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Being highly prolific in academic science: characteristics of individuals and their departments

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Abstract

The prolific (exceptionally high producers of scholarly publications) are strategic to the study of academic science. The highly prolific have been drivers of research activity and impact and are a window into the stratification that exists. For these reasons, we address key characteristics associated with being highly prolific. Doing this, we take a social-organizational approach and use distinctive survey data on both social characteristics of scientists and features of their departments, reported by US faculty in computer science, engineering, and sciences within eight US research universities. The findings point to a telling constellation of hierarchical advantages: rank, collaborative span, and favorable work climate. Notably, once we take rank into account, gender is not associated with being prolific. These findings have implications for understandings of being prolific, systems of stratification, and practices and policies in higher education.

Keywords Prolific publication · Academic science · Faculty · Universities · Stratification

Introduction

The highly prolific are often considered standard-bearers of productivity. At the same time, their performance is baffling and the gist of speculation (and even suspicion) as to factors associated with it (Wager et al. 2015). Exceptionally high publication has been documented for close to a century. Yet few, including the prolific themselves, are able to explain how it occurs (Wolpert and Richards 2007) and the performance gets "mystified." The issue here is not one

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of simply publishing, but rather being highly prolific in academic science. We use “highly prolific” to refer to a group (15.6%) who are in the right tail of the distribution of publication productivity (20 or more articles published/accepted in the prior 3 years). The rationale for this threshold, and the advantages of a 3-year period, appear in the “Method” section.

Academic sciences are a strategic case for the study of exceptional performance in higher education. First, in academic sciences, refereed articles are accepted widely as a measure of productivity. Social sciences and humanities are important in the study of higher education, but their metrics of performance are more variable (Braxton and Del Favero 2002). Second and related, in academic sciences, consensus is relatively high about the value of research performance (Shwed and Bearman 2010). Third, scientific fields have been influential in the shaping of graduate education, research specialization, external funding, and the decentralization of departments (Montgomery 1994). At the same time, findings about academic sciences may not necessarily generalize to fields, broadly.

Why focus on being prolific

We focus on being highly prolific for two fundamental reasons. First, the highly prolific account disproportionately for research activity. A recent study of 11 European nations showed that the highly prolific (upper 10%) accounted for 50% of publications; and without this group, the output of the given nations would be reduced significantly (Kwiek 2016). Another study of the most prolific (representing less than 1% of 15.2 million in the Scopus database) showed that the prolific accounted for 41.7% of papers published (Ioannidis et al. 2014).

The prolific are consequential also because they influence research by being “prescient,” and sometimes “disruptive.” An analysis of 8.86 million authors indicates that the highly prolific have few papers that are isolates, that is, within problem areas that fail to survive into a second year beyond publication; a lower than expected proportion in dying/receding areas; and a higher than expected proportion in areas that challenge the status quo (Klavans and Boyack 2011).

The prolific also garner the bulk of citations. In laser science technology, the prolific produce 25% of total articles, and on a per-paper basis, their articles have higher impact than those of the less prolific (Garg and Padhi 2000). Likewise, in environmental science and ecology, the highly cited are also prolific (Parker et al. 2013). This also occurs among Swedish authors of Web of Science publications (van den Besselaar and Sandstrom 2015). Thus, the prolific warrant our attention because they have been “drivers” of research activity and impact.

Second and related, the highly prolific are a window into stratified structures. Inequality is a persistent and pervasive feature of higher education (Taylor and Cantwell 2019). The factors associated with being highly prolific provide a view into hierarchies of people and groups. This is because the hierarchies are based partly on exceptional performance (Parker et al. 2010; Prpić 1996; van den Besselaar and Sandstrom 2015). The prolific, in turn, are characterized as “stars,” “eminent,” and “elite” (Klavans and Boyack 2011; Kwiek 2016, 2018) within higher education systems that are strongly “status-seeking” in missions and motives (Taylor and Cantwell 2019). Understanding what predicts being prolific then gives insight into structures of stratification in which the prolific are a distinctive group (Kwiek 2019, 27). Thus, the study of being prolific is revealing beyond the study of publication productivity, more broadly; and it provides insights into higher education.

To some extent, positive characterization of the prolific is contested, especially when it comes to the performance as a basis for resources distributed (Kwiek 2016). Stratification provides benchmarks for performance (Collins 2019); and it may also fragment and underserve groups of people (Lincoln et al. 2012). In either case (beneficial or not), the prolific are a special segment that can drive (and reflect) systems of rewards, honors, and accolades (Marginson 2014), bearing widely on academic lives. Thus, being prolific is a sensitive, as well as revealing, topic. This heightens the rationale for our inquiry.

Previous research: extent and limitations

Studies have addressed publication productivity, broadly, and point to individual characteristics, departmental and institutional features, and feedback processes of cumulative advantages and reinforcement, in explaining the number of publications produced (Fox 1985; Kwiek 2019; Ramsden 1994). These studies address the importance of characteristics including gender (Xie and Shauman 2003), research orientation (Cummings and Finkelstein 2012), collaborative practices (Lee and Bozeman 2005), and multiple projects undertaken, simultaneously (Fox and Mohapatra 2007). Features of work settings, such as prestige of institution (Long and Fox 1995), departmental climate (Smeby and Try 2005), and performance of departmental colleagues (Braxton 1983), relate to publication productivity. Feedback processes emphasize the influence of earlier success for continued research through accumulation of advantages (review in DiPrete and Eirich, 2006). A variation of this, termed “Matthew effect” (Merton 1968), points to greater recognition accruing to those with higher compared with lower repute that occurs especially in collaboration and independent multiple discoveries.

Few studies focus on being prolific—despite the importance of this topic. Those studies that do address being prolific rely predominately on bibliometric sources. Bibliometric studies have advantages of large numbers of cases from Scopus or Web of Science databases and enrich understandings. They point to the role of gender, institutional type, number of collaborators, and researchers’ national locations (e.g., US, UK, Israel) (see Abramo et al. 2009; Bosquet and Combes 2013; Garg and Padhi 2000; Parker et al. 2010).

At the same time, the bibliometric approaches do not permit analysis of work settings (resources, work climates) and characteristics such as work practices. Survey methods make it possible to analyze these variables. In doing so, they complement bibliometric inquiries. To date, however, survey approaches to being prolific are limited to two notable studies of European scientists. These show the prolific as older, with high rank, and international collaborations and orientations (Kwiek 2016, 2018; Prpić 1996).

Present study: questions, perspective, and focal constructs and variables

We address the following questions about the prolific in higher education. How does exceptional (prolific) productivity relate to academic scientists’ individual characteristics (gender, rank, work practices) and their reported features of departments (resources, climates)? Why do the patterns matter?

We pursue these questions with a social-organizational perspective. This perspective combines views of individual characteristics and organizational conditions, and the links within and between characteristics and conditions, in understanding exceptional performance. The perspective is aligned with academic sciences because scientific research takes place “on site” within departments; it relies on cooperation of others and is tied with collaborative patterns. The work is fundamentally social and organizational (Fox and Mohapatra 2007; Lee and Bozeman 2005; Zhang 2010). Key issues are then: *Which* social characteristics and departmental conditions are associated with being prolific? *How* do these characteristics and conditions operate, either co-exiting as predictors, or mediating the effects of another? *What* are the implications of the results for understanding higher education? The perspective is identified as one needed—yet often missing—in the study of research activity (Antonelli et al. 2011). The perspective is also potentially consequential for understanding topics related (but not identical) to being prolific, such as exceptional creativity (Amabile et al. 1996) and innovation (Glynn 1996) and the organization of academic labor (Carayol and Matt 2004).

We use sets of constructs (broad concepts) and variables (related measures) that reflect this perspective. As an individual characteristic, gender is key because a range of studies point to the lower productivity of women compared to men (see Ceci et al. 2014)—with potential implications for gender disparity in exceptional performance (Fox et al. 2017). Academic rank is important because those who publish extensively achieve higher rank and those with high rank can accrue positions and networks that enable being prolific (Kwiek 2016; Prpić 1996; Teodorescu 2000). Work practices reflect ways of conducting work and are associated with exceptional productivity (Root-Berstein et al. 1995).

Of these practices, collaboration is important because, increasingly, scientific results are the product of teamwork and the pooling of knowledge and skills (Wuchty et al. 2007). Quality and quantity of collaboration support publication productivity (Lee and Bozeman 2005), and collaboration occurs more extensively among the eminent (Kwiek 2016). Here, our focus is on *span* of collaboration as a variable, in a way not previously analyzed in relationship to being prolific. Frequency of discussion about research is also important because it can help generate and sustain research activity, by providing room for speculation and sharing successes and failures (see Campbell 2003; Katz and Martin 1997).

From a social-organizational perspective, reported features of departmental settings are key constructs. They are important across fields, and especially so in academic science. This is because scientific research revolves strongly on cooperation with others and costly resources—so that settings can be highly salient (Fox and Mohapatra 2007). Quality of faculty and students (human resources) have the potential to shape and reflect research performance (Baird 1986; Braxton 1983). So do material resources of equipment and space. Equipment is essential to scientific discovery, even in some theoretical areas. Likewise, scientific research entails space, sometimes with special conditions such as “clean” areas or exhaust systems (Stephan 2012). Interestingly, Bland and Ruffin (1992) report that the perception of resources available (compared to measurable distribution of them) correlates with productivity.

Work climates are characterizations of settings—meanings that people attach to an organization and its values, practices, and goals (Patterson et al. 2005). Operationally, work climates are ways that people appraise their environments (Patterson et al. 2005) along dimensions that encompass the atmosphere or “personality” of a unit. Departmental work climates are consequential because they can activate interests, convey standards, and stimulate or depress performance (Fox and Mohapatra 2007; Louis et al. 2007; Torrisi 2013). A key study of the “state of research on work climates” points to renewed interest in work climate and the need for more definitive studies of climate and performance (Kuenzi and Schminke 2009). Accordingly, the analysis here of work climate and being prolific is unusual (or unique).

Our “Introduction” section has provided the rationale for studying the prolific; the extent and limitations of previous research; and the questions, perspective, and focal constructs and variables of this study. The following sections address the “Method” and “Findings”. The

"Discussion and conclusions" section summarizes the contributions of the study and addresses broader implications of the findings.

Method

Data

The data are collected in surveys[1] of tenured and tenure-track faculty in departmental fields of computer science, engineering, and six fields of sciences (biology/life sciences, chemistry/microchemistry, earth/atmospheric, mathematics, physics, psychology[2]). These fields encompass the range of classifications of the US National Science Foundation. The faculty members surveyed are in eight research universities identified by a strong baseline university as institutional peers in prestigious, national standing in scientific and technological fields.[3] These universities are within the Research I and Doctoral-Research Extensive categories of the Carnegie Classifications at the time of the survey. They are cross-regional within the USA (one southeast, two northeast, one northcentral, two midwest, one southeast, and two pacific west) and encompass public (four) and private (four) institutions. Research universities constitute an important grouping because they train doctoral students, confer numbers of degrees, receive federal grants, and contribute to research. They also set standards for rewards in other types of institutions (Fairweather 2005).

The survey is distinguished by inclusion of the population of women, except for sampling in life sciences and psychology ($n = 434$), enabling analysis by gender, and a stratified, random (probability) sample of men by field ($n = 527$). We accomplished this sample by (1) canvassing completely the websites of departmental fields within these eight institutions; (2) identifying the total population of tenured and tenure-track faculty; and (3) taking stratified random samples by field from known and specified populations (see Appendix—supplementary materials).

The resulting number of respondents to the survey is 327 men and 280 women. The overall response rate is 65% for both women and men respondents (a response rate that removes 24 ineligible cases from the base because of moves, retirements, and/or being deceased). This response reflects the use of customized letters and follow-ups to non-respondents, based on Dillman et al. (2014) protocols. The response here exceeds the rates of 50% (or less) most commonly reported in surveys of academics and scientists.

Our survey data are revealing but do not permit links to bibliometric (Web of Science, Scopus) data, the weighting of articles by numbers of authors, and inclusion of citations. This is because the identity (names) of survey respondents is protected by the given approval of the institutional review board, and thus, the means are unavailable for "tracing" respondents to other sources. Despite this, our method enabled collection of a range of important indicators that are absent from most bibliometric studies.

[1] The surveys were conducted in 2003–2004. Since 2004, universities have experienced increased entrepreneurial activity, global collaboration, and competition for resources. However, these changes have been stronger outside of, compared with inside, the USA (Bloch et al. 2018).

[2] The National Science Foundation (National Science Board, 2016) categorizes psychology as a distinct scientific field.

[3] The baseline university was surveyed, but not on issues of publication productivity.

Measures of variables

Dependent variable

The dependent variable is prolific (or not) based on self-reported number of articles published or accepted for publication in refereed journals in the prior 3 years and, for computer scientists, the number of refereed proceedings as well. Information on numbers of coauthors is not available.[4] The inclusion of refereed proceedings for computer scientists is in keeping with the Computing Research Association's (1999) "best practices" that, in computing, proceedings are rigorously reviewed and a standard means of publication, along with refereed articles.

The measures of publications take into account: (1) types of publications, (2) time lags, (3) period of time, and (4) self-reporting of data. First, the survey asks respondents to list separately the number of articles published and those fully accepted in refereed journals and in conference proceedings—as well as counts of other types of publications. Collecting counts in other categories helps to reduce or eliminate respondents' mis-categorizing them as "refereed articles" (or proceedings) and thus improves the validity of counts in the "core" publications. Second, the inclusion of the number of articles (and proceedings) published and separately, the number fully accepted for publication, addresses the time lags that occur between submission, acceptance, and publication. Third, specifying a prior 3-year period controls for the effects of seniority (available span of time) for publishing; and publications in a recent period may be analyzed in relationship to current departmental features reported (while a long span could not). Further, the measure goes beyond articles simply published in a 3-year period and includes those fully accepted, as indicated, and thus helps address lags in times to publication. Fourth, self-reported counts correlate highly with those listed in independent sources (Ehrenberg et al. 2009).

Definitions of the prolific commonly reflect a "power law of distribution" (Newman 2005), namely, that the bulk of counts occurs for a small number of cases; that a long-right tail of the distribution exists; and, classically, that about 80% of counts owe to 20% of the cases. Thus, to begin, we examined the distributions of counts of publication productivity for all respondents ($n = 607$) and for those with cases complete ($n = 493$) for our variables. These two distributions were comparable in the concentrations of publications in a small group; and in the percentages of respondents by gender, rank, and departmental field (Table 1). Further, results of Little's MCAR test were not significant ($p = .155$), indicating that data were missing completely at random.

The distribution of publications for cases complete (Fig. 1) has a range of 0 to 80, skewness of 2.2, a mean of 11.6, and a median of 9. Notably, this distribution shows a flattening of counts at 20 or more articles in the 3-year period, representing 15.6% of these academic scientists. This cut-off point provides a fit to the resulting models here. Using points for prolific of (1) the upper 21% and (2) the upper 15% for each of the three major fields did not change results. Further, no significant differences appear in values of the independent variables for the upper 5% compared with the upper 15%; and an upper 5% is restricted because it contains only 25 respondents. The proportion of respondents (15.6%) who constitute the threshold for prolific here is within the range of proportions (10%–25%) identified as prolific in other groups over time (see Garg and Padhi 2000; Kwiek 2016).

[4] At the same time, adjusting for numbers of coauthors does not affect measures of productivity at the individual level (Mairesse and Pezzoni 2015, 290).

Table 1 Characteristics of all respondents and those with cases complete

Strata	Categories	Sample 1 All respondents (%) $N = 607$	Sample 2 Cases complete (%) $N = 493$
Gender			
	Female	46	46
	Male	54	54
Rank			
	Other	1	
	Assistant	21	21
	Associate	20	21
	Full	58	58
Field			
	Engineering	41	42
	Sciences	51	50
	Computer science	8	8

A potential question is whether the men and women differ in the distribution of actual counts *within the categories* of prolific and non-prolific. A box-plot (Fig. 2) shows similar mean and median counts for prolific and non-prolific women and men. This indicates that the cut-off points for prolific/non-prolific are not camouflaging actual counts among the women compared with men.

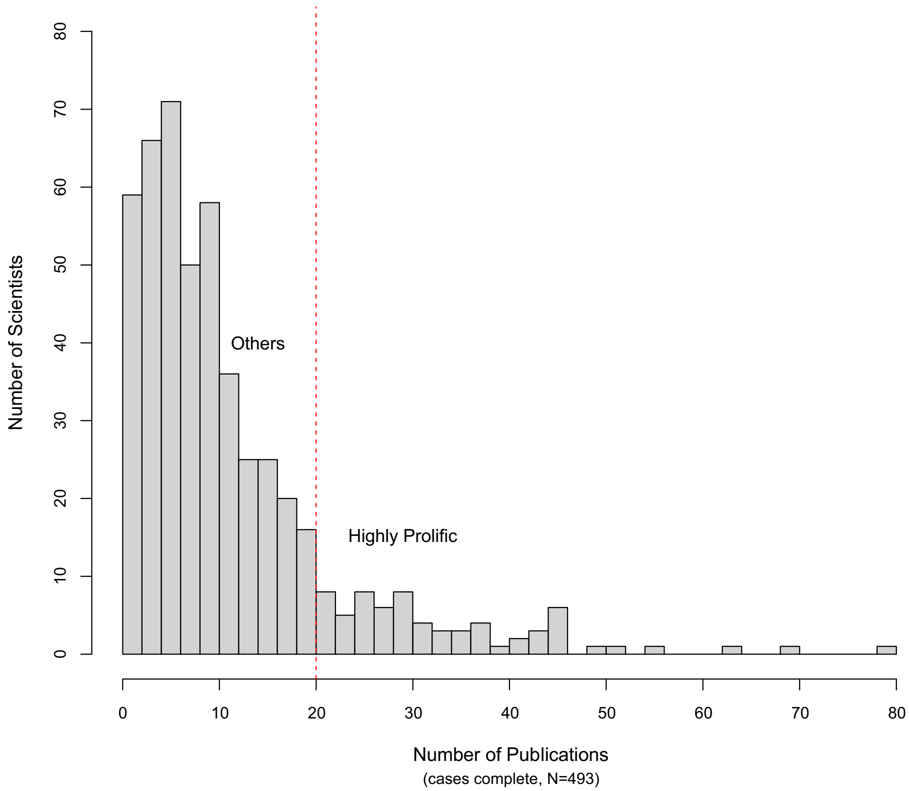

Fig. 1 Frequency of publication counts for scientists in prior 3-year period

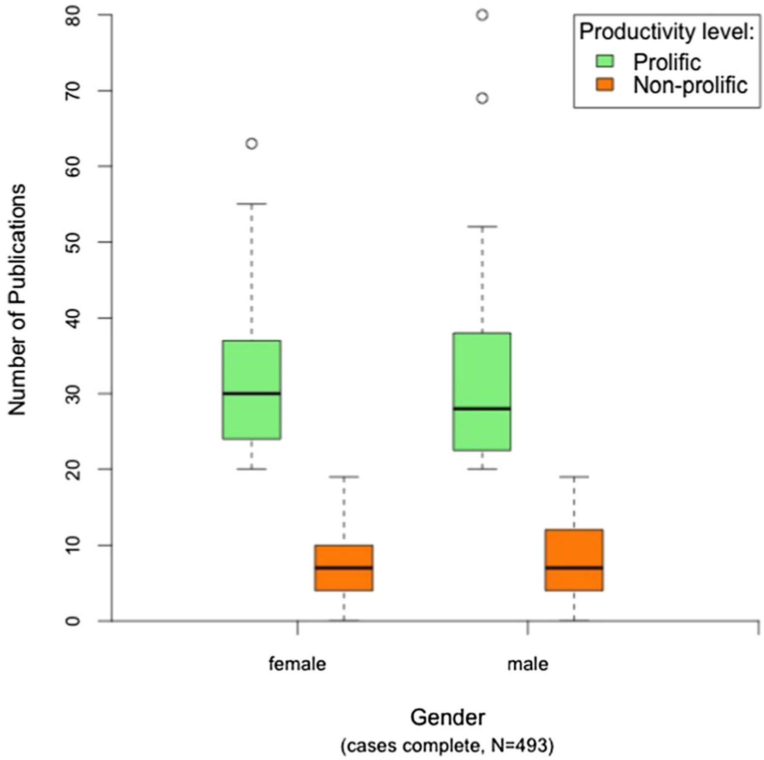

Fig. 2 Box-plots of publication counts for prolific and non-prolific scientists, by gender. Box-plots graphically depict five publication statistics: the first quartile, the median, and the third quartile (see the boxes), the smallest and the largest extremes (the whiskers), and the outliers (circles)

Independent variables

The independent variables encompass (1) characteristics of individuals (gender, rank, and reported work practices) and (2) features of their departments (human and material resources, departmental climates).

Gender is coded as male (female as comparison). Ranks are full professor and associate professor (assistant professor as comparison). Work practices are span of collaboration and frequency of speaking about research. Collaborative span is based on reported collaboration in research proposals or publications (yes/no) in the past 3 years with faculty (a) within the home unit; (b) within the home university, but outside of home unit; and (c) in other institutions. Collaboration at each of these levels (a–c) constitutes a value of 1, so that the resulting measure can extend from 0 to 3. The question about frequency of speaking with faculty in home unit about research refers to speaking about "research projects and research interests." This is coded as a dummy variable of speaking daily or weekly (compared with less than weekly).

For human resources, we considered reported quality (poor to excellent) of (a) faculty, (b) graduate students, and (c) undergraduate majors in the home unit. The quality of faculty and undergraduates had virtually no association with being prolific, while the quality of graduate students did (dummy, $\tau b = .139$, $p < .001$; scaled, $\tau b = .149$, $p < .001$). In keeping with the importance of graduate students for research in academic science, this measure was the stronger of the three variables (especially in its scaled form); and including this meets the need to limit the number of variables (in relationship to cases).

Quality of material resources takes the form of two binary variables of "excellent" (compared with "good," "fair," or "poor") in reported quality of (a) space and (b) equipment. Conceptually, the variables go beyond sufficiency to measure excellence in space and equipment (related potentially to being prolific). Empirically, the recoding permits inclusion of both variables without the level of collinearity ($r = .54$, $p < .001$) that exists for the variables in scaled form.

We measure work climate with questionnaire items asking respondents to rank their home unit along eight, scaled (5-point scale), bipolar dimensions of (1) formal-informal, (2) boring-exciting, (3) unhelpful-helpful, (4) uncreative-creative, (5) unfair-fair, (6) competitive-non-competitive, (7) stressful-unstressful, and (8) noninclusive-inclusive.

We used exploratory factor analysis to detect an underlying structure among these (1–8). The interest was in communality (common variance) among the items. Thus, we used principal axis, rather than maximum likelihood, factoring. The results of oblique (oblimin) rotation were similar to orthogonal, and we chose the orthogonal (varimax) to more clearly separate the factors. One item (formal-informal) did not load on any factors (loadings below 0.5) and was removed.

The factor analysis identified three constructs of departmental climates: (1) "stimulating" (creative, exciting); (2) "collegial" (fair, helpful, inclusive); and (3) "competitive" (stressful, competitive). The correlations among the seven items and factor loadings appear in Table 2. After identifying the factor structure, we created scores (unweighted scales) by adding the items with factor loadings of 0.55 or greater. Reliability tests (Chronbach's alpha) produced values of 0.84 for stimulating, 0.74 for collegial, and 0.68 for competitive climates. The alpha value for competitive climate was lower than the others; and at the same time, the values for each climate are sufficient for inclusion.

Table 2 Dimensions of departmental climate: correlation matrix and factor loadings based on principal axis factoring and varimax rotation ($N = 493$)

	1	2	3	4	5	6	7
1. Boring-exciting	1.000						
2. Unhelpful-helpful	0.494	1.000					
3. Uncreative-creative	0.721	0.556	1.000				
4. Unfair-fair	0.259	0.431	0.296	1.000			
5. Noncompetitive-competitive	0.110	−0.037	0.146	0.110	1.000		
6. Unstressful-stressful	0.003	−0.223	0.045	−0.035	0.515	1.000	
7. Noninclusive-inclusive	0.408	0.542	0.351	0.499	−0.057	−0.189	1.000
Factor Loadings	Stimulating (creative, exciting)		Collegial (helpful, fair, inclusive)			Competitive (stressful, competitive)	
1. Boring-exciting	.853						
2. Unhelpful-helpful			.563				
3. Uncreative-creative	.754						
4. Unfair-fair			.719				
5. Noncompetitive-competitive						.650	
6. Unstressful-stressful						.802	
7. Noninclusive-inclusive			.661				

Factor loadings below 0.5 were suppressed

Sensitivity tests

We considered other variables that do not appear in the final models. These variables did not differentiate faculty in research universities; did not relate closely to the perspective; introduced multicollinearity; and/or extended the number of variables beyond those appropriate for the number of cases.[5] Specifically, "great interest" in research and in teaching did not differentiate prolific and non-prolific faculty, in part, because of limited variation in these. This is also the case for being a principal investigator on a grant within the past 3 years and for the time between bachelor's and doctoral degrees. Age and age-squared were co-linear with academic rank, and in the presence of rank, did not predict.

We explored the impact of fields (Table 3). The box-plots of publication counts in the three broad fields reveal greater similarity among engineering and sciences compared with computer science (Fig. 3). Engineering and sciences have faculty with zero publications and distant outliers. All faculty in computing published at least once in the last 3 years.

We could not use each field of science because some were small[6]; had few faculty members; and were sensitive to zero cell count problem, that is, to the invariance of the dependent and independent variables (Menard 2010). However, we analyzed fields or clusters of fields as predictors of the actual publication counts (a continuous variable rather than being prolific or not) in a negative binomial (and in a Poisson) regression for overdispersed distributions. The results (not displayed) were consistent with those of logistic regression and average field output. They show that, compared with being in engineering, locations in computer science, chemistry, or physics were associated with statistically significant increases in publication counts; being in mathematics decreased the count. Field was a good predictor of counts of publications, but *not* a good predictor of being highly prolific.

Finally, we assessed the potential interaction of gender and rank with being prolific. First, we addressed the interaction in a logistic regression. The product term was not statistically significant and could not be interpreted. A second diagnostic, Jaccard's (2001) method of testing two-way interactions with a moderator (gender), showed the odds of being prolific as a function of gender and rank. The odds ratios for each rank were equal, confirming the absence of interaction of rank and gender. However, further tests showed that rank mediated the relationship between gender and being prolific; and the "Findings" and "Discussion and conclusions" sections address this.

Means of analysis

We use three multi-stage logistic regression models to assess characteristics associated with being prolific. These models express the relationship between being prolific (compared with not) and (1) the individual characteristics of gender and academic rank; (2) the preceding (model 1) with addition of work practices; and (3) the preceding (model 2) with addition of reported departmental features. In the analysis of extremes (as is the case of prolific), logistic regression is advantageous over a linear probability because it can handle extremes, and a linear probability model is likely to yield out-of-bound predicted probabilities (Menard 2010).

[5] The total number of variables included in models is governed in part by the number of positive/negative events available for analysis (Peduzzi et al. 1996).

[6] After removing the smallest academic field of mathematics (n = 21), regression results show that chemistry/biochemistry is the only field associated with being prolific.

Table 3 Fields of prolific and non-prolific Scientists

Fields	Prolific Scientists $n = 77$ % of total (% of prolific)	Non-prolific scientists $n = 416$ % of total (% of non-prolific)
Engineering	6.1 (39)	36 (42)
Sciences	7.5 (48)	42 (50)
Computer Science	2 (13)	6.4 (8)
Totals ($N = 493$)	15.6 (100)	84.4 (100)

Sciences include biology/life sciences, chemistry/microchemistry, earth/atmospheric, mathematics, and psychology

The logistic regressions present the predictive value (log odds) that an independent variable has for being prolific. The coefficients may be interpreted as a change in the log odds of a response per unit of change in the independent variable. The multi-stage models allow us to assess the independent variables in the absence and presence of other variables. Alterations in values and significance can point to covariation between the variables in the earlier model with those in the subsequent model(s).

Cross-sectional data and logistic regression allow us to explore patterns of relationships but do not establish causal order, as addressed in the "Discussion and conclusions" section. With these caveats, we use the term "predictor" for independent variables because this term is commonly used and understood in logistic regression.

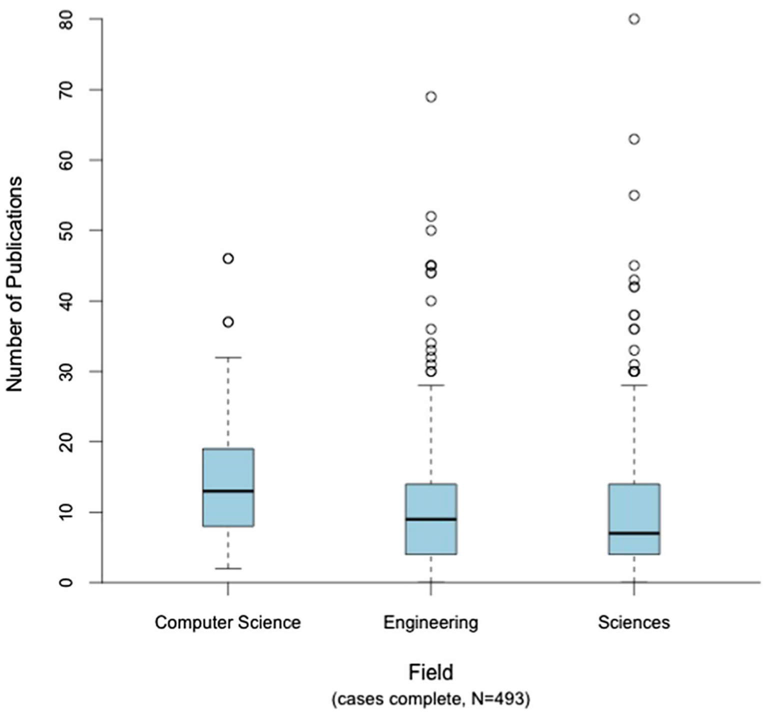

Fig. 3 Box-plots of publication counts, by field. Box-plots graphically depict five publication statistics: the first quartile, the median, and the third quartile (see the boxes), the smallest and the largest extremes (the whiskers), and the outliers (circles)

Findings

The findings depict the results of the sequence of the three logistic regression models with predictors of being prolific (Table 4). This section presents the central results, and further implications appear in the next section.

The first logistic model includes gender and academic ranks. Higher ranks predict being prolific. Having a rank of full professor (compared with assistant professor) strongly and positively predicts being prolific (log odds = 3.254, $p < .01$). Having a rank of associate professor also predicts being prolific (log odds = 2.672, $p < .05$); however, this rank is not as strong a predictor as full professor. In the presence of rank, male gender does not significantly predict being prolific, although, by itself (analyses not shown), gender does. This suggests covariation between gender and rank (but not interaction of gender and rank, addressed in the "Method" section). Notable implications appear in the following section.

In the second logistic model, added are the work practices of speaking daily or weekly about research with faculty in the home unit and the span of collaboration in research proposals and papers within the prior 3 years. Speaking frequently about research is a work practice that

Table 4 Estimated logistic regression coefficients for models 1, 2, and 3

	Model 1 Gender and rank *B* (SE)	Model 2 Plus collaboration and speaking *B* (SE)	Model 3 Plus resources and climates *B* (SE)
Gender	0.282 (0.276)	0.262 (0.280)	0.161 (0.291)
Rank:			
Associate Professor	2.672* (1.049)	2.546* (1.052)	2.626* (1.057)
Full Professor	3.254** (1.021)	3.241** (1.024)	3.324** (1.029)
Work practices:			
Span of Collaboration w/ faculty		0.535** (0.187)	0.455* (0.186)
Daily or Weekly speaking about research		0.218 (0.300)	0.047 (0.315)
Resources:			
Quality of graduate students			0.214 (.280)
Quality (excellence) of research space			− 0.295 (0.313)
Quality (excellence) of research equipment			0.051 (0.321)
Department climate:			
Stimulating			0.281** (0.103)
Collegial			− 0.062 (0.060)
Competitive			− 0.006 (0.074)
Nagelkerke R-squared	0.125	0.161	0.203
Chi-square	2.571	3.313	5.342
-2 log likelihood	390.135	378.800	365.592
N	493	493	493

* $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

encompasses elements of exchange that go beyond formal collaboration in proposals and publications. However, this is not associated with being prolific. Span of collaboration is a predictor (log odds = 0.535, $p < .01$). A wider span of collaboration (with faculty in home unit, on campus but not in home unit, and outside of the home institution), compared with a more narrow span of collaboration (or none at all), is associated with being prolific. This points to the prolific as strongly collaborative researchers with those both near (those in the home department and on campus) *and* far (those outside of their institution). We discuss the complexities of collaborative span in the following section.

In this second model, academic ranks remain strong and significant predictors. The log odds of holding a rank of full professor or associate professor barely reduce with the addition of work practices in the second, compared with the first, model. This indicates that as positive predictors, ranks are not simply a function of collaborative span associated with academic scientists' higher positions. Rather, both rank and collaborative span *coexist* as predictors. Gender remains non-significant in the second, as well as the first, model.

In the third model, added are faculty members' characterizations (perceptions) of their departments in levels of human and material resources and work climates. Among these, the significant predictor of prolific is being in a department characterized as "stimulating" (log odds = 0.281, $p < .01$). Location in a department characterized as "collegial" is not a significant predictor (log odds = −0.062, $p = .302$); nor is location in a strongly "competitive" setting (log odds = −.006, $p = .930$). In the following section, we discuss the prospect that those who are unusually productive may regard their departments as stimulating and/or may create micro-environments within departments that are stimulating.

The human resource of quality of graduate students does not predict being prolific (log odds = 0.214, $p = .444$) in this model. Neither do material resources of space (log odds = −.295, $p = .346$) or equipment (log odds = .051, $p = .875$). Further, the characterizations of departments do not alter notably the levels and significance of the predictors in the earlier models, namely, academic ranks and collaborative span. In this third, final model, being a full professor continues to be a strong and significant predictor (log odds = 3.324, $p < .01$). Being an associate professor is less strong than being full professor, but still a significant predictor (log odds = 2.626, $p < .05$). Likewise, a span of collaboration remains a strong predictor in this third model (log odds = .55, $p < .05$). Thus, the academic scientists' rank and collaboration are predictors that owe little to the characterizations of the departments in which they are located. Overall, outside of the stimulating climate, characterizations of departments are not as strong as rank and collaborative span in capturing prolific productivity among these academic scientists.

Discussion and conclusions

Being prolific is a distinction that underlies depictions of "superstar" (Klavans and Boyack 2011), "eminent" (Kwiek 2016), and "elite" scientists (Parker et al. 2013). In this sense, the prolific constitute a basis of social stratification in higher education that bears on academic lives. Yet, the features associated with being prolific have been only rarely investigated with reliable survey data, particularly with key characteristics of individuals and their departments, and links between them, which reflect a social-organizational perspective. Thus, we take up the widely expressed and long-standing "need to know more" about the highly prolific as a distinctive and revealing group in higher education (Garrison et al. 1992; Kwiek 2016; Parker et al. 2010; Prpić 1996).

We do this using survey data with a strong (65%) response rate among academic scientists in eight US research universities. Scientists in these settings are an important group because their institutions define themselves through research (including external funding and graduate degrees awarded). However, only 15.6% of prolific academic scientists, by our measure, account for 44% of all publications in this study. In the prior section, we identified stable features (across the models) associated with being prolific. Now, we discuss the results in relationship to the social-organizational perspective that frames our study. We consider noteworthy findings and their broader implications and also address limitations of the data and areas for continuing inquiry.

Results from our sequential models (previous section) point to ways that gender and rank, work practices, and reported features of departmental environments operate in predicting being prolific. First, the initial model contains rank and gender because interest persists in gender and research performance; and rank is a fundamental feature of academic positions. As a predictor of being prolific, gender bears on understandings of other disparities (recognition, rewards) among male and female scientists that, in turn, relate to performance (Fox et al. 2017; Xie and Shauman 2003). Rank (especially full professor) is associated with being prolific, and in the presence of rank, gender is not. Moreover, rank remains a stable predictor across models. The implications are notable.

The findings here indicate covariation of gender and rank in relationship to being prolific. This points to rank as key to understandings of gender disparities (Fox 2020; Rørstad and Aksnes 2015; Xie and Shauman 2003). This does not mean that access to academic rank is equitable; evidence exists to the contrary (Fox 2020; Xie & Shaumann, 2003). Rather, we find that rank mediates the relationship between gender and being prolific. This indicates that gender does not directly influence being prolific here; it does so by means of rank (the mediator). To put it another way: among the women here who have high academic rank, the odds of being prolific are not significantly lower than those of men. From a social-organizational perspective, this is a notable social link: rank is a conduit in the relationship between gender and being prolific.

More broadly, being prolific is a senior professors' game, contrary to some popular lore about this. Our measure of prolific is based on publication in the prior 3-year period (not across the career). This means, in turn, that the relationship between rank and being prolific is a complex issue and not simply a matter of longer time to accrue publications for those at higher ranks. Higher rank potentially confers (and reflects) advantages of research experience, lead roles on teams, and integration into scientific communities (Rørstad and Aksnes 2015). Further, ranks are *not* simply a function of collaborative span or perceptions about work climates. As emphasized, the coefficients for rank do not reduce in models with inclusion of these variables. In addition, rank remains strongly associated with being prolific, controlling for fields (Appendix Table 4—supplementary materials).

Funding agencies may be fueling the salience of rank by requiring that proposals contain preliminary results and, in turn, favoring research programs of established scientists (Stephan 2012). Relatedly, increased use of H-index (based on the number of papers and their citations) favors established scientists (Lawrence 2007) and may also support the salience of rank. Fu0rther, gendered processes of evaluation can contribute to the importance of rank as a mediator of gender in being prolific.

Second, the practice of frequency of speaking with departmental faculty about research, introduced in the second model, represents informal exchange. This is not equivalent to formal collaboration, measured here as coauthoring proposals and publications. From a social-organizational perspective, speaking daily or weekly about research may help generate and sustain research activity (Campbell 2003; Katz and Martin 1997). However, compared with actual collaboration in proposals and publications, speaking frequently is not significant in predicting being prolific. This, in turn, may be a potential issue for types of interaction that departments seek to encourage.

Third, we measure *span* of collaborators in a revealing way: a range of having (faculty) collaborators in home department, in units within the university but outside home department, and in other universities. We find that a wider span is associated with being prolific. This reflects teamwork as a mode of scientific production (Wuchty et al. 2007) with benefits derived.[7] In broader implications, however, collaboration may also come with tensions and costs, including time, energy, and interpersonal struggles (see Bikard et al. 2015). As a part of this, Bikard et al. (2015) focus on trade-offs between collaboration and credit for research, and the potential for a junior ranked researcher's credit in publication to be reduced as a member of a collaborative team. Bozeman and Youtie (2017) also point to challenges that exist in assigning credit for teams of authors and to vulnerabilities for junior colleagues. A reasonable consideration is that the prolific may lose less in credit/recognition when collaborating than do the non-prolific. Thus, for the prolific, collaborative span may be relatively low on drawbacks and high on benefits. This would be consistent with the classic "Matthew effect" of those already advantaged becoming yet more advantaged, especially in cases of collaboration where credit accrues to the more eminent coauthors (Merton 1968). Our findings point then to complex social-organizational dimensions of collaboration in "who benefits," depending on the rank and position of academic scientists.

Fourth, overall, the departmental features do not predict as strongly as the individual, social characteristics, and especially rank. Perceptions about human and material departmental resources are not associated with being prolific. A possible factor here is that the distribution of material resources does not correspond to the distribution of prolific performance. One argument is that decision makers at departmental levels may avoid extremely unequal distributions of resources and suppress incentives for the most productive in the resources distributed (Hicks and Katz 2011). Another argument is that the highly prolific in research universities may see themselves as the sources (rather than recipients) for the departments' resources because of their own grants, awards, and networks. It is likely that, outside of research universities, resources would be stronger predictors of being prolific (at the same time, the proportions of prolific in these settings are unknown). From our perspective, the issue exists of social-organizational dimensions of resources in "who benefits" in being prolific and in which types of institutions.

Fifth, the departmental feature associated with being prolific is being a unit perceived as stimulating. This may occur in a range of ways. Being in a stimulating department may promote and/or sustain being prolific. Alternately, or in parallel, being prolific may foster positive perceptions of, and experiences with, work climate. On balance, this means that the prolific may also be cultivating stimulating environments in their labs, and these, in turn, may constitute their own ("micro-level") departmental climates. The decentralization of academic science departments into autonomous laboratories, funded and administered by principal investigators (Roth and Sonnert 2011), is consistent with this. Work climate is a novel dimension in this study of the prolific and merits continuing investigation.

[7] Collaborative span encompasses international collaboration as well. However, this measure is not available here.

Thus, we find a constellation of telling hierarchical advantages associated with being prolific: (1) the individual characteristic of academic rank, (2) the work practice of collaborative span, and (3) the departmental condition of a stimulating work climate. By itself, gender predicts being prolific, but in the presence of rank, it does not. It is the case that the data are cross-sectional and the causal relations between the hierarchical advantages and being prolific can operate in a range of directions, as recognized in this article. At the same time, the analyses point to key *patterns of association*: variables that do and do not predict, variables that co-exist, and variables that mediate in striking ways. The patterns depicted here help to break ground in understanding being prolific among US academic science from a social-organizational perspective: they identify characteristics of individuals and their settings, and links between them, which predict exceptional performance. Understanding these informs a long-standing question, posed in opening of our article: how exceptional performance occurs among academic scientists.

What, then, are the implications of the findings here for educational and science policy makers dealing with broader *aggregates* (beyond individuals in departments)? Policy makers' decisions include whether and how to distribute resources to small groups with established impact and/or whether and how to expand such groups. When seeking to use resources to expand performance, policy makers frequently look to presumed powers of collaboration. Optimism abounds in the efficacy of large, collaborative groups for enhancing innovation and performance. This is evidenced in the research award programs and policies at the highest national levels (as in the US National Institutes of Health and the National Science Board) (Bikard et al. 2015; Bozeman and Youtie 2017). The optimism, however, is infrequently informed, or tempered, by the costs, as well as benefits, of collaboration, and by costs that may assumed disproportionately among the less eminent. This means that efforts to distribute research activity and impact more widely are not easily attained and that existing pockets of the prolific are not easily expanded. While we find that collaborative span is associated with being prolific at the individual-level, it may also be that benefits work more advantageously among the already eminent. From our social organizational perspective, the implications for policy are that returns to investments in collaboration do not exist apart from complex considerations of rank, raised here.

Finally, our study informs and promotes continuing inquiry. Understandings of being prolific can be extended by considering academic scientists' combinations of administrative and research activities (Pelz and Andrews 1976), the presence of sustained research funding (Pao 1991), and partnerships with industry (Warshaw and Hearn 2014). Including rapidly developing fields such as those of biomedicine, would also be valuable, given that the fields are fast moving, well funded, and populated by clusters of prolific authors (Pei and Porter 2011). Such social and organizational dimensions will continue to advance understandings of being prolific, systems of stratification, and implications for practices and policies in higher education, presented here.

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