364
AER (Kalaitzidakis)	340	359	387	325	313	0.171	0.142	0.139	0.132	0.151
Non Top 30 Ph.D.s										
Total Publications	1004	1494	1527	1228	1549					
AER (Combes)	250	377	358	271	352	0.249	0.252	0.234	0.221	0.227
AER (Kalaitzidakis)	72	105	93	68	86	0.072	0.070	0.061	0.055	0.056
Top 30 Ph.D.s relative to Non Top 30 Ph.D.s										
Total Publications	1.98	1.69	1.83	2.01	1.34					
AER (Combes)	3.09	2.33	2.69	3.11	2.15					
AER (Kalaitzidakis)	4.72	3.42	4.16	4.78	3.64					

Notes: The rows labelled Combes and Kalaitzidakis use AER equivalent weights from the Combes and Linnemer (2010) and the Kalaitzidakis et al. (2003) studies to aggregate publications in each cohort.

While it seems clear that the 1987 cohort of top thirty departments' graduates had higher quality publications on average by any measure, the signal to noise ratio decreases from the 1987 cohort to the 1996 cohort. However 1999 cohort performs surprisingly better on quality than the previous three cohorts. Overall there is a clear trend of declining overall average publication quality of top thirty graduates except for the youngest cohort. Turning to cohorts of non-top thirty departments' graduates we find it difficult comparing 1987 cohort to 1990 cohort: whether 1987 cohort outperforms 1990 cohort or not depends on the specific quality index, which can be interpreted as suggesting that the two cohorts don't differ much at all in quality. Younger cohorts perform worse than the oldest two cohorts, and 1999 cohort performs slightly better than 1996 cohort. Thus, we can say that signal to noise ratio has worsened across cohorts graduating from mid 80s until late 90s. This partially confirms the conventional wisdom that the enormous growth of new journals and publication outlets has led to a decline in overall average publication quality.

4.6 Life Cycle and Cohort Effects

Our analysis in preceding sections has shown that the hypothesized gradual downward shift in productivity across cohorts is not entirely obvious when only annual productivity is considered. We detect, however, that older cohorts do outperform younger cohorts if we look at cumulative instead of annual productivity. Comparing AER equivalent publications accumulated at the end of six years after graduation, we observe a gradual downward shift across cohorts. In this section we focus again on annual productivity of Ph.D.s. Our aim is to formally flesh out productivity differences across cohorts which manifest themselves clearly at a cumulative level but which are not as obvious at the annual level when only descriptive tools are used. The goal is to distinguish life cycle and cohort effects in the annual productivity measures. As Figures 2 to 6 reveal, an average Ph.D.'s annual publication productivity follows a distinctive hump-shaped life cycle. The number of AER equivalent publications achieved at any given time is affected both by the location on life cycle after graduation and by cohort specific effects.

We estimate a pooled Tobit model of annual research productivity where we treat the dependent variable as a latent variable. Our dependent variable is the annual research output measured as the number of AER equivalent publications for a given individual at a given time (which is zero for nearly sixty percent of all observations in the raw data). Explanatory variables include time polynomials, dummy variables for the graduation year and a dummy variable to indicate whether the graduate is from a top 30 department. The dummy variables for the graduation year are the key variables of interest since they allow us to test the null hypothesis that younger cohorts are less productive than older ones.

Annual research productivity of individual i at time t is the dependent variable, with time measured as "years after graduation". A third degree polynomial in time captures the life cycle pattern of research productivity. All individuals' publication records from the first until sixth year after graduation are covered because our aim is to compare cohorts within their "tenure-track" period which corresponds to approximately the first six years after graduation. This leaves us with a total of 42,924 observations.[12]

Marginal effects of explanatory variables, their significance levels and 95% confidence intervals are reported in Table 6. Dummy variables for the graduation year span from 1986 to 1999, and individuals with the same year of graduation are described as belonging to the cohort for that year. Observations extend to graduates in the year 2000 but the last dummy is dropped to avoid collinearity between the cohort dum-

[12] Publication records for most cohorts extend beyond six years. If we use all available years for each cohort in our pooled Tobit model, we would be using 81,051 observations. Estimating our model using these observations and correcting for the loss in time dummies' efficiency due to unbalanced panel, we obtain qualitatively the same results as with only six years as far as significance of time dummies and their signs are concerned.

mies. Thus, the marginal effect of a given cohort dummy variable shows how the respective cohort performs relative to the graduates of 2000 cohort. The cohort dummies are not interacted with time polynomials: we are assuming the year of graduation affects the *level* of the life cycle and not its slope at different points in the life-cycle. If a slowdown in the publication process is occurring over time, the coefficients on the cohort dummies should decrease in value as we move in time from 1986 to 1999. Our hypothesis is that the coefficients on the year of Ph.D. dummy will be highest in the initial year and decline over time as publication lags continue their upward trend. The specification also includes, $Top30$, a dummy variable that takes on the value 1 if scholar i is a graduate of a top thirty PhD program. This just shifts the conditional mean of the flow of publications but does not alter the shape of the life-cycle profile or the within-group year effects.

Table 6. Pooled Tobit Model- Marginal Effects

			95% Confidence Interval	
	Marginal Effect	P-Value	Lower Limit	Upper Limit
Top30	0.0208	0.000	0.0191	0.0226
Life cycle effects				
t	0.0359	0.000	0.0266	0.0451
t^2	-0.0054	0.000	-0.0082	-0.0025
t^3	0.00022	0.109	-0.00005	0.0005
Cohort effects				
1986	0.0218	0.000	0.0142	0.0293
1987	0.0157	0.000	0.0098	0.0217
1988	0.012	0.000	0.0066	0.0175
1989	0.0039	0.106	-0.0008	0.0087
1990	0.0059	0.014	0.0012	0.0105
1991	0.0088	0.000	0.0039	0.0137
1992	0.0061	0.013	0.0013	0.0109
1993	0.00299	0.186	-0.0014	0.0074
1994	0.0041	0.074	-0.0004	0.0086
1995	0.00032	0.887	-0.0042	0.0048
1996	0.00051	0.822	-0.0039	0.0049
1997	-0.00228	0.312	-0.0067	0.0021
1998	-0.0008	0.719	-0.0052	0.00356
1999	0.0015	0.503	-0.0029	0.00595

Evidently, cohort effects decrease from older to younger cohorts, which means that the predicted difference in annual number of publications is higher between 2000 cohort and any cohort from late 1980s than between 2000 cohort and any cohort from late 1990s. In order to better visualize the pattern that is revealed by cohort effects of graduates over fourteen years, Figure 11 plots the cohort effects from Table 6. It is evident that there is a downward shift that begins with sharp declines in the late 1980s but which seems to settle into a steady-state pattern in the late 1990s. In the last few years, the annual flow differences across cohorts are too small numerically to be statistically distinguishable. Thus, most of the evidence of the slowdown comes in the first third of the cohort sample. The year 1986 seems somewhat of an outlier, so we discount that evidence, but subsequent nearby years are higher than later years, by a statistically significant amount.

The dummy variable for graduates of top thirty departments is found to be highly significant with a large marginal effect on cumulative performance at the end of the sixth year after graduation, which confirms our earlier discussions and descriptive findings about the performance difference between graduates of top thirty and non-top thirty departments.

Next, we compare cohorts pairwise to find out which cohorts statistically significantly outperform which cohorts. In particular, Table 7 indicates with a '+' sign, cases in which members of cohorts belonging to the year indicated in the row produce more scholarship than members of the cohorts indicated in the columns.

Table 7. Publication comparisons across cohorts

	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
1986	+	+	+	+	+	+	+	+	+	+	+	+	+	+
1987			+	+	+	+	+	+	+	+	+	+	+	+
1988			+	+		+	+	+	+	+	+	+	+	+
1989											+	+		
1990									+	+	+	+		+
1991							+	+	+	+	+	+	+	+
1992									+	+	+	+	+	+
1993											+			
1994											+	+		
1995														
1996														
1997														
1998														
1999														

Note: A "+" indicates the row cohort out-performed the column cohort at the 5% level of significance.

If earlier cohorts outperform later cohorts, the '+' signs should be found above the diagonal of the matrix in Table 7. We see that this is true of all comparisons across cohorts on average. An average member of the 1986 cohort outperforms average members of all subsequent cohorts, the 1990, 1991 and 1992 graduates, on average, consistently outperform graduates from later years, whereas the 1989 graduates outperform only 1997 and 1998 graduates on average. Thus, after controlling for life cycle effects, we reach the following conclusion: there is a significant decrease in Ph.D.s' annual publication productivity from the late 1980s until the mid-1990s. Performance of graduates from 1995 to 2000 cannot be statistically distinguished.

As shown in section 4.1, distribution of research productivity of Ph.D.s is extremely skewed: the top 5% of Ph.D.s produce about 40%, and the top 20% of Ph.D.s produce about 80% of all publications in their respective cohorts. Similar skewedness shows up across all cohorts. Our analysis so far has compared cohorts based on their average performance. The extreme skewedness of productivity distribution within cohorts, however, suggests that comparisons of the output of different productivity percentiles across cohorts would be interesting. To this end, we rank all Ph.D.s within a given cohort based on the number of AER equivalent publications they achieve at the end of sixth year after graduation. We then compare annual productivity of Ph.D.s across cohorts who are in the third quintile range (between 40th and 60th percentiles), and then those who are in the second quintile range (between 60th and 80th percentiles), and finally those in the top quintile range. We run pooled Tobit estimation with the same specification as above on these three quintile ranges[13]. Marginal effects for the top three quintile ranges are reported in Table 8.

Table 8. Marginal Effects for Top Three Quintiles

	P40-P60	P60–P80	P80-P100
Top30	-0.0004618	0.0003573	0.0201221**
Life cycle effects			
t	0.0075388**	0.0230354**	0.0923817**
t^2	-0.0014535**	-0.0036719*	-0.0106398
t^3	0.0000899*	0.0001701	0.0001321
Cohort effects			
1986	0.0034581**	0.0138791**	0.1060625**
1987	0.0048398**	0.0146142**	0.0588261**
1988	0.0039493**	0.0113483**	0.046402**
1989	0.0015597*	0,003843	0,0173163
1990	0.0026034**	0.0064763*	0.0239718*
1991	0.0025138**	0.0064635*	0.0373514**
1992	0.0028776**	0.005512*	0.0287218*
1993	0.0016973*	0,002337	0,0104932
1994	0.0024074**	0.0073632**	0.020059*
1995	0.0016029*	0,0004858	0,0065441
1996	0.0022369**	0,0033282	0,004813
1997	0,0007187	-0,0005396	-0,0068057
1998	0,0002142	0,0008649	-0,000829
1999	0.0018777**	0,0026219	-0,0029431

* denotes significance at 5% level

** denotes significance at 1% level

Interestingly, the positive impact of having graduated from a top thirty department, which is statistically significant for average members of cohorts (see Table 6), has a statistically significant positive impact only for graduates in the top quintile range. Its marginal effect is insignificant for the second and third quintile ranges. This suggests that lower quality graduates of top places are not significantly different from typical graduates

[13]We determine quintile ranges based on cumulative productivity at the end of sixth year after graduation, because annual productivity is highly volatile. If we look at annual productivity, a highly productive graduate may be found in the lowest quintile range at some years due to this volatility. As a result, determining graduates' productivity quintiles in the above manner and comparing the same quintile range across cohorts using marginal effects from the pooled Tobit regression proves to be a more sensible method than using quantile regression on annual productivity. (See e.g. Koenker (2004)).

of any Ph.D. program. For all three quintile ranges, we observe that cohort effects yield a decreasing trend as we move from older to younger cohorts. Pairwise comparisons of cohorts for the third, the second and the first quintile ranges are reported in Tables 9, 10, and 11, respectively.

Table 9. Publication comparisons across cohorts (P40-P60)

	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
1986			+				+		+		+	+	+	+
1987			+	+	+	+	+	+	+	+	+	+	+	+
1988			+				+	+	+	+	+	+	+	+
1989												+		+
1990											+	+		+
1991											+	+		+
1992											+	+		+
1993												+		+
1994											+	+		+
1995												+		+
1996											+	+		+
1997														
1998														
1999														+

Note: A "+" indicates the row cohort out-performed the column cohort at the 5% level of significance.

Table 10. Publication comparisons across cohorts (P60-P80)

	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
1986			+	+	+	+	+	+	+	+	+	+	+	+
1987			+	+	+	+	+	+	+	+	+	+	+	+
1988			+			+	+		+	+	+	+	+	+
1989														
1990									+		+	+		+
1991									+		+	+		+
1992									+		+	+		+
1993														
1994									+		+	+		+
1995														
1996														
1997														
1998														
1999														

Note: A "+" indicates the row cohort out-performed the column cohort at the 5% level of significance.

Table 11. Publication comparisons across cohorts (P80-P100)

	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
1986	+	+	+	+	+	+	+	+	+	+	+	+	+	+
1987			+	+		+	+	+	+	+	+	+	+	+
1988			+	+			+	+	+	+	+	+	+	+
1989											+		+	
1990										+	+	+	+	+
1991							+		+	+	+	+	+	+
1992									+	+	+	+	+	+
1993														
1994											+	+	+	+
1995														
1996														
1997														
1998														
1999														

Note: A "+" indicates the row cohort out-performed the column cohort at the 5% level of significance.

Although pairwise comparisons of cohorts for the top three quintile ranges yield more or less similar results as pairwise comparison of cohorts' average performers (see Table 7), they do reveal an interesting pattern. Comparing the third quintile ranges across cohorts (see Table 9), we observe that 1986, 1987, and 1988 cohorts outperform most of the younger cohorts, and 1997, 1998, and 2000 cohorts are outperformed by most of the older cohorts. As we move to higher quintile ranges, the upper diagonal of the 'pairwise comparison matrix' displays more '+' signs. That is, as we compare higher quintile ranges across cohorts, the dominance of older cohorts over younger cohorts, and the chronological ordering of cohorts in publication productivity become more evident. This means that top performers of each cohort are hit more severely by the publication bottleneck. This in turn suggests that the top performers of the youngest generation are likely to fall most short of productivity expectations formed on the basis of this historical publishing environment, while middle and lower performers may not look much different than their predecessors. Top departments especially should be aware of these facts when evaluating junior faculty for tenure.

We plot cohort effects across percentiles in Figure 12, which shows how cohort effect for a given cohort changes across different percentile ranges[14].

Cohort effects are hard to distinguish in lower percentile ranges, especially up to the range of 40th to 50th percentile, and they don't line up following a chronological ordering. There exists, however, a much clearer pattern for higher percentile ranges, and they line up following chronological ordering, except that 1999 cohort's top percentile range performs poorer than that of the 2000 cohort. One should keep in mind that there will necessarily be more variation in productivity of Ph.D.s in higher percentile ranges, because they produce larger amounts of publications than those in lower percentile ranges. This means that the confidence

[14] We group Ph.D.s in each cohort into percentile ranges of ten increments (range of 90th to 100th percentile, range of 80th to 90th percentile etc) based on their cumulative performance at the end of sixth year after graduation and estimate cohort effects across percentile ranges as we did with quintile ranges. We plot only cohorts 1988, 1991, 1994, and 1999 for illustrative purposes.

intervals around cohort effects are also widening as cohort effects diverge in high percentile ranges, so that some of this divergence may be insignificant. At this point, Tables 9 to 11 assure that although not all of the divergence in cohort effects in high percentile ranges is significant, a considerable amount of it is significant so that the upper diagonal of the 'pairwise comparison matrix' gets filled with more '+' signs as we consider higher percentile ranges.

5 Conclusion

Ellison (2002) documents how most journals require today more than double the time they required thirty years ago to evaluate a submitted paper. It is only natural to wonder how this longer "time to build" production process for published manuscripts affects younger Ph.D.s.. It is particularly important to investigate whether younger cohorts perform significantly more poorly than older cohorts in terms of research output. Promotions, job offers and tenure decisions in academia are based on an individual's publication record. This publication record is not only compared to his/her cohort peers, but also to older cohorts, because institutions may be worried about keeping their established standards. Assuming that younger cohorts are not less smart or working less diligently than older cohorts, a downward trend in publication records as cohorts get younger must have important policy implications for the economics Ph.D. job market.

Reconstructing the journal publication record of 14,271 graduates from U.S. and Canadian Ph.D.-granting economics departments from 1986 to 2000, we obtain strong evidence of productivity decrease as we compare younger to older cohorts. It is evident that there is a downward shift that begins with sharp declines in the late 1980s and seems to settle into a steady-state pattern in the late 1990s. In the last few years, the annual flow differences across cohorts are too small numerically to be statistically distinguishable. Looking at the cumulative number of AER equivalent publications reached at the end of six years after graduation, we see convincing evidence of the expected productivity decline for both top and non-top thirty departments. Thus, unless we believe that recent graduates are fundamentally of poorer quality, the same quality of tenure candidate is significantly less productive today than 10 or 15 years ago.

If we use the number of AER equivalent pages as a measure of productivity, then the above mentioned drop off in productivity is not obvious. This is consistent with Ellison's (2002) documentation of the increasing length and decreasing number of published papers. This exposes a significant methodological question about the best way to measure productivity of departments, graduate programs and individual scholars. Productivity patterns over time look different depending on whether papers or pages is chosen as a basis of comparison. We argue that what the profession values when granting tenure, giving raises, or making senior hires is the number of lines on a CV and the quality of the research papers on those lines. It is much harder to distill this into the number of AER-quality weighted pages, and we suspect that this is seldom attempted in practice.

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6 Appendix

Table A.1. Number of Ph.D.s in Economics by Data Source

Year	AEA	Hasselback	Overlap	Total
1986	264	227	61	425
1987	597	216	95	714
1988	787	196	94	883
1989	953	230	147	1,035
1990	947	164	107	1,001
1991	905	178	122	956
1992	928	155	106	970
1993	1,074	173	110	1,132
1994	1,021	182	122	1,077
1995	1,025	170	109	1,078
1996	955	155	104	1,002
1997	935	167	107	990
1998	981	178	113	1,040
1999	866	182	106	936
2000	969	181	110	1,032

Note: The overlap indicates the number of PhDs common to the AEA and Hasselback data.

Table A.2. Number of Publications

Year	Number
1985	9,918
1986	9,872
1987	9,918
1988	10,552
1989	10,767
1990	11,254
1991	11,905
1992	13,108
1993	13,492
1994	14,374
1995	15,825
1996	17,692
1997	18,385
1998	19,869
1999	20,818
2000	21,835
2001	22,271
2002	21,991
2003	23,510
2004	25,618
2005	25,976
2006	19,722

Table A.3. Journal Weights Relative to the American Economic Review

Journal	Index	Journal	Index
1. American Economic Review	1.000	36. IJGT	0.061
2. Econometrica	0.968	37. Economic Inquiry	0.060
3. Journal of Political Economy	0.652	38. World Bank Economic Review	0.057
4. Journal of Economic Theory	0.588	39. Journal of Risk and Uncertainty	0.056
5. Quarterly Journal of Economics	0.581	40. Journal of Development Economics	0.055
6. Journal of Econometrics	0.549	41. Land Economics	0.051
7. Econometric Theory	0.459	42. IMF Staff Papers	0.051
8. Review of Economic Studies	0.452	43. Canadian Journal of Economics	0.051
9. JBES	0.384	44. Public Choice	0.050
10. Journal of Monetary Economics	0.364	45. Theory and Decision	0.049
11. Games and Economic Behavior	0.355	46. Economica	0.046
12. Journal of Economic Perspectives	0.343	47. Journal of Urban Economics	0.044
13. Review of Economics and Statistics	0.280	48. IJIO	0.043
14. European Economic Review	0.238	49. JLEO	0.041
15. JEEA	0.238	50. Journal of Law and Economics	0.039
16. International Economic Review	0.230	51. National Tax Journal	0.039
17. Economic Theory	0.224	52. Journal of Industrial Economics	0.039
18. Journal of Human Resources	0.213	53. Journal of Economic History	0.038
19. Economic Journal	0.207	54. Oxford Economic Papers	0.037
20. Journal of Public Economics	0.198	55. Journal of Comparative Economics	0.034
21. Journal of Economic Literature	0.188	56. World Development	0.032
22. Economics Letters	0.187	57. Southern Economic Journal	0.031
23. Journal of Applied Econometrics	0.166	58. Explorations in Economic History	0.030
24. JEDC	0.145	59. Economic Record	0.029
25. Journal of Labor Economics	0.128	60. Journal of Banking and Finance	0.026
26. JEEM	0.119	61. Contemporary Economic Policy	0.024
27. RAND Journal of Economics	0.114	62. Journal of Population Economics	0.024
28. Scandinavian Journal of Economics	0.107	63. JFQA	0.021
29. Journal of Financial Economics	0.099	64. JITE	0.020
30 OBES	0.084	65. Applied Economics	0.020
31. Journal of International Economics	0.078		
32. Journal of Mathematical Economics	0.076		
33. JEBO	0.071		
34. Social Choice and Welfare	0.069		
35. AJAE	0.062		

Note: Journal of Business and Economic Statistics (JBES), Journal of the European Economic Association (JEEA), Journal of Environmental Economics and Management (JEEM), Oxford Bulletin of Economics and Statistics (OBES), Journal of Economic Behavior and Organization (JEBO) American Journal of Agricultural Economics (AJAE,), International Journal of Game Theory (IJGT) International Journal of Industrial Organization (IJIO) ,Journal of Law, Economics, and Organization (JLEO), Journal of Financial and Quantitative Analysis (JFQA), Journal of Institutional and Theoretical Economics (JITE)

Table A.4. Top Thirty Economics Departments in US and Canada

Rank	Ordered by faculty productivity	Ordered by productivity of Ph.D.s	Index*
1.	Harvard University	MIT	0,801
2.	University of Chicago	Princeton University	0,741
3.	University of Pennsylvania	Harvard University	0,694
4.	Stanford University	University of Rochester	0,674
5.	MIT	*California Institute of Technology*	0,602
6.	UC-Berkeley	Yale University	0,596
7.	Northwestern University	Northwestern University	0,578
8.	Yale University	Carnegie Mellon University	0,544
9.	University of Michigan	University of Chicago	0,522
10.	Columbia University	UC-San Diego	0,502
11.	Princeton University	University of Pennsylvania	0,487
12.	UCLA	Stanford University	0,477
13.	New York University	University of Toronto	0,421
14.	*Cornell University*	*University of Western Ontario*	0,401
15.	University of Wisconsin	University of Minnesota	0,3842
16.	Duke University	*Brown University*	0,3841
17.	*Ohio State University*	University of British Columbia	0,354
18.	*University of Maryland*	Columbia University	0,353
19.	University of Rochester	*SUNY, Stony Brook*	0,329
20.	*University of Texas, Austin*	UCLA	0,323
21.	University of Minnesota	*University of Iowa*	0,317
22.	*University of Illinois*	UC-Berkeley	0,316
23.	*UC-Davis*	*University of Virginia*	0,296
24.	University of Toronto	Duke University	0,290
25.	University of British Columbia	*Queen's University*	0,271
26.	UC-San Diego	University of Wisconsin	0,270
27.	*University of Southern California*	University of Michigan	0,265
28.	*Boston University*	*Johns Hopkins University*	0,262
29.	*Pennsylvania State University*	New York University	0,260
30.	Carnegie Mellon University	*McMaster University*	0,251

Note: Departments that are ranked top-30 in ONLY one of the two rankings are in italics.

*Index is the average value of AER equivalent publications per research-active graduates at the end of six years after graduation.

FIGURE 1. PRODUCTIVITY BY DEGREE-GRANTING INSTITUTION
AER EQUIVALENT PUBLICATIONS

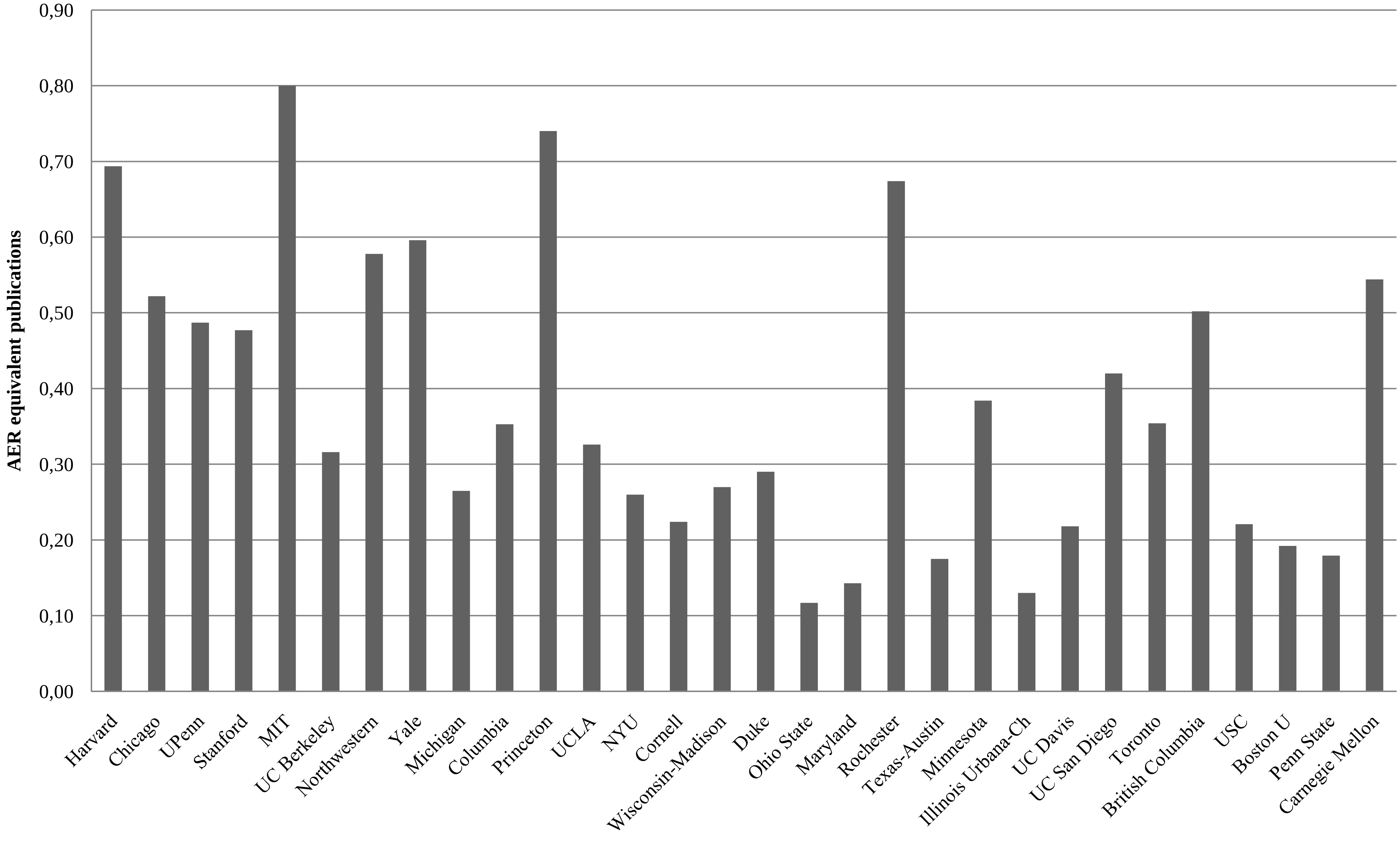

FIGURE 2. LIFE-CYCLE PRODUCTIVITY OF GRADUATES OF TOP 30 PROGRAMS
ANNUAL RAW PAGES

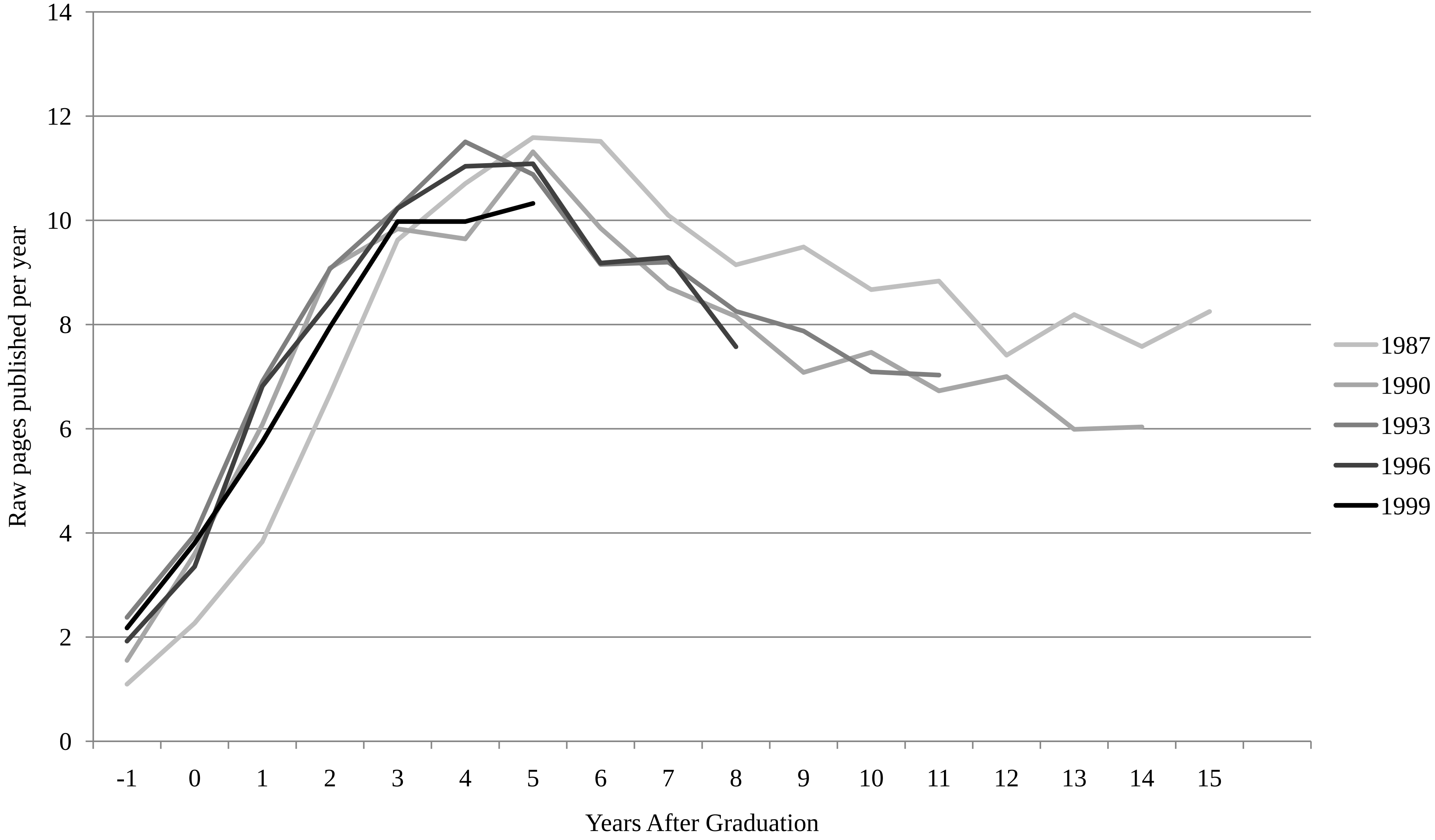

FIGURE 3. LIFE-CYCLE PRODUCTIVITY OF GRADUATES OF NON-TOP 30 PROGRAMS
RAW ANNUAL PAGES

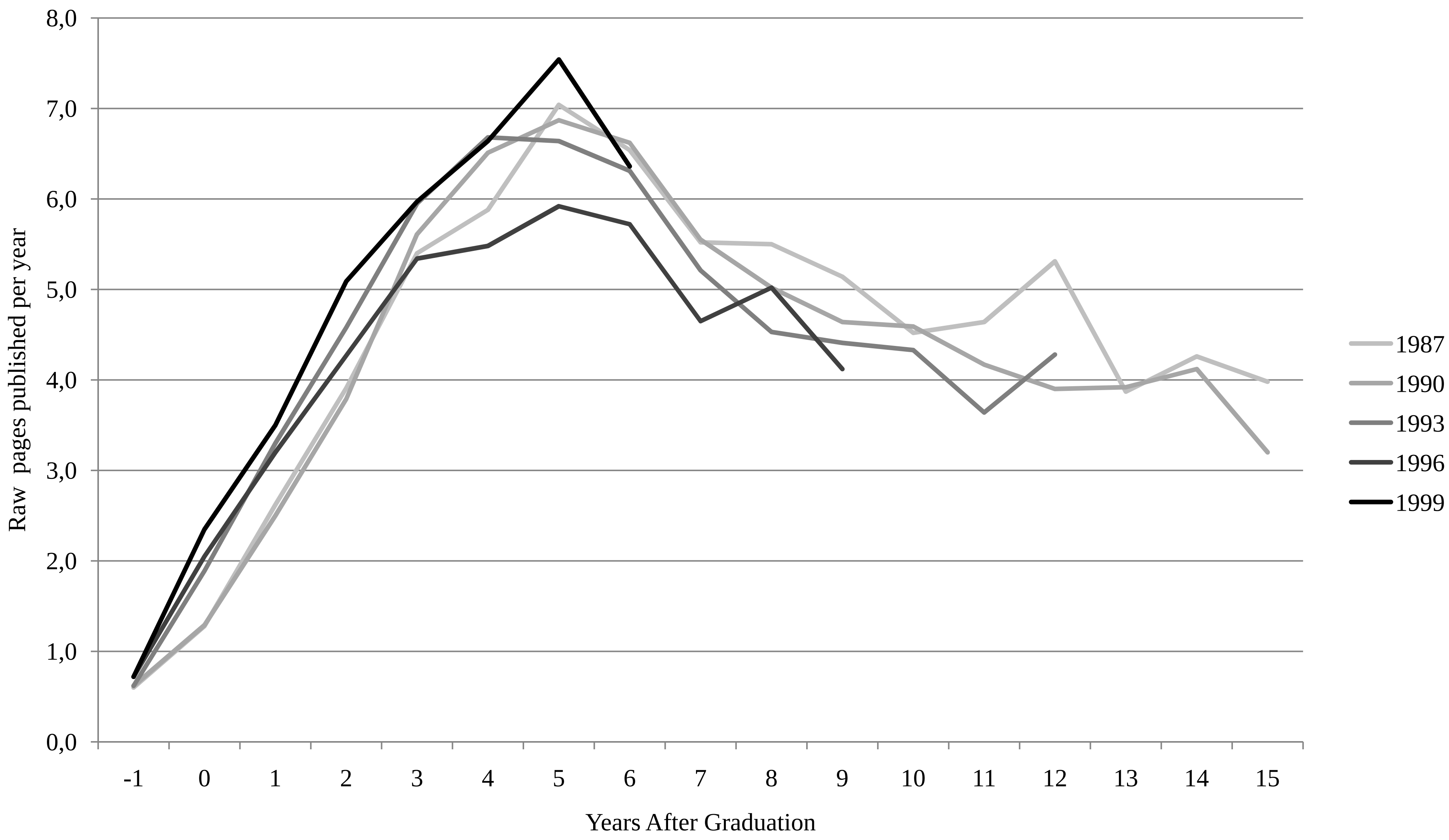

FIGURE 4. LIFE-CYCLE PRODUCTIVITY OF GRADUATES OF TOP 30 PROGRAMS
RAW ANNUAL PUBLICATIONS

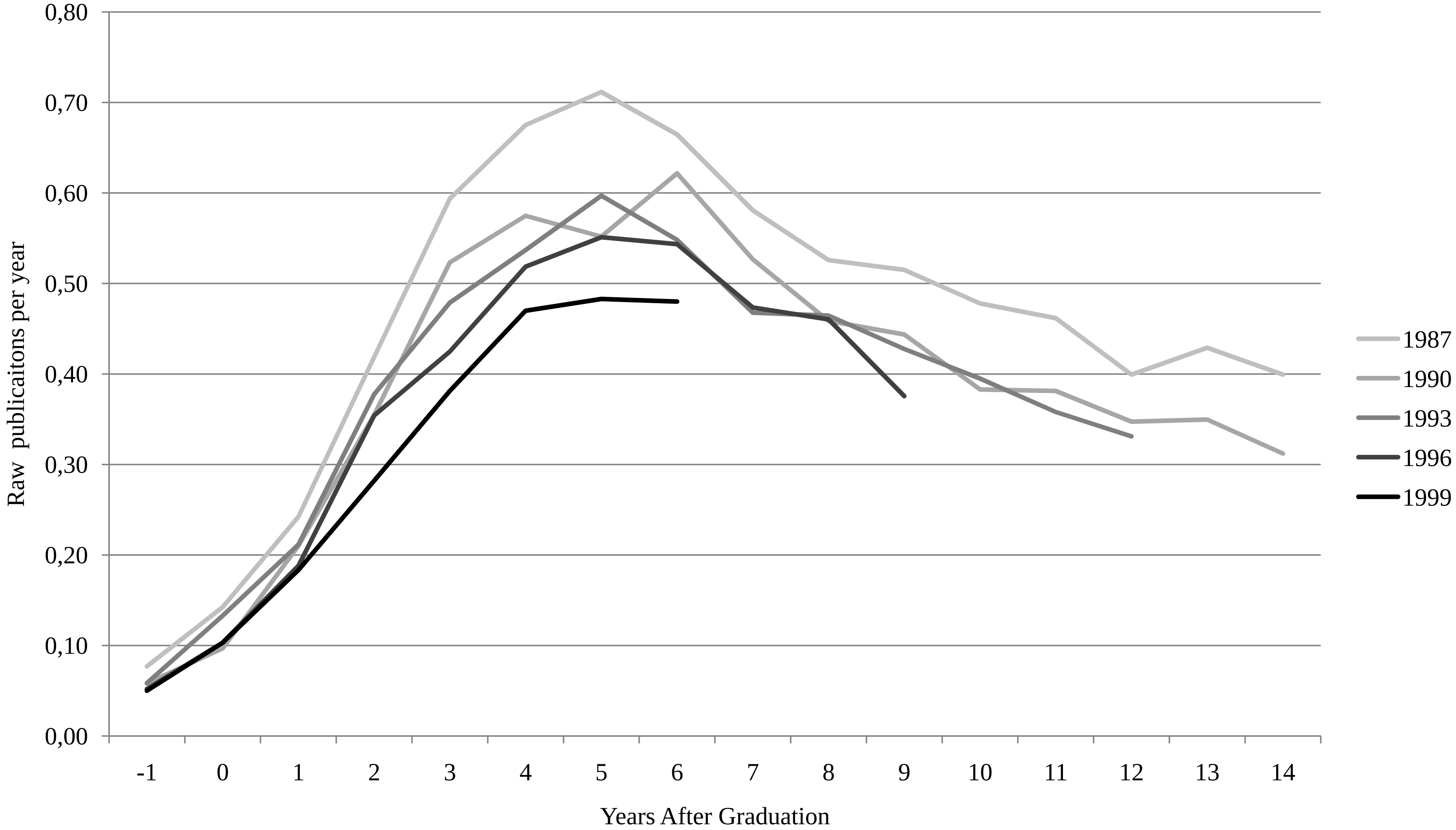

FIGURE 5. LIFE-CYCLE PRODUCTIVITY OF GRADUATES OF TOP 30 PROGRAMS
AER EQUIVALENT PAGES

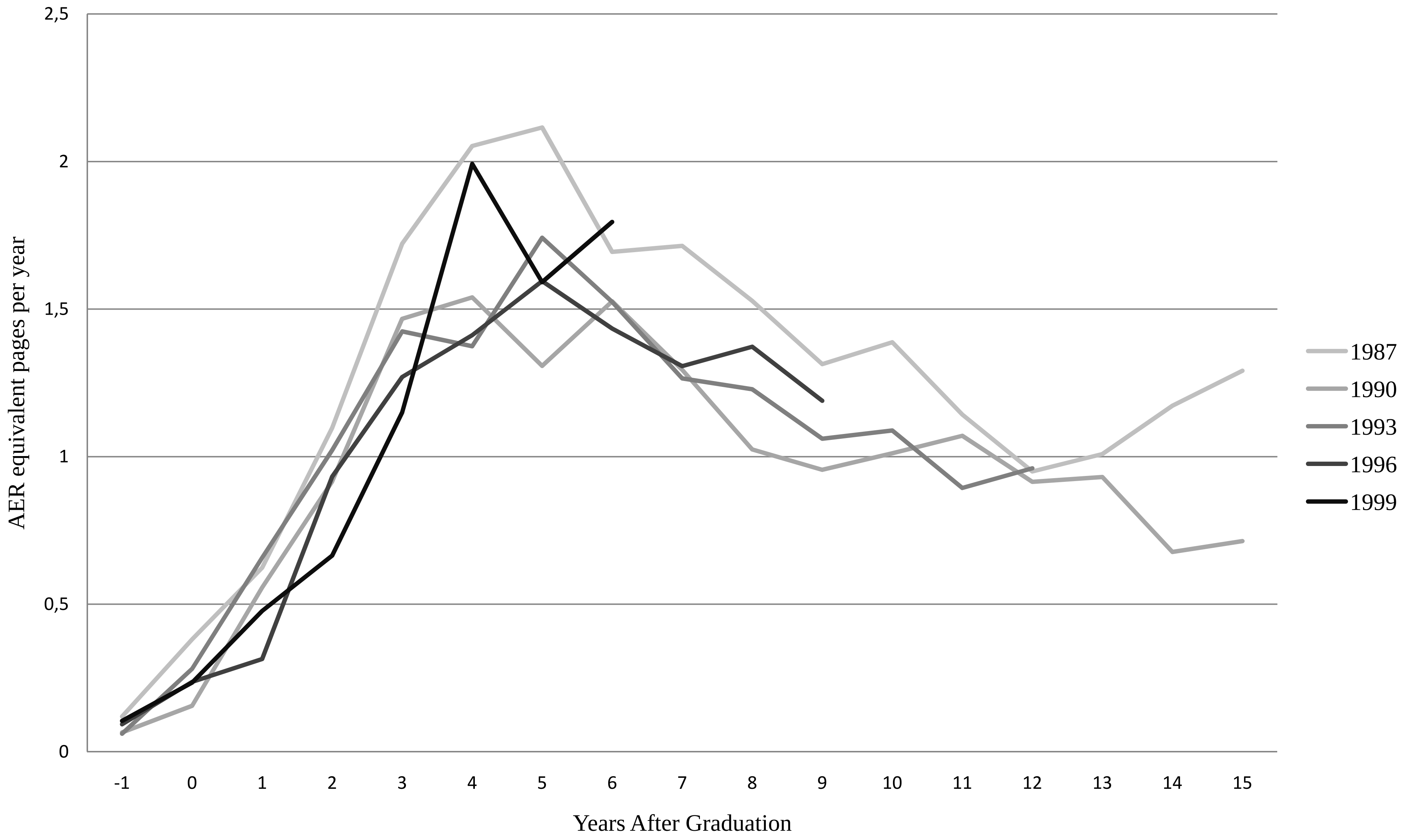

FIGURE 6. LIFE-CYCLE PRODUCTIVITY OF GRADUATES OF TOP 30 PROGRAMS
AER EQUIVALENT PAGES BASED ON DISCRETE QUALITY INDEX

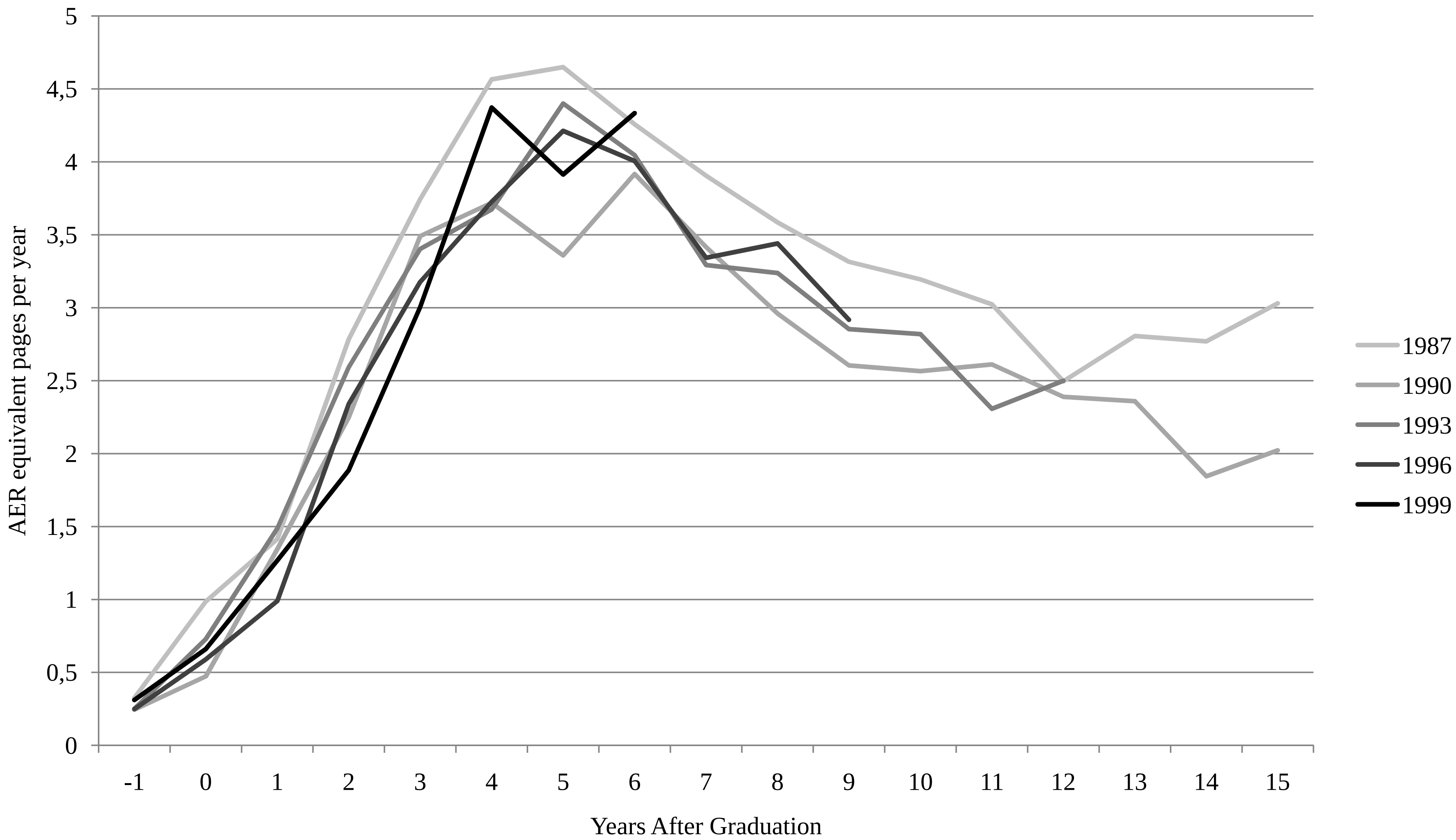

FIGURE 7: COAUTHORSHIP IN ECONLIT JOURNALS

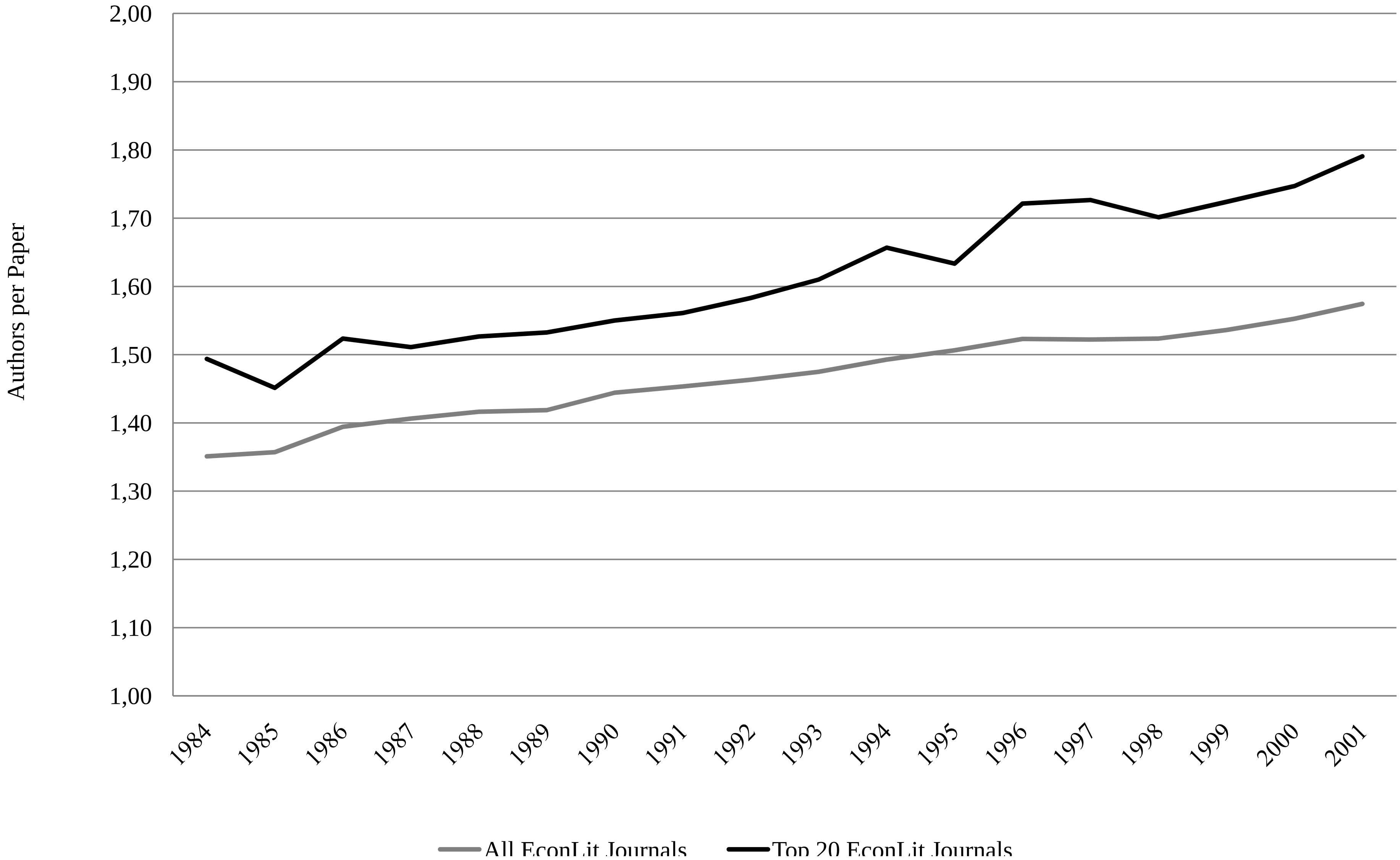

FIGURE 8. LIFE-CYCLE PATTERN OF COAUTHORSHIP

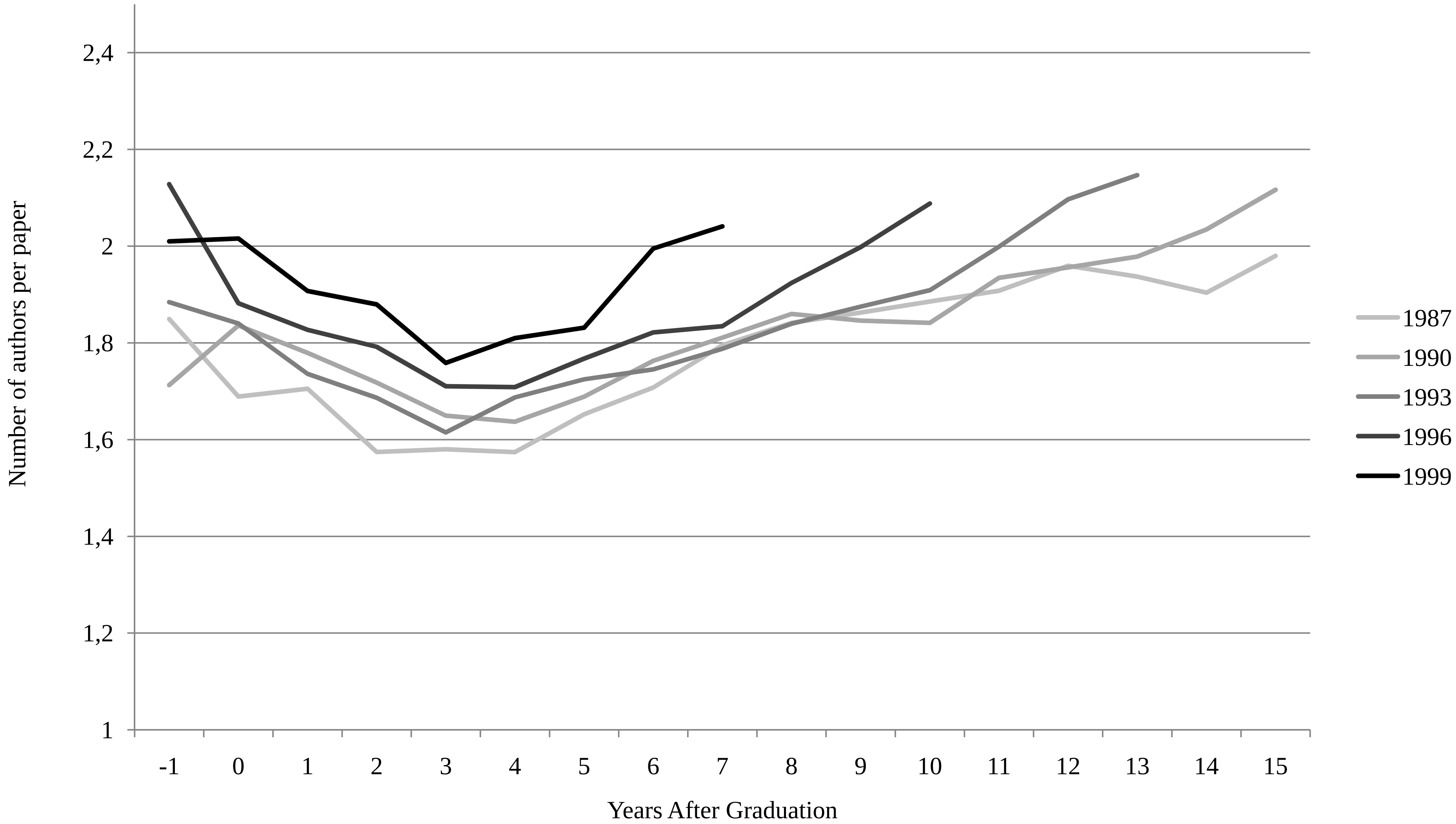

FIGURE 9. CUMMULATIVE NUMBER OF PUBLICATIONS OVER THE LIFE CYCLE
(AVERAGE PRODUCTIVITY OF TOP 30 DEPARTMENTS' GRADUATES BY COHORT)

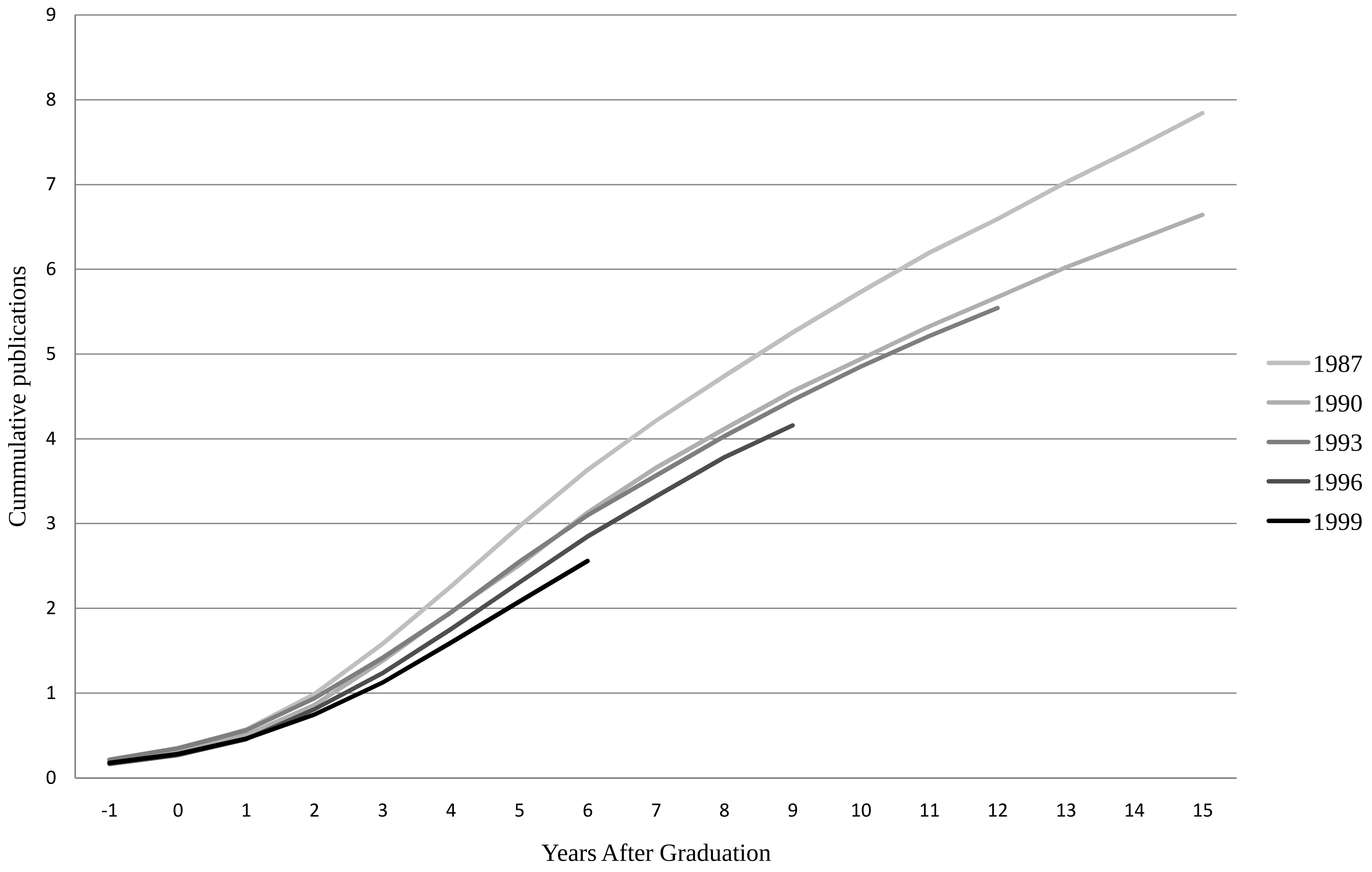

FIGURE 10. CUMMULATIVE AER EQUIVALENT PUBLICATIONS OVER THE LIFE CYCLE
(AVERAGE PRODUCTIVITY OF TOP 30 DEPARTMENTS' GRADUATES BY COHORT)

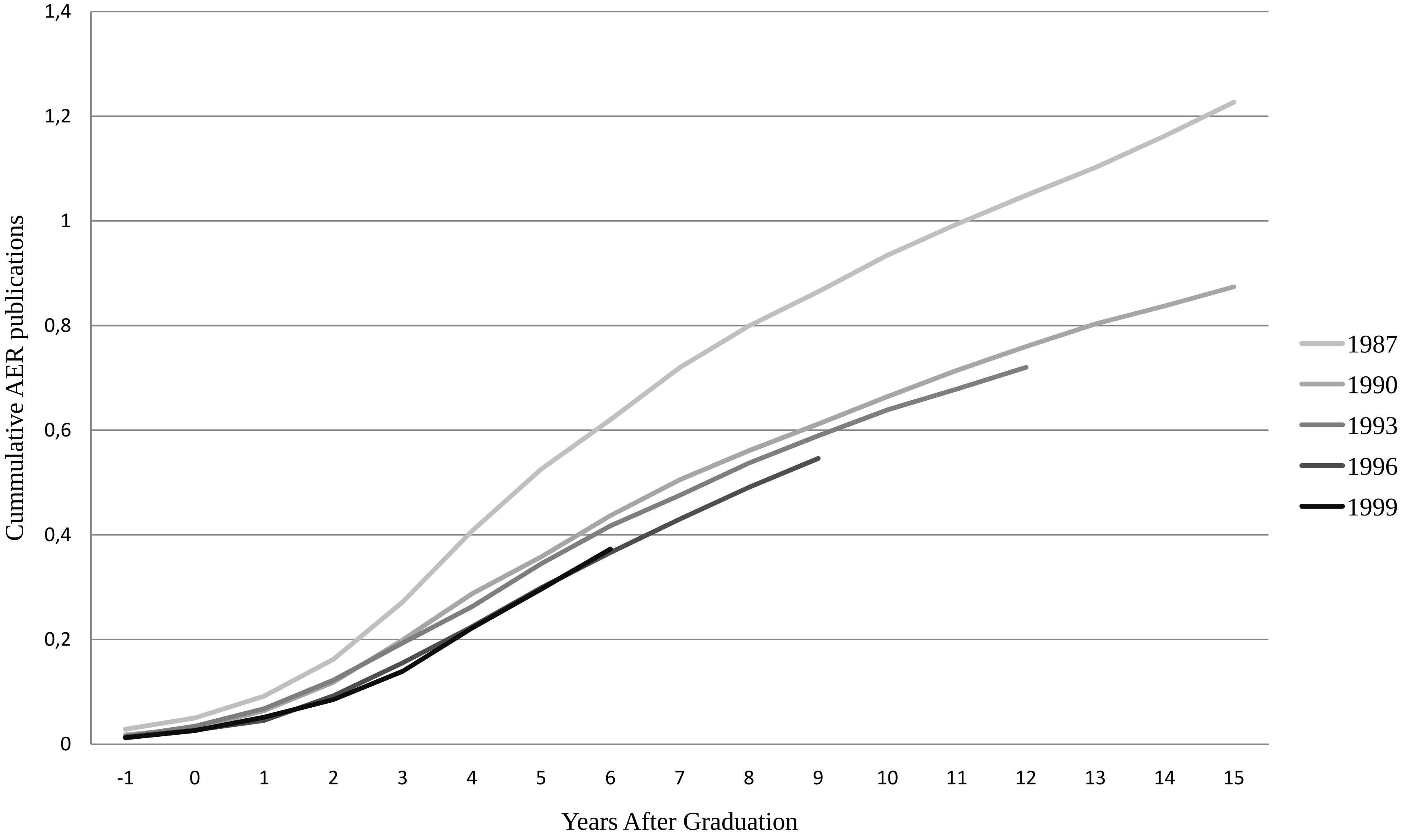

FIGURE 11. COHORT PUBLICATIONS AFTER SIX YEARS
RELATIVE TO 2000 COHORT

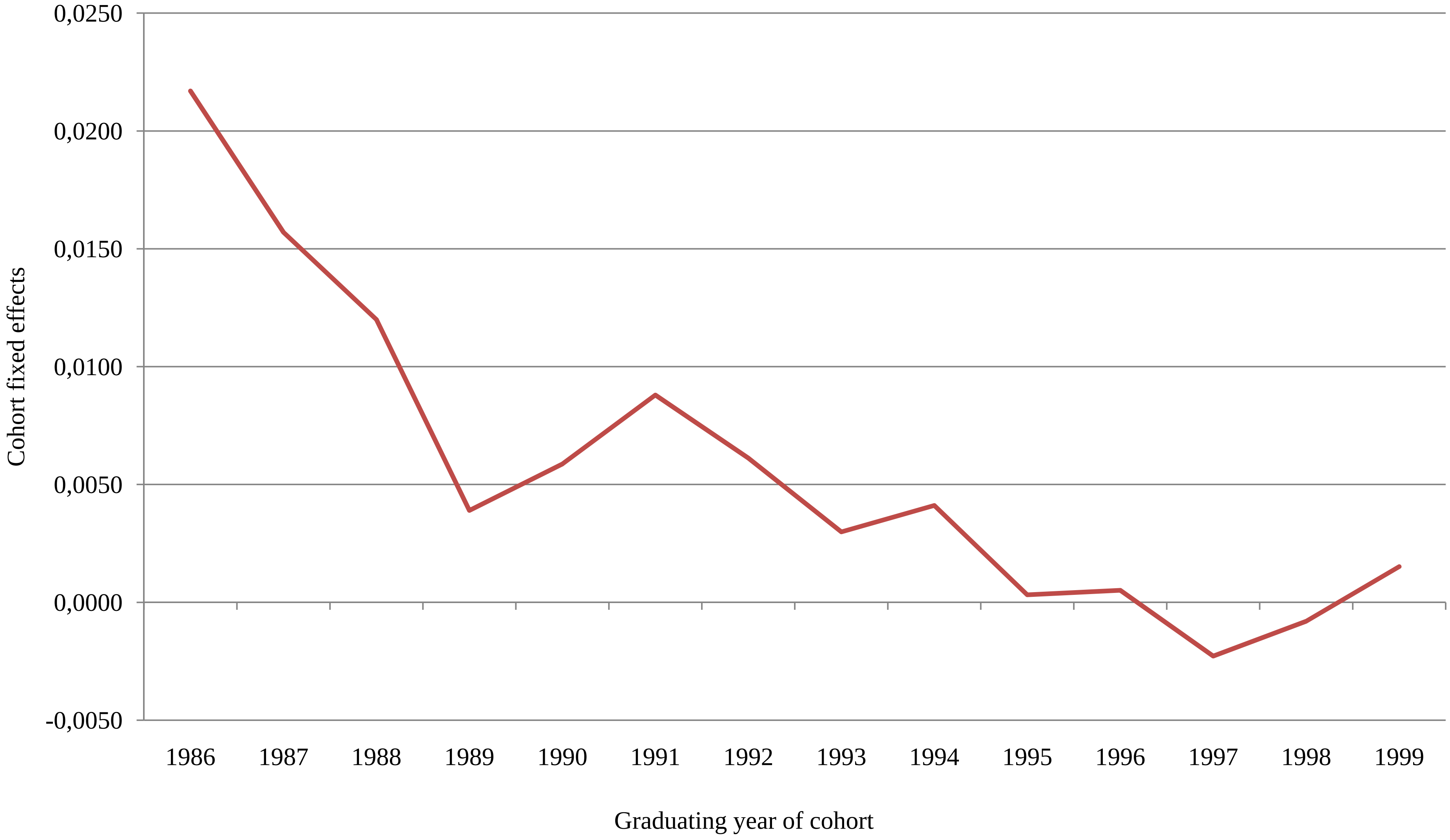

FIGURE 12. COHORT FIXED EFFECTS OF SELECTED COHORTS ACROSS PERCENTILE RANGES