MANAGEMENT SCIENCE
Vol. 58, No. 6, June 2012, pp. 1122–1140
ISSN 0025-1909 (print) | ISSN 1526-5501 (online)
http://dx.doi.org/10.1287/mnsc.1110.1470

Reconceptualizing Stars: Scientist Helpfulness and Peer Performance

Alexander Oettl
College of Management, Georgia Institute of Technology, Atlanta, Georgia 30308,
alex.oettl@mgt.gatech.edu

It is surprising that the prevailing performance taxonomy for scientists (star versus nonstar) focuses only on individual output and ignores social behavior, because innovation is often characterized as a communal process. To develop a deeper understanding of the mechanisms by which scientists influence the productivity of others, I expand the traditional taxonomy of scientists that focuses solely on productivity and add a second, social dimension: helpfulness to others. Using a combination of academic paper publications and citations to capture scientist productivity and the receipt of academic paper acknowledgments to measure helpfulness, I examine the change in publishing output of the coauthors of 149 scientists that die. Coauthors of highly helpful scientists that die experience a decrease in output *quality* but not output *quantity*. Meanwhile, the deaths of high productivity scientists that are not highly helpful do not influence their coauthors' output. In addition, scientists who are helpful with conceptual feedback (critique and advice) have a larger impact on the performance of their coauthors than scientists who provide help with material access, scientific tools, or technical work. Within the context of evaluating scientific productivity, it may be time to update our conceptualization of a "star."

Key words: star scientists; human capital; helpfulness; productivity
History: Received November 19, 2009; accepted September 20, 2011, by Lee Fleming, entrepreneurship and innovation. Published online in *Articles in Advance* January 26, 2012.

1. Introduction

The impact of the "best and brightest" on the production of ideas in science and technology has attracted significant attention recently (Kapur and McHale 2005). The observation that high performers, or stars, account for the generation of a disproportionately large amount of output mainly drives this focus. For instance, Google's vice president of engineering, Alan Eustace, noted to the *Wall Street Journal* in 2005 that "one top-notch engineer is worth 300 times or more than the average" and that he "would rather lose an entire incoming class of engineering graduates than one exceptional technologist" (Tam and Delaney 2005, p. A1). More recently, Mark Zuckerberg, chief executive officer of Facebook, suggested that "[s]omeone who is exceptional in their role is not just a little better than someone who is pretty good ... they are 100 times better" (Helft 2011, p. A1). Why is this? How do stars so greatly influence the production of ideas and the innovation process?

The existing performance taxonomy for scientists focuses exclusively on individual output, classifying a scientist as either a star or a nonstar. The seminal work of Zucker et al. (1998), for example, defines stars as the top 0.75% of contributors to the genetic sequence database GenBank, a group that accounts for almost 17% of contributions. Rothaermel and Hess (2007) define star scientists in the pharmaceutical industry as scientists with cumulative publication and citation counts three standard deviations above the mean. Work by Groysberg et al. (2008) examines the skill portability of the top 3% of security analysts when they move firms using a ranking of the perceived effectiveness of security analysts, whereas Azoulay et al. (2010) look at the impact of eminent scientists using a variety of measures such as research funding, citations, and patenting. In all of these articles, the definition of a star is based solely on individual productivity; in other words, we define stars by what they produce themselves.

This unidimensional classification of star scientists is surprising, because innovation is most often characterized as a collaborative process. Collaborative interactions matter for two reasons. First, innovation is more often a result of the recombination of existing knowledge and ideas rather than the discovery of something fundamentally novel (Gilfillan 1935, Nelson and Winter 1982). As knowledge frontiers continue to expand, combinations of increasingly specialized levels of human capital are required to reach the forefront of knowledge (Wuchty et al. 2007, Jones 2009). It is this recombination of specialized ideas, either through formal collaborations (coauthorships, joint ventures, etc.) or informal means (discussions and comments from helpful individuals), that leads to innovation. Second, the exchange of knowledge is to a large extent governed through social channels. Individuals possess only finite levels of knowledge, and knowledge search is costly. Social forces can reduce barriers to knowledge flow through geographic proximity (Allen 1984, Jaffe et al. 1993), labor mobility (Almeida and Kogut 1999, Oettl and Agrawal 2008), interpersonal networks (Singh 2005), and membership in ethnic communities (Agrawal et al. 2008, 2011).

The importance of social factors in the innovation process and the production of ideas illuminates the deficiency of our current individual productivity-focused conceptualization of star scientists (stars versus nonstars). To deepen our understanding of the mechanisms by which individuals influence the performance of others, I expand the current conceptualization of star scientists by developing a new taxonomy that incorporates a social dimension: helpfulness to others. The development of this taxonomy allows an individual to be a "star" not only along a productivity dimension but also a helpfulness dimension. In turn, this taxonomy serves as a tool in evaluating the relative influence of both a scientist's productivity and helpfulness on the scientific productivity of others.

I define an all-star as an individual with both high productivity and high helpfulness. A lone wolf is someone who has high productivity but average helpfulness. A maven is an individual with average productivity but high helpfulness, and a nonstar has both average productivity and helpfulness. Restrictively, the current dichotomous conceptualization of stars groups both all-stars and lone wolves together, while overlooking mavens. By expanding on the current classification, I am able to examine the influence of individuals who vary in both their productivity and helpfulness.

Examining the changes in productivity from coauthoring with various star types would be an appropriate empirical exercise if coauthoring relationships were chosen at random, but clearly they are not. The problem with endogenous coauthor selection is that the coauthors selected by a scientist may be chosen because of their own productivity, thus producing spurious correlations between an individual's productivity and their coauthorship network. For this paper, I examine the *decrease* in productivity of coauthors when a scientist dies.

Following prior studies (Allison and Long 1990, Azoulay et al. 2010), I measure individual productivity using a combination of citation-weighted and impact factor-weighted publication counts. I extend prior research by constructing a new measure of helpfulness using academic journal acknowledgments, because such acknowledgments are generally made to those who have helped in the development of the work. Using these measures of productivity and helpfulness, I identify a sample of 149 scientists that have died and examine (using their death as a natural experiment) their influence on the productivity of their coauthors. I use coauthorship to pinpoint the timing of the formation of an interpersonal tie between a scientist and a potential recipient of performance benefits. It is this colocation in social space that allows stars to impact the performance of their peers.

Across a number of specifications, the output *quality* (as measured by impact factor- and citation-weighted publications) of the coauthors of all-stars who die decreases on average by 16% relative to the decrease when a nonstar dies. Conversely, coauthors of mavens who die experience a 14% decrease in the quality of their output, whereas the coauthors of lone wolves who die do not experience a change in output quality that is statistically distinct from the change in output quality when a nonstar dies. Interestingly, helpfulness stars (all-stars and mavens) impact only the *quality* of their coauthors' scientific output, and not the *quantity*. In addition, helpfulness that is difficult to replace or where the peer benefits from helpful behavior do not persist over time, such as when scientists provide conceptual help (comments, criticism, or advice), has a larger impact on the performance of coauthors than when scientists help by performing tests, providing technical help, or sharing materials.

2. Star Scientists and Spillovers

As Lotka (1926) observes, the top 6% of physicists produce more than 50% of all papers. This skewed distribution of human capital—the Pareto principle—is ubiquitous across scientific disciplines (de Solla Price 1986) and is a strong determinant of inventive productivity (Narin and Breitzman 1995). Individuals in the right tail of the quality distribution, so-called stars, generate a disproportionately large share of output (Rosen 1981, Ernst et al. 2000).

Human capital, however, can be important for innovation in ways other than generating direct output: human capital can generate spillovers. Since the early work of Lucas (1988), human capital spillovers have been at the center of economic growth models. Lucas (1988) classifies human capital into two types: internal and external. Internal effects of human capital capture the extent to which human capital affects the individual's own productivity, whereas external effects capture the influence individuals have on the performance of others. If these external effects generate an unpriced spillover onto the productivity of others, then the spillover constitutes an externality (Acemoglu 1996). The endogenous growth theory of Romer (1990) captures the notion that these human capital externalities and their effect on the increase in knowledge stock can lead to increasing economic returns. Because knowledge flows and spillovers lie at the center of many of our models of innovation (Audretsch and Feldman 1996) and because human capital externalities are a key input in the generation of knowledge flows, understanding the parameters within which human capital spillovers are generated is of utmost importance.

Despite the importance of human capital spillovers, the strategy and economics literature has mostly focused on the skewed nature of the productivity distribution when examining the relationship between stars and performance. The seminal work of Zucker et al. (1998) reports strong correlations between the location of star scientists and the formation of biotechnology ventures. In more recent work, Groysberg et al. (2008) examine the firm specificity of the human capital of stars. They find that many of the performance premiums accruing to stars are firm specific and that when stars move, their productivity decreases. Neither of these studies, however, explicitly examines these stars' human capital spillovers.

One notable and important exception is the work of Azoulay et al. (2010; henceforth referred to as AGW). AGW examine the effect that the death of an eminent life scientist has on the performance of coauthors.[1] They find that, following the death of a star, a coauthor's performance decreases by 5% to 10%. Because coauthors were benefiting from their tie with a star, the cessation of the coauthoring relationship (due to death) ended these benefits, resulting in a decline in coauthor performance. This paper builds upon the work of AGW by developing and using a new taxonomy of star scientists to identify a separate dimension of human capital productivity—helpfulness—and in turn deepens our understanding of the mechanisms that influence scientific productivity.

3. A New Taxonomy of Star Scientists

One reason for the limited empirical evidence on the relationship between human capital spillovers and scientific performance may be the lens through which the literature has largely peered. In the context of scientific performance, the current strategy and economics literature largely focuses on stars, that is individuals classified along the single dimension of productivity. In other words, individuals are classified as stars if they lie in the right tail of some productivity distribution, normally output. For example, Zucker et al. (1998) classify the top 0.75% of GenBank contributors as stars. Yet, if social behaviors influence the impact that stars have on the performance of others, then including a dimension of social behavior in the conceptualization of star scientists is surely needed. I extend the current conceptualization of star scientists that focuses solely on productivity and add a second, social dimension to the taxonomy of scientists: helpfulness. Where productivity encapsulates an individual's output that is personally beneficial, helpfulness encapsulates an individual's output that is beneficial to others.

Scientists can be helpful in a number of ways. They can influence the formation and quality of new ideas through discussion, feedback, encouragement, and criticism. They can supply others with cell lines, allergens, antibodies, DNA, and other physical inputs. They can provide help with technical procedures, tests, tools, and techniques. Last, they can be helpful by introducing others to scientific "norms" such as how to write well or facilitating social introductions (Cronin 1995).

The area of research examining the helpfulness of individuals in organizations is well-trodden. A large literature in industrial psychology examines what is known as organizational citizenship behavior (Smith et al. 1983). The literature finds that a combination of altruism and courtesy greatly influences the level of helpfulness individuals extend to one another within organizations. A large literature in social psychology exists on the personality characteristics associated with helpful behavior. Among the many factors that influence an individual's helpfulness, three are most applicable to the setting of academic scientists: situational, social, and person. Situational factors deal with the costs associated with helping, social factors involve the influence of social norms on helpful behavior, and person factors capture the prosocial traits of an individual (Fletcher and Clark 2003). This study is focused primarily on the person factor of helpfulness that captures an individual's output that is beneficial to others.

The role of helpfulness within the context of science, however, is less explored. The Mertonian norm of *communalism*, whereby scientists voluntarily disclose new discoveries in exchange for scientific priority, places great emphasis on the importance of idea exchange for the advancement of science (Merton 1973). Yet, as recent work by Haeussler et al. (2009) demonstrates, the extent to which ideas are shared (one possible form of helpfulness) among those in academe is not uniform. Furthermore, little evidence exists on the performance implications of coauthoring relationships with helpful scientists. It is the goal of this paper to examine precisely that, and to do so, I expand the current conceptualization of what it means to be a star scientist.

[1] AGW classify scientists as eminent if they match a number of performance-related criteria. In general, one can view these life scientists as being in the top 5% of the life scientist productivity distribution.

Table 1 A New Taxonomy for Star Scientists

	Average productivity	High productivity
High helpfulness	Maven	All-star
Average helpfulness	Nonstar	Lone wolf

Table 1 presents a new taxonomy for star scientists that incorporates productivity and helpfulness. Not only do scientists vary along a dimension of productivity, they also vary along a measure of helpfulness. In this way, I define three new star types. An all-star is an individual with both high productivity and helpfulness. A lone wolf is an individual with high productivity but average helpfulness.[2] A maven is an individual with average productivity but high helpfulness. A nonstar has both average productivity and helpfulness.

Why does this taxonomy matter? Conventionally, scholars have classified both all-stars and lone wolves as stars because they both have high productivity. This aggregation has large implications if the effects of all-stars and lone wolves on the production of ideas and innovation differ. On the other hand, I classify mavens as individuals with average productivity. But mavens may have the largest impact on the performance of others because of their level of helpfulness. As such, we may be overvaluing lone wolves while undervaluing mavens. Given that human capital spillovers are at the core of our innovation and economic growth models, it is paramount to identify which inputs into the scientific production function have the potential to generate spillovers.[3]

4. Econometric Estimation

The empirical goal of this study is to examine the extent to which different star types influence the performance of others. A star has the ability to influence the performance of individuals across multiple levels: coauthors, peers in the same department, peers within the same institution, etc. For this study, I focus solely on a star's influence on the performance of coauthors. The most straightforward empirical approach would be to examine the change in a coauthor's performance after the formation of the coauthoring relationship (i.e., after the first time the two scientists collectively author a paper). Unfortunately, both the decision to coauthor at all and the decision of whom to coauthor with are clearly not random decisions. This endogeneity would bias my regression coefficients because the choice of coauthors may be related to their future productivity, resulting in a spurious relationship between a coauthor's productivity and coauthorship network. As such, the empirical challenge becomes finding an exogenous change in the coauthoring relationship. An alternative to examining the formation of coauthoring ties is to examine the cessation of coauthoring ties, but cessation that is exogenous. For this paper, I examine the change in productivity of a coauthor when a scientist dies.

The empirical model is

$$\begin{aligned} Y_{-ijt} = \exp\big[&\beta_1 Death_{it} + \beta_2 Death_{it} \times AllStar_i \\ &+ \beta_3 Death_{it} \times LoneWolf_i + \beta_4 Death_{it} \times Maven_i \\ &+ \gamma_{it} + \mu_{jt} + \delta_t + \phi_{ij} + \varepsilon_{ijt}\big]. \end{aligned} \tag{1}$$

Because my objective is to capture the change in performance of a coauthor after a scientist's death, the dependent variable, Y_{-ijt}, measures the number of impact factor-weighted publications coauthor j wrote in year t where star i is *not* a coauthor. I use quality adjusted publication counts instead of raw publication counts to ensure that I am observing changes in the quality of publishing rather than changes in the frequency of publishing. The indicator variable $Death_{ijt}$ switches to 1 the year scientist i dies; β_1 captures the net change in productivity of coauthor j after star i dies, irrespective of star type; and β_2, β_3, and β_4 capture the change in productivity of coauthor j if scientist i is an all-star, lone wolf, or maven, respectively. I omit the nonstar category, and so the coefficients of β_2, β_3, and β_4 should be interpreted as the change in productivity relative to the productivity change when a nonstar dies. Because the star types of i are time invariant, I can only identify them through the interaction with $Death_{it}$; γ_{it}, and μ_{jt} are sets of career age cohort dummies that capture the changes in research productivity across the academic lifecycle (Levin and Stephan 1991).[4] I capture time effects with δ_t; ϕ_{ij} is a series of dyad fixed effects, which in practice condition out during estimation and as such I do not estimate them directly. If the coefficients on β_1 through β_4 are less than zero, then the death of star i has a negative influence on the performance of coauthor j, which provides some evidence that star i is indeed influencing the performance of coauthor j.

[2] The label lone wolf is meant to capture a scientist who is lone in the helping sense and is not meant to imply that the scientist necessarily collaborates less with others.

[3] To be clear, this study cannot make the claim that the positive performance impact of stars on their coauthors constitutes a spillover because data on how these exchanges are priced are not readily available.

[4] In practice, I generate these age cohort dummies in three-year intervals, whereby the first dummy captures scientists in their first three years of publishing, the second dummy captures scientists in their fourth through sixth years of publishing, etc. Constructing these age cohort dummies at six-year intervals does not change the results.

The identification of $Death_{ijt}$ comes from the variation in the deaths of scientists i. By employing dyad fixed effects (ϕ_{ij}), I absorb all time-invariant attributes common to the dyad, forcing the parameters to be identified solely from within-dyad variation. Because of the count nature of the dependent variable and the high percentage of zero values (38%) across the sample, a count model is most appropriate. Specifically, I employ the fixed-effects Poisson estimator developed by Hausman et al. (1984). Apart from being computationally straightforward, the fixed-effects poisson estimator estimated via quasi maximum likelihood (QML) has strong robustness features, even allowing for consistent parameter estimates of non-count dependent variables. In addition, standard errors can be made robust to deviations from the poisson distribution, in particular the equality requirement of the first and second moments. Furthermore, these robust standard errors are valid under any conditional variance assumption and allow for arbitrary serial correlation (Wooldridge 1999). I report these robust standard errors for all QML specifications.

5. Data

An ideal empirical setting for this study satisfies three criteria. First, it should take place in a setting where collaboration exists. Because this paper aims to identify which types of individuals have the largest impact on the performance of their coauthors, a setting in which collaboration takes place is clearly necessary. Second, from a measurement standpoint, the ability to separate individual- from group-level performance is necessary because the focus of interest is on star individuals and not star teams or departments. Third, a field or discipline that engages in the practice of manuscript acknowledgments is necessary to identify individual helpfulness. A discipline that satisfies all three of these conditions is the field of immunology.

From a research standpoint, immunology is an important discipline. The National Institute of Allergy and Infectious Diseases (NIAID), which oversees the distribution of immunology-related research grants, allocated \$940 million to immunology research in 2005, up from \$646 million in 2003 (Hackett et al. 2007). More importantly, however, the structure of immunology research is organized in a very similar fashion to other medical sciences, such as biochemistry, microbiology, and pharmacology.

5.1. Measures

One major hurdle to extending the dichotomous conceptualization of stars has been the lack of data. I propose to use the receipt of acknowledgments as a measure of an individual's helpfulness. Academic acknowledgments are a central and convenient way of recognizing a nonauthor's contributions to the development of a manuscript without extending ownership rights in the form of coauthorship (Cronin 1995).[5]

The goal of this study is to examine how different types of stars affect the output of their coauthors when they die.[6] Scientists have high productivity if they were ever in the top 5% of both the annual citation and annual impact factor-weighted publication distributions in a given year at any time throughout their career.[7] As an example, for a scientist to be classified as highly productive in 1995, the papers written in 1995 must have a cumulative impact factor weighting of more than 21.38 and must have received more than 240 citations by 2010 (the year in which aggregate forward citation data were collected).[8] Citation and impact factor-weighted publication data come from the Institute for Scientific Information's (ISI's) Web of Science. I collected these publication data for all articles published in the set of 136 journals classified by the ISI as "immunology" journals between 1910 and 2010. I obtained impact factor weights from the Journal Citation Reports from the ISI, which published impact factors for all immunology journals on a yearly basis between 2000 and 2007. I use the average impact factor across these eight years to create a time-invariant quality measure for each of these 136 journals.

Conversely, scientists have high helpfulness if they were in the top 20% of the annual acknowledgment distribution in a given year at any time throughout their career. For example, I classify a scientist who receives three or more acknowledgments from *The Journal of Immunology* (henceforth referred to as

[5] Of course, acknowledgments mainly come in two forms. They may represent an acknowledgment of another scientist's useful comments (that is, the scientist is selected on quality) or they may accrue as a result of the scientist's influence on the publishing process, the field, etc. (the scientist is selected on status). Although I am unable to empirically separate out these two types of acknowledgments directly, attempts are made to distinguish between "status" acknowledgments and helpful acknowledgments in §§6 and 7.

[6] Although examining the output of local colleagues may appear to be an easier task, recent work by Waldinger (2012) explores changes in the productivity of scientists from the exogenous dismissal of colleagues in Nazi Germany. He examines peer effects at two local levels: the department level and the same specialization within the same department. In both instances he is unable to find any evidence of peer effects at the local level.

[7] However, the scientist's membership in the top 5% of the impact factor-weighted publication distribution and the citation distribution need not occur in the same year. Requiring that the scientist be in the top 5% of both distributions in the same year generates coefficients that are quantitatively and qualitatively similar.

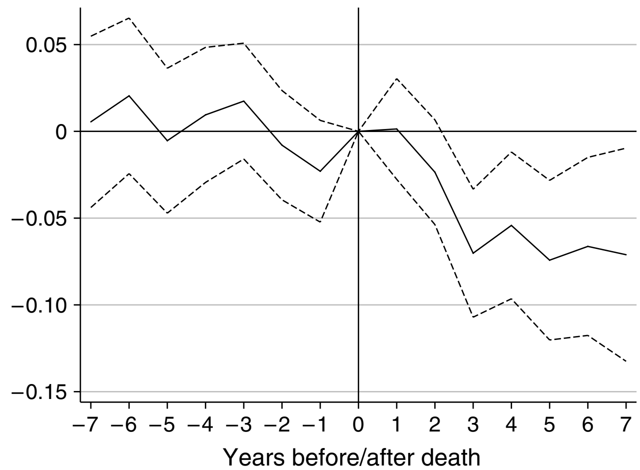
[8] The calculation of annual distributions allows me to deal with changes in publication rates across time as well as citation truncation issues for more recent papers.

The JI) in 1995 as a helpfulness star. *The JI* was chosen because it was the preeminent academic journal for the discipline of immunology for the greater part of the past century.[9] I obtained acknowledgment data by applying natural language processing and name identification algorithms (Councill et al. 2005) to the acknowledgment sections of the 50,541 articles published in *The JI* between 1950 and 2007. Acknowledgments operate very similarly in immunology as they do in the social sciences, albeit with fewer acknowledgments per paper. From the articles published in *The JI* between 1950 and 2007, scientists included 3.04 acknowledgments on average. The following acknowledgment in Bennett (1965, p. 663) is typical: "The author wishes to thank Drs. L. J. Old and E. A. Boyse of the Sloan-Kettering Institute, New York, for their suggestions and encouragement, and Mrs. Patricia Hubertus for technical assistance."

I measure coauthor productivity by their annual impact factor-weighted publications. I also run robustness checks whereby I measure coauthor productivity by their annual raw publication output and their forward citation rate to papers written in the focal year.

I collected data on deaths in a hybrid form by extracting obituaries from the titles of over 400,000 immunology articles from the Web of Science and from the American Association of Immunology newsletter, which includes an "In Memoriam" column. Although ideally I would like to identify unexpected deaths so that the "treatment" of losing a coauthor is fully exogenous, it is often difficult to distinguish between untimely deaths and expected deaths from the obituaries retrieved. Although I make efforts to exclude older scientists who are more likely to have died from natural causes, there is a chance that coauthors may have anticipated some deaths. However, allowing for the possibility that coauthors anticipated the deaths should generate conservative estimates of the productivity effect, because presumably the coauthors had time to make alternate arrangements to minimize the anticipated decrease in productivity. To directly address this concern, I regress whether or not the scientist dies in year t on one-, two-, three-, and four-year lags of *Publications*, *Impact Factor-Weighted Publications*, *Citations*, and *Acknowledgments* (while controlling for career age). Results (not reported, but available upon request) indicate that a scientist's output along these four dimensions does not decrease in advance of death, providing some additional support that these deaths are unanticipated, or at least are not related to scholarly output. In addition, Figure 1, plots the impact factor-weighed publishing output of the coauthors of stars who die before and after the star's death. To the extent that authors anticipated the deaths of stars, it does not appear that their publishing performance was statistically or economically distinct from the publishing performance of coauthors of stars who did not die. Only after the death of a star does the publishing performance of coauthors begin to differ from the coauthors of the control scientists (those who did not die).

Figure 1 **Coauthor Impact Factor-Weighted Publications Before and After Death**



Notes. This figure presents a plot of the coefficients of the regression run in Table 6, column (1), including a set of interactions between *Death* and year dummy variables corresponding to the years before and after the death of scientist i. The dependent variable is the impact factor-weighted publication count of coauthor j written without star i in year t. The year of death is omitted. This spline regression includes star–coauthor dyad, year, star life cycle, and coauthor life cycle fixed effects. The dashed line corresponds to the 95% confidence interval.

5.2. Sample

The sample for this study draws on all immunologists, identified from obituaries and newsletters, who died between 1978 and 2008. I identify 360 such immunologists. I take two steps to make these death instances appropriate for my empirical setting. First, I remove all immunologists with common surnames[10] to reduce the likelihood of Type II errors.[11] Second, I remove all immunologists who have a career age greater than 50 at the time of their death.[12] Imposing

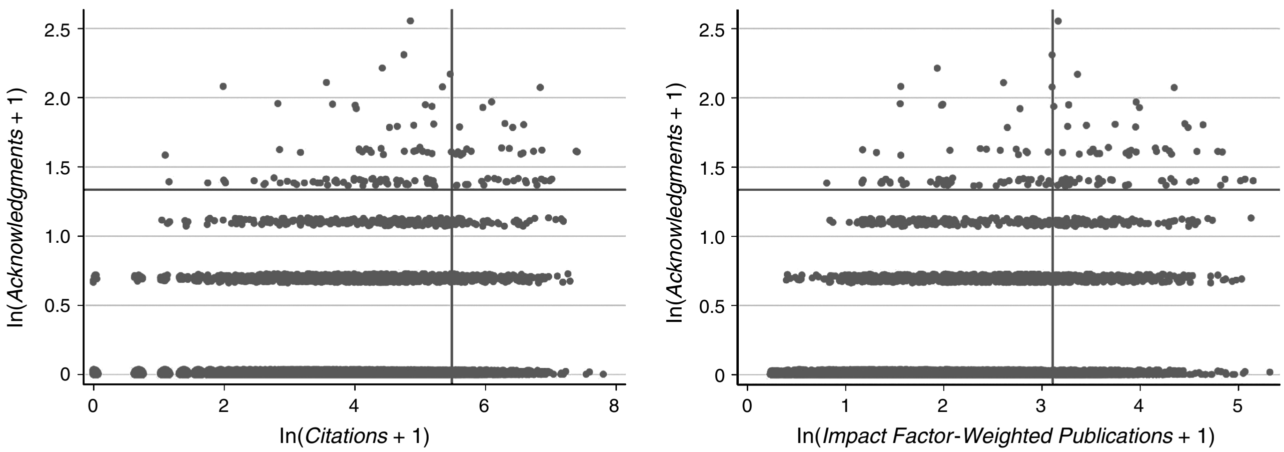
[9] *The JI* in 2007 had an impact factor of 6.068, ranking it 13th among all immunology journals. It is, however, by far the most widely cited journal in immunology and has been in print since 1916, making it one of the oldest immunology journals in the world.

[10] I make use of the U.S. surname frequency chart as constructed from the 1990 U.S. census and remove all surnames that occur more than 0.05% of the time in the U.S. population. See http://www.census.gov/genealogy/names/.

[11] An example would be erroneously assuming that all immunologists named "Fred Smith" are the same person.

[12] Career age is a count of the number of years since the immunologist's first publication. Analysis is also conducted with career age cutoffs of 45, 40, and 35. The results are qualitatively similar.

Figure 2 Productivity and Helpfulness Distributions



Note. This figure presents two scatter plots of the relationship between acknowledgments and citations, and acknowledgments and impact factor-weighted publications for immunologists in 1995. Both scatter plots include the "jitter" option. The correlation between acknowledgments and citations is 0.17, and the correlation between acknowledgments and impact factor-weighted publications is 0.22.

these restrictions reduces the sample from 360 immunologists to 161 immunologists.

I construct a sample of control immunologists using the coarsened exact matching (CEM) approach of Iacus et al. (2010).[13] A well-constructed control sample will consist of immunologists who appear similar to the treated immunologists along all relevant productivity, helpfulness, and age dimensions and differ only with respect to the timing of their death. For each of the 161 treated immunologists, I construct discrete bins at year t, where t is the year before the focal immunologist dies, for the following variables: year of first publication, number of coauthors by year t, sum of publications by year t, sum of impact factor-weighted publications by year t, sum of citations received by 2010 for papers written by year t, and sum of acknowledgments received by year t. Once I construct these strata, I select a random immunologist who is not in the set of 360 immunologists and who does not die in year t from the same strata to serve as the control immunologist. I find matches for 149 of the 161 immunologists. These 149 immunologists constitute my final sample. Assigning the sample of 149 immunologists to the taxonomy results in the following classification: 35 immunologists are all-stars, 28 are mavens, 17 are lone wolves, and 69 are nonstars.

Figure 2 provides a scatter plot of the relationship between *Acknowledgments* and both *Impact Factor-Weighted Publications* and *Citations* for all immunologists in 1995. Although I identify high helpfulness and high productivity by their presence in the right tails of their annual distributions across all immunologists, it is informative to view the sizable presence of immunologists in the "off axis," that is, in the upper left quadrant (immunologists who receive three or more acknowledgments, but have average productivity) and in the lower right quadrant (immunologists who are very productive but who receive few, if any, acknowledgments).

5.3. Unit of Analysis

To what extent do different star types influence the productivity of others? To answer this question, I look at the change in performance of coauthors of stars who die. As such, my unit of analysis is a scientist–coauthor–year triad. The cross-sectional unit, however, is the scientist–coauthor dyad, where the scientist is one of four star types. To identify coauthors, I identify all coauthorships (as shown from articles written in the set of 136 "immunology"-classified journals) formed with scientists who have at least three lifetime publications in immunology (again from the set of 136 journals). The treated and control scientists in the sample have 64 coauthors on average, resulting in 19,088 scientist–coauthor dyads.[14] I further reduce this sample of 19,088 scientist–coauthor dyads to 18,999 for specifications employing the dependent variable that consists of impact factor-weighted publications without the focal star.[15] The average publishing lifespan for immunology coauthors in my sample is 26.1 years, resulting in a final sample size of 497,895 observations.

[13] For recent applications of the CEM approach, see Ganguli (2011) and Singh and Agrawal (2011).

[14] Seventy-nine percent of the coauthors in the sample coauthor with only one of the focal 298 treated and control scientists, 14% coauthor with two scientists in the sample, 4% coauthor with three scientists in the sample, and 3% coauthor with four or more scientists in the sample.

[15] I droped 89 dyads from the estimation because they coauthored solely with the focal stars and as such exhibit no cross-time variation within their dyad panel.

Table 2 Summary Statistics of Treated and Control Scientists

	Variable	Treated scientists Mean	Treated scientists Std. dev.	Control scientists Mean	Control scientists Std. dev.	Diff.	t-stat. of diff.
$N = 298$	*Year of First Publication*	1,971.72	11.34	1,972.21	11.12	−0.50	0.38
Treated $N = 149$	*Career Age at Treated Death*	28.30	11.37	27.80	11.43	0.50	0.38
Control $N = 149$	*Publications*	41.89	40.39	36.87	30.42	5.02	1.21
	IF Publications	192.07	245.10	172.93	194.47	19.14	0.75
	Citations	1,805.21	2,784.92	1,694.58	2,132.40	110.62	0.38
	Acknowledgments	3.72	6.11	3.85	7.28	−0.13	0.16
	Conceptual Acknowledgments	1.72	3.03	1.61	3.59	0.11	0.30
	Materials Acknowledgments	1.06	2.74	1.02	2.66	0.04	0.13
	Testing & Tools Acknowledgments	0.11	0.34	0.10	0.38	0.01	0.32
	Technical Acknowledgments	0.13	0.37	0.33	1.16	−0.20	2.02
	Publications as First Author	8.79	9.46	7.64	7.00	1.15	1.19
	Publications as Last Author	21.34	28.13	15.38	18.88	5.97	2.15

Notes. This table reports descriptive statistics of the 149 focal (treated) and 149 control scientists. Section 5.2 describes the construction of the control sample. *IF Publications* refer to impact factor-weighted publications. All values listed are the sum of the focal variable at the year of death of the treated scientist except for *Year of First Publication* and *Career Age at Treated Death*.

Table 3 Summary Statistics of Focal Scientists by Star Type

Variable	All-star ($N = 35$) Mean	All-star Std. dev.	Lone wolf ($N = 17$) Mean	Lone wolf Std. dev.	Maven ($N = 28$) Mean	Maven Std. dev.	Nonstar ($N = 69$) Mean	Nonstar Std. dev.
Year of First Publication	1,966.89	11.64	1,972.94	7.15	1,966.54	10.08	1,975.97	10.87
Career Age at Death	33.31	10.65	28.35	8.22	31.79	10.88	24.32	11.30
Number of Coauthors	78.00	42.57	80.53	54.20	41.25	33.97	33.36	26.99
Coauthorship Intensity	2.29	0.71	2.08	0.62	1.75	0.54	1.73	0.61
Authors per Publication	4.70	1.41	5.14	1.28	4.99	1.52	5.53	1.98
Publications	82.63	46.00	59.29	35.24	27.50	19.66	22.78	25.70
IF Publications	488.90	345.47	217.59	79.22	107.82	67.29	69.39	63.96
Citations	4,905.11	4,300.98	2,106.76	902.12	977.18	809.05	494.51	430.46
Acknowledgments	11.51	8.26	1.88	2.39	3.25	2.14	0.41	0.71
Conceptual Acknowledgments	5.46	4.14	0.82	1.29	1.54	1.43	0.13	0.45
Materials Acknowledgments	3.69	4.70	0.53	0.87	0.54	0.84	0.07	0.26
Testing & Tools Acknowledgments	0.23	0.43	0.06	0.24	0.21	0.50	0.03	0.17
Technical Acknowledgments	0.23	0.43	0.12	0.49	0.11	0.42	0.09	0.28
Ever Journal of Immunology Editor	0.09	0.28	0.00	0.00	0.00	0.00	0.01	0.12
% of Interlab Papers	0.46	0.21	0.46	0.21	0.48	0.21	0.51	0.25
% of Solo Papers	0.03	0.03	0.05	0.05	0.04	0.09	0.04	0.07
% of Publications as First Author	0.18	0.09	0.24	0.15	0.27	0.18	0.27	0.22
% of Publications as Last Author	0.55	0.18	0.46	0.15	0.38	0.20	0.36	0.24

Notes. This table reports descriptive statistics of the 149 focal (treated) scientists by their star type. Section 5.1 describes the classification procedure for the four star types. *Coauthorship Intensity* is the mean number of times a treated scientist has coauthored with a coauthor. *Authors per Publication* is the mean number of authors on a paper written by the treated scientist. *IF Publications* refer to impact factor-weighted publications. % *of Interlab Papers* is the percentage of papers that the focal scientist has written where two or more institutions are listed on the paper.

5.4. Descriptive Statistics

Table 2 presents descriptive statistics of the characteristics of the treated and control focal scientists. The table reveals good balance between the 149 treated scientists and the 149 controls scientists. The only dimension where the two samples differ is in the number of publications where the scientist's name is last in the authorship list.[16] Whereas the treated scientists are listed as the last author on 21.34 publications on average, control scientists are last authors on just 15.38 papers. Although this difference is statistically significant, it is not immediately obvious that more last-author publications would systematically bias the results, because the main dependent variables only examine impact factor-weighted publications of coauthors written without the focal star.

Of greater interest is a comparison of the treated 149 scientists by the four star types shown in Table 3. As expected, the average all-star and lone wolf publish more papers and receive more citations than the average maven and nonstar, whereas the average all-star and maven receive more acknowledgments than the average lone wolf and nonstar. The four star types

[16] Principal investigators of labs are traditionally listed last on research that is carried out in their labs.

Table 4 Summary Statistics of Coauthors of Focal and Control Scientists by Star Type

		Coauthors of treated scientists		Coauthors of control scientists	
Focal scientists	Variable	Mean	Std. dev.	Mean	Std. dev.
All-stars		$N = 50{,}986$		$N = 82{,}149$	
Treated $N = 35$	*Year of First Publication*	1,975.49	9.73	1,976.29	10.05
	Publications	1.88	3.14	1.87	3.50
	Publications w/o Focal Scientist	1.78	3.12	1.81	3.49
	IF Publications	8.86	15.57	8.61	17.08
	IF Publications w/o Focal Scientist	8.26	15.32	8.26	16.91
	Citations	87.31	221.11	79.25	207.00
	Citations w/o Focal Scientist	80.24	214.64	75.26	201.91
Lone wolves		$N = 26{,}108$		$N = 33{,}225$	
Treated $N = 17$	*Year of First Publication*	1,977.12	9.92	1,977.43	10.22
	Publications	2.23	4.43	2.05	3.93
	Publications w/o Focal Scientist	2.14	4.40	1.97	3.88
	IF Publications	8.62	17.98	8.43	16.07
	IF Publications w/o Focal Scientist	8.29	17.84	8.04	15.80
	Citations	74.92	196.39	72.05	169.69
	Citations w/o Focal Scientist	71.29	192.16	68.65	167.28
Mavens		$N = 20{,}024$		$N = 13{,}734$	
Treated $N = 28$	*Year of First Publication*	1,975.91	9.96	1,976.16	10.37
	Publications	1.78	3.00	1.92	3.18
	Publications w/o Focal Scientist	1.71	2.99	1.87	3.17
	IF Publications	7.77	14.29	7.52	13.90
	IF Publications w/o Focal Scientist	7.49	14.18	7.31	13.81
	Citations	73.86	211.82	65.28	153.64
	Citations w/o Focal Scientist	71.35	210.56	63.46	152.91
Nonstars		$N = 43{,}722$		$N = 49{,}475$	
Treated $N = 69$	*Year of First Publication*	1,976.22	10.04	1,975.50	10.43
	Publications	1.78	3.51	1.56	2.72
	Publications w/o Focal Scientist	1.70	3.49	1.48	2.70
	IF Publications	6.48	13.40	5.18	10.82
	IF Publications w/o Focal Scientist	6.25	13.31	4.99	10.76
	Citations	58.71	155.89	47.31	133.22
	Citations w/o Focal Scientist	57.02	155.20	45.72	132.13

Notes. This table reports descriptive statistics on coauthors split by star type and treated/control scientists. All variables except for *Year of First Publication* are annual means taken up to the year of death of the treated scientist. *IF Publications* refer to impact factor-weighted publications.

all work on interlab projects and solo projects with similar probabilities, but the lone wolves work on more solo papers (5%) than the other star types. All-stars and lone wolves also exhibit a higher tendency to be listed as the last author on a publication than mavens and nonstars, but lone wolves, mavens, and nonstars all publish papers as first author with equal likelihood.

Table 4 provides descriptive statistics that allow for the comparison of the coauthors of treated scientists and control scientists, but split by the focal scientist's star type. Of particular interest is the good balance of impact factor-weighted publications between treated scientists and control scientists for the coauthors of all-stars, lone wolves, and mavens. In addition, upon examining the means of the coauthors of the treated scientists who are all-stars and lone wolves, one sees that the means are very similar: The average coauthor of an all-star who dies publishes 8.86 Impact Factor-weighted publications a year, and 8.26 impact factor-weighted publications a year without the focal all-star. Conversely, the average coauthor of a lone wolf who dies publishes 8.62 impact factor-weighted publications a year, and 8.29 impact factor-weighted publications a year without the focal lone wolf coauthor. As such, it appears that the coauthors of all-stars and lone wolves appear to be fairly similar, despite their own large differences in helpfulness.

Table 5 presents a preview of the regression results I will report in the following section and provides basic intuition for the use of control scientists in examining the relationship between the death of various star types and coauthor performance. Table 5 consists of a matrix reporting mean values of a coauthor's impact factor-weighted publications written without the focal scientist along two dimensions: the timing of death and the scientist type. The second column with the header Predeath provides the aforementioned means for coauthors of treated scientists and of control scientists. I provide first-difference means of the treated

Table 5 Annual Impact Factor-Weighted Publication Frequency

	Predeath		Postdeath		Row first difference	
	Mean	N	Mean	N	Diff.	t-stat.
Scientists who die						
All scientists	7.53	140,840	11.17	63,045	3.64	39.69
All-star	8.26	50,986	11.25	24,774	2.99	20.49
Lone wolf	8.29	26,108	12.52	10,193	4.23	16.27
Maven	7.49	20,024	10.36	10,121	2.87	13.70
Nonstar	6.25	43,722	10.73	17,957	4.48	27.76
Control scientists						
All scientists	7.24	178,583	11.26	115,434	4.02	54.11
All-star	8.26	82,149	13.94	48,701	5.68	44.46
Lone wolf	8.04	33,225	10.51	17,683	2.47	13.91
Maven	7.31	13,734	11.03	6,266	3.72	13.12
Nonstar	4.99	49,475	8.57	42,784	3.58	34.80
Column first difference	Diff.	t-stat.	Diff.	t-stat.	Diff.-in-diff.	
All scientists	0.29	5.42	−0.09	0.78	−0.38	
All-star	0.00	0.02	−2.69	12.37	−2.69	
Lone wolf	0.25	1.81	2.01	6.09	1.76	
Maven	0.18	1.15	−0.67	1.76	−0.85	
Nonstar	1.26	15.89	2.16	11.06	0.90	

Notes. This table presents mean impact factor-weighted publications (written without the focal scientist) of the coauthors of all scientists and the four star types, before and after focal scientist death, and for the coauthors of treated scientists and control scientists.

scientists and control scientists at the bottom of the table. Taking all-stars as an example, the coauthors of treated all-stars publish the same amount as the coauthors of the control scientists during the period before the treated star dies. However, in the postdeath period, the coauthors of treated stars publish 2.68 fewer impact factor-weighted publications than the coauthors of the control scientists, indicating that the coauthors of all-stars who die publish significantly less after the death than the coauthors of control scientists during the same period. Taking the difference of these two (predeath and postdeath) differences gives some insight into the effect of death on coauthor productivity. Although I omit a number of important controls from this univariate analysis, the strength and clarity of these mean differences are promising.

6. Results

6.1. Main Results

Before estimating the specification presented in Equation (1) from §4, Table 6 provides estimates of the effect of the death of a coauthor on various subsamples. Specification (1) estimates the effect of the death of any type of scientist on the performance of coauthors relative to scientists who haven't died yet and the control scientists. The coefficient on death is −0.118, which translates into an 11% decrease in performance.[17] Specification (2) presents a sample similar to what was used by AGW in that it includes only scientists (and their controls) with high productivity, which includes both lone wolves and all-stars. The death of a high-productivity star is associated with a 12% decrease in the performance of their coauthors. This point estimate is only slightly larger than the estimate provided in AGW, who report a decrease of 8% in their base specification. This closeness in results for a similar sample is reassuring. Specification (3) restricts the sample to include only high-helpfulness stars. Their death is associated with a 19% decrease in coauthor productivity. Notably, this translates to an almost 60% larger negative impact on the performance of coauthors than when a productivity star dies.

Specifications (4)–(7) in Table 6 split the sample to only include scientists of the four star types. As may be expected, the deaths of nonstars do not have a statistically significant negative impact on the performance of their coauthors. All-stars and mavens, however, do affect the productivity of their coauthors negatively when they die. The deaths of all-stars are associated with a 20% decrease in the performance of their coauthors, and the deaths of mavens are associated with a 10% decrease in performance, although this value is only statistically distinct from zero at the 10% level. Interestingly, the deaths of lone wolves have a *positive* impact on the performance of their coauthors. At first blush, this appears to indicate that whereas the death of an all-star or

[17] $\exp(-0.118) - 1 = -0.111$.

Table 6 Fixed-Effects Poisson QML Split-Sample Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	IF pubs.-star	IF pubs.-star	IF pubs.-star	IF pubs.-star	IF pubs.-star	IF pubs.-star	IF pubs.-star
Sample:	All	Prod. stars	Help. stars	Nonstars	All-stars	Lone wolves	Mavens
Death	-0.118^{**}	-0.132^{**}	-0.211^{**}	-0.032	-0.222^{**}	0.116^{*}	-0.106^{+}
	(0.025)	(0.033)	(0.035)	(0.047)	(0.041)	(0.055)	(0.063)
Dyad fixed effects	✓	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓	✓
Star Age cohort fixed effects	✓	✓	✓	✓	✓	✓	✓
Coauthor Age cohort fixed effects	✓	✓	✓	✓	✓	✓	✓
Observations	497,214	293,419	256,439	153,691	206,335	87,084	50,104
No. of dyads	18,999	11,195	9,728	5,884	7,808	3,387	1,920
Log-likelihood	−2,613,716	−1,661,499	−1,461,165	−677,276	−1,194,922	−460,970	−259,412

Notes. Observations are at the star$_i$–coauthor$_j$–year$_t$ level. The dependent variable is the impact factor-weighted publication count of coauthor j written without star i in year t. The independent variable, *Death*, equals 1 if star i died in year t or before. Column (1) includes all focal and control scientists. Column (2) includes all focal and control scientists who are productivity stars (all-stars and lone wolves). Column (3) includes all focal and control scientists who are helpfulness stars (all-stars and mavens). Columns (4)–(7) include only stars and controls that are of a specific star type. All specifications include a full set of star–coauthor dyad, year, star life cycle, and coauthor life cycle fixed effects. Estimates can be interpreted by taking the antilog of the coefficient and subtracting 1: $\exp(-0.118) - 1 = -0.111$. Robust standard errors clustered at the star–coauthor dyad level are in parentheses.

$^{+}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$.

maven marks a significant loss with a sizable negative impact on coauthor performance, the death of a lone wolf may free resources, such as time, for coauthors, which allows them to be more productive in the absence of the former wolf. This table clearly demonstrates the problems that arise when one treats all-stars and lone wolves as the same (high productivity). Although high-productivity stars clearly have a negative impact on the performance of their coauthors (column (2)), the differential effect between all-stars and lone wolves when high-productivity stars are disaggregated and segmented along helpfulness is stark: all-stars negatively affect the performance of their coauthors when they die significantly more than lone wolves.

Although the split-sample results provide suggestive evidence of differences between star types, it is cumbersome to compare the impact of different star types across different samples. I present the main results of Equation (1) from §4 in Table 7. Specifications (1)–(4) show different interactions between death, productivity stars, and helpfulness stars. Specification (1) interacts the death variable with scientists who are productivity stars (have high productivity, i.e., both lone wolves and all-stars). When I include the entire sample (the sample includes all star types), it appears that having high productivity has no additional negative effect on the performance of coauthors. Specification (2) interacts the death variable with scientists who are helpfulness stars (have high helpfulness, i.e., both mavens and all-stars). The baseline death coefficient becomes insignificant, indicating that the deaths of nonhelpful star scientists have no negative effect on the performance of their coauthors, whereas the deaths of helpfulness stars appear to have a large negative impact. Specification (3) includes an interaction for both helpfulness and productivity stars. The results indicate that, controlling for a star's productivity, the marginal impact of being a helpfulness star on the performance of coauthors is slightly larger. Specification (4) includes an interaction between productivity stars and helpfulness stars to determine whether these two forms of stardom are complements or substitutes. The coefficient on the interaction, Although negative, is statistically insignificant.

Having examined the relative importance of high helpfulness and high productivity, specification (5) turns to the estimates of the taxonomy for star scientists.[18] The omitted category for specification (5) is the death of a nonstar, and so all coefficients should be interpreted as the impact on a coauthor relative to the performance effect of the death of a nonstar on a nonstar's coauthors. In line with the results seen previously in Tables 5 and 6, the death of an all-star decreases the performance of coauthors by 16% (−0.175), and the death of a maven decreases the performance of coauthors by 14% (−0.153). The estimates for lone wolves and the baseline death coefficient (representing nonstars) are both statistically insignificant.[19]

[18] It can be seen that specifications (4) and (5) are numerically identical. The coefficient reported for *Death* × *All-Star* in specification (5) is identical to the sum of the *Death* × *Productivity Star*, *Death* × *Helpfulness Star*, and *Death* × *Productivity Star* × *Helpfulness Star* coefficients in specification (4).

[19] Results are both quantitatively and qualitatively similar when I run these regressions without the inclusion of the control scientists. Results are available upon request.

Table 7 Fixed-Effects Poisson QML Main Results

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	IF pubs.-star	IF pubs.-star	IF pubs.-star	IF pubs.-star	IF pubs.-star
Death	−0.095*	−0.013	−0.025	−0.044	−0.044
	(0.037)	(0.035)	(0.040)	(0.045)	(0.045)
Death × *Productivity Star*	−0.040		0.030	0.077	
	(0.048)		(0.050)	(0.069)	
Death × *Helpfulness Star*		−0.201**	−0.211**	−0.153*	
		(0.048)	(0.051)	(0.075)	
Death × *Productivity Star* × *Helpfulness Star*				−0.099	
				(0.099)	
Death × *All-Star*					−0.175**
					(0.059)
Death × *Lone Wolf*					0.077
					(0.069)
Death × *Maven*					−0.153*
					(0.075)
Dyad fixed effects	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓
Star Age cohort fixed effects	✓	✓	✓	✓	✓
Coauthor Age cohort fixed effects	✓	✓	✓	✓	✓
Observations	497,214	497,214	497,214	497,214	497,214
Number of dyads	18,999	18,999	18,999	18,999	18,999
Log-likelihood	−2,613,648	−2,612,026	−2,611,991	−2,611,897	−2,611,897

Notes. Column (1) includes an interaction between *Death* and a dummy if the star is a productivity star (all-star or lone wolf). Column (2) introduces an interaction between *Death* and a dummy if the star is a helpfulness star (all-star or maven). Column (5) includes interactions between *Death* and dummies if star *i* is an all-star, lone wolf, or maven. Coefficients can be interpreted relative to the omitted category of nonstars. Robust standard errors clustered at the star–coauthor dyad level are in parentheses.

$^{+}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$.

Overall, the significance of the star types from the new taxonomy appear both significant and stable. It does appear that mavens are different from lone wolves. Furthermore, the deaths of high-productivity scientists—all-stars and lone wolves—impact the impact factor-weighted publication rates of their coauthors differently. To provide additional inquiry to these findings, Table 8 moves away from impact factor-weighted publications not written with the focal star as a dependent variable and explores other outcome variables for coauthors. Specification (1) replicates specification (5) in Table 7 and serves as a reference specification. Specification (2) loosens the restriction of excluding papers written with the focal scientist by including all impact factor-weighted publications of the coauthors. Results change only slightly between specifications (1) and (2). Specifications (3) and (4) present results for raw publication counts of coauthors without and with the focal scientist, respectively. These results indicate that the deaths of all-stars, lone wolves, and mavens have no impact on the volume of output of coauthors relative to the decrease in publishing output of nonstars. This finding is interesting because it appears to indicate that death negatively affects the raw publishing output of coauthors of all star types. Yet, relative to the decrease in performance of the coauthors of nonstars, the coauthors of all-stars and mavens experience only a decrease in the quality, though not the volume, of their work relative to nonstars. Specifications (5) and (6) present citation count data of citations received to papers published without and with the focal scientist, respectively. In the case of citations to papers not written with the focal scientist, the deaths of both all-stars and mavens are associated with a large decrease in the citations received by future work of their coauthors. When an all-star dies, coauthors receive 22% (−0.244) fewer citations to their future work, and the coauthors of mavens receive 27% (−0.317) fewer citations to their future work. The death of a nonstar has no discernible effect on the level of citations coauthors subsequently receive. In aggregate, it appears that, relative to nonstars, all-stars and mavens significantly affect the *quality* of output produced by their coauthors, as measured by impact factor-weighted publications and Citation count, but not the *quantity* of output, as measured by raw publication counts.

6.2. Analysis of Helpfulness Types

This study has thus far treated all forms of helpfulness as homogenous, yet scientists may receive acknowledgments for a multitude of helpful behavior. A large body of work in the information sciences

Table 8 Fixed-Effects Poisson QML Main Results—Different Dependent Variables

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	IF pubs.-star	IF pubs.	Pubs.-star	Pubs.	Cites-star	Cites
Death	−0.044	−0.056	−0.129**	−0.151**	0.035	0.031
	(0.045)	(0.044)	(0.047)	(0.046)	(0.068)	(0.067)
Death × *All-Star*	−0.175**	−0.216**	−0.046	−0.064	−0.244**	−0.311**
	(0.059)	(0.058)	(0.062)	(0.061)	(0.080)	(0.078)
Death × *Lone Wolf*	0.077	0.073	0.115	0.114	−0.023	−0.060
	(0.069)	(0.069)	(0.073)	(0.072)	(0.093)	(0.092)
Death × *Maven*	−0.153*	−0.146*	−0.063	−0.050	−0.317**	−0.304**
	(0.075)	(0.074)	(0.076)	(0.075)	(0.091)	(0.089)
Dyad fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓
Star Age cohort fixed effects	✓	✓	✓	✓	✓	✓
Coauthor Age cohort fixed effects	✓	✓	✓	✓	✓	✓
Observations	497,214	497,895	497,214	497,895	496,869	497,883
No. of dyads	18,999	19,088	18,999	19,088	18,958	19,084
Log-likelihood	−2,611,897	−2,698,851	−806,754	−834,056	−20,451,969	−21,332,698

Notes. The dependent variable in column (1) is the impact factor-weighted publication count of coauthor j written without star i in year t. The dependent variables in column (2) is the Impact Factor-weighted count of all publications of coauthor j in year t (including publications written with star i). The dependent variable in column (3) is the raw publication count of coauthor j written without star i in year t. The dependent variable in column (4) is the raw count of all publications of coauthor j in year t (including publications written with star i). The dependent variable in column (5) is the sum of citations to publications written by coauthor j without star i in year t. The dependent variable in column (6) is the sum of citations to all publications of coauthor j in year t (including publications written with star i). Robust standard errors clustered at the star–coauthor dyad level are in parentheses.

$^{+}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$.

by Cronin and coauthors has paratextually examined and classified the contents of acknowledgments to develop acknowledgment typologies (Cronin 1995, Cronin and Franks 2006). In the case of the life sciences and in the context of this study, four types of acknowledgments are most appropriate in examining coauthor productivity: conceptual acknowledgments, technical acknowledgments, testing and tools acknowledgments, and materials acknowledgments.[20] Although conceptual, technical, testing and tools, and materials acknowledgments may all affect scientist productivity, they do so in differing ways. For example, some forms of helpfulness may involve rudimentary tasks (or tasks in which a thick labor supply exists), such as providing technical help, and consequently may be more easily replaceable. In turn, the death of a helpfulness star (either a maven or an all-star) who primarily assists with technical work may not have a large adverse effect on the performance of coauthors. Conversely, forms of helpfulness that are more difficult to replace, where few substitutes for them exist, or where the skill distribution is highly skewed, such as providing conceptual help, may have a larger impact on the performance of their coauthors. As a result, the death of a helpfulness star who primarily provides conceptual help or assistance with testing and tools may have a very large adverse effect on the performance of coauthors. Finally, in between these two poles are forms of helpfulness that may impact performance only in the short run due to switching and/or search costs. For example, the death of a helpfulness star who helps primarily by providing scientific materials may negatively affect the productivity of coauthors in the short run in that they are required to negotiate a new source of reagents, mice, etc., but once they find a new supply of materials, the reduction in productivity will end.

Table 9 presents four specifications for the four helpfulness types of interest: conceptual, materials, testing and tools, and technical. Specification (1) interacts a dummy set to 1 if scientist i is a conceptual helpfulness star (at least once above the 80th percentile of the annual conceptual acknowledgment distribution). Conceptual acknowledgments primarily thank scientists for intellectual feedback, critique, and encouragement. For example, "The authors thank Drs. Laura B. Martin and Kelly M. Nikcevich for helpful critique of the manuscript" (Karpus et al. 1995, p. 5009), and "We thank Drs. Marty Springer and Nolan Sigal for their support and interests throughout this study" (Koo et al. 1993, p. 6740). I classify acknowledgment types using keywords, and conceptual acknowledgments are captured with such terms as "suggestion," "review," "discussion," "advice,"

[20] This stream of literature has also identified manuscript preparation/editorial work and institutional funding as important acknowledgment types. Editorial work is not applicable within this context, because few (if any) immunologists are thanked for manuscript preparation. Institutional funding, conversely, is beyond the scope of this study.

Table 9 Fixed-Effects Poisson QML Supplementary Analysis—Different Acknowledgment Types

	(1)	(2)	(3)	(4)
Dependent variable:	IF pubs.-star	IF pubs.-star	IF pubs.-star	IF pubs.-star
Death	−0.040	-0.068^{+}	-0.087^{*}	-0.091^{*}
	(0.042)	(0.039)	(0.037)	(0.038)
Death × *Productivity Star*	0.040	0.000	−0.027	−0.037
	(0.053)	(0.052)	(0.048)	(0.048)
Death × *Conceptual Helpfulness Star*	-0.168^{**}			
	(0.054)			
Death × *Materials Helpfulness Star*		-0.106^{*}		
		(0.052)		
Death × *Testing & Tools Helpfulness Star*			-0.156^{+}	
			(0.081)	
Death × *Technical Helpfulness Star*				−0.045
				(0.074)
Dyad fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
Star Age cohort fixed effects	✓	✓	✓	✓
Coauthor Age cohort fixed effects	✓	✓	✓	✓
Observations	497,214	497,214	497,214	497,214
No. of dyads	18,999	18,999	18,999	18,999
Log-likelihood	−2,612,751	−2,613,226	−2,613,281	−2,613,607

Notes. Columns (1)–(4) disaggregate the helpfulness measure used in previous analyses. The focal scientist i is a star in any of the three acknowledgment types if the scientist has ever been above the 80th percentile of the annual distribution of the specific acknowledgment "type." These helpfulness "type" stars are similar to the productivity and helpfulness stars in that they are time invariant. Robust standard errors clustered at the star coauthor dyad level are in parentheses.

$^{+}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$.

"criticism," etc. As can be seen from column (1), the death of a conceptual helpfulness star has a large and statistically significant negative effect on the performance of coauthors. Specification (2) includes an interaction with a materials helpfulness star dummy. Materials acknowledgments capture the transfer of supplies and materials, for example, "The authors are grateful to Drs. T. Mosmann and R. Tigelaar for their generous supply of mAb" (Matsue et al. 1993, p. 6018). The keywords used to identify materials helpfulness include "supply," "use of," "cells," "reagents," "antibodies," etc. The coefficient on materials helpfulness is negative and statistically significant but smaller than the coefficient on conceptual helpfulness, lending some support to the hypothesis that the death of a materials helpfulness star may negatively affect the performance of coauthors in the short run but that it is not as permanent or large as the effects from the death of a conceptual helpfulness star.

Specification (3) includes an interaction with a testing and tools helpfulness star. Testing and tools acknowledgments thank scientists for providing help performing tests and technical assistance, for example, "We are grateful to … Dr. John Abrams for performing ELISA assays to detect GM-CSF" (Quill et al. 1989, p. 817). The keywords used to classify Testing & Tools helpfulness include "expertise," "analysis," "surgical," "testing," "technique," etc. The death of a testing and tools helpfulness star has a large and statistically significant negative effect on the performance of coauthors, although the estimate precision is low, indicating high variance in the impact of testing and tools stars on the performance of coauthors.

Specification (4) includes an interaction with a technical helpfulness star. Technical acknowledgments thank scientists for providing help performing technical assistance, for example, "The authors thank Darien E. Wilson and Alvin Wray for expert technical assistance" (Chin et al. 1980). The keywords used to classify technical helpfulness include "technical," "laboratory assistance," "able assistance," "excellent assistance," etc. The death of a technical helpfulness star has a negative effect on the performance of coauthors, although this effect is statistically insignificant.

In all, it appears that not all deaths of scientists who are helpful have a uniform impact on the performance of their coauthors. However, scientists who provide conceptual input have the largest impact on the performance of their coauthors.

6.3. Robustness Checks

Table 10 presents a series of specifications to examine the robustness of the findings shown so far. One drawback from using collaboration data from 298 immunologists (treated and controls) is that coauthors of one star scientist may actually be stars themselves. Column (1) removes all coauthors who are also star scientist. Only 93 dyads contain a coauthor who is also a star scientist, resulting in coefficients that are largely unchanged and similar to those presented so far. A related issue may be the case where some coauthors coauthor with multiple star scientist. Column (2) removes all coauthors who coauthor with more than one scientist who dies. The results are robust to the exclusion of these coauthors. Column (3) includes only coauthors who had become coauthors with the star scientist in a "planned" way, that is, either the star or the coauthor were first or last authors and thus were not both "interior" coauthors whose coauthoring relationship may be viewed as accidental. Not surprisingly, the coefficient estimates increase in magnitude when I restrict the sample to planned coauthoring relationships. Column (4) presents results that are robust to the inclusion of an interaction with a dummy for close coauthoring relationships (coauthors who coauthored more than six times with the star). Column (5) controls for the degree to which a star

Table 10 Fixed-Effects Poisson QML Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	IF pubs.-star	IF pubs.-star	IF pubs.-star	IF pubs.-star	IF pubs.-star	IF pubs.-star	IF pubs.-star
Sample:	Exclude coauthor stars	Exclude multiple-death coauthors	Planned coauthors	Full	Full	Full	Full
Death	−0.041	−0.007	0.041	−0.034	−0.048	−0.033	−0.029
	(0.045)	(0.044)	(0.050)	(0.045)	(0.043)	(0.045)	(0.042)
Death × *All-Star*	−0.179**	−0.168**	−0.220**	−0.187**	−0.157*	−0.168**	−0.174**
	(0.059)	(0.056)	(0.067)	(0.059)	(0.070)	(0.060)	(0.053)
Death × *Lone Wolf*	0.076	0.026	0.119	0.055	0.102	0.078	0.010
	(0.069)	(0.062)	(0.074)	(0.069)	(0.069)	(0.069)	(0.061)
Death × *Maven*	−0.157*	−0.150*	−0.227**	−0.154*	−0.162*	−0.318**	−0.151*
	(0.075)	(0.064)	(0.088)	(0.076)	(0.073)	(0.088)	(0.069)
Death × *Close Coauthor*				−0.354*			
				(0.165)			
Death × *All-Star* × *Close Coauthor*				0.380			
				(0.250)			
Death × *Lone Wolf* × *Close Coauthor*				0.608			
				(0.384)			
Death × *Maven* × *Close Coauthor*				−0.090			
				(0.326)			
Death × % *of Papers as Last Author*					−0.555**		
					(0.190)		
Death × *All-Star* × % *of Papers as Last Author*					0.465		
					(0.283)		
Death × *Lone Wolf* × % *of Papers as Last Author*					0.221		
					(0.420)		
Death × *Maven* × % *of Papers as Last Author*					−0.145		
					(0.393)		
Death × *Age of Star at Death*						0.005	
						(0.004)	
Death × *All-Star* × *Age of Star at Death*						−0.010+	
						(0.006)	
Death × *Lone Wolf* × *Age of Star at Death*						0.009	
						(0.008)	
Death × *Maven* × *Age of Star at Death*						0.018*	
						(0.007)	
Death × *Age of Coauthor at Death*							−0.004
							(0.005)
Death × *All-Star* × *Age of Coauthor at Death*							−0.001
							(0.007)
Death × *Lone Wolf* × *Age of Coauthor at Death*							0.014*
							(0.007)
Death × *Maven* × *Age of Coauthor at Death*							−0.004
							(0.008)
Dyad fixed effects	✓	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓	✓
Star age cohort fixed effects	✓	✓	✓	✓	✓	✓	✓
Coauthor Age cohort fixed effects	✓	✓	✓	✓	✓	✓	✓
Observations	493,653	400,924	323,266	497,214	497,214	497,214	497,214
No. of dyads	18,906	16,245	12,243	18,999	18,999	18,999	18,999
Log-likelihood	−2,585,309	−1,776,594	−1,705,828	−2,611,524	−2,610,706	−2,609,914	−2,611,178

Notes. Column (1) excludes coauthors j who are also in the set of stars i. Column (2) excludes coauthors who coauthor with multiple stars i who die. Column (3) includes only coauthors who were "planned" (either the star i or the coauthor j was a first or last author on their collaborating paper). Column (4) includes an interaction with a dummy set to 1 if coauthor j is a close collaborator (star i and coauthor j have collaborated more than six times). Column (5) includes an interaction with a centered variable of the percentage of papers that star i wrote as the last author. Column (6) includes an interaction with a centered variable of the career age of star i at the time of death. Column (7) includes an interaction with a centered variable of the career age of coauthor j at the time of death of star i. Robust standard errors clustered at the star–coauthor dyad level are in parentheses.

$^{+}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$.

may control resources through lab ownership.[21] Here, the percentage of papers in which star i appears as the last author serves as a proxy for lab ownership. The main coefficients of interest are robust to this inclusion, yet a one standard deviation increase in the percentage of papers written as the last author for nonstars (0.24 from Table 3) is associated with a 12.5% decrease in the performance of their coauthors when they die. Columns (6) and (7) directly control for the age of the stars and coauthors, respectively, at the time of the star's death. In addition to the percentage of papers as last author introduced in column (5), the age at death variables are centered to facilitate interpretation of the star type dummy coefficients. The inclusion of the age of the stars at the time of the death changes the base coefficients slightly, but the results are qualitatively unchanged. Interestingly, older all-stars have the greater negative impact on the performance of their coauthors, whereas younger mavens have the largest negative impact on their coauthors. The noneffect of lone wolves on the performance of their coauthors, on the other hand, does not change with age. The inclusion of the age of coauthors at the time of the star's death results in base coefficients that are largely unchanged from the results reported in Table 7. In additional robustness checks (not reported, but available upon request), the removal of the four stars from each of the four star types (total of 16 stars) that are closest to the cutoffs in their adjacent cells leaves the main results both quantitatively and qualitatively largely unchanged.[22] This robustness check ensures that scientists who are just above or just below the productivity and helpfulness classification thresholds aren't influencing the results.

7. Alternate Explanations

At least three alternate explanations may account for the relationship observed between the death of the different star types and the subsequent decrease in performance of their coauthors. First, the focal star may have influence over the publishing process, which is unrelated to helpfulness but related to the number of acknowledgments received. Second, the status of a scientist is artificially increasing the perceived performance of coauthors and thus, after death, the coauthors return to their natural steady state. Third, lone wolves may actually be quite helpful, but in lieu of receiving acknowledgments, they become coauthors.

[21] The percentage of papers written as the last author is taken over the star's entire career and thus is time invariant.

[22] This is accomplished through the removal of the two all-stars with the fewest number of acknowledgments, the two all-stars with the lowest number of impact factor-weighted publications and citations, the two mavens with the most impact factor-weighted publications and citations, the two mavens with the fewest number of acknowledgments, etc.

The first alternative explanation is closely related to a gatekeeping explanation, whereby scientists receive acknowledgments because they have influence over the publishing process in *The JI*. In regressions run using Equation (1) (not reported, but available upon request) with a coauthor's articles published in *The JI* excluded, the coefficients on *Death* × *All-Star* ($\beta = -0.136$, $p < 0.05$) and *Death* × *Maven* ($\beta = -0.126$, $p < 0.1$) are slightly lower than those reported in Table 7, although still quite similar. In addition, the main results are robust to the exclusion of any scientists who ever served on the editorial board of *The JI*. Here the coefficients on *Death* × *All-Star* ($\beta = -0.173$, $p < 0.01$) and *Death* × *Maven* ($\beta = -0.152$, $p < 0.05$) are virtually unchanged from the main results reported in Table 7. In both of the above specifications, the coefficient on *Death* × *Lone Wolf* is insignificant.

The second alternate explanation for the reported results is that a star's status is driving coauthor performance. The concern is that a coauthor experiences positive performance because of an association with a high-status scientist (Merton 1973). If status is driving my results, then one would expect the effect of a lone wolf's death on their coauthor productivity to be negative and significant, as all-stars and lone wolves are considered high-status individuals. Furthermore, for the status concern to hold, status cannot act as an information signal, wherein, because of information asymmetry, association with a scientist conveys quality onto the coauthor, consequently increasing performance. If in this context status acts as a quality signal, then the signal should not be weakened once the scientist dies, and consequently a decrease in a coauthor's performance after the death of a scientist is unlikely to be associated with status effects. Moreover, if status is driving the results reported, then it would be difficult to explain the strong effect of the death of a maven.

Last, it may be the case that lone wolves are so helpful to former coauthors that instead of receiving acknowledgments for their help, they are offered coauthorship. If this were the case, however, then the lone wolf would surely not receive first author placement (as this is usually reserved for the intellectual steward of the project), nor last author placement (as this is usually reserved for the owner of the lab where the research took place), and instead most likely become an "interior" author. In turn, we would imagine that lone wolves would have a disproportionately high level of "interior" authorships, but this does not appear to be the case. Lone wolves occupy "interior" authorship positions 38.5% of the time, more often than all-stars (32.8%) but less often than mavens (42.2%), providing little evidence that lone wolves receive more "interior" authorships in exchange for being helpful.[23]

8. Discussion and Conclusion

By expanding the current conceptualization of star scientists and focusing on both the productivity and helpfulness dimensions of scientists, I find that the quality (but not quantity) of a coauthor's output is most heavily influenced by ties to scientists with high helpfulness and not by ties to scientists who are merely prolific. Consequently, any assumption held by scholars that high-productivity individuals also produce the largest spillovers may not be entirely justified. These findings have important implications for understanding the inputs into the idea production function and the productivity of science. For example, although I characterize lone wolves by high productivity, they appear to have very little effect on the performance of their coauthors. Mavens, conversely, produce half as many papers and receive half as many citations as lone wolves, yet have a much larger impact on the performance of their coauthors. As a result, the literature on scientific productivity may overemphasize the importance of lone wolves and underemphasize mavens.

The focus of this study is on individual scientific productivity. The strategy and economics literatures, however, focus on performance measures at the organization and regional levels, and as such, mechanisms in which individuals influence the productivity of others become important as these mechanisms directly influence the performance of organizations and regions. Hence, mechanisms by which individuals improve the performance of others are of paramount concern to scholars of strategy and economics. Likewise, this study has important implications for academic and research organization. For example, what types of individuals should research groups recruit? Helpful stars may not only influence the productivity of coauthors and colleagues, but may also facilitate the hiring of new research personnel. Relatedly, what is the ideal composition of human capital within research-intensive organizations? Although all-stars and lone wolves have greater output than mavens and nonstars (by definition), mavens may need to be present within research groups for aggregate organizational output to exceed the sum of its parts.

Although this study has focused on academic science, these results might be representative of knowledge-intensive environments more generally, including those beyond academic and research organizations. Understanding the inputs into the ideas production function is of great importance not only to private-sector firms engaged in frontier research and development, but also consulting, financial services, and even law firms. Indeed, helpful individuals may play a large role anytime critical information needs to be exchanged. Yet, as this paper demonstrates, individuals with high personal productivity, the stars that so many organizations in knowledge-intensive environments covet, do not necessarily positively impact the performance of their peers. The traditional literature on star performers has also largely focused on what individuals produce, yet from a firm strategy standpoint, the greatest source of competitive advantage may stem from the ability to generate human capital spillovers within the boundaries of the firm. Recent work by Singh and Fleming (2010) shows that teams within firms produce higher impact knowledge, even controlling for individual and team characteristics. A better understanding of the extent to which firms encourage helpful behavior may reveal large variation in knowledge production capacity across firms. Relatedly, although critique and testing and tools helpfulness have similar impacts on coauthor performance, their reliance on complementary assets (lab space, infrastructure to conduct certain procedures, etc.) differ. Where individual performance can be firm (Huckman and Pisano 2006) and team (Groysberg et al. 2008) dependent, organizations will need to understand not only which forms of helpfulness are appropriate for their setting, but also the degree to which they can appropriate the returns from different helpfulness stars.

However, it is first paramount to ascertain the extent to which the performance benefits generated by all-stars and mavens are priced. If all-stars and mavens are not compensated for their helpful behavior, then these performance benefits can be viewed as uncompensated spillovers or externalities. Yet, without compensation data, which may be in the form of in-kind or be reciprocity based, we do not know. Furthermore, the main conduit in this study by which stars impact the performance of others comes from the establishment of a social tie through the formation of a coauthoring relationship. Clearly, this is not the only forum by which stars impact the performance of others. Both productivity and helpfulness can have differential impacts on the performance of not only coauthors, but also colleagues, students, one's scientific field, and regions. These extensions are left for future research.

This study presents evidence of the performance gains associated with coauthoring with helpful scientists. In doing so, it makes four important contributions. First, it extends the current dichotomous

[23] Neither the mean of all-star "interior" coauthorships nor the mean of maven "interior" coauthors are statistically distinct from the mean of lone wolf "interior" coauthorships at the 10% level.

conceptualization of star scientists by explicitly defining star classification not only along the dimension of productivity but also the spectrum of helpfulness, thus developing a new taxonomy of star scientists. Second, it provides a measure by which helpfulness can be empirically tested: acknowledgments. Third, it demonstrates a causal link between coauthoring with all-stars and mavens and an increase in the output *quality* of their coauthors but not the output *quantity* of their coauthors. Finally, I identify a strong mechanism linking helpfulness with coauthor performance, whereby scientists who are disproportionately helpful in providing conceptual help and assisting with tests and tools have the largest impact on their coauthors.

The traditional method of bundling together all-stars and lone wolves is quite problematic. All-stars and lone wolves are quite different in their impact on the performance of others. Furthermore, mavens, who under the current dichotomous conceptualization of star scientists are classified as nonstars, in fact have a large impact on the performance of others. Consequently, the current focus on individual productivity has caused us to potentially overlook an important mechanism by which individuals who are helpful greatly improve the quality of their colleagues' output. Scientists can be productive in being helpful, and thus are stars of a different sort. As such, it is time to update our conceptualization of who really is a "star."

Acknowledgments
Special thanks go to Olav Sorenson, Joanne Oxley, and especially Ajay Agrawal for immeasurable advice and guidance. The author is grateful to the associate editor and three anonymous referees for insightful and constructive comments that greatly improved the quality of this work. He also thanks Taylor Aldridge, Pierre Azoulay, Christian Catalini, Ken Corts, Alberto Galasso, Matt Higgins, Anita McGahan, Gabriel Natividad, Samila Sampsa, Scott Stern, Colleen Stuart, and audiences at numerous seminars for helpful critique and suggestions. Jennifer Gommerman of the immunology department at the University of Toronto provided valuable insight. Hyun Jung and Vincenzo Palermo provided excellent research assistance. This research was graciously funded by the Social Sciences and Humanities Research Council of Canada [Grant 410-2004-1770] and the Martin Prosperity Institute Program on Innovation and Creative Industries. All errors and omissions are the author's own.

References

Acemoglu, D. 1996. A microfoundation for social increasing returns in human capital accumulation. *Quart. J. Econom.* **111**(3) 779–804.
Agrawal, A., J. McHale, D. Kapur. 2008. How do spatial and social proximity influence knowledge flows? Evidence from patent data. *J. Urban Econom.* **64**(2) 258–269.
Agrawal, A., J. McHale, D. Kapur, A. Oettl. 2011. Brain drain or brain bank? The impact of skilled emigration on poor-country innovation. *J. Urban Econom.* **69**(1) 43–55.
Allen, T. J. 1984. *Managing the Flow of Technology.* MIT Press, Cambridge, MA.
Allison, P. D., J. S. Long. 1990. Departmental effects on scientific productivity. *Amer. Sociol. Rev.* **55**(4) 469–478.
Almeida, P., B. Kogut. 1999. Localization of knowledge and the mobility of engineers in regional networks. *Management Sci.* **45**(7) 905–917.
Audretsch, D. B., M. P. Feldman. 1996. R&D spillovers and the geography of innovation and production. *Amer. Econom. Rev.* **86**(3) 630–640.
Azoulay, P., J. G. Zivin, J. Wang. 2010. Superstar extinction. *Quart. J. Econom.* **125**(2) 549–589.
Bennett, B. 1965. Specific suppression of tumor growth by isolated peritioneal macrophages from immunized mice. *J. Immunol.* **95**(4) 656–664.
Chin, Y., G. D. Carey, J. J. Woodruff. 1980. Lymphocyte recognition of lymph node high endothelium. I. Inhibition of in vitro binding by a component of thoracic duct lymph. *J. Immunol.* **125**(4) 1764–1769.
Councill, I. G., C. Lee Giles, H. Han, E. Manavoglu. 2005. Automatic acknowledgement indexing: Expanding the semantics of contribution in the citeseer digital library. *K-CAP'05. Proc. 3rd Internat. Conf. Knowledge Capture*, ACM, New York, 19–26.
Cronin, B. 1995. *The Scholar's Courtesy.* Taylor Graham, London.
Cronin, B., S. Franks. 2006. Trading cultures: Resource mobilization and service rendering in the life sciences as revealed in the journal article's paratext. *J. Amer. Soc. Inform. Sci. Tech.* **57**(14) 1909–1918.
de Solla Price, D. J. 1986. *Little Science, Big Science*. Columbia University Press, New York.
Ernst, H., C. Leptien, J. Vitt. 2000. Inventors are not alike: The distribution of patenting output among industrial R&D personnel. *IEEE Trans. Engrg. Management* **47**(2) 184–199.
Fletcher, G. J. O., M. S. Clark. 2003. *Blackwell Handbook of Social Psychology: Interpersonal Processes.* Blackwell, Malden, MA.
Ganguli, I. 2011. Saving soviet science: The impact of grants when government R&D funding disappears. Mimeo, Harvard University, Cambridge, MA.
Gilfillan, S. C. 1935. *Inventing the Ship.* Follett, Chicago.
Groysberg, B., L.-E. Lee, A. Nanda. 2008. Can they take it with them? The portability of star knowledge workers' performance. *Management Sci.* **54**(7) 1213–1230.
Hackett, C. J., D. Rotrosen, H. Auchincloss, A. S. Fauci. 2007. Immunology research: Challenges and opportunities in a time of budgetary constraint. *Nat. Immunol.* **8**(2) 114–117.
Haeussler, C., L. Jiang, J. Thursby, M. C. Thursby. 2009. Specific and general information sharing among academic scientists. Working Paper 15315, National Bureau of Economic Research, Cambridge, MA.
Hausman, J., B. H. Hall, Z. Griliches. 1984. Econometric models for count data with an application to the patents-R&D relationship. *Econometrica* **52**(4) 909–938.
Helft, M. 2011. For buyers of Web start-ups, quest to corral young talent. *New York Times* (May 17) A1.
Huckman, R. S., G. P. Pisano. 2006. The firm specificity of individual performance: Evidence from cardiac surgery. *Management Sci.* **52**(4) 473–488.
Iacus, S. M., G. King, G. Porro. 2010. Causal inference without balance checking: Coarsened exact matching. Working paper, Institute for Quantitative Social Science, Harvard University, Cambridge, MA.
Jaffe, A. B., M. Trajtenberg, R. Henderson. 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. *Quart. J. Econom.* **108**(3) 577–598.
Jones, B. F. 2009. The burden of knowledge and the "death of the renaissance man": Is innovation getting harder? *Rev. Econom. Stud.* **76**(1) 283–317.

Kapur, D., J. McHale. 2005. *Give Us Your Best and Brightest.* Center for Global Development, Washington, DC.

Karpus, W. J., N. W. Lukacs, B. L. McRae, R. M. Strieter, S. L. Kunkel, S. D. Miller. 1995. An important role for the chemokine macrophage inflammatory protein-1 alpha in the pathogenesis of the *t* cell-mediated autoimmune disease, experimental autoimmune encephalomyelitis. *J. Immunol.* **155**(10) 5003–5010.

Koo, G. C., H. Rosen, A. Sirotina, X. D. Ma, L. D. Shultz. 1993. Anti-cd11b antibody prevents immunopathologic changes in viable moth-eaten bone marrow chimeric mice. *J. Immunol.* **151**(12) 6733–6741.

Levin, S. G., P. E. Stephan. 1991. Research productivity over the life cycle: Evidence for academic scientists. *Amer. Econom. Rev.* **81**(1) 114–132.

Lotka, A. J. 1926. The frequency distribution of scientific productivity. *J. Washington Acad. Sci.* **16**(12) 317–325.

Lucas, R. E. 1988. On the mechanisms of economic development. *J. Monetary Econom.* **22**(1) 3–42.

Matsue, H., P. R. Bergstresser, A. Takashima. 1993. Keratinocyte-derived il-7 serves as a growth factor for dendritic epidermal *t* cells in mice. *J. Immunol.* **151**(11) 6012–6019.

Merton, R. K. 1973. *The Sociology of Science: Theoretical and Empirical Investigations.* University of Chicago Press, Chicago.

Narin, F., A. Breitzman. 1995. Inventive productivity. *Research Policy* **24**(4) 507–519.

Nelson, R. R., S. G. Winter. 1982. *An Evolutionary Theory of Economic Change.* Belknap Press, Harvard University Press, Cambridge, MA.

Oettl, A., A. Agrawal. 2008. International labor mobility and knowledge flow externalities. *J. Internat. Bus. Stud.* **39**(8) 1242–1260.

Quill, H., A. Gaur, R. P. Phipps. 1989. Prostaglandin e2-dependent induction of granulocyte-macrophage colony-stimulating factor secretion by cloned murine helper *t* cells. *J. Immunol.* **142**(3) 813–818.

Romer, P. M. 1990. Endogenous technological change. *J. Political Econom.* **98**(5) S71–S102.

Rosen, S. 1981. The economics of superstars. *Amer. Econom. Rev.* **71**(5) 845–858.

Rothaermel, F. T., A. M. Hess. 2007. Building dynamic capabilities: Innovation driven by individual, firm-, and network-level effects. *Organ. Sci.* **18**(6) 898–921.

Singh, J. 2005. Collaborative networks as determinants of knowledge diffusion patterns. *Management Sci.* **51**(5) 756–770.

Singh, J., A. Agrawal. 2011. Recruiting for ideas: How firms exploit the prior inventions of new hires. *Management Sci.* **57**(1) 129–150.

Singh, J., L. Fleming. 2010. Lone inventors as sources of breakthroughs: Myth or reality? *Management Sci.* **56**(1) 41–56.

Smith, C. A., D. W. Organ, J. P. Near. 1983. Organizational citizenship behavior: Its nature and antecedents. *J. Appl. Psych.* **68**(4) 653–663.

Tam, P.-W., K. J. Delaney. 2005. Talent search: Google's growth helps ignite Silicon Valley hiring frenzy. *Wall Street Journal* (November 23) A1.

Waldinger, F. 2012. Peer effects in science—Evidence from the dismissal of scientists in Nazi Germany. *Rev. Econom. Stud.* Forthcoming.

Wooldridge, J. M. 1999. Distribution-free estimation of some nonlinear panel data models. *J. Econometrics* **90**(1) 77–97.

Wuchty, S., B. F. Jones, B. Uzzi. 2007. The increasing dominance of teams in production of knowledge. *Science* **316**(5827) 1036–1039.

Zucker, L. G., M. R. Darby, M. B. Brewer. 1998. Intellectual human capital and the birth of U.S. biotechnology enterprises. *Amer. Econom. Rev.* **88**(1) 290–306.