The Young and the Old, the Fast and the Slow: Age, Productivity, and Rank Advancement of 16,000 STEMM University Professors

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Abstract

We examined a large population of Polish science, technology, engineering, mathematics and medicine (STEMM) scientists (N = 16,083) to study rank advancement and productivity. We used two previously neglected time dimensions—promotion age and promotion speed—to construct individual biographical profiles and publication profiles. We used a classificatory approach and the new methodological approach of journal prestige-normalized productivity. All scientists were allocated to different productivity, promotion age, and promotion speed classes (top 20%, middle 60%, and bottom 20%). The patterns were consistent across all disciplines: scientists in young promotion age classes (and fast promotion speed classes) in the past were currently the most productive. In contrast, scientists in old promotion age classes (and slow promotion speed classes) in the past were currently the least productive. In the three largest disciplines, the young-old promotion age productivity differential for associate professors was 100-200% (150-200% for full professors); and the fast-slow promotion speed productivity differential for associate professors was 80-150% (100-170% for full professors). Our results were confirmed by a regression analysis in which we found odds ratio estimates of membership in top productivity classes. We combined data collected from the national register of all Polish scientists and scholars (N = 99,935) and publication metadata on all Polish articles indexed in Scopus (N = 935,167).

1. Introduction

The relationship between a scientist's age and research productivity has long been examined in the literature (Bayer and Dutton 1977; Cole 1979; Diamond 1984; Abramo et al. 2011). Productivity and age have also been found to be associated with promotions in academic careers (Tien and Blackburn 1996; Altbach et al. 2012; Finkelstein et al. 2016). Promotions to each successive stage in an academic career occur at a certain age and after a certain period has elapsed following an earlier promotion. Thus, two independent time dimensions affect successful careers: promotion age and promotion speed. Sociologists have long argued that "scientists are not only concerned with achieving high rank, but in doing so as quickly as possible. Some measure of recognition is garnered by the distinction of being a 'young' associate or a 'young' full professor" (Cole and Cole 1973: 130; Cole J.R. 1979: 56). The timing of promotions is considered indicative of success (Long et al. 1993).

Moving up the academic career ladder is a common aspiration in academe, the success of which can be examined using biological age and time between promotions. Some receive successive promotions at a young age and others at an older age. Additionally, some are promoted quickly, while others are promoted slowly, and the amount of time between promotions is shorter or longer. A global pattern shows that while promotion age is not specified, promotion speed is similar in each successive career stage (Altbach et al. 2012; Yudkevich et al. 2015). However, the Polish system differs: promotions are determined mainly based on research, and at each stage, production needs to be assessed as satisfactory. The time factor is not important in terms of research achievement. In the science, technology, engineering, mathematics and medicine (STEMM) disciplines studied here, publications indexed in international publication databases (e.g., Web of Science and Scopus) have been of particular importance for scientific advancement for at least 20 years.

A critical step in the present study was the allocation of all scientists to Young (top 20%), Middle (middle 60%), and Old (bottom 20%) classes at each career stage in terms of promotion age and to Fast (top 20%), Typical (middle 60%), and Slow (bottom 20%) classes at each career stage in terms of promotion speed or time in rank. Using the time dimension in an academic career, scientists at each stage were classified separately into segments of 20/60/20 in each discipline. Our main research questions concerned whether scientists in the Young and Fast classes were substantially more productive than those in the Old and the Slow classes, and whether similar patterns held across different academic disciplines. Are these retrospectively constructed classes in scientists' careers—Young, Middle, and Old; and Slow, Typical, and Fast—correlated with current research productivity?

Within our Polish Science Observatory database, we have a full history of academic careers of all scientists currently employed full-time in the higher education sector, including, in particular, a full publication profile (all publications lifetime from the Scopus database) and a full biographical profile (detailed history of scientific promotions from the national register of scientists). We are able to link the current scientific productivity of scientists to their retrospectively constructed promotion age classes and promotion speed classes. We constructed these classes retrospectively by looking back at the respective dates of scientific promotion and retrospectively assigning all scientists in our sample to the tripartite promotion age classes and promotion speed classes in the past. We also assigned each scientist to their current productivity class (in 20/60/20 terms: Top, Middle, and Bottom class).

This paper is structured as follows: the Introduction is followed by the Theoretical Framework and Results sections. The Results section presents descriptive findings, followed by logistic regression results where we move from two-dimensional to multidimensional analyses (section 4.5). First, we describe the distribution of promotion age and promotion speed in our sample (section 4.1). Then, we present a coexistence analysis of promotion age classes and promotion speed classes (section 4.2), followed by two sections on productivity: current productivity and past promotion age classes (section 4.3), and current productivity and past promotion speed classes (section 4.4). The Discussion and Conclusions section concludes the paper.

2. Theoretical Framework

As classical students of social stratification in science have described, "the critical part of recognition associated with rank is the achievement of high rank in a high-prestige department at a relatively early age" (Cole and Cole 1973: 131). Abramo et al. (2016: 15) have recently shown that "an individual who gains promotion to full professor at young age then maintains and increases his/her productivity more than colleagues who are promoted at later age." Furthermore, "the post-promotion productivity of full professors who are nominated at a young age is higher than that of their colleagues who are promoted at a later age" (Abramo et al. 2016: 15). The association between productivity, rank advancement, and age has long been a scholarly theme in the sociology of science and the economics of science (e.g., Levin and Stephan 1991; Stephan and Levin 1992; Long et al. 1993; David 1994; Stephan 2012). In the present study, the young and fast promotion age classes and the old and slow promotion speed classes of three academic ranks were compared in terms of their current productivity.

In the US, faculty ranks have been examined for decades (see Finkelstein et al. 2016). Ranks stratify the academic profession, and each career step represented in subsequent promotions results in upgrades in prestige and salaries (Tien and Blackburn 1996). Research has traditionally been conducted to achieve promotion, which is an extrinsic motivation, rather than for the sake of contributing to knowledge, which is an intrinsic motivation (see Stephan and Levin 1992; Stephan 2012). Moreover, research production has been shown to evidence observable pre-promotion peaks and post-promotion pauses (Katz 1973). Promotion requirements tend to shape publishing behavior until the chosen few achieve full professorship (Tien and Blackburn 1996). In Poland, the ranks achieved are individual career markers of individuals rather than institutions. Therefore, they are retained by faculty when they move between institutions.

Both age at rank (promotion age) and years between ranks (promotion speed) are factors in perceptions of success and failure in an academic career (Cole and Cole 1973: 130; Long et al. 1993: 704). Full professorship is the ultimate career goal, to which many aspire but seldom achieve. Among the chosen few, the amount of time to full professorship differs by gender and discipline. However, in the present study, our focus was on those who achieved this rank early (the Young class) and quickly after habilitation (the Fast class). The selective attrition (Bayer and Dutton 1977: 274) of low-productive and non-productive scientists is extremely rare despite the recent increasing pressure to publish, especially in international journals (Antonowicz et al. 2021).

The questions of how productivity is associated with age and promotions and whether promotion age and promotion speed are differentiating factors regarding productivity are linked to wider issues of inequality in science. In research productivity, inequality has been explained according to the cumulative advantage theory and the "sacred spark" hypothesis (David 1994; Kyvik 1990). First, the implications for productivity in the cumulative advantage theory and the accompanying reinforcement theory are clear (Stephan and Levin 1992: 29): "Scientists productive in an early period are productive in later periods; those not productive at an early date are less likely to be productive at a later date.… Those who enjoy success continue to be productive throughout their lives." In another formulation, "productive scientists are likely to be even more productive in the future, while scientists who produce little original work are likely to decline further in their productivity" (Allison and Stewart 1974: 596). An "initial success" in publishing entails increasing productivity; a "bad start" may subsequently lead to quitting research altogether (Turner and Mairesse 2005: 3). Full professors nominated at a young age show higher post-promotion productivity than peers promoted at an older age (Turner and Mairesse 2005: 17), and less productive full professors tend to focus on teaching and administrative duties. According to Allison et al. (1982: 615), "Scientists who are rich in recognition find it easier to get the resources that facilitate research: grants, free time, laboratories, stimulating colleagues, capable students, etc." Each step rewards research success with access to the means for future research successes (David 1994: 12).

Second, the "sacred spark" hypothesis also links inequality in research production and promotions. According to this hypothesis, "there are substantial, predetermined differences among scientists in their ability and motivation to do creative scientific research" (Allison and Stewart 1974: 596). Scientists are a heterogeneous population that contains a separate class of "rare individuals of great talent" (David 1994: 12). Indeed, "those with the spark always are productive. Those without it, however, never see their careers take off and flourish" (Stephan and Levin 1992: 30). The hypothesis emphasizes that a differential distribution of talent among scientists affects inequality in scientific production more than the way in which recognition is awarded in science. The few that have the "spark" coexist in science with "the sparkless mass" (David 1994: 13). The evidence in support of the accumulation advantage hypothesis does not disconfirm the heterogeneity and sacred spark hypotheses (Allison and Stewart 1974: 605). The academic profession is characterized by stable productivity stratification and "the persistence of productivity hierarchies" (Kelchtermans and Veugelers 2011: 298). Hence, productivity is related to aging and promotion.

The academic profession has been aging across the Western world for the past few decades, as numerous studies have shown (Bayer and Dutton 1977; Kyvik 1990; Kyvik and Olsen 2008). As a result, studies by psychologists, sociologists, and economists have focused on the relationship between the aging of the academic profession and productivity at both individual (Gingras et al. 2008; Abramo et al. 2016; Sugimoto et al. 2016) and institutional (Bentley and Blackburn 1990; Bonaccorsi and Daraio 2003; Kyvik and Olsen 2008) levels, which, however, has led to inconclusive results. Psychologists have focused on changes in individuals leading to a decline in research output with age, sociologists have focused on the reward structure of science and the processes of cumulative advantage, and economists have focused on declining financial rewards associated with research (Levin and Stephan 1989; Diamond 1984). Levin and Stephan (1991) developed a model of scientific productivity in which scientists engage in research in anticipation of future financial rewards (investment motivation) and because of their fascination with solving research puzzles (consumption motivation). While the investment motive implies a decline in productivity over a career with a finite time horizon, the consumption motive does not (Levin and Stephan 1991: 115).

Perhaps the most useful perspective for understanding the age-productivity-promotion nexus is that of the traditional sociology of science at the Merton school in which recognition and reputation for scientific discovery are key currencies in the science reward system (e.g., Cole and Cole 1973). Incentives in research are largely non-monetary and reputation-based (Turner and Mairesse 2005). Publications and citations are central to a reward system that guides the allocation of resources (David 1994). Productivity stratification in science is associated with persistent hierarchies of productivity throughout the life of a cohort: “Once scientists enter the current productivity elite, it is rare for them to exit from it in the next period” (David 1994: 10). There is stability of the relative positions of researchers in the distribution of productivity over time (Turner and Mairesses 2005).

Regarding age, the differential in productivity tends to increase with age between top scientists and other researchers, as suggested by the accumulative advantage theory and reinforcement theory (Cole and Cole 1973; Allison and Stewart 1974; Fox 1983). Top scientists accumulate financial and reputational assets, and their collaboration networks grow, which allows them to maintain their high productivity levels (Kwiek 2021b). Other scientists, especially those in low-productivity classes, realize they will never achieve peer recognition, and their motivation for research declines. In this context, early success is understood as promotion at a young age, which accelerates a career; late success (bordering on failure) is understood as promotion at an old age, which does not. Therefore, regarding promotion, the young and the fast should be much more productive than the old and the slow.

In the Polish case, promotions to associate and full professorships are nationally governed. Full professorships are centrally awarded based on nationwide regulations. The association between academic promotion and research productivity is very strong, and research output presented for peer assessment is the single most important component of applications for promotion. Although direct promotion rewards (e.g., prestige and pay) are the same across the Polish system, including discipline and gender, indirect promotion rewards vary between the young and the old, such as in grant application success and failure. Early promotions in academic careers, as shown in academic vitae, generally strengthen grant applications; late promotions weaken them. Low producers and non-producers are not eliminated from the science system. In the absence of “up or out” policies in universities, promotion age matters in perceptions of scientific success, and substantial differences in productivity patterns exist between the Young and Old classes. Therefore, we examine the idea that promotion age and “years since promotion” influence productivity, not “rank per se” (Tien and Blackburn 1996: 17).

Our research is the first large-scale country-level examination of the relationships between rank advancement (promotion age and promotion speed classes in three academic ranks) and productivity in the whole internationally visible STEMM academic community. We posed the following three research questions: 1) What are the relationships between current individual productivity and the past *promotion age* classes? 2) What are the relationships between current individual productivity and past *promotion speed* classes? 3) What are the effects of past promotion age and past promotion speed on current membership in the top productivity classes, based on the combined effects of other variables?

The above research questions led us to the three hypotheses tested in this study:

Hypothesis 1. *Current individual productivity vs. past promotion age classes.* The current individual productivity of the young promotion age classes (young associate and full professors) is higher than that of the middle and old promotion age classes (middle and old associate and full professors). (Supported for almost all STEMM disciplines)

Hypothesis 2: *Current individual productivity vs. past promotion speed classes.* The current individual productivity of the fast promotion speed classes (fast associate and full professors) is higher than that of the typical and slow promotion speed classes (typical and slow associate and full professors). (Supported for almost all STEMM disciplines)

Hypothesis 3. *Model approach to current top productivity classes, logistic regression analysis*. Promotions at a young age and fast promotions significantly increase odds ratio estimates of membership in current top productivity classes based on the combined effects of individual and organizational variables. (Partly supported)

3. Data and Methods

3.1. Dataset and Sample

Data were collected from two sources: (1) the Polish Science Observatory, which is a database created and maintained by the authors and used in five strands of academic career research in the past few years (man–woman collaboration patterns in Kwiek and Roszka 2021b; gender disparities in international research collaboration in Kwiek and Roszka 2021a; academic age vs. biological age in academic career studies in Kwiek and Roszka 2022b; gender solo research gap in Kwiek and Roszka 2022a; and persistence of high research productivity from a life-cycle perspective in Kwiek and Roszka 2022c). The Observatory database was constructed by merging two large datasets: the official national administrative and biographical register of all Polish scientists and scholars, "The Polish Science"; and the Scopus publication and citation database from 2009–2018 for scientists and scholars with Polish affiliations (N = 99,935 scientists; N = 380,000 publications); (2) the Observatory database was enriched using Scopus raw data provided by the International Center for the Studies of Research Lab (ICSR Lab), a cloud-based service provided by Elsevier for research purposes, through a collaboration agreement, including data on all articles published from 1973–2021 by authors with Polish affiliations (N = 935,167).

Data were collected on the entire (Scopus-indexed) academic production of every scientist in the sample. In particular, regarding lifetime publication data, we enriched our Observatory dataset as follows: (1) the year of the first publication, which allowed us to calculate academic age, a proxy of experience; (2) metadata on all journals in which articles were published, which were used to calculate two additional variables of the median individual prestige level (based on Scopus CiteScore metrics ranging from 0–99, aggregated from all articles published by scientists, lifetime) and the median individual team size (based on the number of coauthors, aggregated from all articles published by scientists during their lifetime). From this database, we selected only scientists in 12 STEMM disciplines (N = 16,083). All scientists had at least a doctorate, were employed full-time in higher education, and had published at least one Scopus-indexed article (the list of disciplines is provided in Table 2). Figure 1 shows the distribution of the sample by biological age: the Polish academic profession in the 12 STEMM disciplines was mainly middle-aged: 45.8% of scientists were in the 40–54 age group, and 25% were older than 55 years. The academic hierarchy was reflected in the age distribution: the mean ages were as follows: assistant professors, 41.0 years; associate professors, 50.8 years; and full professors, 61.7 years. Over half of the scientists in our sample were assistant professors (56.5%), and one in seven were full professors (14.2%) (Table 1).

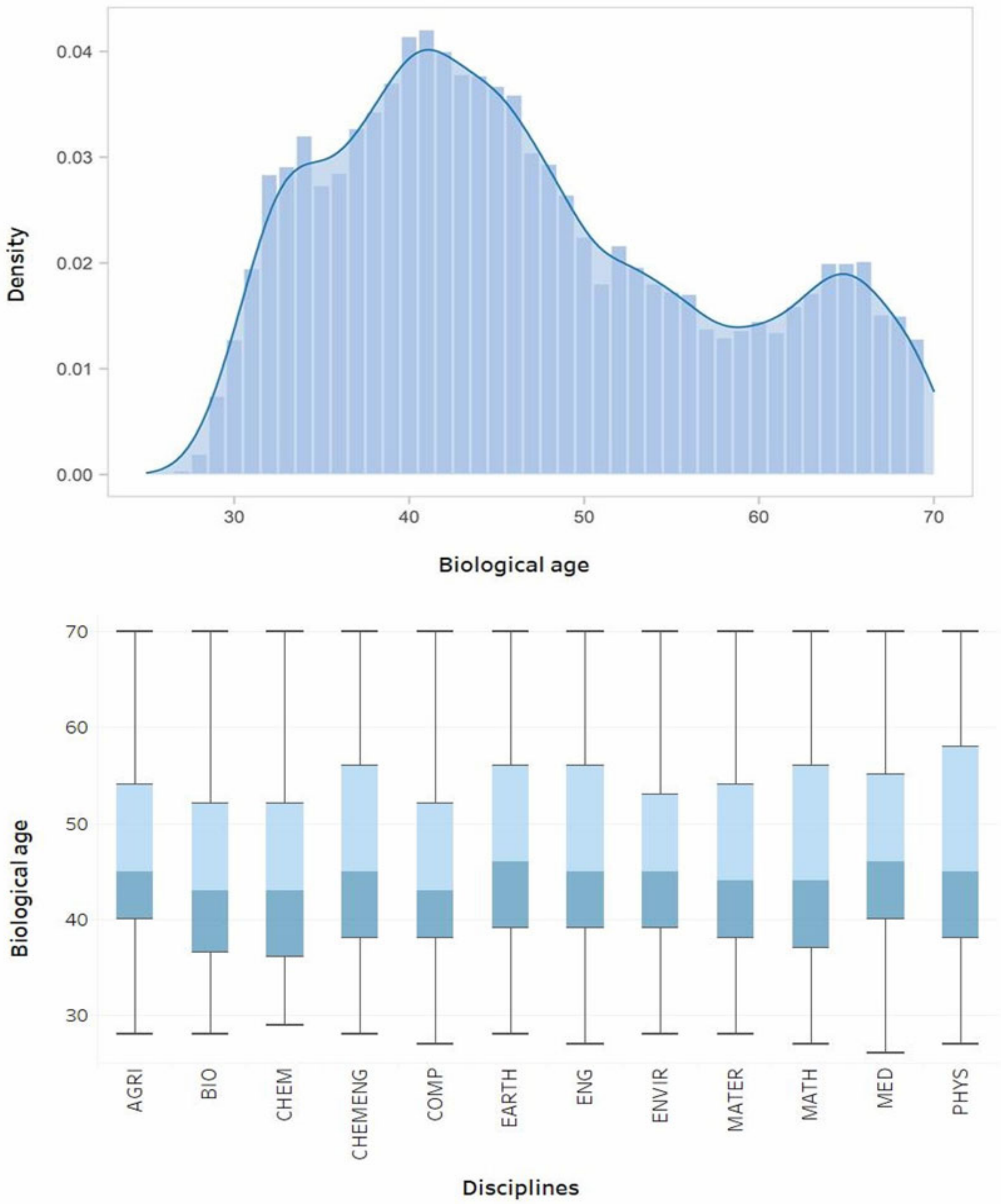


Figure 1. Distribution of biological age: kernel density plot (all STEMM academic fields combined) (top panel) and distribution of biological age by discipline (bottom panel, N = 16,083).

Our dataset included gender in binary form (male or female) and year of birth. We obtained the year of first publication, which allowed us to calculate academic age or number of years since the first publication indexed in Scopus using the application programming interface (API) protocol. We collected all Scopus-indexed publications (type: article) in individual lifetime publication profiles for every scientist, and we determined the predominant discipline (the modal value) for each scientist as the most often occurring value.

Table 1. Structure of the sample: all Polish university professors in STEMM with at least a single Scopus-indexed article by gender, age group, academic position, and discipline

		Female			Male			Total		
		N	% col	% row	N	% col	% row	N	% col	% row
Age group	39 and less	2,180	34.0	46.4	2,516	26.0	53.6	4,696	29.2	100.0
	40–54	3,094	48.2	42.0	4,277	44.2	58.0	7,371	45.8	100.0
	55 and older	1,139	17.8	28.4	2,877	29.8	71.6	4,016	25.0	100.0
Academic position	Assistant Prof.	4,148	64.7	45.7	4,936	51.0	54.3	9,084	56.5	100.0
	Assoc. Prof.	1,725	26.9	36.6	2,990	30.9	63.4	4,715	29.3	100.0
	Full Professor	540	8.4	23.6	1,744	18.0	76.4	2,284	14.2	100.0
Discipline	AGRI	1,130	17.6	53.7	976	10.1	46.3	2,106	13.1	100.0
	BIO	865	13.5	61.8	535	5.5	38.2	1,400	8.7	100.0
	CHEM	595	9.3	50.6	581	6.0	49.4	1,176	7.3	100.0
	CHEMENG	135	2.1	39.0	211	2.2	61.0	346	2.2	100.0
	COMP	126	2.0	16.3	645	6.7	83.7	771	4.8	100.0
	EARTH	284	4.4	33.7	559	5.8	66.3	843	5.2	100.0
	ENG	380	5.9	14.8	2,181	22.6	85.2	2,561	15.9	100.0
	ENVIR	685	10.7	51.9	635	6.6	48.1	1,320	8.2	100.0
	MATER	397	6.2	32.9	808	8.4	67.1	1,205	7.5	100.0
	MATH	195	3.0	25.2	580	6.0	74.8	775	4.8	100.0
	MED	1,478	23.0	54.5	1,233	12.8	45.5	2,711	16.9	100.0
	PHYS	143	2.2	16.5	726	7.5	83.5	869	5.4	100.0
	Total	6,413	100.0	39.9	9,670	100.0	60.1	16,083	100.0	100.0

3.2. Variables

We used eight individual independent variables and a single organizational independent variable. Three Polish academic degrees were used as proxies of internationally comparable academic positions: doctoral degree only, which was regarded as a proxy for working at the rank of assistant professor (N = 9,084); habilitation or postdoctoral degree, which was regarded as a proxy for working at the rank of associate professor (N = 4,715); and professorship title, which was regarded as a proxy for working at the rank of full professor (N = 2,284). (Full, associate, and assistant professor ranks as proxies of national academic hierarchies in 28 countries are provided by Altbach et al. 2012: 342–343). The three dates in our dataset, that is, the years in which doctorates, habilitations, and professorships were awarded, were used to classify scientists into three academic ranks: the period between achieving doctoral degree and the habilitation degree (if awarded) was regarded as a period of assistant professorship; the period between achieving the habilitation degree and the professorship title (if awarded) was regarded as a period of associate professorship; and the period following the attainment of the professorship title was regarded as a period of full professorship.

3.3. Methodology

3.3.1. Individual lifetime biographical and publication profiles

Our Polish Science Observatory database allowed us to create individual lifetime biographical profiles and individual lifetime publication profiles for every scientist in our sample (N = 16,083). Biographical profiles included relevant dates in academic careers, and publication profiles included lifetime publication and citation metadata. The quality of the biographical data collected from the national registry was nearly perfect, and the quality of the publication and citation metadata collected from Scopus was very high. There has been intensive collaboration between the Polish Ministry of Science and Higher Education and Elsevier as the data provider in metric-focused reforms of research assessment procedures for a decade. Biographical profiles included the year of birth and the dates of doctorates, habilitations, and professorships (if applicable).

Publication profiles included metadata on all Scopus-indexed publications. By combining publication data and biographical data, we were able to allocate every publication to the appropriate stage of the academic career and calculate prestige-normalized individual productivity for every scientist in our dataset.

Table 2. Variables used in the analysis

No.	Variable	Description	Source
1.	Biological age	Biological age as provided by the national registry of scientists (N = 99,935). Age in full years as of 2017.	Observatory
2.	Academic age	The number of years passed between the first publication (any type) registered in the Scopus database and 2017, the reference year.	Observatory
4.	Gender	Binary variable, male or female, as provided by the national registry of scientists (N = 99,935). No other options are possible in the registry.	Observatory
5.	Academic position	Doctoral degree only (assistant professor; N = 9,084), habilitation degree only (associate professor; N = 4715), and professorship title (full professor; N = 2,284).	Observatory
6.	Mean publication prestige (percentile rank)	Mean prestige represents the median prestige value for all publications (journal articles only) written by a scientist throughout their careers (lifetime) and indexed in Scopus (journal percentile ranks: 0-99). For journals for which the Scopus database did not ascribe a percentile rank, we ascribed the percentile rank of 0.	Observatory, based on Scopus data
7.	STEMM disciplines	Twelve STEMM disciplines examined: 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 medicine, and PHYS, physics and astronomy. Other STEMM disciplines used in the Scopus ASJC (All Sciences Journal Classification) system were removed from the analysis based on a too-low number of observations (below 300). Dominant disciplines were used, i.e., the mode discipline for each scientist in their lifetime articles included in their individual publication profiles.	Scopus
8.	Individual median team size	The median number of publication coauthors (journal articles only) in all publications indexed in Scopus, lifetime.	Observatory, based on Scopus data
9.	Research-intensive institution (IDUB)	Research-intensive institutions are the 10 institutions (from among 85 examined) selected in 2019 for the IDUB (or "Excellence Initiative–Research University") national excellence program.	Ministry

3.3.2. Prestige-normalized research productivity

In our prestige-normalized approach, articles published in prestigious journals were given more weight in individual productivity than those published in less prestigious journals within each discipline. Productivity normalized to journal quality was used before (see, for example, "quality-adjusted publications" in the USA in Stephan and Levin 1992; weighting by publication channel in Norway in Nygaard et al. 2022; and ERA-related (Excellence in Research in Australia) top journal publications in Mishra and Smyth 2013). Our approach reflected the general idea that articles published in high-impact journals require, on average, more scholarly effort and lead to, on average, greater effects on the scholarly community. Consequently, articles in journals located higher in the Scopus CiteScore percentile ranks (40,562 journals in 2022) were given more weight than articles in journals located lower in these percentile ranks in the 1–99 percentile range. An annually allocated percentile rank reflects the interest that articles previously published in a journal raise among the scholarly community. As we have shown elsewhere in a global study of top journals in higher education (Kwiek 2021a), highly prestigious journals in each discipline, with low acceptance rates and wide global readership, tend to be in the 90–99th CiteScore percentiles (both *Higher Education* and *Studies in Higher Education* were in the 96th percentile of Scopus journals in 2022).

In a non-normalized approach, an article published in any journal traditionally receives a value of 1, whereas in our prestige-normalized approach, articles in journals with a percentile rank of 90 received a value of 0.90; articles in journals with a percentile rank of 40 received a value of 0.40; and articles published in journals with percentile ranks of 10 and less received a value of 0.1. In all cases, the full counting method rather than the fractional counting method was used; credits were not divided by the number of coauthors.

The prestige-normalized approach allows for a fair measurement of scholarly effort in STEMM disciplines. Counting all publications evenly, which is routinely done in research based on academic profession surveys, tends to disregard vastly different individual scholarly efforts submitted to a highly stratified system of academic journals (Shibayama and Baba 2015; Hammarfelt 2017). Highly selective top journals are discipline-specific, and journal stratification in science plays a powerful role in academic careers, including academic employment, promotions, and access to competitive research funds, especially in STEMM disciplines (Fochler et al. 2016).

The difference in productivity distribution between prestige-normalized and standard non-normalized approaches is substantial. When prestige normalization is used, the productivity distribution is much steeper for scientists in all disciplines combined (Figure 2) and in each separate discipline (Figure 3). The focus on prestige-normalized articles by discipline enables cross-disciplinary differentiation in the stratification of scientists according to individual productivity. As shown in Figure 2, in both productivity types, there were low percentages of highly productive scientists and high percentages of low-productive scientists (see Kwiek 2019). The most intense stratification of scientists by prestige-normalized productivity was observed in MATH and ENG, where the productivity distribution was steeper, and the least intense stratifications were in PHYS, MATER, and CHEM, where productivity distribution was flatter.

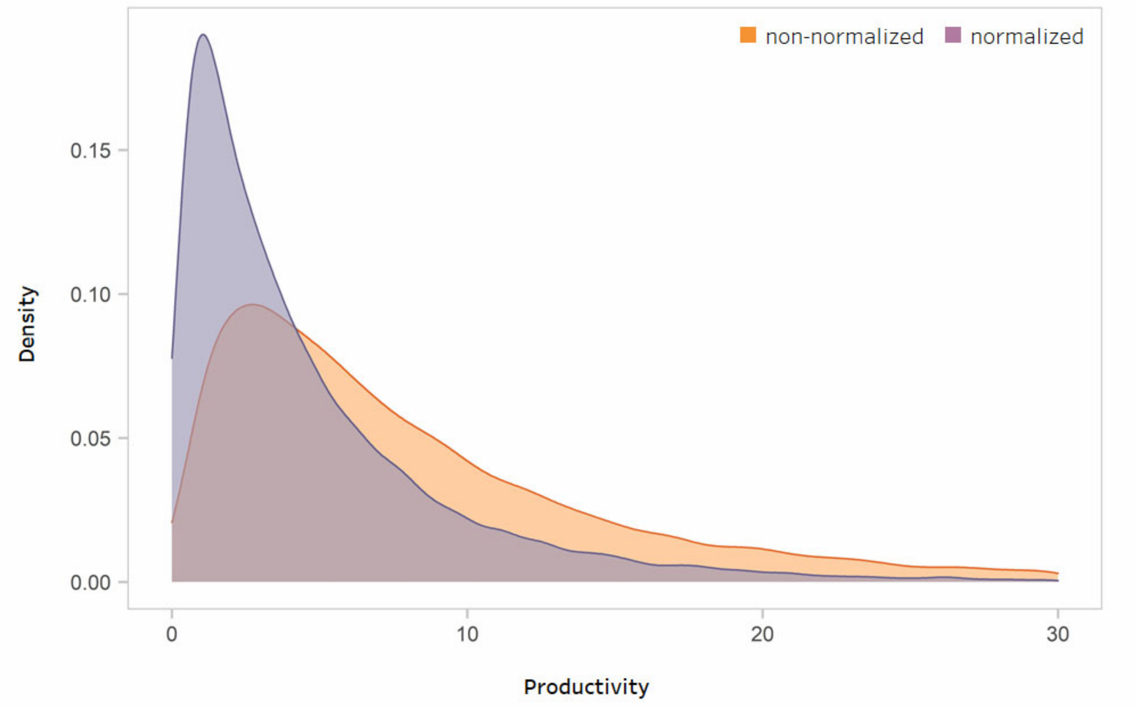


Figure 2. Individual productivity distribution for the four-year study period (2014–2017). Kernel density plot, prestige-normalized and standard (non-normalized) articles, full counting method, articles only, all disciplines combined, STEMM scientists only, N = 16,083

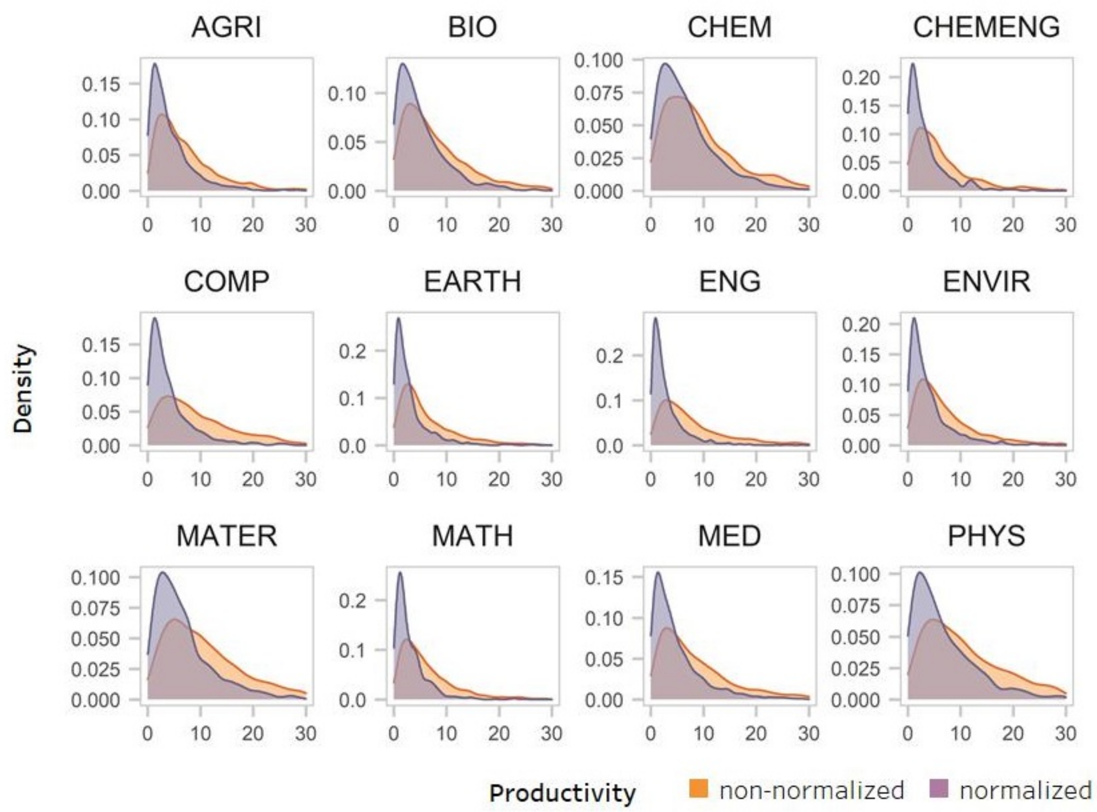


Figure 3. Productivity distribution for the four-year study period (2014-2017). Kernel density plot, prestige-normalized and standard (non-normalized), full counting method, articles only, by discipline, N = 16,083

3.3.3. A classificatory approach to studying academic careers: productivity, promotion age, and promotion speed classes

We allocated all scientists to three types of academic career classes—productivity, promotion age, and promotion speed classes—based on the 20/60/20 pattern. We assigned eight academic career classes to each full professor, five to each associate professor, and two to each assistant professor, as shown in Figure 4. In the case of full professors, there were three productivity classes (current, past as assistant professor, and past as associate professor), three promotion age classes (age at promotion to an assistant professor, to an associate professor, and to a full professor), and two promotion speed classes (amount of time prior to a promotion to associate professor and to full professor). The current and past productivity classes used were the top 20%, middle 60%, and the bottom 20% in a prestige-normalized approach (separately within each of the 12 STEMM disciplines). The promotion age classes of full professors were young, middle, or old associate professors and young, middle, or old full professors. The promotion speed classes were fast, typical, and slow associate professors, and fast, typical, and slow full professors—that is, the top 20%, middle 60%, and bottom 20%, respectively—in terms of the transition time between subsequent promotions, expressed in years. Analogous procedures for constructing current and retrospective academic career classes were applied to associate and assistant professors (for the latter, there were no promotion speed classes).

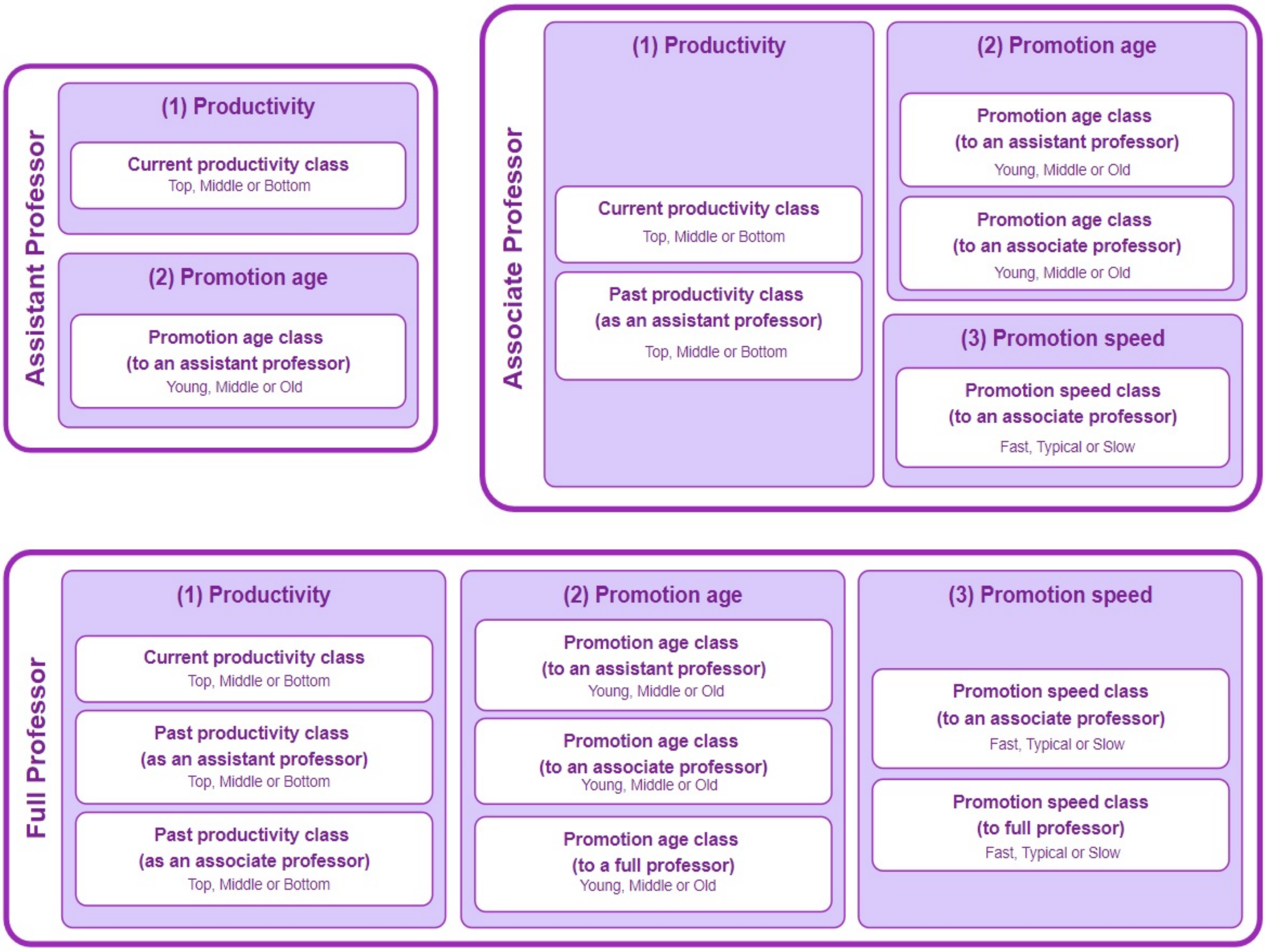


Figure 4. Academic career classes. The 20/60/20 classification scheme used in the analyses. Current and retrospectively constructed productivity (top, middle, bottom), promotion age (young, middle, old), and promotion speed (fast, typical, slow) classes

3.4. Limitations

A major limitation of this study is "the success bias" or "the survivor bias": only successful scientists were examined, that is, those who were continuously recorded in the system as receiving promotions and publishing research. The unsuccessful, unpromoted, and unpublished were underexplored, mainly because data on them were missing from the Observatory dataset and its components, including Scopus. Scientists who remain in academe are "systematically different from those that have left" and thus are not included in the sample (as in Sugimoto et al. 2016: 1013). However, the selection bias in Poland is smaller than in other science systems: as scientists age, both the most productive and the least productive tend to stay in academe.

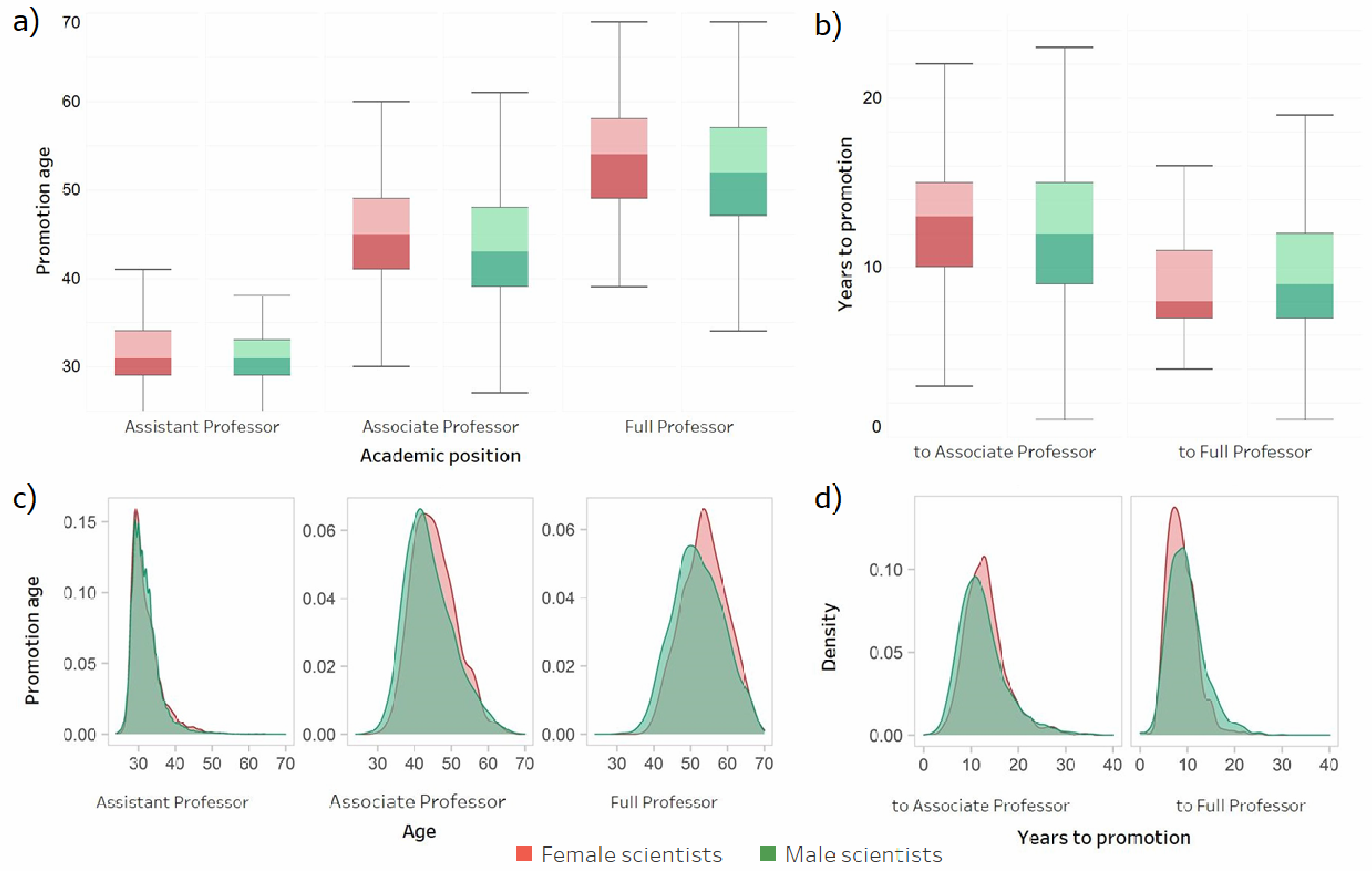
There are also other limitations to this study. First, because of the heterogeneous character of our dataset, data on real scientists in the national registry were combined with data on individual Scopus author IDs collected from Scopus, with a possible error (marginal due to the role of Scopus as a provider of data on Polish reforms) between "real individuals" and their identification in a global indexing system. Second, while all major global bibliometric datasets have linguistic, geographic, and disciplinary biases, which have long been discussed in the literature, in our study, no other data sources were available to retrospectively construct individual (lifetime) publication profiles for every scientist, as well as determine their academic age, STEMM discipline, individual median team size, and individual mean publication prestige for use in regression models.

4. Results

4.1. Distribution of Promotion Age and Promotion Speed

Having identified current professors of different ranks and defined their biographical profiles, we examined their biological age at previous promotions (promotion age). We also examined the amount of time between promotions (promotion speed). Thus, we examined the current ranks of professors and the distribution of their biological ages at the times of their respective previous promotions. Figure 5 shows the distribution of promotion age (left panels a and c) and promotion speed (right panels b and d) in detail and from a gender perspective. While the median promotion age for male and female scientists was equal in the rank of assistant professor, it was higher for female scientists in the ranks of both associate and full professors (panel a), as shown in the density plots (panel c). However, interestingly, gender differentiation was greatest in promotion speed (right panels b and d). Although it took longer for women to be promoted to the rank of associate professor, it took less time for women to be promoted to a full professorship, based on a comparison between the median values and the density plots.

Figure 5. Promotion age (panel: a) Distribution of the promotion age to academic ranks, by gender. Promotion speed (panel b): Distribution of time passed to promotion from assistant professors to associate professors (N = 6565) and from associate professors to full professors (N = 2275), in years, by gender. Density plots show the distribution of promotion age to academic ranks (panel c) and time passed to promotion from assistant professors to associate professors (N = 6565) and from associate professors to full professors (N = 2275), in years (panel d), by gender (N = 16,083).



4.2. Coexistence Analysis: Promotion Age Class and Promotion Speed Class

A coexistence analysis showed that membership in some classes is accompanied by membership in other classes. Figure 6 shows the results of the coexistence analysis of the promotion speed and promotion age classes. The results for the promotion speed classes are shown in the left panel (two ranks), and the results for the promotion age classes are shown in the right panel (three ranks). The results are presented in columns.

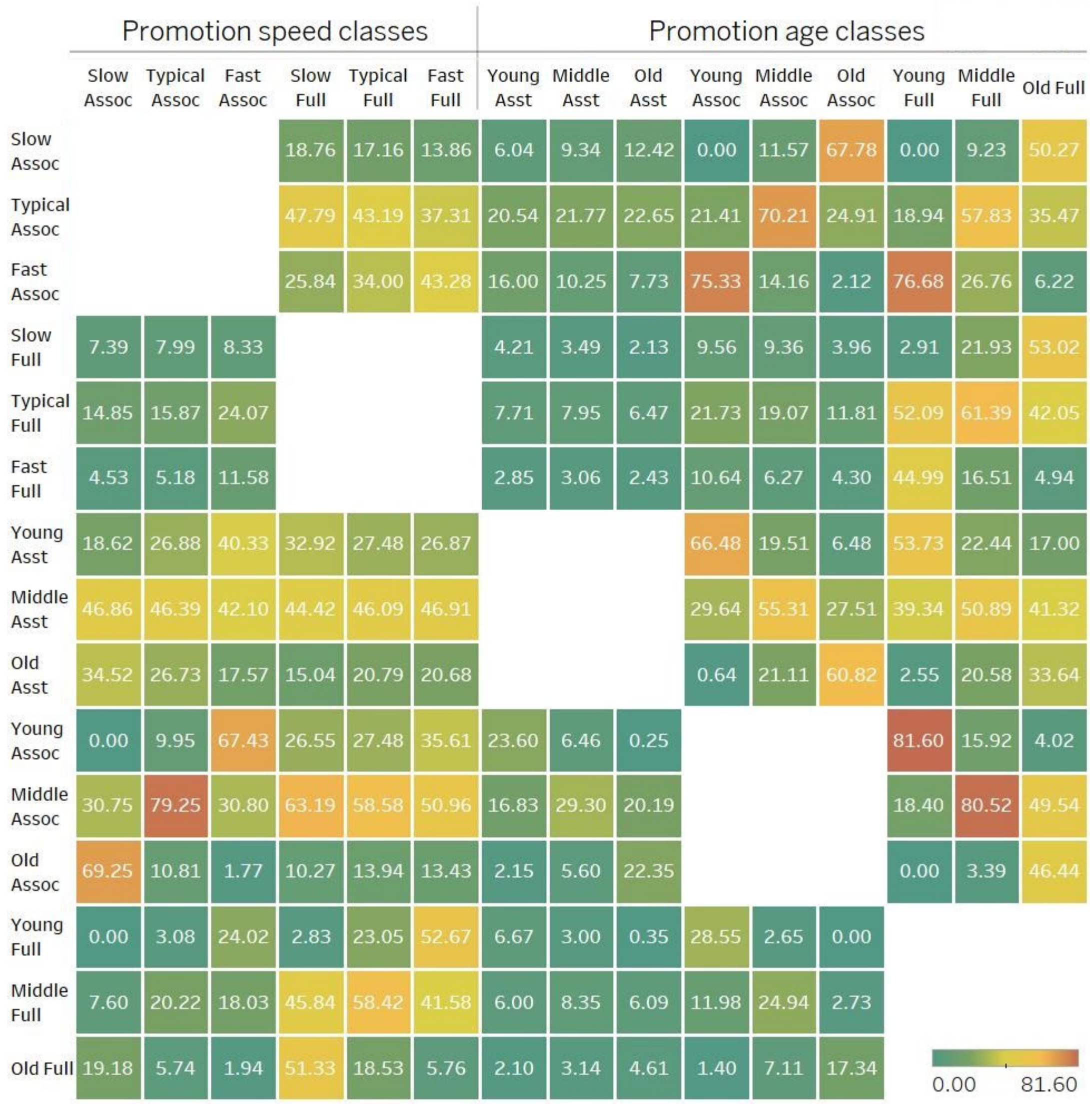


Figure 6. Coexistence analysis. Coexistence of academic promotion classes (promotion speed classes, left panel; promotion age classes, right panel), column percentages. Fast/typical/slow and young/middle/old classes of three university ranks (assistant, associate, and full professor). Diagonal pairs are intentionally left blank (0% or 100%) (N = 16,083).

We were especially interested in two selected classes: Young Full Professors and Fast Full Professors. The members of Young Full Professors class had a distinct professional trajectory: more than half (53.73%) belonged to the Young Assistant Professors class, 81.60% belonged to Young Associate Professors class, and 76% had previously belonged to the Fast Associate Professors class (76.68%). Most members of the Fast Full Professors class had previously belonged to the Fast Associate Professors class (43.28%). They were also predominantly Young Full Professors (52.67%) and very rarely Old Full Professors (7.76%). Lifetime biographical profiles of associate and full professors show continuity between promotion age and promotion speed classes: large proportions of the young promotion age classes belong to the same class in subsequent career stages, and large proportions of the fast promotion speed classes belong to the same class in subsequent stages.

4.3. Current Productivity and Past Promotion Age Classes

In this section, we analyze the current median individual productivity (in the study period of four years) according to the three promotion age classes (Young, Middle, and Old) for three academic ranks. Table 3 shows the median productivity in the assistant, associate, and full professor promotion age classes by discipline. Across all disciplines, the young promotion age class was consistently the most productive, and the old promotion age class was consistently the least productive in terms of median productivity.

Thus, the results showed that the younger promotion age at all levels, the higher current productivity. The age classes of past promotions were highly significantly related to current productivity. The differences were astonishingly and systemically similar across all disciplines. For instance, in the three largest disciplines of medical sciences (MED) (2,711 scientists), engineering (ENG) (2,561 scientists), and agricultural sciences (AGRI) (2,106 scientists), the comparison of the medians showed that young assistant professors accounted for, on average, 156.6%, 171.8%, and 187.9% of the productivity of old assistant professors, respectively. Young associate professors accounted for 210.3%, 308.2%, and 315.8% of the productivity of old associate professors. Young full professors accounted for 252.4%, 292.3%, and 313.8% of the productivity of old full professors, respectively. The productivity differential was the highest for young and old associate professors and the lowest for young and old assistant professors (Figures 7–9).

Although promotions have occurred in the past, the current productivity of young scientists in terms of promotion age (Young class) in all disciplines, was clearly higher than the productivity of the other two promotion age classes, especially the Old class. These findings were refined using the results of statistical tests, especially pairwise comparisons. Typically, the value of the test statistic in pairwise comparisons was the highest for the Old–Young class pair. The higher the value of the test statistic, the greater the discrepancy between the distributions. When there was a large discrepancy between distributions, we also found large discrepancies in the characteristics of these distributions.

The results of the Kruskal–Wallis test showed that among assistant professors, the main axis of significant differences in productivity was along the Young–Old line. In every field (except COMP), the pair was characterized by a significant difference. Among associate professors, all pairs were characterized by significantly different productivity, and in all fields, the Young–Old pairs were consistently significantly different. Among full professors in all disciplines (except CHEMENG and COMP), the productivity of Young–Old pairs was consistently significantly different. Therefore, Hypothesis 1 was confirmed in almost all disciplines.

Table 3. Median productivity (prestige-normalized, full counting) in the four-year study period (2014–2017) by discipline, academic rank, and promotion age classes. In parentheses, values for the 95% confidence interval, N = 16,083

	Assistant professor promotion age classes (N = 8891)			Associate professor promotion age classes (N = 4565)			Full professor promotion age classes (N = 2277)		
	Young assistant professors	**Middle assistant professors**	**Old assistant professors**	**Young associate professors**	**Middle associate professors**	**Old associate professors**	**Young full professors**	**Middle full professors**	**Old full professors**
AGRI	3.2 (2.8-3.9)	2.51 (2.3-2.8)	1.7 (1.4-2.2)	7.11 (5.7-8)	3.69 (3.3-4.3)	2.25 (1.8-2.8)	8.4 (5.3-9.9)	3.49 (3-4)	2.68 (1.7-4.2)
BIO	4.39 (3.7-4.9)	2.96 (2.6-3.4)	1.97 (1.6-2.5)	9.98 (8.8-11.8)	5.28 (4.2-5.9)	3.58 (3.1-4.3)	11.52 (7.7-15.2)	7.19 (5.5-8.6)	5.13 (3.4-7.8)
CHEM	6.05 (5.5-6.7)	3.8 (3.4-4.3)	3.05 (2.3-3.8)	11.08 (8.5-12.7)	6.23 (5.5-7.1)	4.35 (3.2-5)	17.23 (12-21)	10.08 (8.4-11.8)	6.52 (4.4-9.1)
CHEMENG	3.11 (1.8-4.2)	1.67 (1.3-2)	1.14 (0.8-1.5)	7.36 (0.7-15.8)	3.4 (2-4.2)	1.52 (1-2.2)	11.74 (0-0)	4.88 (3.1-6.9)	3.46 (1.1-6.5)
COMP	2.95 (2.5-3.6)	2.17 (1.9-2.5)	1.64 (1.3-2.2)	7.65 (6.5-10.4)	3.54 (2.4-4.6)	1.55 (0.8-2.8)	6.87 (3.2-9.8)	4.71 (3.2-6.8)	4.04 (1.9-5.4)
EARTH	2.24 (1.5-2.6)	1.52 (1.3-1.8)	1.13 (0.8-1.6)	5.66 (2.7-7.8)	2.66 (2.2-3.3)	2.1 (1.6-2.5)	5.49 (2-8)	2.63 (1.7-3.4)	1.9 (0.9-3.1)
ENG	2.17 (1.9-2.5)	1.64 (1.5-1.8)	1.26 (1-1.4)	4.9 (3.7-6)	2.86 (2.6-3.2)	1.59 (1.4-1.9)	6.49 (4.8-8.4)	2.98 (2.6-3.6)	2.22 (1.7-3.3)
ENVIR	2.7 (2.2-3.1)	2.06 (1.7-2.5)	1.44 (1.2-1.8)	6.27 (4.8-8.5)	3.45 (2.9-4.1)	2.64 (1.8-3)	5.93 (4.4-11)	3.23 (1.8-5.4)	3.47 (2.7-5.4)
MATER	5.48 (4.7-6.5)	4.55 (4-5)	3.15 (2.6-4.1)	9.27 (7.3-13.2)	5.97 (4.9-7.2)	3.74 (3.2-6)	13.16 (6-21.7)	9.56 (8.3-11.4)	5.83 (4.2-8)
MATH	2 (1.7-2.6)	1.62 (1.3-1.9)	1.49 (1.2-1.8)	3.25 (2.1-4.5)	2.6 (1.9-3.2)	2.22 (1.4-4.4)	3.82 (3.1-6.6)	2.46 (1.7-3.7)	1.73 (1.1-3.9)
MED	3.07 (2.7-3.4)	2.33 (2.1-2.6)	1.96 (1.7-2.2)	8.44 (7.1-9.2)	5.28 (4.7-5.7)	4.01 (3.7-4.7)	14.06 (10.9-16.2)	6.7 (6-8.3)	5.57 (4.4-6.5)
PHYS	6.1 (5.2-8)	4.1 (3.4-4.7)	2.51 (1.6-2.9)	11.22 (9-15.6)	5.13 (4.2-6.6)	2.91 (2-3.7)	12.3 (9.3-14.3)	7.94 (6.3-10.5)	6.04 (2.7-9.8)

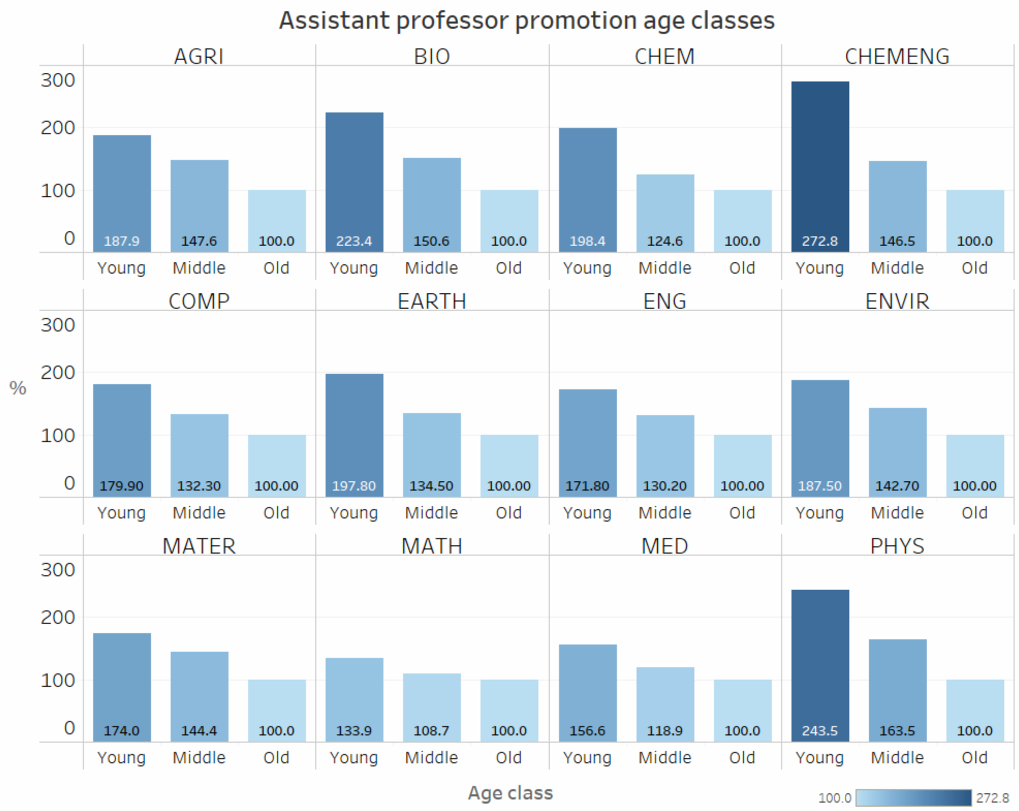


Figure 7. Productivity differential for assistant professors between promotion age classes (Young, Middle, Old) and discipline. Prestige-normalized productivity, full counting, 2014-2017. The productivity of the Old class = 100% (N = 9,084).

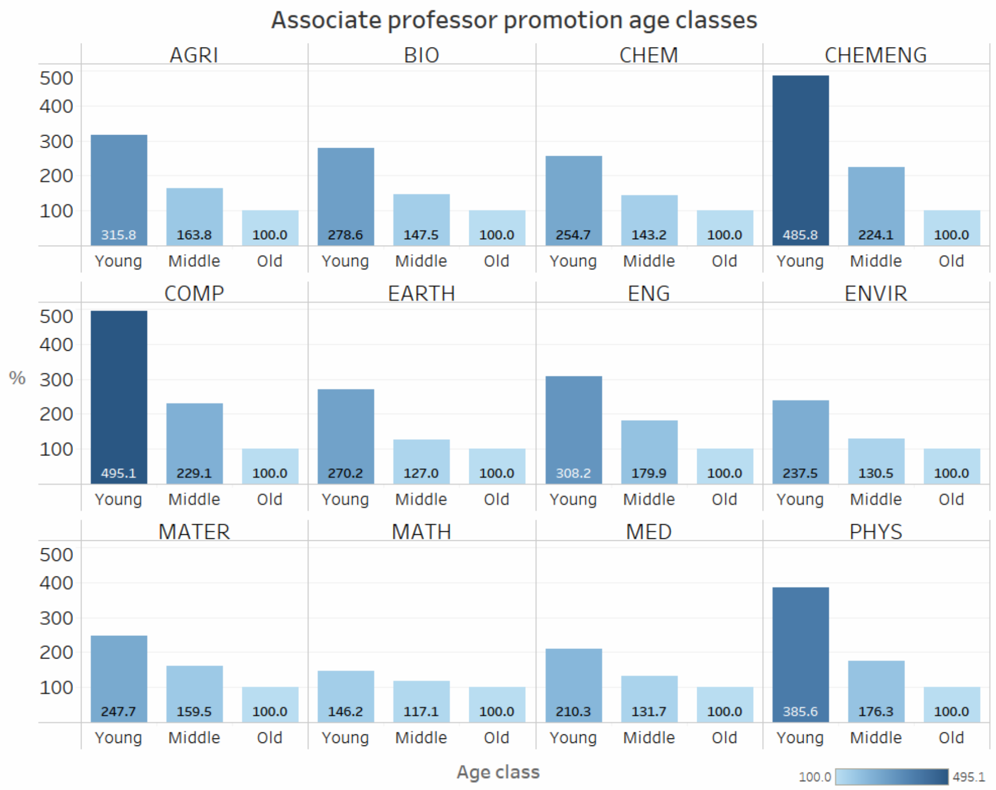


Figure 8. Productivity differential for associate professors between promotion age classes (Young, Middle, Old) and discipline. Prestige-normalized productivity, full counting, 2014-2017. The productivity of the Old class = 100% (N = 4,715).

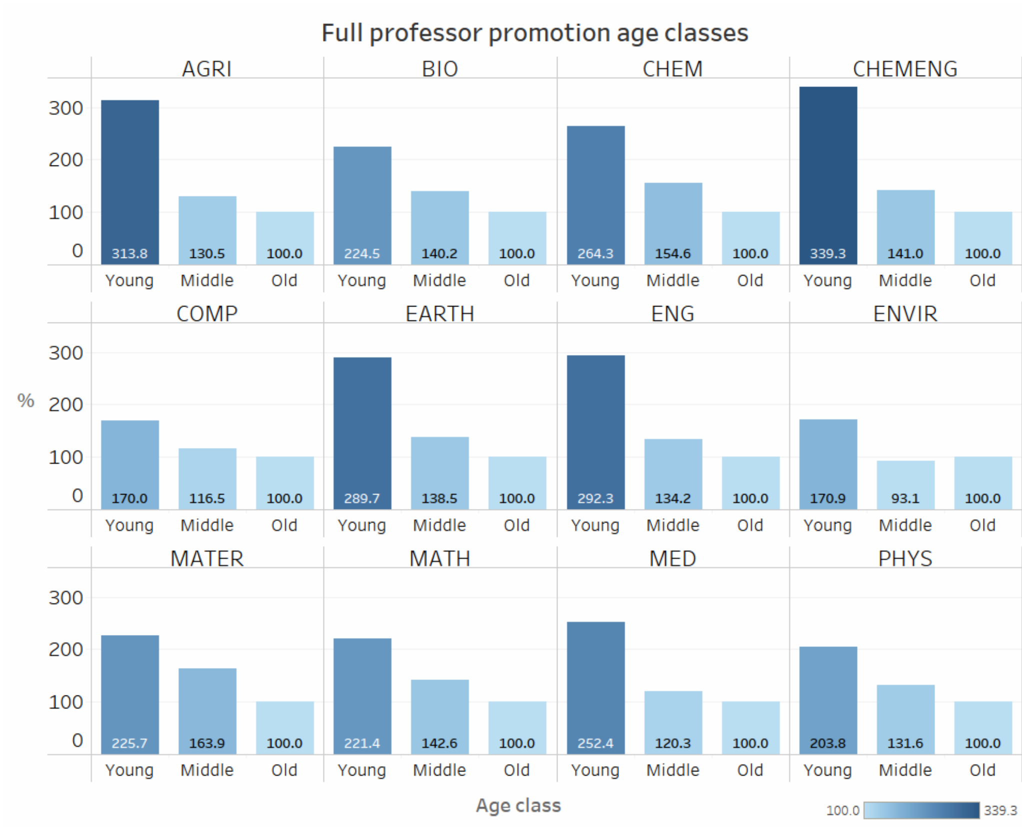


Figure 9. Productivity differential for full professors between promotion age classes (Young, Middle, Old) and discipline. Prestige-normalized productivity, full counting, 2014–2017. Productivity of the Old class = 100% (N = 2,284).

4.4. Current Productivity and Past Promotion Speed Classes

In this section, we analyze the current median individual productivity according to the three promotion speed classes (Fast, Typical, and Slow classes) for two academic ranks: associate professor and full professor. Table 4 shows the median productivity in the four-year study period for the associate professor promotion speed classes (left panel) and the full professor promotion speed classes (right panel) by discipline. Across all disciplines, the results showed that the class that promoted the most quickly in the past (Fast) was consistently the most currently productive, and the class that promoted the most slowly in the past (Slow) was consistently the least productive in terms of the median.
Thus, the higher the previous promotion speed, the higher the median current productivity. In all disciplines, Fast associate professors were on average the most productive, and Slow associate professors were on average the least productive. Similarly, across all disciplines, Fast full professors were, on average, the most productive, and Slow full professors were, on average, the least productive.

For instance, in the case of the three largest disciplines—MED, ENG, and AGRI —based on the medians, the productivity of Fast associate professors was, on average, 184.2%, 245.9%, and 250.7%, respectively, of the productivity of Slow associate professors. The productivity of Fast full professors was, on average, 222.8%, 271.3%, and 195.9%, respectively, of the productivity of slow full professors. The productivity differential was higher for Fast and Slow associate professors than for Fast and Slow full professors (Figures 10 and 11).

The results of the Kruskal–Wallis test showed significant differences in the productivity of the three promotion speed classes in all disciplines in the case of associate professors, and in all disciplines except CHEMENG, COMP, and MATH in the case of full professors. Regarding associate professors, in each significantly different pair, scientists in the Fast promotion class were more productive. When the null hypothesis was rejected in the Kruskal–Wallis test, the productivity of Slow-Fast promotion speed pairs was always significantly different. Among the full professors, the main axis of significant differences, as in the case of associate professors, was along the Fast–Slow line. In all disciplines, except for the three mentioned above, the productivity differences between the Slow and Fast promotion speed classes were statistically significant. Therefore, Hypothesis 2 was confirmed in almost all disciplines.

Table 4. Median productivity (prestige-normalized, full counting) in the four-year study period (2014–2017) by discipline, academic rank, and promotion speed classes. The values of the 95% confidence interval are shown in parentheses.

	Associate professor promotion speed classes (N = 4,422)			Full professor promotion speed classes (N = 2,275)		
	Fast associate professors	Typical associate professors	Slow associate professors	Fast full professors	Typical full professors	Slow full professors
AGRI	6.18 (5.2–7.7)	3.66 (3.2–4.2)	2.47 (1.9–3.1)	6.17 (4.7–8.5)	3.44 (3–4)	3.15 (1.9–4.2)
BIO	9.98 (8.8–11.4)	5.34 (4.3–6.1)	3.66 (3.2–4.4)	14.69 (7.7–18.6)	6.87 (5.1–8.8)	5.72 (3.4–7.9)
CHEM	11.08 (8.3–13.5)	6.87 (5.9–7.8)	4.25 (2.8–5.3)	12.48 (8.2–17.3)	10.24 (9.2–13)	6.48 (4.6–9.6)
CHEMENG	5.61 (0.7–12.4)	2.82 (1.3–4)	1.72 (0.8–2.6)	6.94 (1.5–12.7)	5.21 (2.4–7)	3.69 (1.5–8)
COMP	8.43 (6.5–10.5)	3.45 (2.2–4.7)	2.02 (1.4–3.5)	7.96 (3.8–17)	4.19 (3.2–7.2)	4.52 (2.8–6.8)
EARTH	5.41 (2.8–7.6)	2.63 (2.1–3.1)	2.01 (1.4–2.6)	3.79 (1.7–8.7)	2.91 (2.2–5.5)	1.54 (0.9–2.1)
ENG	3.91 (3–4.7)	2.91 (2.6–3.3)	1.59 (1.3–1.9)	6.05 (3.5–10.1)	3.52 (2.8–4.3)	2.23 (1.7–2.9)
ENVIR	5.93 (4.9–8)	3.28 (2.8–4)	2.21 (1.7–2.8)	6.01 (4.9–10.8)	3.48 (2.3–5.3)	1.76 (1.1–4.9)
MATER	7.96 (7.2–11.8)	5.74 (4.7–6.7)	4.00 (3–6.3)	15.52 (5.5–30.5)	9.7 (8.3–11)	5.64 (3.9–7.5)
MATH	3.87 (1.9–5.1)	2.7 (2.3–3.5)	1.76 (1.5–2.8)	3.59 (1.7–6.9)	3.26 (2.2–3.9)	2.05 (1.6–4)
MED	7.72 (6.8–8.9)	4.88 (4.3–5.5)	4.19 (3.4–5.1)	13.35 (11.5–14.6)	6.05 (5.4–6.9)	5.99 (4.4–6.9)
PHYS	14.02 (9.6–19.5)	5.13 (4.3–6.4)	3.25 (2.4–4.1)	13.45 (8–28.7)	9.76 (6.8–12.4)	7.17 (5–9.4)

4.5. Logistic Regression

The two-dimensional approach does not capture the effects of a variety of other predictors on productivity. Consequently, a multidimensional logistic regression model was applied. Three logistic regression models were created for assistant, associate, and full professors, in which success was defined as membership in the class of the top 20% of the most productive scientists. The selection of variables was guided by previous studies in the literature on high research productivity and the availability of data. The leverage value was used for variable selection. Leverage is a measure of how far away the values of the independent variables in an observation are from the values of other observations. High-leverage points, if any, are outliers with respect to the independent variables. In practice, this means that high-leverage observations are influential observations that strongly affect parameter estimates (Chatterjee and Hadi 1986). In each model, several such observations were found and removed from the set of observations.

In the next step, an analysis of the presence of collinearity among the independent variables was performed using inverse correlation matrixes and the values of their main diagonals. Variables that had values significantly higher than others were considered significantly correlated. Variables with a relatively high degree of multivariate correlation were as follows (Table 5): the age of associate professors; age at obtaining habilitation (postdoctoral degree) in the models of associate professors and full professors; and age at obtaining full professorship in the model of full professors. Because of the centrality of these variables and because the degree of their correlation was not high, they remained in the analysis.

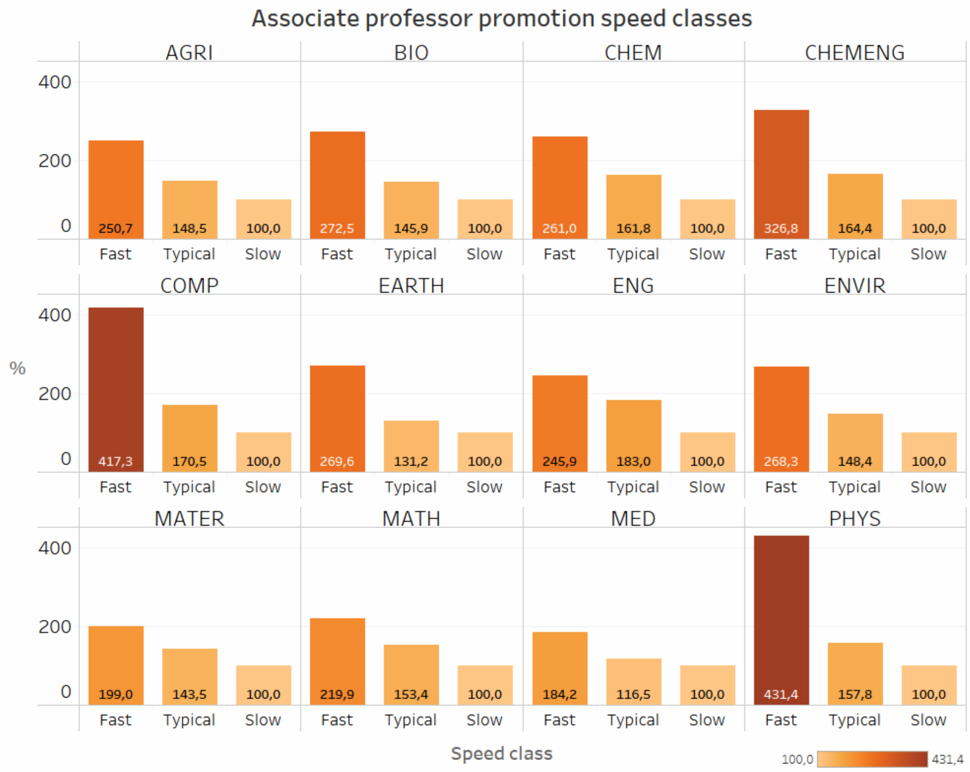


Figure 10. Productivity differential for associate professors between promotion speed classes (Fast, Typical, Slow) and discipline. Prestige-normalized productivity, full counting, 2014–2017. The productivity of the Slow class = 100% (N = 4,715).

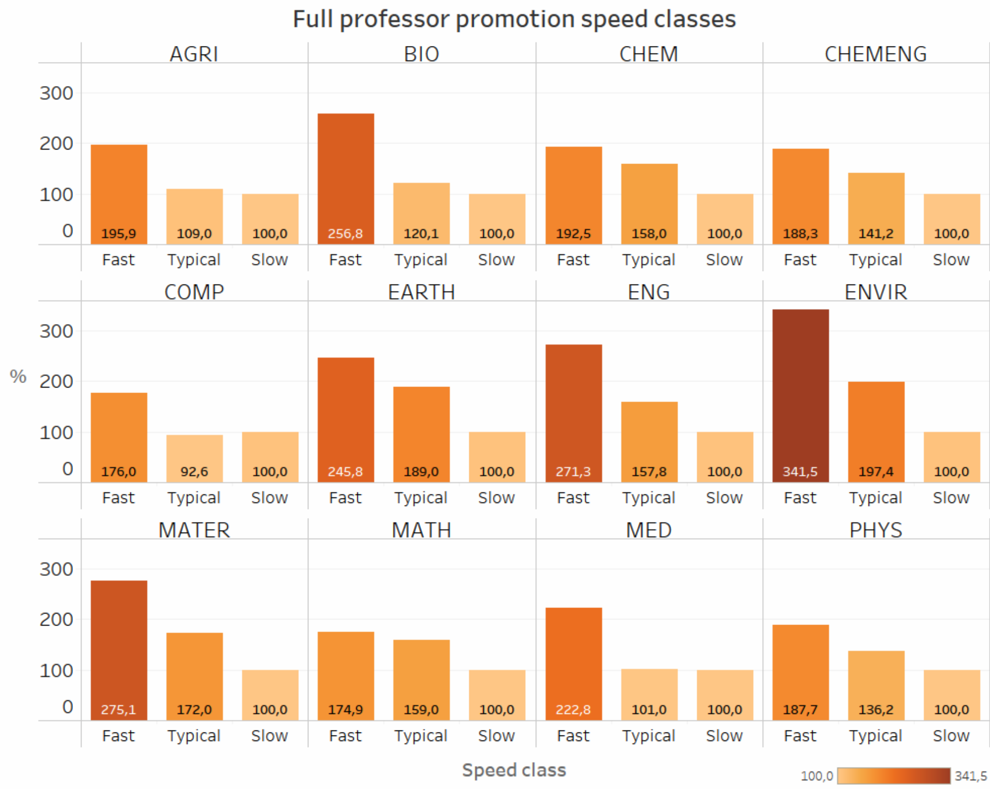


Figure 11. Productivity differential for full professors between promotion speed classes (Fast, Typical, Slow) and discipline. Prestige-normalized productivity, full counting, 2014–2017. The productivity of the Slow class = 100% (N = 2,284).

The distribution of residual statistics in our models was not normal. For example, the D statistic of the K-S normality test was 0.29–0.325, with p-values less than 0.001 (Table 6). The normality of the distribution of the residuals allowed for statistical inference regarding the properties of the models because all tests of statistical significance assume the normality of the distribution. To overcome the model's inconsistency with assumptions, robust standard errors were estimated. Based on the estimates, a significance test was conducted to determine the individual coefficients in the model. The results of the next step in analyzing the distribution of residuals indicated that there were no influential observations because the range of standardized residuals was unlikely to exceed ±3 standard deviations. Consequently, the conclusions drawn from our model were valid.

Table 5. Inverse correlation matrix main diagonals in the models' independent variables

Variable	Highly productive assistant professors	Highly productive associate professors	Highly productive full professors
Academic age	1.82	6.26	2.52
Biological age	1.57	1.66	1.86
Average team size (lifetime)	1.01	1.01	1.02
Assistant promotion age	1.02	2.55	2.90
Associate promotion age		5.35	6.88
Fast associate professor class		2.14	2.51
Fast associate professor class			1.61
Research intensity (IDUB): Rest	1.03	1.04	1.08
Top assistant professor class		1.74	1.41
Top associate professor class			1.42
Median prestige rate (lifetime)	1.08	1.13	1.11
Full professorship age			6.29
Male scientists	1.03	1.05	1.10
Young assistant professor class	1.20	1.86	2.06
Young associate professor class		2.50	2.98
Young full professor class			2.70

Table 6. Standardized residual statistics

Statistics	Highly productive assistant professors	Highly productive associate professors	Highly productive full professors
Mean	0.00	0.00	0.00
Standard Deviation	1.00	1.00	1.00
Median	-0.37	-0.31	-0.27
Q1	-0.64	-0.64	-0.60
Q3	0.00	0.09	0.12
Interquartile Range	0.64	0.74	0.71
Minimum	-1.62	-1.51	-1.93
Maximum	2.81	2.94	3.04
N Valid	9077	4225	1754
D	0.325	0.297	0.290
p-value	<0.001	<0.001	<0.001

In the models, we used both individual-level and organizational-level predictors: biological age, academic age; age of receiving doctorate, habilitation, and full professorship as thresholds for proxies of internationally comparable academic seniority levels; individual average team size, individual median publication prestige rate; and research-intensive institutions labeled IDUB. The individual median journal prestige rate in a scientist's individual lifetime publication profile (range, 0–99) was calculated based on all publications in a lifetime. The average individual team size was the median value of the number of collaborators per article in all articles published in a lifetime. Our variables included also the classes of Young Assistant, Associate, and Full Professors (promotion age); the classes of Fast Associate and Full Professors (promotion time); and the classes of Top Assistant and Associate Professors (past productivity). In the models, we included both the promotion age factor, the promotion speed factor, and the productivity factor at earlier stages of the academic career, whenever applicable.

The results of the regression analysis (Table 7) showed that the promotion age and promotion speed classes played different roles among the predictors of membership in current top productivity classes. In the model of full professors (Model 1), the strongest predictor was membership in the class of highly productive associate professors earlier in academic careers, on average increasing the odds by as much as 358%. While gender was statistically insignificant, biological age decreased the odds and academic age increased the odds (by 4.1% and 2.7% with every additional year). The associate professor promotion age was significant, with an increase of 9.6% for promotion every additional year. The individual median prestige rate was also significant: every increase in percentile rank increased the odds by 5%. Promotion age and promotion speed classes were statistically insignificant. Average team size was only marginally significant, and institutional research intensity (i.e., the environment) was insignificant.

In the model of associate professors (Model 2), the results showed a single powerful predictor of membership in the current top productivity class: top productivity in the past as an assistant professor, which increased the odds, on average, by 482%. Six other variables were significant: being male on average increased the odds by about one third (32.1%), biological age decreased the odds and academic age increased the odds (by 6.8% and 5.1% with every additional year); average team size had marginal impact and median prestige rate had a small effect (every increase in percentile rank increased the odds by 3.2%.). Membership in the fast associate professor class increased the odds by about one third (35.6%) on average. In this model, institutional research intensity was significant and decreased the odds by about one fourth (26.1%).

Finally, in the model of assistant professors (Model 3), the two strongest predictors were membership in the class of young assistant professors and being a male scientist, which on average increased the odds by about a half (53.5% and 48.4%, respectively). Both biological age and academic age were much stronger significant predictors for assistant professors than for associate and full professors: every additional year of age substantially decreased the odds of being among the current top productive assistant professors, and every additional year of academic experience substantially increased the odds (20.8% and 13.9%, respectively). As in Model 1 and Model 2, the median prestige rate was significant, and every percentile rank increased the odds by 2.8%.

Overall, the results of the multidimensional analysis of all predictors indicated that the roles of the promotion age and promotion speed classes were not as significant as expected based on the two-dimensional analysis. The most powerful predictors were membership in high productivity classes in the past. We also ran 36 regression models separately on the disciplines (three for each discipline), which showed that the roles of the promotion age and promotion speed classes were statistically significant in selected disciplines (BIO, EARTH, and MED), similar to the role of the past productivity classes (BIO, CHEM, CHEMENG, EARTH, ENG, ENVIR, MATER, MATH, and MED). However, these results are not discussed because of space restrictions. Thus, Hypothesis 3 was partly confirmed.

Table 7. Logistic regression statistics: odds ratio estimates of belonging to the highly productive classes (the top 20%)

Model	**Model 1: Highly Productive Full Professors N=1754 R^2 = 0,202**				**Model 2: Highly Productive Associate Professors N=4225 R^2 = 0,265**				**Model 3: Highly Productive Assistant Professors N=9077 R^2 = 0,239**			
	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**	
(Intercept)	0.199	0.013	2.981	0.239	0.934	0.299	2.917	0.906	1.575	0.811	3.059	0.215
Academic age	1.027	1.003	1.051	0.028	1.051	1.034	1.069	0.000	1.139	1.122	1.157	0.000
Biological age	0.959	0.928	0.991	0.010	0.932	0.907	0.957	0.000	0.792	0.778	0.805	0.000
Average team size	1.031	1.016	1.046	0.002	1.025	1.014	1.037	0.004				
Assistant promotion age									1.167	1.139	1.195	0.000
Associate promotion age	1.096	1.019	1.178	0.026					-	-	-	-
Fast associate professor class					1.356	1.029	1.787	0.033	-	-	-	-
Fast full professor class					-	-	-	-	-	-	-	-
Research intensity (IDUB): Rest					0.739	0.619	0.883	0.001				
Top assistant professor class					5.824	4.646	7.302	0.000	-	-	-	-
Top associate professor class	4.581	2.872	7.307	0.000					-	-	-	-
Median prestige rate	1.050	1.039	1.061	0.000	1.032	1.028	1.036	0.000	1.028	1.026	1.031	0.000
Full professorship age					-	-	-	-	-	-	-	-
Male scientists					1.321	1.107	1.576	0.002	1.484	1.323	1.664	0.000
Young assistant professor class									1.535	1.334	1.765	0.000
Young associate professor class									-	-	-	-
Young full professor class					-	-	-	-	-	-	-	-

Only statistically significant results, “- “ = observations structurally not applicable

5. Discussion and Conclusions

We combined data collected from the national administrative and biographical register of all Polish scientists and scholars (N = 99,935) with publication data collection from the Polish Science Observatory, enriched with metadata of all Polish articles published from 1973–2021 (N = 935,167). We constructed individual lifetime biographical profiles and individual lifetime publication profiles for every scientist in our final sample of STEMM scientists with doctorates (N = 16,083). Our research shows the new opportunities provided by large-scale national and global datasets to study academic careers.

We used a new methodological approach: instead of traditional productivity, which is based on publication counts, we used prestige-normalized productivity to avoid comparing "apples with oranges," that is, articles in unselective and low-prestige journals with articles in highly selective and high-prestige journals, which would reflect differing scholarly efforts and effects on the academic community. Our approach is in line with a rarely used methodological approach, in which "quality-adjusted publications" are used to determine productivity (Stephan and Levin 1992). Articles located in Scopus journal percentile ranks (N = 40,562 journals) were weighted differently in productivity, where articles in top-tier journals were weighted more than articles in low-tier journals. Finally, we used a classificatory approach to academic careers, allocating all scientists to different productivity, promotion age, and promotion speed classes based on the 20/60/20 division (top 20%, middle 60%, and bottom 20% of scientists, separately, for each of the 12 STEMM disciplines).

Our research showed that rank advancement and productivity are strongly linked in ways that have not been discussed in the literature: through the two time-related dimensions, promotion age and promotion speed. Recent studies on productivity, age, and seniority (but not promotions) have been inconclusive in their findings, and different results have been obtained for different systems and disciplines. For instance, in a large-scale study of faculty members, age did not emerge as determining overall publishing productivity but as influencing its mode: older scholars published fewer articles and conference proceedings but more books and book chapters (Savage and Olejniczak 2021). Senior academics were found to publish fewer articles in top journals (Mishra and Smyth 2013) and to be more productive than junior academics (Abramo et al. 2011). However, in higher ranks, as age increased, a decline in the productivity of full professors' productivity was reported (Abramo et al. 2016). In contrast, the present study focused on prestige-normalized productivity and promotions at all levels of professorship (assistant, associate, and full) and for all STEMM scientists with internationally Scopus-indexed articles.

In contrast to scattered and episodic remarks in previous research (e.g., Cole, and Cole 1973; Cole J.R. 1979; Long et al. 1993; Abramo et al. 2016), our study showed that assistant, associate and full professors who were promoted at a young age, regardless of their current age, were on average much more productive than their counterparts who were promoted at a later age. The highly productive classes largely overlapped with the young promotion age classes. The Polish case is special because rank advancement is based solely on research output assessments, and the time factor does not play a role. There are no time limits within which, for example, associate professors may apply for a promotion to full professorship. Most of them never do so because their research output is deemed unsatisfactory.

The patterns that emerged from our research are surprisingly consistent. First, in all disciplines, scientists in the young promotion age classes (the young, top 20%) were consistently the most productive, and scientists in the old promotion age classes (the old, bottom 20%) were consistently the least productive in all three ranks studied. Thus, current prestige-normalized productivity levels across all disciplines were strongly related to past promotion age classes.

Second, regarding associate and full professors in all disciplines, scientists in the fast promotion speed classes (the fast, top 20%) were consistently the most productive, and scientists in the slow promotion speed classes (the slow, bottom 20%) were consistently the least productive. Thus, the median productivity was the highest for scientists in both the young promotion age and fast promotion speed classes. And it was the lowest for scientists in the old promotion age and slow promotion speed classes. Our results were partially confirmed by the results of regression analyses, in which we examined odds ratio estimates of membership in top productivity classes (the highly productive, top 20%). Membership in the promotion age and promotion speed classes emerged as important predictors. However, its role was less significant than that of membership in top productivity classes at previous stages of an academic career.

On average, professors in all ranks who were promoted quickly and at a young age were substantially more productive than their counterparts who were promoted slowly and at an older age. Based on the medians, in the three largest disciplines of medical sciences (MED), engineering (ENG), and agricultural sciences (AGRI), the young-old promotion age productivity differential for associate professors was 100-200% (150-200% for full professors); and the fast-slow promotion speed productivity differential for associate professors was 80-150% (100-170% for full professors). The results of the coexistence analysis showed transitions between promotion classes over time. For example, two-thirds of young associate professors belonged to the class of young assistant professors, three-fourths belonged to the class of fast associate professors, and the largest proportion had become young full professors later in their careers (66.48%, 75.33%, and 28.55%, respectively). This pattern was even more significant for young full professors, of which 81.60% belonged to the class of young associate professors and 76.68% belonged to the class of fast associate professors. The time factor was found to be a significant factor because aging is unavoidable. When they are locked in a given promotion age or promotion speed class, scientists find it hard to change classes as they age.

The results of the analyses performed in this study revealed patterns. However, to speculate about their underlying causes, we need to return to the productivity theories discussed in section 2. Cumulative advancement, reinforcement, and the "sacred spark" theories shed some light on the relationships found in this study. Our findings showed that a small group of highly talented and motivated scientists was consistently highly productive, and they were promoted quickly and at a young age. Their career trajectories in each discipline were evident in individual micro-level data. Thus, for some, the "sacred spark" theory works well and is useful in explaining their productivity success throughout their careers.

For others, the cumulative advancement and reinforcement theories were more applicable: scientists who were perceived as more successful by peers were given more financial and reputational resources and were promoted quickly and at a young age. These scientists were successful and recognized by their peers in a system in which promotions were based almost exclusively on publications. Their high productivity was due in part to external stimuli. Promotions to associate professorships at a young age often led to promotions to full professorships at a young age, which was evident in our micro-level data.

Finally, the low productivity of scientists in the old promotion age and slow promotion speed classes tended to continue throughout their careers. Compared with others, being old and slow in receiving promotions makes it difficult for scientists to change the perceptions of colleagues in research grant panels and peers in their own disciplines. In their case, external awards traditionally accompanying young promotions and fast promotions – peer recognition, access to grants, and higher pay – do not reinforce sustained focus on research. For scientists in these two comparatively disadvantaged promotion classes (the old and the slow), promotion to associate professorship is finally achieved. A select few may even be promoted to full professors without sustaining high productivity over time. But external awards come too late to be effective as external stimuli that promote high productivity in the absence of internal stamina (Fox 1983) and "spark" (Allison and Stewart 1974; David 1994; Stephan and Levin 1992).

Our research contributes to aging and productivity research in academic career studies. A novel prestige-normalized approach was used to examine productivity within a national system and two new time-related dimensions of rank advancement—promotion age and promotion speed—were applied. We highlighted the role of path dependence in academic careers. In the Polish case, careers were developed over decades as long-term investments in research, with differentiated distributions of academic promotions over the life cycle of scientists. The findings of our study indicate that high productivity is strongly associated with fast promotion at a young age, and low productivity is associated with slow promotion at an older age.

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