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Are Scientists Changing their Research Productivity Classes When They Move up the Academic Ladder?

Abstract

Our approach is longitudinal: we track scientists over time, allocate them to productivity classes, and seek patterns of mobility between classes. We use individual-level data on academic careers (from a national registry of scientists) and individual-level metadata on publications (from Scopus). Specifically, journal prestige-normalized productivity is contrasted with non-normalized productivity. Even though anecdotal knowledge suggests that radical changing productivity levels (upward or downward) is always possible, our data show that it actually almost never happens in practice. Scientists with a very weak past track record in publications emerge as having marginal chances of becoming scientists with a very strong future track record across all STEMM disciplines. Consequently, our research shows a long-term character of careers in science, with productivity in an apprenticeship period of assistant professorship heavily influencing productivity in a more independent period of associate professorship. Our micro-level data reveal that Polish associate professors tend to be stuck in their productivity classes for years: high performers tend to remain high performers, and low performers tend to remain low performers. Our logistic regression analysis powerfully supports our two-dimensional results. We examine the changing productivity of all internationally visible Polish associate professors in 12 STEMM (Science, Technology, Engineering, Mathematics, and Medicine) disciplines (N = 4,434).

Keywords: productivity types; longitudinal design; classificatory approach; academic career; micro-level data; journal prestige normalization

Introduction

In the present article, we address a simple research question about the impact of prior individual research productivity on current research productivity. Assuming that scientists change productivity classes during their careers, we seek patterns of mobility between classes, depending on the disciplines and productivity measurement methods used.

In the current research, we examine the changing productivity of 4,434 Polish STEMM (science, technology, engineering, mathematics, and medicine) scientists as they move up the academic ladder. They are all full-time associate professors employed in the higher education sector, and they all have both doctoral and postdoctoral (habilitation) degrees. Combining demographic and biographical data based on a national registry of scientists (N = 99,935) with own computations based on the Scopus metadata on all Polish research articles indexed over the past half a century (1973–2021, N = 935,167), we examine individual scientists changing their productivity classes over time, here for a period spanning up to 40 years (range of biological age: 30–70). Our focus is on the two career stages of assistant professorship and associate professorship, at which the majority of Polish academic scientists are currently located.

Our point of departure is allocating all associate professors who are internationally visible in the Scopus database to three current productivity classes for 2018–2021 (according to the top 20%, middle 60%, and bottom 20% formula) by the selected productivity types. Then, we could examine their past productivity when they were assistant professors, compare them with their peers in their own disciplines, and allocate them retrospectively to the three past productivity classes (again top, middle, and bottom). We unpack the details of scientists' individual trajectories in these two career stages, linking current and past productivity for each individual scientist, and examine the mobility between productivity classes by discipline and productivity type. In particular, we are interested in comparing mobility patterns between productivity classes in terms of four types of productivity—full counting and fractional counting—in both non-normalized and journal prestige–normalized versions.

Based on prior research on high productivity (Abramo et al. 2009; Fox and Nikivincze 2021; Kwiek 2016; Yin and Zhi 2017), our intuitions have led us to focus on the persistence of top productivity and the persistence of bottom productivity over time as scientists move up the academic ladder. Our hypotheses have been based on prior theories in the sociology of science and economics of science, according to which top-productive scientists tend to keep being top-productive and bottom-productive scientists tend to keep being bottom productive, while nonproductive scientists tend to leave the academic science sector (Allison and Stewart 1974: 596; Allison et al. 1982: 615; Cole and Cole 1973: 114; Turner and Mairesse 2005: 3).

Consequently, our approach is longitudinal (tracing the productivity of the very same scientists over time) and classificatory (examining productivity changes in terms of productivity classes rather than publication numbers). We examine scientists from the top and from the bottom productivity classes changing classes over time from a relative perspective: class identification is possible by studying the productivity of individuals in relation to the productivity of other individuals (as in the studies of research stars; see, e.g., Aguinis and O'Boyle 2014: 313–315; DiPrete and Eirich 2006: 282).

We have previously examined the persistence of productivity classes in the top levels of Polish academia (i.e., among full professors) from a lifetime perspective. Therefore, the link between the previous contribution (Kwiek and Roszka 2023a) and this paper needs clarification. For a sample of 2,326 full professors from 14 STEMM disciplines—all internationally visible through Scopus publications—we have previously observed several consistent productivity patterns. Using the same 20/60/20 classification into top performers, middle performers, and bottom performers, we analyzed current full professors retrospectively—how they changed productivity classes earlier in their careers. We have tracked current full professors when they were assistant professors and then later in their careers, when they were associate professors, and have compared their productivity.

We have shown that for the sample of current full professors, half of the highly productive assistant professors in the past continued to become highly productive associate professors, and half of the highly productive associate professors continued to become highly productive full professors (52.6% and 50.8%, respectively). In logistic regression models, there were two powerful predictors of membership in the top productivity class for full professors: first, being highly productive as assistant professors and second, being highly productive as associate professors earlier in their careers (powerfully increasing the odds: Exp(B) = 2.793, 95% confidence interval 2.140–3.646, and Exp(B) =

4.61, 95% confidence interval 3.558–5.974, respectively). Interestingly, in the context of the previous literature, neither gender nor age (biological or academic) emerged as statistically significant predictors in our regression models. Consequently, for this elite level of Polish scientists (all of our observations being real success stories of Polish academic science in terms of reaching the crowning of the academic career), we have shown that there is an unexpectedly high level of immobility in the system. Top research performers continue in their careers as top research performers (in large proportions), and bottom research performers continue in their careers as bottom research performers (also in large proportions).

In this paper, we go beyond our initial work by testing additional hypotheses. We use a much larger, non-overlapping sample of scientists from a different career stage and extend our methodology, as explained below. As our initial work on full professors has clearly exhibited a "success bias" (all scientists in the sample were highly successful in their careers, with the presidential professorship title belonging to the upper 13% of academics with doctorates), we contemplated whether the mobility patterns found for this elite level may have a wider application for the Polish academic profession. Our guiding question was whether productivity patterns found for a small, successful minority of scientists are also observable for a much larger, more internally differentiated segment of Polish academia.

Consequently, in this research, we examine a much more representative layer of Polish academia, namely associate professors, who constitute 30% of Polish academics with doctorates (RADON 2023). Our sample of current associate professors does not overlap with that of current full professors. We can study the mobility patterns between productivity classes for lower levels of scientists, scattered widely across mid-career and late-career age groups. In Poland, associate professors have worked at this rank for decades, as shown by their biological age distribution (Figure 1). Becoming a full professor is exceptional, with approximately 500–600 new full professorships awarded a year (GUS 2022).

Additionally, we examine the extent to which the productivity patterns that we found in previous research may have been influenced by the specific productivity type applied: a journal prestige normalized, full counting method. Consequently, in this research, we go beyond a single account of productivity to use four productivity types, both in two-dimensional analysis and in regression analysis. This enables us to examine whether the mobility patterns found are dependent on the productivity measurement methods used. (We found our journal prestige-normalized approach to productivity useful also in our paper on the impact of productivity on promotion age and promotion speed in the Polish higher education system: scientists in young promotion age classes and in fast promotion speed classes in the past emerged as currently the most productive, see Kwiek and Roszka 2023b).

In regression models, for each productivity type we seek both the predictors increasing the odds of belonging to top productivity classes among current associate professors and the odds of belonging to bottom productivity classes. The four productivity types are the following: prestige-normalized, full counting; non-normalized, full counting; prestige-normalized, fractionalized counting; and non-normalized, fractional counting. We examine whether the direction of predictors changing the odds of membership in bottom productivity classes is generally opposite to the direction of predictors for membership in top classes and whether their strength is similar. Our initial research focused on the "once highly productive, forever highly productive" theme, and in this research, we examine in greater detail also the mirror theme: "once bottom productive, forever bottom productive," specifically through a modeling approach.

Finally, in the current research, we studied the extent of extreme upward and downward mobility between productivity classes. We were interested in whether the bottom-to-top and top-to-bottom mobility for associate professors occurs as marginally as our data for full professors indicate. Our references to radical moving up or radical dropping down in productivity classes were cursory only, with no further details. Therefore, in this research, we present a comprehensive account of both bottom-to-top mobility and top-to-bottom mobility by discipline for the four productivity types.

Persistent inequality in academic knowledge production

The steep performance stratification of scientists and persistent inequality in academic knowledge production have been examined for a long time, with foundational analyses by Alfred Lotka (1926), Derek J. de Solla Price (1963), Robert K. Merton (1968), Jonathan R. Cole and Stephen Cole (Cole and Cole 1973), and others inspiring generations of theoreticians. The old research theme, summarized as “the majority of scientific work is performed by a relatively small number of scientists” (Crane 1965: 714), has been at the core of these theories of individual research productivity.

The mechanisms behind accumulative advantage (and disadvantage) have been studied for decades (Alison et al. 1982; Allison and Stewart 1974; Cole and Cole 1973; DiPrete and Eirich 2006; Merton 1968), as have other major theories of research productivity, such as sacred spark theory (Allison and Stewart 1974; Cole and Cole 1973; Fox 1983; Zuckerman 1970) and utility maximization theory (Kyvik 1990; Stephan and Levin 1992). Built-in undemocracy seems to be part and parcel of the research performance, and “inequality has been, and will always be, an intrinsic feature of science” (Xie 2014: 809). In Poland, as elsewhere, low productive scientists work in STEMM laboratories alongside highly productive scientists (Abramo et al. 2013; Piro et al. 2016)—and 10% of the most productive scientists (“research top performers”) have been shown to be producing as much as 50% of all publications in Poland (Kwiek 2018). The role of research stars, who are concentrated in the right tail of research productivity distribution in every national science system—where the vast majority of scientists publish little and a tiny minority of scientists publish a lot—has endured over time (Agrawal et al. 2017: 1). The skewness of science has been the topic of numerous bibliometric publications (e.g., Albarrán et al. 2011; Carrasco and Ruiz-Castillo 2014; Ruiz-Castillo and Costas 2014). Recent studies include research on variously termed highly productive scientists: stars and superstars (Abramo et al. 2009; Aguinis and O’Boyle 2014; Sidiropoulos et al. 2016; Yair et al. 2017; Agrawal et al. 2017), the best (O’Boyle and Aguinis 2012), prolific professors (Piro et al. 2016), as well as top researchers (Abramo et al. 2013; Cortés et al. 2016) and the academic elite (Yin and Zhi 2016).

Research productivity

Research productivity is one of the most important dimensions—although not the only one—determining the trajectory of academic careers in most science systems (Leisyte and Dee 2012; Stephan 2015). Research productivity has been widely studied from both single-nation and cross-national perspectives (see, e.g., Allison et al. 1982; Drennan et al. 2013; Fox 1983; Lee and Bozeman 2005; Shin and Cummings 2010; Ramsden 1994; Stephan and Levin 1992; Teodorescu 2000; Wanner et al. 1981). In addition to publications, a successful academic career is determined by factors such as external research funding obtained, patterns of international collaboration, awards and honors, membership in associations and academies, physical mobility and international experience, professional networks, institutional placement (i.e., institutional and national affiliation), and luck (Carvalho 2017; Hermanowicz 2012). Career success is also determined by the internationalization of research, citations received, working time distribution, distribution of academic roles, and other factors. The main drivers behind productivity fall into two types: individual and environmental (encompassing both institutions, in the form of, e.g., “work climate,” as shown by Fox and Mohapatra

2007, and entire national science systems, in the form of, e.g., academic promotion and recognition systems, as shown by Leisyte and Dee 2012).

Within the most general, traditional tripartite division of academic tasks into teaching, research, and service, it is extremely difficult to compare researchers' achievements in the first and third areas, mainly because of data limitations. In contrast, it is relatively simple, though not without controversies, to compare achievements in the area of research through publications, which are usually indexed in global databases, and their citations. Because publication and citation databases (despite their limitations and biases, as widely discussed in the literature; see Baas et al. 2020; Boekhout et al. 2021; Sugimoto and Larivière 2018) have metadata of publications spanning for decades, it is possible to analyze individual productivity (calculated as the number of publications of a selected type per unit time) changing over time.

However, studying changes in productivity over time requires the data at the individual scientist level rather than at the publication level, which, in turn, requires massive processing of publication-oriented bibliometric data into a different unit of analysis: the individual scientist. In addition, studying productivity changes over time using publication numbers faces additional limitations because of the different pace of development of bibliometric databases depending on the discipline.

In some disciplines, the increasing number of publications may be because of increasing individual productivity, while in others, it may be because of the increasing number of journals successively included in the database. Moreover, the average productivity increases at different rates in different disciplines with successive generations of scientists—scientists not only start publishing earlier on average, but they also publish more per year on average (Wang and Barabási 2021). Higher productivity is also associated with the growing role of multiauthored and internationally coauthored publications and the increasing average size of research teams (Adams 2013; Wuchty et al. 2007), which, in turn, have been associated with increasing specialization in science and a stronger imperative to show the contributions of all, even minor, participants in research.

Therefore, we find it reasonable to take an approach to productivity change over time, in which authors use productivity classes (see Costas and Bordons 2005; Costas and Bordons 2007; Costas et al. 2010) within disciplines rather than publication numbers. In our study, we additionally use a journal prestige–normalized approach to productivity, which locates scientific articles within a highly stratified global structure of journals, taking into account the fact that those articles published in high-prestige journals require, on average, more effort than articles published in low-prestige journals because the former benefit from more critical reviewers. The prestige of a journal as expressed as percentile ranks in the Scopus database is an important element of individual productivity, especially in systems—as in the Polish case (Antonowicz et al. 2021)—in which both the quantity and quality of articles captured by a proxy of journal prestige count toward academic promotion (according to the basic rule of the Polish research assessment exercise termed institutional research evaluation: "academic journals are not equal").

Our single-nation, longitudinal, and classificatory approach to individual research productivity is new and promising, especially for systems in which digital biographical and demographic data on scientists from national registries are available. In the literature, we have found a somewhat structurally similar, single-nation research: Abramo et al. (2017) studied the persistence of "stardom" of scientists (or their belonging to the upper 10% in terms of productivity), focusing on the top performance of Italian professors over three 4-year periods (2001–2012). They identified the top performers in the first period (N = 2,883) and tracked them over time in the next two periods. They showed that about one-third of top performers retain their stardom for three consecutive periods, and about half retain it for two periods (35% and 55%, respectively, with some disciplinary differentiation and with higher percentages for male scientists, Abramo et al. 2017: 793–794). Our approach is different in several respects: in terms of the direction of tracking scientists over time (retrospective tracking of individuals vs. forward tracking); the period covered (two career periods, assistant professorship and associate professorship, up to 45 years vs. 12 years divided into three periods); the construction of the sample (all internationally visible associate professors vs. professors of all ranks); and methodology (analysis of top, middle, and bottom productivity classes vs. analysis of top performers and unproductive scientists and the four approaches to productivity vs. the Fractional Scientific Strength model developed by the authors). Finally, we have used logistic regression analysis to identify major predictors of membership in the top and bottom productivity classes. However, in very general terms, Abramo et al.'s measurement of the "stardom" of scientists over time within a national population of scientists bears interesting similarities to our measurement of the mobility between top productivity classes and bottom productivity classes over time as the individuals move up the academic ladder.

Our research questions and hypotheses

Our research questions (Table 1) were based on previous findings in the productivity and high productivity literature, as briefly discussed above, and the questions refer to top (H1) and bottom (H2) productivity persisting over time at the two career stages of assistant professorship and associate professorship; differentiation by discipline in mobility patterns between productivity classes (H3); extreme interclass mobility patterns (H4); differentiation of mobility patterns by productivity type used (H5); and logistic regression models, run separately for each of the four productivity types, here seeking predictors of membership in top (H6) and bottom (H7) productivity classes of current associate professors. Compared with our previous study, all hypotheses were tested against a much wider, less "success biased" sample of associate professors and three of them have not been tested before: (H4) about extreme interclass mobility patterns, (H5) about productivity type differentiation of mobility patterns, and (H7) about model approach to bottom productivity.

Dataset, Sample, and Methodology

Dataset

For the present research, two major data sources are combined: national and international. The national dataset is the "Polish Science Observatory" dataset that is created and maintained by the present authors. The international dataset is Scopus raw publication and citation data for 1973–2021 for all Polish scientists and scholars who are active in performing research during the period. The "Observatory" database has been created by merging a national biographical and administrative register of all Polish scientists and scholars (N = 99,935) with the Scopus bibliometric database (2009–2018, metadata on N = 380,000 publications of authors with Polish affiliations). The Observatory database includes 25,463 unique authors working full time in the higher education sector, with at least a doctoral degree and who authored 158,743 journal articles. The Observatory includes relevant data such as gender, date of birth, dates of academic promotions (doctoral degree, postdoctoral degree, professorship title, if applicable), present institutional affiliations, disciplines in which degrees have been obtained, and selected dissertation-related data.

Table 1. Research questions, hypotheses, and support.

Research Questions	Hypotheses	Support
RQ1. What is the relationship between membership in the current top productivity classes and prior membership in top productivity classes?	**Top productivity persisting over time** **H1:** Current top-productive (top 20%) associate professors were top-productive (top 20%) assistant professors.	Supported
RQ2. What is the relationship between membership in the current bottom productivity classes and prior membership in bottom productivity classes?	**Bottom productivity persisting over time** **H2:** Current bottom-productive (bottom 20%) associate professors were bottom-productive (bottom 20%) assistant professors.	Supported
RQ3. What is the relationship between membership in current top (and bottom) productivity classes and academic disciplines?	**Disciplinary differentiation of mobility patterns** **H3:** Moving up the academic ladder, from assistant professorship to associate professorship, the mobility patterns between productivity classes vary by discipline.	Supported
RQ4. Is extreme interclass mobility a rare academic career trajectory?	**Extreme interclass mobility patterns** **H4:** Moving up the academic ladder, from assistant professorship to associate professorship, extreme mobility patterns (top to bottom, bottom to top) characterize a negligible share of scientists.	Supported
RQ5. Do mobility patterns between productivity classes differ by the productivity type used?	**Productivity type differentiation of mobility patterns** **H5:** Mobility patterns between productivity classes vary by productivity type used to a limited degree only.	Supported
RQ6. Do the predictors of membership in the top productivity classes differ by the productivity type used?	**Model approach to top productivity: logistic regression analysis** **H6:** Past membership in the top productivity classes significantly increases the odds ratio estimates of current membership in the top productivity classes, regardless of productivity type.	Supported
RQ7. Do the predictors of membership in the bottom productivity classes differ by the productivity type used?	**Model approach to bottom productivity: logistic regression analysis** **H7:** Past membership in the bottom productivity classes significantly increases the odds ratio estimates of current membership in the bottom productivity classes, regardless of productivity type.	Supported

The official national register and the 2009–2018 Scopus publication and citation database have been merged using probabilistic and deterministic methods (the creation of the Observatory database has been described in detail in Kwiek and Roszka 2021: 4–6). The Observatory database is subsequently enriched with publication metadata for all scientists and scholars with Polish affiliations for the past half century collected from Scopus and obtained through a multiyear collaborative agreement with the ICSR Lab, a cloud-computing platform provided by Elsevier for research purposes (N = 935,167 articles from 1973–2021).

Our final sample includes 4,434 scientists currently employed at the rank of associate professors, with both doctoral and postdoctoral (habilitation) degrees and working in 12 STEMM disciplines (their list is provided in Table 2).

Sample

Our sample (N = 4,434 scientists with N_{art} = 71,841 articles) includes about one-third of female scientists and about two-thirds of male scientists (36.7% and 63.3%, respectively), generally reflecting the gender structure of the Polish academic profession in STEMM disciplines at the rank of assistant and associate professors. As elsewhere, the share of female scientists in Poland is the highest for lower ranks and the lowest for higher ranks, reaching 27.94% of women working at the rank of full professors for all STEMM and non-STEMM disciplines combined in 2021 (GUS 2022: 30–38).

Almost half of associate professors in our sample are aged 51–70 (46.4%), and both male and female associate professors are scattered across several age groups, with only about one-tenth aged 40 or younger (9.7%). The kernel density plot in Figure 1 indicates that the current age distribution of associate professors by gender differs, especially for older age groups. Specifically, the share of older age group associate professors is higher for men than for women, which may reflect a higher inflow of women to STEMM disciplines 30 years ago and earlier. In terms of disciplinary distribution of scientists (Table 2), about half of all scientists come equally from three disciplines (engineering ENG 15.7%, agricultural and biological sciences AGRI 14.7%, and medicine MED 14.7%). The three smallest disciplines are chemical engineering CHEMENG (2.0%), computer science COMP (4.1%), and mathematics MATH (5.1%). One in three scientists (30.8%) come from research-intensive institutions defined as IDUB institutions, that is, the participants in the first Polish national excellence initiative (funded with an additional 1 billion USD for 2020–2026). The age distribution of scientists by discipline is highly differentiated, as the kernel density plots in Figure 2 indicate: although in some disciplines younger age groups dominate (e.g., AGRI, materials science MATER), in others, scientists are distributed in a much flatter manner (e.g., MATH, physics and astronomy PHYS), with some (e.g., CHEMENG, ENG) having larger shares of older scientists. Higher percentages of younger scientists currently may mean a higher inflow of young scientists in the past one or two decades because academic careers overwhelmingly start right after obtaining doctoral degrees.

Methodology

Unit of analysis: Individual scientists rather than individual publications

Individual scientists with unambiguously defined biographical and publication-related attributes are the unit of analysis in the present research (as in the other strands of research we have conducted, as mentioned above). Scientists have individual identification numbers (IDs), so their career-related biographical data can be derived from a national registry. The focus is on the individual academic careers of research producers developing over time, in this case on changing productivity classes while moving up the academic ladder rather than on research products (i.e., publications) themselves.

Constructing individual publication portfolios

For each scientist, a unique individual publication portfolio is constructed. The portfolio includes all Scopus-derived metadata on their publications. Specifically, publication metadata are journal metadata (e.g., Scopus CiteScore percentile rank) and publication metadata (e.g., year of publication, number of coauthors and their affiliations, citation numbers). Each publication is linked to the dates in individual biographical history; that is, they are linked to two career steps: assistant professorship and associate professorship, which is clearly defined as the period between obtaining a doctoral degree and a habilitation degree and the period following the conferral of a habilitation degree, respectively. The date of the first publication (any type) in the Scopus database allows the construction of publication-derived academic age, a proxy of academic experience, which has been used in logistic regression models.

Table 2. Structure of the sample of all Polish internationally visible associate professors by gender, age group, and STEMM discipline (N = 4,434)

		Female scientists			Male scientists			Total		
		n	row %	col %	n	row %	col %	n	row %	col %
Age groups	Total	1629	36.7	100.0	2805	63.3	100.0	4434	100.0	100.0
	up to 40	136	31.6	8.3	294	68.4	10.5	430	100.0	9.7
	41 - 50	797	40.9	48.9	1150	59.1	41.0	1947	100.0	43.9
	51 - 60	476	37.8	29.2	783	62.2	27.9	1259	100.0	28.4
	61 - 65	155	30.1	9.5	360	69.9	12.8	515	100.0	11.6
	65 - 70	65	23.0	4.0	218	77.0	7.8	283	100.0	6.4
IDUB	IDUB	379	27.7	23.3	988	72.3	35.2	1367	100.0	30.8
	Rest	1250	40.8	76.7	1817	59.2	64.8	3067	100.0	69.2
Academic discipline	AGRI	326	50.2	20.0	324	49.8	11.6	650	100.0	14.7
	BIO	194	61.2	11.9	123	38.8	4.4	317	100.0	7.1
	CHEM	143	43.6	8.8	185	56.4	6.6	328	100.0	7.4
	CHEMENG	18	20.5	1.1	70	79.5	2.5	88	100.0	2.0
	COMP	30	16.4	1.8	153	83.6	5.5	183	100.0	4.1
	EARTH	90	33.3	5.5	180	66.7	6.4	270	100.0	6.1
	ENG	98	14.0	6.0	600	86.0	21.4	698	100.0	15.7
	ENVIR	208	47.9	12.8	226	52.1	8.1	434	100.0	9.8
	MATER	91	26.3	5.6	255	73.7	9.1	346	100.0	7.8
	MATH	50	21.9	3.1	178	78.1	6.3	228	100.0	5.1
	MED	344	52.7	21.1	309	47.3	11.0	653	100.0	14.7
	PHYS	37	15.5	2.3	202	84.5	7.2	239	100.0	5.4

Note: STEMM disciplines included in the study: AGRI, agricultural and biological sciences; BIO, biochemistry, genetics, and molecular biology; CHEMENG, chemical engineering; CHEM, chemistry; COMP, computer science; EARTH, earth and planetary sciences; ENG, engineering; ENVIR, environmental science; MATER, materials science; MATH, mathematics; MED, medical sciences; and PHYS, physics and astronomy.

Constructing individual biographical histories

For each scientist, apart from a unique individual publication portfolio, an individual biographical history is also constructed, here with the relevant dates: the date of birth (which allows us to infer biological age at the beginning of both career stages, assistant professorship and associate professorship), the date of obtaining a doctoral degree, and the date of obtaining a postdoctoral (or habilitation) degree.

All scientists in our sample are associate professors—but also all of them have been assistant professors earlier in their careers. The first stage of their academic career started when they were awarded their doctoral degrees and the second stage when they were awarded their habilitation degree. For both degrees, we have full administrative data, including the date of degree conferral, dissertation title, employing institution and city, defense institution and city, academic discipline and academic field, and the names of the reviewers. The data, coming from a manually curated national registry of scientists, can be treated as fully reliable (for the purposes of international comparability, we use holding a doctoral degree as a proxy of assistant professorship and holding a postdoctoral degree as a proxy of associate professorship).

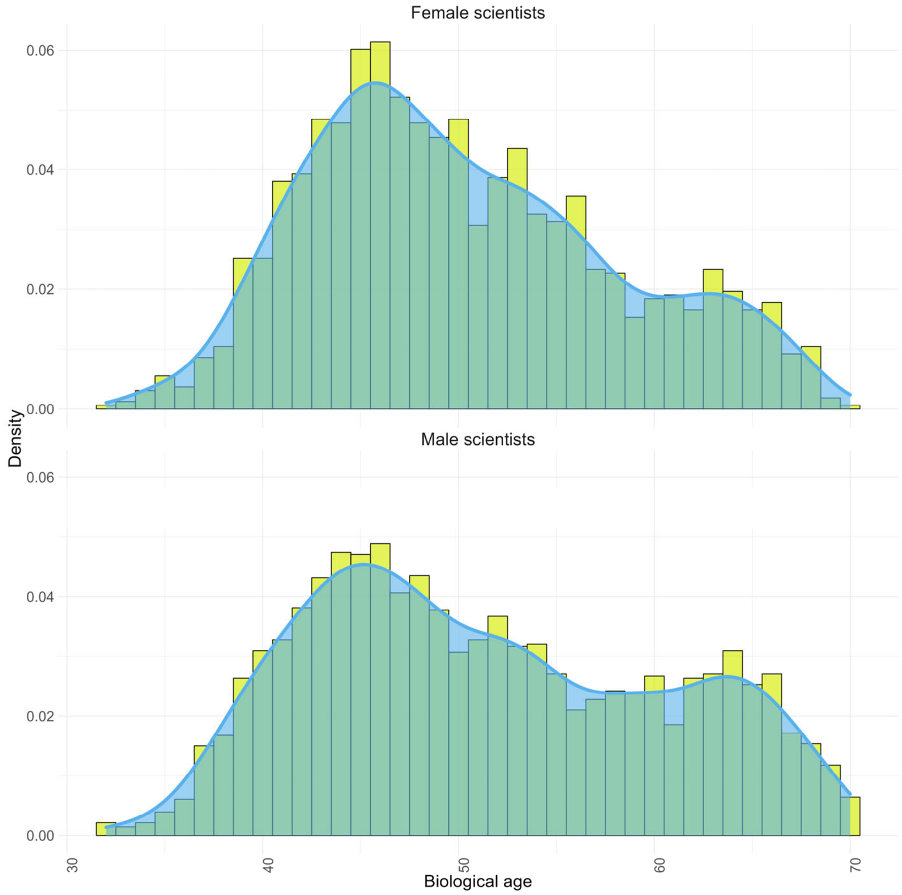

Figure 1. Distribution of biological age: kernel density plot, associate professors in 12 STEMM academic disciplines combined by gender. Female scientists (top panel) and male scientists (bottom panel) (N = 4,434)

Longitudinal approach to studying academic careers

For our analyses, we have chosen all current internationally visible associate professors (i.e., with at least one journal article indexed in the Scopus database), and we look back at their professional careers: we examine their current publishing behavior in a four-year period of 2018–2021 and their past publishing behavior when they have been assistant professors in four-year equivalents in the past.

In traditional longitudinal research designs, the same individuals are followed over time with selected points in time to enable comparative research (Menard 2002). In following academic careers, a longitudinal design has not been used for technical and cost-related reasons. Our combination of individual biographical histories (professional life data) with individual publication portfolios (publication and citation data) allows us to produce a retrospective view in which a sizable group of scientists is traced back for several decades in terms of their publishing behavior. Such a nontraditional longitudinal approach opens new possibilities for studying academic careers over time.

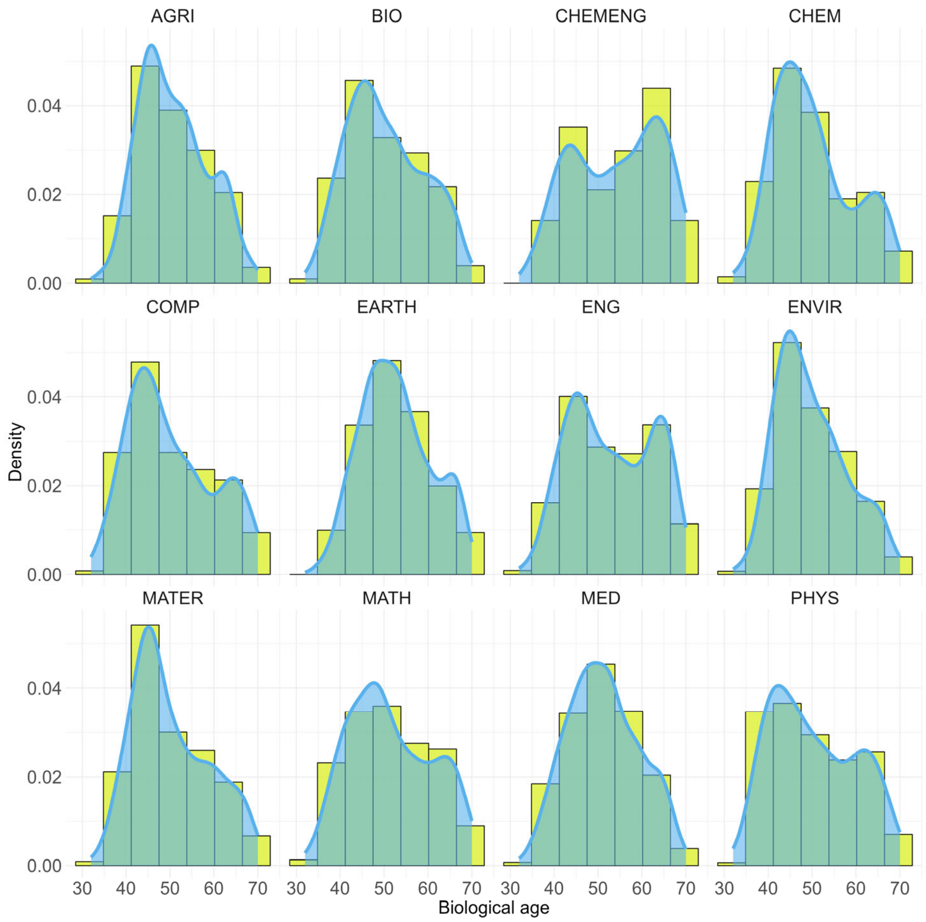

Figure 2. Distribution of biological age: kernel density plot, associate professors by academic discipline (N = 4,434)

The application of four major dimensions to examine biographical and bibliometric data becomes possible: gender, age, discipline, and, most importantly, time. Instead of time-limited snapshot views, using a series of cross-sectional accounts, longitudinal analyses that can focus on the change of the scientific workforce over time by various dimensions become possible.

Defining gender, biological age, academic age, and disciplines

All scientists in our sample have unambiguously defined gender (a binary approach used in the national registry: male or female) and year of birth. Consequently, their biological age at any point in time is easy to calculate. Their academic age—or the number of years since the first Scopus-indexed publication used in the logistic regression models—has been collected using the application programming interface (API) protocol. We use individual publication portfolios (all Scopus-indexed publications lifetime) to determine the dominant discipline: the modal value of ASJC (All Science Journal Classification) disciplines used in Scopus for each scientist. We link all publications (type: article) in the portfolios to ASJC disciplines, and if there are two or more values with the same high occurrence in the portfolio, the discipline is randomly selected from among them. The Polish classification of disciplines could not be used because it has been changing drastically over the past two decades (with the official list of disciplines ranging from 40 to 100), especially in the past few years.

Measuring individual research productivity

We measure productivity in the four-year reference period of 2018–2021 (termed "current productivity of associate professors") and in earlier periods of their assistant professorship (termed "past productivity of associate professors when they were assistant professors") by using publication data (articles only) from individual publication portfolios. We need exact dates to determine when current associate professors were working as assistant professors, so we have allocated publications from the 2018–2021 reference period and from the assistant professorship period, which have varying lengths, for each individual scientist. Four-year productivity is used in both cases.

Prestige-normalized vs. non-normalized approaches to productivity

Having individual publication portfolios for each scientist in our sample, we use the idea of a prestige-normalized approach to productivity, in which articles are linked to the Scopus journals in which they were published (we have found this approach useful previously in Kwiek and Roszka 2023a, 2023b). All Scopus journals (N = 42,403 in 2024) have their distinct locations in the Scopus CiteScore percentile ranks, in the range of 0–99, with more prestigious journals generally located in the 90th percentile or higher.

Although in non-normalized approaches the value of an article in calculating productivity is 1, using a full counting methodology, in a prestige-normalized approach, the value will be normalized to journal percentile ranks: it will be 0.95 for journals located in the 95th journal percentile and 0.3 for journals located in the 30th journal percentile (articles published in journals located in the 10th percentile and lower will receive a value of 0.1). Linking articles to their location in a highly stratified system of academic journals reflects a more general idea that, on average, publications in more highly ranked journals require more scholarly effort and that their preparation is more time-consuming, especially because of more rigorous peer review processes and more demanding peer reviewers, than publications in lower-ranked journals. Journals more highly ranked tend to be more selective (with acceptance rates lower than 10% in the top journals) than journals in the low ranks.

In Scopus, the ranking system that uses percentiles is based on citations received in the previous four years. So although journal percentile ranks are a proxy of quality (representing the impact of a journal on the academic community), the articles in these journals are, on average, more or less cited. The measures are somehow crude, but there seem to be no other reliable data on publications by Polish scientists from the past half a century available.

Full counting vs. fractional counting approaches to productivity

Using either a full counting approach or fractional counting approach does not make a big difference in the productivity studies examining humanities, with considerable shares of solo publications being found. However, our sample includes STEMM scientists only where collaborative publications are the rule and solo research is the exception. In the full counting methods, equal full credits go to all coauthors; in fractional counting methods, credits are divided by the number of coauthors (our sample does not include articles with more than 100 coauthors). We want to examine the transitions between the productivity classes of assistant professors becoming associate professors by different productivity types and assess to what extent the differences in transition patterns found depend on productivity counting and normalization methods.

The four productivity types examined

Consequently, the four combinations of counting and normalization methods have been considered in examining productivity—two full counting methods and two fractional counting methods—leading to four productivity types being used in the present research:

(1) Productivity 1 (prestige normalized, full counting)
(2) Productivity 2 (non-normalized, full counting)
(3) Productivity 3 (prestige normalized, fractional counting)
(4) Productivity 4 (non-normalized, fractional counting)

Allocating scientists to productivity classes

A methodologically critical element of the present research is the allocation of scientists to the three productivity classes along the 20/60/20 pattern. First, separately within each discipline, all current associate professors are ranked according to their four-year productivity in the 2018–2021 reference period. There are four ranking procedures because there are four productivity types. The upper 20% of scientists within each discipline (according to Productivities 1 through 4) are classified as the top productivity class, the middle 60% as the middle productivity class, and the lowest 20% as the bottom productivity class (cutoff points permitting so that, in some disciplines and some productivity types, the 20%, 60%, and 20% classes may need rounding).

Next, again separately within each discipline and separately by the four productivity types, all current associate professors are ranked according to their average four-year productivity when they were assistant professors. The period examined differs because there are different lengths of working at the rank of assistant professorship; however, rankings are based on productivity in a four-year equivalent period.

Additionally, in logistic regression models only, we have used an analogous 20/60/20 classificatory scheme for all scientists based on their individual biographical profiles. We classify all scientists based on their promotion age for doctorates and promotion age for habilitation degrees; and based on their promotion speed, or the number of years passed between doctoral and habilitation degrees. Scientists are classified as belonging to the classes of young, middle, and old associate professors (based on the conferral date of habilitation degree); as belonging to the classes of young, middle, and old assistant professors (based on the conferral date of doctoral degree); and as belonging to the class of fast, typical, or slow associate professors (based on the number of years passed between the two conferrals). All scientists within their disciplines have been distributed across the above promotion age and promotion speed classes.

Mobility patterns between productivity classes

Our focus is on the mobility between the three productivity classes (top, middle, and bottom) based on the four basic productivity types (Productivity 1 through 4). Assistant professors from top, middle, and bottom productivity classes can change their productivity class while being associate professors to the top, middle, and bottom productivity classes. Our focus is on the mobility patterns of scientists between productivity classes over time. Specifically, we analyze the following mobility types by discipline and productivity type:

(1) *Top-to-top mobility* (assistant professors belonging to top productivity class continue to belong to top productivity class as associate professors);

(2) *Bottom-to-bottom mobility* (assistant professors belonging to bottom productivity class continue to belong to bottom productivity class as associate professors);

(3) *Extreme downward and extreme upward mobility: top-to-bottom mobility and bottom-to-top mobility* (assistant professors belonging to top productivity class move down to the bottom productivity class as associate professors; and, analogously, assistant professors belonging to bottom productivity class move up to the top productivity class as associate professors).

Limitations

We do not analyze the productivity classes of all assistant professors: our focus is on associate professors publishing in the most recent four-year period for which publication data are available (2018–2021) and, retrospectively, when they were assistant professors. This means that the longitudinal comparison over time cannot be conducted for those assistant professors who have left the national science system. Our study also does not pertain to those male and female scientists who never earned their postdoctoral degrees (they are not in our sample).

It needs to be kept in mind that, at an individual level, generally, although productivity can always be higher in the higher education and science system, it cannot be much lower or zero (meaning nonpublishers, nonperformers) for a long time because these unsuccessful scientists tend to leave the Polish higher education system. Consequently, our study of current associate professors does not include failures in science; unsuccessful scientists are not present in the national registry. From this perspective, all current associate professors in our sample are successes in science, and it is merely a statistical approach that allocates them to the top, middle, and bottom productivity classes. No matter how highly productive the scientists in the system are, the system can always be divided into three classes, and there will always be bottom productivity classes in each discipline (cutoff points permitting).

Our study is confined to a single national science system. The generalizability of the results depends on the similarities and dissimilarities with other systems. Science systems have differently constructed career ladders, and they differ in their internal competitiveness, incentive structures, teaching and research mix, funding opportunities, the attractiveness of academic careers, and so forth. We use internationally understandable notions of assistant and associate professorships, even though, in fact, we use the two Polish academic degrees (doctorate and habilitation).

Results

We discuss mobility between productivity classes based on the four productivity types first (1) for all disciplines combined and, second, by (2) zooming in on cross-disciplinary differences: horizontal top-to-top mobility, horizontal bottom-to-bottom mobility and extreme upward and downward mobility (bottom-to-top mobility, top-to-bottom mobility). Finally, the results section will present (3) the logistic regression analysis, which examines the predictors of entering the classes of top productivity and bottom productivity associate professors.

Mobility between Productivity Classes by Productivity Type: All Disciplines Combined

The Sankey diagram in Figure 3 provides a guiding visualization to better understand what is meant by scientists' mobility across productivity classes while moving from the career stage of assistant professor to that of associate professor. The Sankey diagram shows all possible flows of scientists between the three classes of assistant professors (left: top, middle, and bottom) and associate professors (right: top, middle, and bottom): specifically, horizontal top-to-top and bottom-to-bottom mobility, as well as downward top-to-bottom and upward bottom-to-top mobility, are of interest to us here.

The example in Figure 3 shows the mobility of all scientists (N=4019) from all disciplines combined and uses Productivity 1 type (prestige-normalized, full counting approach). The left column shows the distribution of assistant professors within the three classes (totaling 100% in each class), and the right column shows the distribution of associate professors within the three classes.

For instance, among top productivity assistant professors, 55.0% continue their careers as top productivity associate professors (and they constitute 51.3% of associate professors); among bottom productivity assistant professors, 43.1% continue their careers as bottom productivity associate professors (and they constitute 51.0% of associate professors). The horizontal top-to-top and bottom-to-bottom mobility is represented by thick flows. Extreme vertical top-to-bottom and bottom-to-top mobility is rare and is represented in the diagram as thin downward and thin upward flows: only 2.1% of top productivity assistant professors land in the class of bottom productivity associate professors (constituting 2.5% of them)—and only 2.8% of bottom productivity assistant professors land in the class of top productivity associate professors (constituting 2.6% of them). The Sankey diagram allows us to better understand the different horizontal and vertical flows between productivity classes while moving up the academic ladder, here by 12 disciplines and by four productivity types, as examined in detail below.

From a discipline-aggregated view, that is, for all STEMM disciplines combined (Table 3 and Supplementary Table 1), the mobility patterns are unambiguous: no matter which productivity type we use, more than 50% of scientists allocated to the top productivity classes stay in the same top class in their academic career, and about 40% of scientists allocated to the bottom productivity classes stay in the same bottom class.

The above discipline-aggregated data suggest that there is powerful horizontal top-to-top and bottom-to-bottom mobility between productivity classes among the current associate professors in our sample. The majority of top productive scientists stay in the top productivity classes as they move up the academic ladder, and a large proportion, though not the majority, of bottom-productive scientists stay in the bottom productivity classes. There is an interesting locking-in mechanism in academic careers that deserves further scholarly attention—which is especially interesting because advancement in academic careers (in the specific Polish case) is closely related to publishing and its pace over time.

Analyzing the current biological age distribution of associate professors (Figure 1) and their current distribution by age groups (Table 2), we can conclude that STEMM scientists are somehow stuck in productivity classes for years, sometimes decades: almost half of associate professors are aged 51–70 (46.4%), including about one-fourth in the 51–60 age group (28.4%) and about one-fifth in the 61–70 age group (18%); they became assistant professors when they were, on average, aged about 28–32. In a system in which full professorship is the crowning achievement of one's academic career, available to few only, associate professors are scattered across all age groups. Consequently, our analyses span several decades of the academic careers of current associate professors.

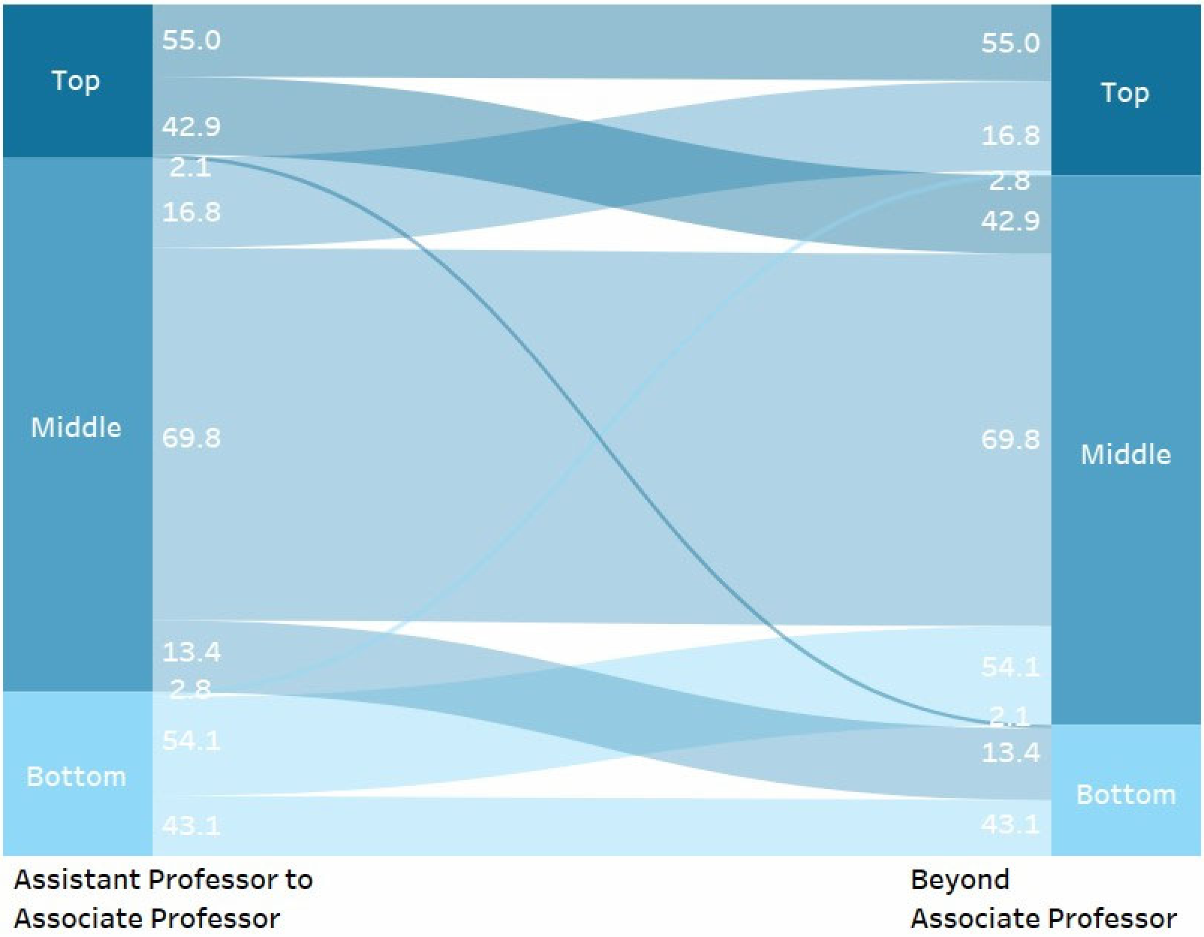

Figure 3. Example: Scientists' mobility between productivity classes in the two stages of an academic career. Productivity 1: prestige-normalized, full counting approach. All 12 STEMM disciplines combined, current associate professors. All observations in the top (upper 20%), middle (middle 60%), and bottom (lower 20%) productivity classes total 100% (or rounded) in each class. N = 4,019.

Importantly, in our approach, we do not refer to publication numbers because productivity has been on the rise across the board over the past decade. We rank all associate professors in terms of productivity ("target academic position" in productivity mobility in Table 3) and allocate them to the top, middle, and bottom productivity classes, separately in each discipline and separately by each productivity type. Subsequently, we rank associate professors retrospectively when they were assistant professors in terms of productivity at that time, as measured for a four-year period ("source academic position" in productivity mobility in Table 3). We examine 4,019 individual academic trajectories across 12 STEMM disciplines using full biographical, administrative, and bibliometric data at the micro-level of individual scientists.

What are the chances for extreme upward or downward mobility between productivity classes? Can scientists, over the years of their assistant professorship, radically change their publishing behavior (compared with their peers in disciplines), upon reaching associate professorship?

Our data show that the chances are slim, and these transitions include only exceptional cases. The chances are in the range of 2.8%–5.6% for assistant professors in the bottom productivity classes. Table 3 shows both the mobility percentages and mobility numbers: using Productivity 1, in the top productivity class, the percentage of associate professors whose career trajectory has included extreme upward mobility is merely 2.8% (23 scientists out of 815); in other words, only 23 assistant professors from the bottom productivity class managed to get to the top productivity class for associate professors.

Interestingly, the odds are not much higher for extreme downward mobility between productivity classes, and they are in the range of 2.1%–3.7% for assistant professors in top productivity classes: 2.1% of assistant professors experience this mobility (17 scientists out of 815) for Productivity 1.

In summary, out of 4019 scientists, only 23–45 scientists experience extreme upward mobility between productivity classes (bottom to top), and only 17–30 experience extreme downward mobility (top to bottom), depending on the productivity type used in the analysis. Thus, extreme mobility between productivity classes is marginal and includes 0.52%–1.01% of all scientists in our sample in upward mobility and 0.38%–0.68% scientists in downward mobility.

Zooming on Cross-Disciplinary Differences

Horizontal top-to-top mobility between productivity classes

To analyze mobility patterns in more detail, we need micro-level data combining individual biographical histories (date of birth, date of PhD, date of habilitation degree, and gender) and individual publication portfolios with publication data and metadata (all lifetime publications, with dates of publication, publication type, and journal metadata, hence allowing the use of the two prestige-normalized productivity types, as well as discipline).

The aggregated picture of all disciplines combined hides a much more nuanced picture of individual STEMM disciplines, with their distinct disciplinary mobility patterns between productivity classes. Focusing on Productivity 1 and the horizontal top-to-top mobility first: for all disciplines except one—mathematics (MATH)—the majority of assistant professors continue in top productivity classes as associate professors (Table 4). Although 55.0% of assistant professors from top productivity class move to top productivity class as associate professors for all disciplines combined (Total), constituting 51.3% of this class, the highest share is observed for chemical engineering (CHEMENG), with as much as 68.8%, followed by environmental science (ENVIR) with 62.8%, and earth and planetary sciences (EARTH) with 62.5%. The lowest share is observed for mathematics (MATH), the only discipline in which the majority of scientists from the top productivity class continue in the middle productivity class and where 45.2% continue in the same top productivity class. High cross-disciplinary differentiation is also observed for top-to-top mobility between productivity classes by the other three productivity types.

The conclusion is straightforward: no matter which of the four productivity types we use—specifically whether the method includes full counting or fractional counting and whether productivity is normalized to journal prestige or not—slightly more than half of all current associate professors belong to the top productivity class both as associate professors and earlier in their careers as assistant professors, with some disciplinary differentiation. We analyze the issue in more depth and from a multidimensional perspective using a model approach in the Model Approach: Logistic Regression section.

Table 3. Mobility between productivity classes while moving up from the assistant professorship stage to associate professorship stage by four productivity types, all disciplines combined (Productivity 1 only, prestige normalized, full counting; the other productivity types, see Supplementary Table 1)

Transition from source academic position		Transition from productivity class	Transition to target academic position	Transition to productivity class	Number of scientists in transition	Number of scientists in each productivity class	%
Productivity 1 (prestige normalized, full counting)	Asst Prof.	Bottom	Assoc Professor	Bottom	351	815	43.1
	Asst Prof.	Bottom	Assoc Professor	Middle	441	815	54.1
	Asst Prof.	Bottom	Assoc Professor	Top	23	815	2.8
	Asst Prof.	Middle	Assoc Professor	Bottom	320	2389	13.4
	Asst Prof.	Middle	Assoc Professor	Middle	1667	2389	69.8
	Asst Prof.	Middle	Assoc Professor	Top	402	2389	16.8
	Asst Prof.	Top	Assoc Professor	Bottom	17	815	2.1
	Asst Prof.	Top	Assoc Professor	Middle	350	815	42.9
	Asst Prof.	Top	Assoc Professor	Top	448	815	55
	Asst Prof.	Bottom			688	688	100
	Asst Prof.	Middle			2458	2458	100
	Asst Prof.	Top			873	873	100
	Assoc Pr.	Bottom			815	815	100
	Assoc Pr.	Middle			2389	2389	100
	Assoc Pr.	Top			815	815	100

Table 4. Four mobility types by discipline (Productivity 1 only, prestige-normalized full counting)

Discipline	Top-to-top mobility		Bottom-to-bottom mobility		Bottom-to-top mobility		Top-to-bottom mobility	
	Assistant professors: top to top (%)	As % of top associate professors	Assistant professors: bottom to bottom (%)	As % of bottom associate professors	Assistant professors: bottom to top (%)	As % of top associate professors	Assistant professors: top to bottom (%)	As % of bottom associate professors
AGRI	56.2	48.8	40.9	54.0	1.7	1.6	2.7	3.4
BIO	50.8	50.0	46.8	51.8	1.6	1.6	3.3	3.6
CHEM	54.0	52.3	50.0	54.7	0.0	0.0	0.0	0.0
CHEMENG	68.8	68.8	50.0	61.5	0.0	0.0	0.0	0.0
COMP	52.9	51.4	58.8	66.7	2.9	2.9	0.0	0.0
EARTH	62.5	55.6	38.0	45.2	0.0	0.0	4.2	4.8
ENG	55.3	50.0	38.2	46.1	4.1	3.7	4.1	4.9
ENVIR	62.8	57.0	35.4	45.2	5.1	4.7	2.6	3.2
MATER	51.6	50.8	40.0	44.1	3.1	3.1	0.0	0.0
MATH	45.2	41.3	47.6	62.5	2.4	2.2	0.0	0.0
MED	52.3	50.8	45.2	51.4	4.0	3.8	1.6	1.8
PHYS	54.3	53.2	46.8	51.2	4.3	4.3	2.2	2.3
Total	**55.0**	**51.3**	**43.1**	**51.0**	**2.8**	**2.6**	**2.1**	**2.5**

Horizontal bottom-to-bottom mobility between productivity classes

Similarly, we have analyzed horizontal bottom-to-bottom mobility between productivity classes by discipline and productivity type. For all disciplines combined, the bottom-to-bottom mobility is experienced by about 40% of current bottom-productive associate professors, and it is the highest when Productivity 1 is used and the lowest when Productivity 4 is used (43.1% and 36.6%, respectively). However, the differentiation by discipline within and across productivity types is considerably higher than in the case of top-to-top mobility (Table 4). For instance, using Productivity 1, the share of assistant professors from the bottom productivity class continuing their career in the bottom productivity class of associate professors is 50% and more in several disciplines: computer science (COMP) with as much as 58.8%, followed by CHEM and CHEMENG (both 50.0%).

The discipline-aggregated picture of about 40% of scientists from the bottom productivity class as assistant professors staying in the same bottom productivity class as associate professors hides a much more differentiated disciplinary picture. In some disciplines, using some productivity types, the percentage reaches 50%–60%; in others, it is about one-third or less. Overall, between 30% and 60% of bottom performers in the first stage of their careers continue as bottom performers in the second stage.

Extreme upward and downward mobility between productivity classes

Scientists representing bottom-to-top mobility (Table 4) constitute between 2.8% and 5.6% of assistant professors from the bottom productivity class in our sample: 2.8% for all disciplines combined in Productivity 1 (and 3.3% in Productivity 2, 4.8% in Productivity 3, and 5.6% in Productivity 4). Scientists representing top-to-bottom mobility (Table 4), in turn, constitute between 2.1% and 3.7% of assistant professors from the top productivity class in our sample: 2.1% for all disciplines combined in Productivity 1 (and 3.7% in Productivity 2, 3.4% in Productivity 3, and 2.9% in Productivity 4).

Our analyses show that more than 50% of top productivity scientists continue as top productivity scientists, about 40% of bottom productivity scientists continue as bottom productivity scientists, and a very small percentage of scientists (1%–2%) change their productivity class radically, from bottom-to-top classes or from top-to-bottom classes.
Extreme upward and downward mobility is very rare and highly differentiated by discipline; in some disciplines, it almost never (CHEMENG, COMP, ENG, upward mobility) or never (CHEMENG, COMP, downward mobility) occurs, regardless of the productivity type. The highest chances to enter the top mobility class are when non-normalized fractional counting is used, which, in some disciplines, is twice as high as when prestige-normalized counting is used (BIO, EARTH, MATER), which may suggest a generally lower status of journals to which the articles in these disciplines are published. In CHEMENG and COMP, there are no chances for radical downward mobility: once they have become top-productive assistant professors, they will always remain top productive as associate professors.

Model Approach: Logistic Regression

First, we discuss four models—one for each productivity type—by estimating the odds of membership in the top productivity class for associate professors (top 20%); and second, we discuss four models estimating the odds of membership in the bottom productivity class for associate professors (bottom 20%).

Logistic Regression: Top Productivity Associate Professors

Four logistic regression models have been constructed for four productivity types, where success is entering the class of the 20% most productive associate professors. The selection of variables is guided by literature on productivity (e.g., Lee and Bozeman 2005; Ramsden 1994; Shin and Cummings 2010; Teodorescu 2000) and high productivity (e.g., Abramo et al. 2009; Fox and Nikivincze 2021), as well as by data availability.

In the first step, observations are selected for the model to be built. Leverage value is used for extraction of outliers (Field at al. 2012: 269–271). Leverage is a measure of how far the values of the independent variables in an observation are from the values of other observations. High leverage points, if present, are outliers with respect to the independent variables. In practice, this means that observations with high leverage are influential observations that strongly affect parameter estimates (Chatterjee and Hadi 1986). Several such observations are observed and removed from the set of observations.

In the next step, an analysis of the presence of collinearity among the independent variables is performed. For this purpose, inverse correlation matrices are estimated, and the values from their main diagonals are used (see Supplementary Table 6). The values show the degree of correlation of a given variable with all other variables. The variables that have a value significantly higher than the others are considered significantly correlated. In our case, the variables with a relatively high degree of multivariate correlation are biological age and the age of receiving habilitation. Because of the centrality of these variables to the advancement of academic careers (and to the analysis) and the fact that the degree of correlation of these variables is not high, the variables remain in the analysis. The residual statistics distribution is discussed in Electronic Supplementary Material.

One predictor proves to be the most important in the four models used: associate professors' membership in the class of top productivity assistant professors earlier in their careers (we track exactly the same scientists changing productivity classes over time.) This prior membership in top productivity classes turns out to be statistically significant in all models to a similar, extremely high degree, increasing the chances of entering the class of top-productive associate professors by about 4–6 times, depending on the type of productivity.

The odds increase significantly more for Models 2 and 4 (i.e., non-normalized) compared with Models 1 and 3 (i.e., prestige normalized). This could mean that the Polish academic system is already stratified along the lines of journal prestige: the publishing patterns in prestigious journals differ from those in journals in general. For prestige-normalized productivity models, the odds increase 4 times (fractional counting) and 4.5 times (full counting). In contrast, for non-normalized productivity models, the odds increase 5.5 times (fractional counting) and almost 6 times (full counting). In all four cases, the significance level is lower than 0.001, with reasonable 95% confidence (Table 5).

Thus, the multidimensional analysis strongly confirms the results of the two-dimensional analysis presented in previous sections: given the joint effect of all variables, the impact of membership in top productivity class in the past as an assistant professor (all other things being equal) is by far the strongest predictor of the current membership top productivity class. The models confirm our exploratory intuitions about changing productivity classes between the two career stages from a longitudinal perspective: when scientists are currently top productive at the stage of associate professorship, they tend to have been top productive at the earlier stage of assistant professorship. No matter how productivity is measured—full counting or fractional counting or prestige-normalized or non-normalized approaches—the patterns emerging from our regression analysis are very similar.

Prior membership in the promotion speed class of fast associate professors also proves to be statistically significant in all models. Fast associate professors are the scientists belonging to the 20% of scientists having the shortest time between their doctorate and habilitation, that is, between the start of their career as assistant professors and start of their career as associate professors. Belonging to a class of fast associate professors increases the probability of success by half to three-quarters (from 52% in Model 4 to 77% in Model 2). A very interesting result that is common to all productivity types is that neither membership in the class of scientists receiving a doctorate at a young age (variable: young assistant professor class) nor membership in the class of scientists receiving a habilitation at a young age (variable: young associate professor class) is statistically significant. Based on the literature, it may seem that the variable of membership in the young assistant professors class (the top

20%) and that in the young associate professors class (the top 20%) are important predictors of membership in the top productivity class. However, they are not statistically significant.

Interestingly, gender does not appear in any of the four models. The logistic regression analysis powerfully supports our two-dimensional results, in which the differences between men and women in horizontal top-to-top transitions are noticeable across most disciplines but, except for a few disciplinary cases, statistically insignificant (not shown here because of space limitations). This is a finding with important implications in the context of the literature on gender disparities in research productivity. Our results show that, with no gender differences, once male and female scientists gain membership in top productivity classes early in their careers, they tend to continue to belong to top productivity classes later on as associate professors.

In three of the four models (Models 1–3), biological age significantly and negatively affects the probability of success. Each additional year of age lowers the probability greatly, on average by as much as 3.7% to 6.3%. Also important here, academic age does not appear to be a predictor in any model. Membership in the class of the most productive associate professors is strongly negatively affected by biological age and, thus, by biological aging rather than by academic age as a proxy of academic experience. In an earlier study, we have shown (Kwiek and Roszka 2022) that the correlation between biological age and academic age for STEMM fields is very high (correlation coefficient $r=0.9$ for chemistry and $r=0.88$ for physics and astronomy, where we surveyed 20,569 Polish scientists with at least a PhD and compared their biological age and academic age). Our models indicate that aging has a negative effect and longer academic experience has no positive effect on membership in the class of top-productive associate professors.

Importantly, the direction and, to a large extent, the strength of predictors generally do not depend on the model, that is, on the approach to productivity selected. Regardless of how productivity is measured, the statistically significant predictors are the same. By far, the strongest predictor of membership in the top productivity class of associate professors is prior membership in the top productivity class as assistant professor, which is consistent with our two-dimensional analyses of horizontal top-to-top mobility between productivity classes.

Table 5. Logistic regression statistics: odds ratio estimates of membership in the class of top-productive associate professors (upper 20%, separately for each discipline) (N=4019).

Model	Model 1: Prestige-normalized full counting $R^2 = 0.174$, N=4019				Model 2: Non-normalized full counting $R^2 = 0.183$, N=4019				Model 3: Prestige-normalized fractional counting $R^2 = 0.168$, N=4019				Model 4: Non-normalized fractional counting $R^2 = 0.159$, N=4019			
	Exp(B)	95% C.I. for Exp(B)		Sig.	Exp(B)	95% C.I. for Exp(B)		Sig.	Exp(B)	95% C.I. for Exp(B)		Sig.	Exp(B)	95% C.I. for Exp(B)		Sig.
		Lower	Upper			Lower	Upper			Lower	Upper			Lower	Upper	
Male																
Research intens.: Rest																
Biological age	0.937	0.908	0.966	<0.001	0.963	0.936	0.992	0.006	0.940	0.911	0.969	<0.001				
Academic age																
Assistant_age									1.051	1.005	1.098	0.032				
Associate_age													0.951	0.916	0.987	0.011
Top_Assistant_class	4.490	3.64	5.538	<0.001	5.944	4.896	7.217	<0.001	4.148	3.384	5.084	<0.001	5.466	4.527	6.600	<0.001
Young_Assistant_class																
Young_Associate_class																
Fast_Associate_class	1.686	1.282	2.219	<0.001	1.771	1.345	2.330	<0.001	1.596	1.214	2.098	0.001	1.516	1.154	1.993	0.004
Constant	2.919	0.879	9.687	0.081	1.267	0.405	3.967	0.687	2.135	0.671	6.793	0.195	1.677	0.544	5.166	0.369

Logistic Regression: Bottom Productivity Associate Professors

Subsequently, four logistic regression models have been built for four productivity types, where success is entering the 20% bottom-productive associate professors. Prior research on the productivity and productivity of Polish scientists in particular (e.g., Antonowicz et al. 2019) is instrumental in constructing the models. We will not discuss the results of standardized residuals statistics and the inverted correlation matrix main diagonal (see Supplementary Table 7) for the four models. Suffice it to say that the variables with a relatively high degree of multivariate correlation are biological age and age of obtaining habilitation. Given the centrality of these variables to the analysis and the fact that the degree of correlation of these variables is not high, the variables are retained in the analysis. The residuals statistics distribution in our models is not normal; see Supplementary Table 9). To overcome the model's inconsistency with assumptions, robust standard errors are estimated, and based on the estimates, a significance test has been conducted for each coefficient in the model (Croux et al. 2004), as in the case of top-productive associate professors above.

The strongest predictor increasing the probability of membership in the class of bottom-productive associate professors is earlier membership in the class of bottom-productive assistant professors (Table 6). The probability of success increases by about one-fourth (in the range of 21%–27%, depending on the productivity type used in the model), with prior membership emerging as a major positive predictor in all models. At the same time, it should be noted that the confidence intervals of the parameters of each model overlap so that membership in the class of bottom productivity assistant professors has the same negative effect in each case. Again, logistic regression analysis supports our two-dimensional results showing the role of high horizontal bottom-to-bottom mobility, although not as strongly as in the case of top-productive associate professors.

In all four models, the role of age-related predictors is important. Both biological and academic age are statistically significant predictors, though in different directions: biological age with positive effects and academic age with negative effects. With every additional year of age, the probability of membership in the bottom productivity class for associate professors increases by 1.7% (in Model 1 and Model 3), and it increases slightly in the other two models. In contrast, in two models, every additional year of academic age slightly (below 1%) decreases the probability of membership in this class. Membership in the old associate professor class decreases the probability by 5.1%–6.4% only in Models 3 and 4, and membership in the late associate professor class increases the odds by 6.8% only in Model 3. The age at which scientists receive their habilitation degree (variable: associate_age) is statistically significant: an increase by one year then increases the probability of membership in this class by about 1% or less, depending on the model; and in Model 3, the probability of membership in this class decreases by 1% with every additional year of age at which the doctoral degree has been awarded (variable: assistant_age).

Generally, the predictors in the models constructed for bottom productivity associate professors are much weaker than the predictors in the models constructed for top productivity associate professors. The directions of impact are usually opposite, which is especially visible in the case of age-related predictors. In both cases, the most powerful predictor in all models, that is, regardless of the productivity type used, is prior membership in top productivity (or bottom productivity) class at the stage of assistant professorship.

Table 6. Logistic regression statistics: odds ratio estimates of membership in the class of bottom productive associate professors (the bottom 20%, separately for each discipline).

Model	Model 1: Prestige-normalized full counting $R^2 = 0.177$, N=4019				Model 2: Non-normalized full counting $R^2 = 0.123$, N=4019				Model 3: Prestige-normalized fractional counting $R^2 = 0.158$, N=4019				Model 4: Non-normalized fractional counting $R^2 = 0.092$, N=4019			
	Exp(B)	95% C.I. for Exp(B)		Sig.	Exp(B)	95% C.I. for Exp(B)		Sig.	Exp(B)	95% C.I. for Exp(B)		Sig.	Exp(B)	95% C.I. for Exp(B)		Sig.
		Lower	Upper			Lower	Upper			Lower	Upper			Lower	Upper	
Male																
Research intens.: Rest																
Biological age	1.017	1.013	1.020	<0.001	1.004	1.001	1.008	0.03	1.017	1.014	1.021	<0.001	1.002	0.998	1.006	0.329
Academic age	0.997	0.995	0.999	0.004					0.997	0.995	0.999	0.007	1	0.998	1.002	0.923
Assistant_age					0.990	0.984	0.996	<0.001								
Associate_age					1.009	1.005	1.014	<0.001	0.993	0.989	0.998	0.011	1.008	1.003	1.013	0.003
Bottom_Assistant	1.246	1.207	1.287	<0.001	1.270	1.229	1.313	<0.001	1.215	1.177	1.255	<0.001	1.226	1.187	1.267	<0.001
Old_Assistant_class																
Old_Associate_class									0.936	0.897	0.977	0.005	0.949	0.907	0.992	0.031
Late_Associate_class									1.068	1.025	1.114	0.006				
Constant	0.724	0.618	0.848	<0.001	0.842	0.712	0.994	0.04	0.73	0.622	0.857	<0.001	0.801	0.676	0.95	0.011

Discussion and Conclusions

The strength of the present research comes from its unique national datasets and its methodological approach. First, this research has solid empirical foundations: the productivity of all Polish internationally visible associate professors in 12 STEMM disciplines (N = 4,434) has been studied, and their full individual publication portfolios and full individual biographical histories are examined. Biographical and demographic data from a national registry of scientists are combined with publication metadata, including all Polish articles published in the past half a century and indexed in Scopus (1973–2021, N = 935,167). Second, in terms of methodology, the individual scientist, rather than the individual publication, has been used as a unit of analysis; productivity by four major types is used to assess the extent to which measurement methods can impact the patterns found; and productivity classes (top 20%, middle 60%, bottom 20%) rather than publication numbers are used. Specifically, prestige-normalized productivity (in which articles' locations in the global stratified journal system are applied) is contrasted with non-normalized productivity (both in full counting and fractional counting types). Finally, a longitudinal research design has been used, in which productivity over years and decades, as linked to two subsequent career stages of assistant professorship and associate professorship, can be traced. Individuals are followed over time with full promotion and demographic (national registry of scientists) and publication (Scopus-indexed) data.

Our dataset includes publishing patterns of assistant professors and associate professors spanning over decades because, in the Polish system, there are no externally imposed requirements for promotions: the associate professors in our sample work for decades in the system, and more than half of them (46.4%) are aged 50 or older.

Our longitudinal analyses have focused on the mobility between productivity classes for assistant and associate professors. Our results show that the majority of top productivity scientists continue as top productivity scientists, about 40% of bottom productivity scientists continue as bottom productivity scientists, and a very small percentage of scientists change their productivity classes radically, from bottom to top or from top to bottom. Extreme interclass mobility (downward top-to-bottom mobility, upward bottom-to-top mobility) have emerged in our research as a marginal phenomenon: less than 2% (1.00%–1.86%, depending on productivity type) of all current associate professors experience either type of this mobility in their career histories. They are very rare scholarly species: there are about three dozen of the former and two dozen of the latter in a sample of 4,019 scientists.

In the current research on associate professors (who constitute a substantial segment of the Polish academic profession with doctorates, 30% in 2022), we have confirmed all the patterns previously found in our research on full professors (who constitute a small top level of the Polish academic profession with doctorates, 13% in 2022) (Kwiek and Roszka 2023a). Our current study, based on a different, non-overlapping sample and four productivity types shows, somewhat surprisingly, almost identical patterns compared to our initial study based on a single productivity type (prestige-normalized, full counting method only). Both general patterns for all disciplines combined and for separate discipline-level patterns are similar, and the regression models show similar predictors. Consequently, more telling generalizations can be formulated about the powerful class-based productivity immobility characterizing the Polish system.

Both for scientists and decision makers in science policy at various levels, the message is challenging: even though anecdotal knowledge suggests that radical changing productivity levels (upward or downward) in STEMM is always theoretically possible, our data show that it actually almost never happens in practice. Low-probability transitions do happen, as the individual micro-level data in our dataset show, but their role should not be overestimated.

In other words, some scientists tend to be highly productive for years and decades, and others—their colleagues in institutions and their peers within disciplines—tend to be bottom productive for years. There are marginal probabilities that scientists will be radically more or radically less productive when they move up the academic ladder.

Importantly, no matter which of the four productivity types are used, more than 50% of assistant professors from top productivity class continue as top productivity class associate professors (53.3%–56.5%, depending on productivity type). The cross-disciplinary differentiation is notable, and the patterns differ across productivity types: in some disciplines, the percentage of scientists experiencing top-to-top mobility reaches almost 70% (e.g., 68.8% in chemical engineering CHEMENG in Productivity 1, 69.6% in physics and astronomy PHYS, and 67.3% in earth and planetary sciences EARTH in Productivity 2).

Also, the discipline-aggregated picture of about 40% of scientists from the bottom productivity class as assistant professors staying on in the same bottom productivity class as associate professors hides a much more differentiated picture. In some disciplines, using some productivity types, the percentage reaches 50%–60% (e.g., 58.8% in computing COMP in Productivities 1 and 3); and in others, it is about one-third or less (e.g., 29.2% in materials science MATER in Productivity 2 and 28.5% in medicine MED in Productivity 4). In sum, depending on the discipline, between 30% and 60% of bottom-productive assistant professors continue their careers as bottom-productive associate professors. Compared with the persistence of "stardom" examined by Abramo et al. (2017) for Italy, the shares of Polish top performers in both career stages are considerably higher (55.0% for all STEMM disciplines combined) than the shares of top scientists maintaining their high productivity or "stardom" over a period of 12 years (35%). Productivity stratification seems deeper and more long-lasting in Poland than in Italy, possibly because of decades of severe research underfunding.

Logistic regression analysis powerfully supports our two-dimensional results. In the case of the odds ratio estimates of the membership in the top productivity class of associate professors, one predictor proves to be the most important in the four models used: the associate professors' membership in the class of top-productive assistant professors earlier in their careers. This prior membership is statistically significant in all models to a similarly high degree, increasing the odds 4–6 times, depending on productivity type. Prior membership in the promotion speed class of fast associate professors (scientists belonging to the 20% group with the shortest time between starting their careers as assistant professors and starting their careers as associate professors) also is statistically significant in all models. Membership increases the chances of success by one-half to three-quarters (52%–77%, depending on the model). In the case of the odds ratio estimates of the membership in the bottom productivity class of associate professors, the strongest predictor is prior membership in the class of bottom-productive assistant professors. The probability of success increases by about one-fourth (in the range of 21%–27%, depending on the productivity type used in the model). Interestingly, gender does not emerge as a statistically significant predictor of membership in either class.

From a larger perspective, our study shows that the traditional notion of "strong" and "weak" individual track record in research—here linked only to productivity and not linked to citation impact, generation of research funding, or other dimensions of academic careers—makes good sense in evaluating individual scientists.

Scientists with a very weak past track record in research emerge from our research as having marginal chances of becoming scientists with a very strong future track record across all STEMM disciplines. Traditionally, the science edifice has been so constructed that highly productive scientists—those with significant impact on disciplinary scientific communities—are highly recognized. Our always-top scientists—those staying in top productivity classes at both assistant professorship and associate professorship levels of academic careers—constitute about 10% of our sample.

The takeaway from the present research for academic careers is that early achievements in science, when viewed through a proxy of early top productivity, significantly influence achievements at a later stage, that is, late top productivity. If the assistant professorship period is strong in publications, the associate professorship period tends to be strong too; analogously, if it is weak in publications, associate professorship also tends to be weak. Our micro-level data show that scientists tend to be stuck in their productivity classes for years and decades: top performers tend to be top performers, and bottom performers tend to be bottom performers; the former becoming the latter or the latter becoming the former are extremely rare phenomena. Consequently, increasing the productivity limits early on in academic careers tends to pay off later on in careers, with later productivity being powerfully supported by earlier productivity.

The transition patterns found are understandable in light of traditional productivity theories (especially sacred spark theory, e.g., Allison and Stewart 1974; Cole and Cole 1973; Fox 1983; and cumulative advantage theory, e.g., David 1994; DiPrete and Eirich 2006; Merton 1973). However, the strength of the patterns found in our research across different disciplines and different productivity types is somehow unexpected; what is especially surprising is the very high persistence of membership in productivity classes across academic careers and very low chances of radically changing productivity classes.

Consequently, our research shows a long-term character of careers in science, with productivity (and possibly other working patterns) in an apprenticeship period of assistant professorship heavily influencing productivity in a more independent period of associate professorship. We can assume that working patterns, often based on the role models of academic supervisors, research orientation, weekly working time distribution, writing habits, and collaboration habits, take years to form and tend to stay with individuals in their careers for years. Science takes a lot of time (weekly, monthly, yearly); additionally, the academic careers of highly productive scientists take time to form: years or decades of previous high productivity. It is difficult to assess the generalizability of our results to other national systems at this point; however, our future research includes a large cross-national comparative study of 38 OECD countries.

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Declarations

Conflicts of interests/Competing interests

The authors state that there is no conflict of interest.

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Electronic Supplementary Material to:

Are Scientists Changing their Research Productivity Classes When They Move up the Academic Ladder?

Supplementary tables

Supplementary Table 1. Mobility between productivity classes while moving up from assistant professorship stage to associate professorship stage, by four productivity types, all disciplines combined

Transition from source academic position		**Transition from productivity class**	**Transition to target academic position**	**Transition to productivity class**	**Number of scientists in transition**	**Number of scientists in each productivity class**	**%**
Productivity 2 (non-normalized, full counting)	Asst Prof.	Bottom	Assoc Professor	Bottom	328	814	40.3
	Asst Prof.	Bottom	Assoc Professor	Middle	447	814	54.9
	Asst Prof.	Bottom	Assoc Professor	Top	39	814	4.8
	Asst Prof.	Middle	Assoc Professor	Bottom	360	2377	15.1
	Asst Prof.	Middle	Assoc Professor	Middle	1637	2377	68.9
	Asst Prof.	Middle	Assoc Professor	Top	380	2377	16
	Asst Prof.	Top	Assoc Professor	Bottom	28	828	3.4
	Asst Prof.	Top	Assoc Professor	Middle	331	828	40
	Asst Prof.	Top	Assoc Professor	Top	469	828	56.6
	Asst Prof.	Bottom			716	716	100
	Asst Prof.	Middle			2415	2415	100
	Asst Prof.	Top			888	888	100
	Assoc Pr.	Bottom			814	814	100
	Assoc Pr.	Middle			2377	2377	100
	Assoc Pr.	Top			888	888	100
Productivity 3 (prestige-normalized, fractionalized counting)	Asst Prof.	Bottom	Assoc Professor	Bottom	332	811	40.9
	Asst Prof.	Bottom	Assoc Professor	Middle	452	811	55.7
	Asst Prof.	Bottom	Assoc Professor	Top	27	811	3.3
	Asst Prof.	Middle	Assoc Professor	Bottom	335	2395	14
	Asst Prof.	Middle	Assoc Professor	Middle	1649	2395	68.9
	Asst Prof.	Middle	Assoc Professor	Top	411	2395	17.2
	Asst Prof.	Top	Assoc Professor	Bottom	30	813	3.7
	Asst Prof.	Top	Assoc Professor	Middle	350	813	43.1
	Asst Prof.	Top	Assoc Professor	Top	433	813	53.3
	Asst Prof.	Bottom			697	697	100
	Asst Prof.	Middle			2451	2451	100
	Asst Prof.	Top			871	871	100
	Assoc Pr.	Bottom			811	811	100
	Assoc Pr.	Middle			2395	2395	100
	Assoc Pr.	Top			813	813	100
Productivity 4 (non-normalized, fractionalized counting)	Asst Prof.	Bottom	Assoc Professor	Bottom	295	807	36.6
	Asst Prof.	Bottom	Assoc Professor	Middle	467	807	57.9
	Asst Prof.	Bottom	Assoc Professor	Top	45	807	5.6
	Asst Prof.	Middle	Assoc Professor	Bottom	401	2396	16.7
	Asst Prof.	Middle	Assoc Professor	Middle	1607	2396	67.1
	Asst Prof.	Middle	Assoc Professor	Top	388	2396	16.2
	Asst Prof.	Top	Assoc Professor	Bottom	24	816	2.9
	Asst Prof.	Top	Assoc Professor	Middle	353	816	43.3
	Asst Prof.	Top	Assoc Professor	Top	439	816	53.8
	Asst Prof.	Bottom			720	720	100
	Asst Prof.	Middle			2427	2427	100
	Asst Prof.	Top			872	872	100
	Assoc Pr.	Bottom			807	807	100
	Assoc Pr.	Middle			2396	2396	100
	Assoc Pr.	Top			816	816	100

Supplementary Table 2. Top-to-top mobility by discipline and productivity type (Productivity 2 through 4)

Discipline	Productivity 2. Non-normalized full counting		Productivity 3. Prestige-normalized fractional counting		Productivity 4. Non-normalized fractional counting	
	Assistant professors: top to top (%)	**As % of top associate professors**	**Assistant professors: top to top (%)**	**As % of top associate professors**	**Assistant professors: top to top (%)**	**As % of top associate professors**
AGRI	55.6	48.1	53.2	45.7	53.1	46.2
BIO	52.5	50.8	52.5	50.8	54.1	51.6
CHEM	53.1	50.7	60.3	56.7	56.5	53.0
CHEMENG	62.5	58.8	68.8	64.7	56.2	52.9
COMP	52.9	52.9	55.9	54.3	55.9	54.3
EARTH	67.3	62.3	50.0	45.3	67.3	64.7
ENG	55.7	50.7	51.6	47.0	53.7	48.5
ENVIR	60.8	55.8	57.0	53.6	57.7	52.9
MATER	56.1	51.4	50.8	49.2	46.2	46.2
MATH	55.8	52.2	50.0	45.7	54.8	50.0
MED	51.9	51.1	51.6	50.8	46.5	45.8
PHYS	69.6	66.7	50.0	47.9	58.7	56.3
Total	**56.6**	**52.8**	**53.3**	**49.7**	**53.8**	**50.3**

Supplementary Table 3. Bottom-to-bottom mobility by discipline and productivity type (Productivity 2 through 4)

Discipline	Productivity 2. Non-normalized full counting		Productivity 3. Prestige-normalized fractional counting		Productivity 4. Non-normalized fractional counting	
	Assistant professors: bottom to bottom (%)	**As % of bottom associate professors**	**Assistant professors: bottom to bottom (%)**	**As % of bottom associate professors**	**Assistant professors: bottom to bottom (%)**	**As % of bottom associate professors**
AGRI	35.3	42.7	43.0	53.3	40.4	47.9
BIO	40.7	42.9	41.0	43.9	38.3	39.7
CHEM	46.7	50.9	51.7	56.6	44.8	48.1
CHEMENG	50.0	57.1	43.8	58.3	62.5	76.9
COMP	52.9	64.3	58.8	69.0	55.9	67.9
EARTH	42.9	48.8	38.0	43.2	30.0	31.9
ENG	40.7	48.1	36.1	41.1	37.7	44.2
ENVIR	41.0	48.5	34.2	45.0	29.5	33.8
MATER	29.2	32.2	33.8	39.3	29.7	31.1
MATH	35.7	44.1	47.6	57.1	38.1	44.4
MED	43.2	45.4	39.5	44.1	28.5	30.7
PHYS	38.3	42.9	43.5	48.8	37.0	41.5
Total	**40.3**	**45.8**	**40.9**	**47.6**	**36.6**	**41.0**

Supplementary Table 4. Bottom-to-top mobility by discipline and productivity type (Productivity 2 through 4)

Discipline	Productivity 2. Non-normalized full counting		Productivity 3. Prestige-normalized fractional counting		Productivity 4. Non-normalized fractional counting	
	Assistant professors: bottom to top (%)	As % of top associate professors	Assistant professors: bottom to top (%)	As % of top associate professors	Assistant professors: bottom to top (%)	As % of top associate professors
AGRI	2.6	2.3	6.9	5.9	4.4	3.8
BIO	3.3	3.2	5.1	4.8	10.0	9.4
CHEM	1.7	1.5	5.0	4.5	6.9	6.1
CHEMENG	0.0	0.0	6.2	5.9	0.0	0.0
COMP	0.0	0.0	0.0	0.0	2.9	2.9
EARTH	0.0	0.0	0.0	0.0	4.0	3.9
ENG	4.1	3.7	4.9	4.5	4.1	3.7
ENVIR	8.9	8.3	3.8	3.5	2.6	2.4
MATER	3.1	3.1	3.1	2.8	7.8	7.7
MATH	0.0	0.0	7.1	6.5	7.1	6.5
MED	4.8	4.6	6.4	6.0	8.1	7.6
PHYS	2.2	2.1	4.3	4.2	4.3	4.2
Total	**3.3**	**3.1**	**4.8**	**4.4**	**5.6**	**5.1**

Supplementary Table 5. Top-to-bottom mobility by discipline and productivity type (Productivity 2 through 4)

Discipline	Productivity 2. Non-normalized full counting		Productivity 3. Prestige-normalized fractional counting		Productivity 4. Non-normalized fractional counting	
	Assistant professors: top to bottom (%)	As % of bottom associate professors	Assistant professors: top to bottom (%)	As % of bottom associate professors	Assistant professors: top to bottom (%)	As % of bottom associate professors
AGRI	3.6	4.3	3.4	4.2	1.8	2.1
BIO	1.6	1.8	3.3	3.6	4.9	5.2
CHEM	0.0	0.0	1.6	1.8	1.6	1.9
CHEMENG	0.0	0.0	0.0	0.0	0.0	0.0
COMP	0.0	0.0	0.0	0.0	0.0	0.0
EARTH	8.3	9.1	0.0	0.0	4.1	4.3
ENG	5.7	6.5	2.5	2.9	3.3	3.8
ENVIR	5.1	6.7	7.6	9.1	3.8	4.4
MATER	1.6	1.8	3.0	3.4	3.1	3.3
MATH	4.8	5.7	4.7	5.9	4.8	5.6
MED	3.9	4.5	5.3	5.9	3.1	3.5
PHYS	4.3	4.9	2.2	2.4	2.2	2.4
Total	**3.7**	**4.3**	**3.4**	**3.9**	**2.9**	**3.3**

Supplementary Table 6. Inverted correlation matrix, main diagonal, top classes models

Variable	Productivity 1. Prestige-normalized full counting	Productivity 2. Non-normalized full counting	Productivity 3. Prestige-normalized fractional counting	Productivity 4. Non-normalized fractional counting
Male	1.046	1.048	1.046	1.048
Research intensive: Rest	1.028	1.028	1.027	1.027
Biological age	6.549	6.207	6.422	5.999
Academic age	2.065	2.097	2.056	2.077
Assistant_professor_age	2.642	2.651	2.644	2.652
Associate__professor_age	5.785	5.652	5.750	5.606
Top_Assistant_Professor_class	1.365	1.230	1.311	1.182
Young_Assistant_Professor_class	1.875	1.872	1.875	1.873
Young_Associate_Professor_class	2.507	2.513	2.507	2.505
Fast_Associate_Professor_class	2.151	2.144	2.144	2.150

Supplementary Table 7. Inverted correlation matrix main diagonal, bottom classes models

Variable	Productivity 1. Prestige-normalized full counting	Productivity 2. Non-normalized full counting	Productivity 3. Prestige-normalized fractional counting	Productivity 4. Non-normalized fractional counting
Male	1.034	1.034	1.034	1.034
Research intensive	1.027	1.028	1.027	1.027
Biological age	8.026	7.469	7.514	6.970
Academic age	2.156	2.239	2.154	2.238
Assistant_age	4.596	4.600	4.587	4.602
Associate_age	8.584	8.277	8.427	8.115
Bottom_Assistant_professor_class	1.539	1.424	1.435	1.333
Old_Assistant_professor_class	2.796	2.796	2.797	2.795
Old_Associate_professor_class	3.098	3.097	3.098	3.098
Late_Associate_professor_class	2.839	2.837	2.836	2.836

The residual statistics distribution in our models is not normal (i.e., the D statistic of the K-S normality test is equal to 0.268–0.292, with a p-value smaller than 0.001 in each case, which means rejecting the null hypothesis that the empirical distribution conforms to a normal distribution; see Table 9). The normality of the distribution of the residuals allows statistical inference about the properties of the model because all tests of statistical significance assume the normality of the distribution. To overcome the model's inconsistency with assumptions, robust standard errors are estimated, and based on the estimates, a significance test is conducted for the specific coefficients in the model (Croux et al. 2004). The next step in analyzing the distribution of residuals indicates that there are no influential observations (because the range of standardized residuals is unlikely to exceed ± 3 standard deviations). Consequently, the conclusions drawn from our model are valid.

Supplementary Table 8. Standardized residual statistics, top classes models

Statistics	**Productivity 1. Prestige-normalized full counting**	**Productivity 2. Non-normalized full counting**	**Productivity 3. Prestige-normalized fractional counting**	**Productivity 4. Non-normalized fractional counting**
Mean	0.00	0.00	0.00	0.00
Median	1.00	1.00	1.00	1.00
Std.Dev	-0.30	-0.28	-0.28	-0.28
Q1	-0.43	-0.46	-0.43	-0.44
Q3	-0.07	-0.07	-0.08	-0.07
IQR	0.36	0.39	0.35	0.38
Min	-1.83	-1.86	-1.93	-1.90
Max	2.70	2.70	2.66	2.75
K-S statistic	0.277	0.268	0.276	0.292
p-value	<0.001	<0.001	<0.001	<0.001

Supplementary Table 9. Standardized residuals statistics, bottom classes models

Productivity 1. Prestige-normalized full counting	**Productivity 2. Non-normalized full counting**	**Productivity 3. Prestige-normalized fractional counting**	**Productivity 4. Non-normalized fractional counting**	**Productivity 1. Prestige-normalized full counting**
Mean	0.00	0.00	0.00	0.00
Median	-0.23	-0.28	-0.24	-0.30
Std.Dev	1.00	1.00	1.00	1.00
Q1	-0.47	-0.46	-0.49	-0.51
Q3	-0.03	-0.12	-0.05	-0.16
IQR	0.44	0.34	0.44	0.35
Min	-1.83	-1.75	-1.78	-1.48
Max	2.97	2.71	2.94	2.66
K-S statistic	0.306	0.313	0.308	0.321
p-value	<0.001	<0.001	<0.001	<0.001