Research Policy 46 (2017) 853–867

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

How stars matter: Recruiting and peer effects in evolutionary biology☆

Ajay Agrawal[a,b], John McHale[c], Alexander Oettl[d,*]

[a] Rotman School of Management, University of Toronto, Canada
[b] NBER, United States
[c] National University of Ireland, Galway and Whitaker Institute for Innovation and Societal Change, Ireland
[d] Scheller College of Business, Georgia Institute of Technology, United States

ARTICLE INFO

Article history:
Received 5 February 2016
Received in revised form 23 February 2017
Accepted 24 February 2017
Available online 11 March 2017

JEL classification:
O31
J24
I23

Keywords:
Stars
Innovation
Peer effects
Spillovers
Recruiting

ABSTRACT

The peer-effects literature highlights several distinct channels through which colleagues may affect individual and organizational performance. Building on this, we examine the relative contributions of different channels by decomposing the productivity effect of a star's arrival on (1) incumbents and (2) new recruits. Using longitudinal, university-level data, we report that hiring a star does not increase overall incumbent productivity, although this aggregate effect hides offsetting effects on related (positive) versus unrelated (negative) colleagues. However, the primary impact comes from an increase in the average quality of subsequent recruits, an effect that is most pronounced at non-highly-ranked institutions. We discuss the implications of our results for star-focused strategies to improve organizational performance.

1. Introduction

One of the most prominent and persistent features of the production of scientific knowledge is the role of superstars. The highly skewed distribution of output per individual is well documented. Almost a century ago, Lotka (1926) observed that 6% of physicists produced more than 50% of all papers. Since then, the relative importance of scientists in the right tail of the output distribution – stars – has endured (Rosen, 1981; Narin and Breitzman, 1995; Ernst et al., 2000).

How do stars affect the productivity of their organization? Although stars themselves have been carefully examined, their effect on the organizations they join is less well studied. We examine two channels: incumbents and joiners. These channels are not mutually exclusive. Stars may increase the productivity of incumbents – scientists already present at the organization when the star arrives – by raising the standards, collaborating, or by sharing their knowledge, for instance. Stars may also increase the productivity of the average worker at their organization by enhancing the quality of subsequent recruits ("joiners") due to their reputation. We find evidence in support of both channels, but the effect on joiners dominates the effect on incumbents.

We base our empirics on a sample of 140 evolutionary biology departments that published 149,947 articles over the 29-year period 1980–2008. We employ a difference-in-differences estimation, comparing the productivity of "treated" versus "control" departments before versus after the arrival of a star, to estimate the impact of a star hire on department productivity, where treatment refers to the recruitment of a star.

☆ We greatly benefited from thoughtful comments and suggestions from Rajshree Agarwal, Aneil Agrawal, Christian Catalini, Iain Cockburn, Richard Freeman, Joshua Gans, Avi Goldfarb, Dietmar Harhoff, Carolin Häussler, Ben Jones, Bill Kerr, Francine Lafontaine, Matt Mitchell, Paula Stephan, Scott Stern, Will Strange, and seminar participants at DRUID, NBER, UC Berkeley, Carnegie Mellon, Emory, Georgia Tech, Harvard, National University of Ireland, National University of Singapore, Passau, Stanford, Temple, and Toronto, as well as three anonymous referees. We gratefully acknowledge funding support from the Centre for Innovation and Entrepreneurship at the Rotman School of Management, the Kauffman Foundation, the Martin Prosperity Institute, and the Social Sciences and Humanities Research Council of Canada. Errors remain our own.

* Corresponding author.
E-mail addresses: ajay.agrawal@rotman.utoronto.ca (A. Agrawal), john.mchale@nuigalway.ie (J. McHale), alex.oettl@scheller.gatech.edu (A. Oettl).

http://dx.doi.org/10.1016/j.respol.2017.02.007
0048-7333/

We report three main results. First, the arrival of a star is highly correlated with a subsequent increase in the productivity of the group. Specifically, we estimate that a department's productivity (output per scientist) increases by 46% after the arrival of a star. Second, productivity gains are primarily due to an increase in the quality of subsequent recruits who join after the arrival of the star, as opposed to an increase in the productivity of incumbents who were already in the group prior to the star's arrival. The mean quality of joining scientists increases by more than 64% after the arrival of a star. Third, the "no net effect on incumbent" result obscures a subtler effect that stars do seem to enhance the productivity of incumbents who work in areas related to the star, but they also diminish the relative productivity of incumbents who work in areas unrelated to the star, perhaps due to crowding out resources that would have otherwise gone to the unrelated areas.

We interpret our results as causal – that the arrival of a star scientist causes an increase in the subsequent productivity of their department – with caution. Stars may move to departments that are on the rise (reverse causality). In addition, an omitted variable, such as a positive shock to department resources (e.g., philanthropic gifts, sharp increases in government funding, the construction of a new building), may cause the department to both hire a star and increase its overall productivity in terms of incumbent productivity and the quality of subsequent recruits. Our difference-in-differences estimation method partially addresses these concerns by controlling for general productivity trends (time fixed effects) and department-specific attributes (department fixed effects). However, a concern remains that time-specific department-level shocks could lead to a misidentification of causal effects. Thus, we conduct three additional tests; they all produce results consistent with a causal interpretation. Still, we view the causal interpretation of our results with caution due to the possible endogeneity of the arrival of a star at a department.

This star-effect-on-recruiting finding is important because it has a direct bearing on strategy and policy. From a strategy perspective, organizations with capacity for further hiring will enjoy higher returns from recruiting a star than will otherwise similar organizations. This would not be the case if the benefits were instead due to enhancing incumbent productivity. In addition, from a policy perspective, our findings, while not conclusive, are more consistent with a zero-sum, splitting-the-pie interpretation rather than a growing-the-pie interpretation. Given the main effect of star arrival is enhancing the quality of subsequent recruits rather than increasing the productivity of incumbents, the focal department's gain comes at the expense of other departments' loss. Our results do not offer an obvious case for intervention by the central planner with respect to allocating stars across organizations to optimize welfare.

Overall, this paper offers three primary contributions to the literature. First, we introduce a theoretical model that generates testable predictions for the implications of star arrivals on the productivity of related versus unrelated incumbents and the quality of related versus unrelated joiners. Second, we link the literatures on direct peer effects (e.g., via collaboration) and indirect peer effects (e.g., enhanced recruiting), and report that the latter dominates the former, at least in our empirical setting. Finally, we report evidence that collaboration may be an important mechanism through which stars enhance incumbent productivity, although only for those working in related areas.

The paper proceeds as follows. We review the related literature in Section 2 and then present our theoretical framework in Section 3. We describe our data in Section 4 and our empirical strategy in Section 5. We report results in Section 6 and, in Section 7, provide further evidence that supports a causal interpretation. We discuss the implications of our findings in Section 8.

2. Related literature

Evidence is mixed concerning the effect of stars on peer productivity. Using unexpected star scientist deaths as an exogenous source of variation in peer groups, Azoulay et al. (2010) find a lasting impact on the quality-adjusted publication output of co-authors. Also using star deaths as an exogenous source of variation, Oettl (2012) finds evidence that co-authors of highly helpful scientists that pass away experience a decrease in the quality but not the quantity of output. In contrast, Waldinger (2012), who uses the natural experiment of the dismissal of distinguished scientists in Nazi Germany to measure the effect on colleagues left behind, does not find evidence of adverse effects on former peers within the dismissed scientists' department. One explanation for the difference in these findings may be that the Waldinger study is based on data from an earlier period and the role of teams in the production of science has become significantly more important (Wuchty et al., 2007; Jones, 2009; Conti and Liu, 2015; Bercovitz and Feldman, 2011).[1]

Evidence of peer effects has also been found in other domains. In the context of a retail firm, Mas and Moretti (2009) find evidence of productivity spillovers when a high productivity worker arrives, but the benefit is limited to those who see the star in their daily work and is stronger when there are more frequent interactions with the new arrival. Using data on the performance of randomly assigned college roommates, Sacerdote (2001) finds that peers have an impact on grade point averages and decisions to join social groups.[2]

[1] An important question addressed in the literature is how the relationship with the arriving star mediates the impact on incumbents. Conceptualizing knowledge development as a process of search and recombination, Grigoriou and Rothaermel (2014) develop the idea of a "relational star." They argue that a focus on individual productivity presents an under-socialized view of inventor capacity, and instead emphasize the importance of the star's position in intraorganizational knowledge networks. In this regard there is growing evidence that having a cadre of incumbents with skills that complement an arriving star matters for the productivity enhancing effect of the star's arrival. In a study of security analysts, Groysberg et al. (2008) find that a star's own productivity drops significantly on arrival, but that this effect is attenuated when they move to firms with better capabilities or when they move together with prior team members. This suggests difficulties in effective matching with new colleagues where incumbent capabilities are unrelated to the star. In a related study, Groysberg and Lee (2009) find that star security analysts who join firms to initiate new activities ("exploration") suffer long-run performance declines while those who join to reinforce existing activities ("exploitation") suffer only short-term declines. Kehoe and Tzabbar (2015) find that the positive effect of a star on incumbent productivity is greatest where the star has broad expertise and collaborates frequently. (See also Kehoe et al., 2016.) In a study of translational research in medicine, Ali and Gittelman (2016) find evidence of a licensing penalty for teams that comprise MDs and PhDs, suggesting the challenges of combining expertise that bridge different knowledge domains and thus the limited benefits of star arrivals for unrelated incumbents.

[2] Collaboration is one mechanism through which star arrivals could affect incumbent productivity, especially where the incumbent works in areas related to the star. The benefit could be influenced by the "Matthew effect," made famous by Merton (1968) in a study of Nobel laureates. Azoulay et al. (2013) provide evidence that status-conferring prizes lead to increased citations to prior work, especially where there is uncertainty about the quality of the article. Such citation boosts will also positively impact co-authors, even though there may be a retrospective reallocation of credit when prizes are awarded. There is also direct evidence that collaboration with stars can increase the probability of publication independent of the quality of the work. Simcoe and Waguespack (2011) exploit a natural experiment where new submissions to the Internet Engineering Task Force were announced with the first author followed by "et al." The importance of status is identified by variation in whether a high-status name is obscured or not in the announcement of the submission. They find name-based signals significantly affect publication rates and attention on electronic discussion boards, indicating a publication advantage from collaboration with a star. Lu et al. (2013) provide intriguing evidence of the citation implications of the Matthew effect in reverse–where an article has to be retracted and blame attributed. They find that retractions impose little citation penalty on the star, but non-star co-authors face substantial declines in citations to prior work. Hohberger (2016) examines the effects of a star on non-star inventors in biotechnology. He finds that having a star directly involved in building on

A second potential effect of a star's arrival is that it can help to attract more talented colleagues. This "recruitment externality" could be due to productivity, reputational, or consumption spillovers from being co-located with the star. Although Waldinger (2012) finds no evidence of negative productivity effects on incumbents left behind when star scientists were dismissed in Nazi Germany, in a subsequent study Waldinger (2016) finds that the dismissal of stars caused large reductions in departmental output due to the impact on the recruitment of other successful scientists. In a study of economics departments, Kim et al. (2009) find that although the productivity dividend from co-location with talented colleagues has fallen over time (possibly due to the effects of new communication technologies), there is still a strong tendency for the most productive researchers to agglomerate at the top departments. This suggests significant reputational spillovers from co-location with highly productive peers independent of direct productivity benefits. In the context of firms undergoing IPOs, Higgins et al. (2011) find that the affiliation of a Nobel laureate provides a signal of quality, with the effect being more pronounced the worse the alternative measures of firm quality that are available. This again suggests the importance of inferences of quality by association and the reputational benefits of joining firms or departments where stars are present.

Overall, the literature on peer effects suggests star colleagues may significantly enhance the productivity of incumbent peers, although the effects are sensitive to the nature of the relationship with the star. Moreover, the presence of a star may attract talented recruits. These latter effects may be present even if the direct productivity benefits from co-location are limited. A core contribution of this paper is to quantify the relative importance of star arrivals for related versus unrelated incumbent productivity and subsequent related versus unrelated joiner quality.

3. Theoretical framework

To better delineate the channels through which a star arrival could affect departmental performance, we draw on the existing literature to motivate a simple model that allows for differential effects of star arrivals on incumbent productivity depending on their relationship to the star. The model also allows for the arrival to affect the composition of subsequent recruitment and in particular to bias it towards recruitment of related joiners. This creates an indirect channel through which unrelated incumbents can be harmed by the star's arrival even where that arrival improves the pool of unrelated potential recruits that are attracted to the department. The model generates testable predictions for the implications of star arrivals on the productivity of related versus unrelated incumbents and the quality of related versus unrelated joiners.

3.1. Direct productivity effects on incumbents

We begin with the direct effect of a star hire on the productivity of incumbents, ignoring initially any potential impacts through a changed composition of subsequent hires. We assume there are two types of scientists: type-1 and type-2. Type-1 scientists work on topic 1, and type-2 scientists work on topic 2. We further assume that the star is of type-1, so that type-1 incumbents are "related" and type-2 incumbents are "unrelated" to the star. Individual scientist productivity is measured by the flow of citation-weighted publications. For a given scientist of type-1, productivity is given by a Romer-style research production function:

$$P_{1\iota} = \lambda_{1i} A_1^{\theta_{11}} A_2^{\theta_{12}}, \tag{1}$$

where λ_{1i} is an individual productivity parameter for scientist i, A_1 is the total citation-weighted local knowledge stock of type-1 scientists, A_2 is the total citation-weighted local knowledge stock of type-2 scientists, and θ_{11} and θ_{12} are elasticities of individual productivity with respect to the local knowledge stocks of type-1 and type-2 scientists, respectively. Although the most obvious productivity channel is through local knowledge spillovers, we remain agnostic on the local knowledge-stock effect. In addition to knowledge spillovers, an increased local knowledge stock could affect incumbents through such channels as mentoring, access to funding or broader access to external networks. We assume $\theta_{11} > \theta_{12}$, so that the knowledge spillover effect is greater within than across types. A similar productivity equation applies to type-2 scientists:

$$P_{2\iota} = \lambda_{2i} A_1^{\theta_{21}} A_2^{\theta_{22}}, \tag{2}$$

where $\theta_{22} > \theta_{21}$.

How does the hiring of a star type-1 scientist directly affect the productivity of the two scientist types? We assume that the knowledge stock of the star is sA_1, where s is the star's knowledge stock as a share of the initial type-1 knowledge stock at the institution. Focusing first on type-1 scientists, the marginal productivity benefit of a one unit increase in the local knowledge stock of type-1 scientists is:

$$\frac{\partial P_{1\iota}}{\partial A_1} = \theta_{11} \lambda_{1i} A_1^{\theta_{11}-1} A_2^{\theta_{12}}. \tag{3}$$

The total impact on the productivity of type-1 scientists is then given by the linear approximation:

$$\Delta P_{1\iota} \approx \frac{\partial P_{1\iota}}{\partial A_1} \Delta A_1 = \frac{\partial P_{1\iota}}{\partial A_1} s A_1. \tag{4}$$

Using (1) and (3), we can write the proportional effect on type-1 productivity as:

$$\frac{\Delta P_{1\iota}}{P_{1\iota}} \approx s\theta_{11}. \tag{5}$$

Similarly, we can write the proportional effect on type-2 scientists as:

$$\frac{\Delta P_{2\iota}}{P_{2\iota}} \approx s\theta_{21}. \tag{6}$$

Thus, the direct productivity effect will be larger for type-1 scientists and also larger for institutions where the star represents a larger share of the initial type-1 knowledge stock (i.e., a large s). Assuming this share tends to rise with the rank of the institution, the direct proportional productivity effect of the hiring of a star will be larger at lower-ranked institutions.

3.2. Indirect productivity effects on incumbents through subsequent hiring

In addition to these direct effects, the productivity of incumbents also will be affected by any impacts of the hiring of the star on subsequent recruitment. We therefore allow for the possibility of "recruitment externalities" in addition to the "knowledge spillover externalities" discussed above. We assume the department has a fixed number of hiring slots, H (not including the star). The hiring

previous star inventions is positively related to invention performance. However, stars are not found to be better than non-stars in building on earlier star inventions, and having stars focused on building on their own previous inventions can adversely affect their subsequent productivity. This suggests that non-stars could benefit from opportunities to build on the work of co-located stars even if there is limited actual collaboration as stars move on to new areas of research.

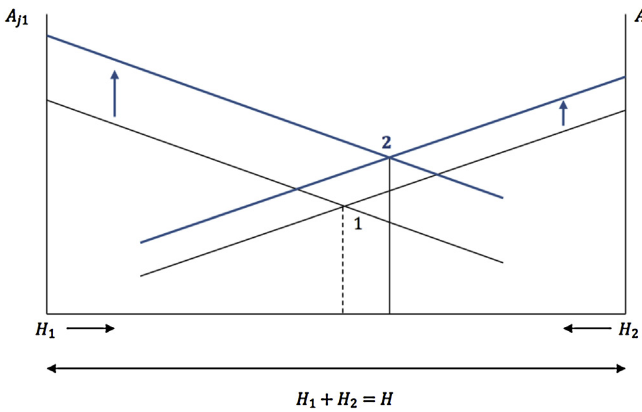


Fig. 1. Impact of a type-1 star hire on subsequent recruitment.

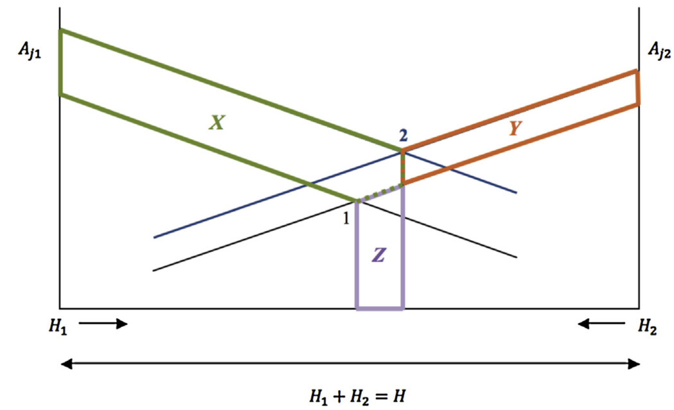


Fig. 2. Decomposition of the impact on subsequent hiring-related knowledge stocks.

of a star may change the composition of the applicant pool for these slots and thus the composition of the hires.

Letting $\Delta_H A_{H1}$ be the change in the knowledge stock of type-1 scientists who are hired due the hiring of the type-1 star and $\Delta_H A_{H2}$ the change in the knowledge stock of type-2 scientists who are hired due to the type-1 star, the indirect effect on the productivity of type-1 scientists through the hiring channel is:

$$\Delta_H P_{1\iota} \approx \frac{\partial P_{1\iota}}{\partial A_1} \Delta_H A_{H1} + \frac{\partial P_{1\iota}}{\partial A_2} \Delta_H A_{H2}. \tag{7}$$

This in turn can be rewritten in terms of the proportional change in the productivity of type-1 scientists as:

$$\frac{\Delta_H P_{1\iota}}{P_{1\iota}} \approx \left(\frac{\theta_{11}}{A_1}\right) \Delta_H A_{H1} + \left(\frac{\theta_{12}}{A_2}\right) \Delta_H A_{H2}. \tag{8}$$

For type-1 incumbents, we further assume that the marginal product of type-1 knowledge stock is greater than the marginal product of type-2 knowledge stock, that is, $\frac{\theta_{11}}{A_1} > \frac{\theta_{12}}{A_2}$.

Similarly, the proportional indirect effect for type-2 scientists is:

$$\frac{\Delta_H P_{2\iota}}{P_{2\iota}} \approx \left(\frac{\theta_{21}}{A_1}\right) \Delta_H A_{H1} + \left(\frac{\theta_{22}}{A_2}\right) \Delta_H A_{H2}, \tag{9}$$

where it is assumed that $\frac{\theta_{22}}{A_2} > \frac{\theta_{21}}{A_1}$.

We next consider how the hiring of the type-1 star affects the composition of hiring. We assume the institution hires the best scientists from the applicant pool for its open positions, where quality is measured by the citation-weighted knowledge stocks of the applicants. To solve for the optimal composition of hiring, we introduce the idea of a recruitment function. For type-1 scientists, the recruitment function gives the quality of the applicant in the jth position in the quality ranking, where the applicants are ranked from best to worst. Letting H_1 represent the number of type-1 scientists hired, the quality of the marginal hire is given by:

$$A_{j1} = \phi_{11}(1+s)A_1 + \phi_{12}A_2 - \beta_1 H_1, \tag{10}$$

where the parameter β_1 measures how the quality of the marginal recruit falls with additional hires. In Fig. 1, we graph from left to right the relationship between the quality of the marginal hire and the number of hires. Critically, the quality of the existing scientists (including the star scientist) is a shift factor for the recruitment function. An increase in the quality of incumbents will shift the recruitment curve upwards in Fig. 1. Thus, the initial recruitment of the star scientist can support the hiring of better quality scientists for the additional available positions through a recruitment spillover. Note that we allow for the possibility that potential recruits are attracted by the quality of existing scientists of the other type, though we assume $\phi_{11} > \phi_{12}$. A similar recruitment function applies for type-2 hires:

$$A_{j2} = \phi_{21}(1+s)A_1 + \phi_{22}A_2 - \beta_2 H_2, \tag{11}$$

where β_2 measures the rate of decline in the quality of the marginal type-2 recruit and $\phi_{22} > \phi_{21}$.

Assuming the institution seeks to maximize the total quality of recruits, the marginal quality of recruits will be equalized at the optimal composition of hires. The initial optimal composition is at point 1 in Fig. 2. Imposing the condition $H_1 + H_2 = H$, the optimal number of type-1 hires is given by:

$$H_1 = \left(\frac{\phi_{11} - \phi_{21}}{\beta_1 + \beta_2}\right)(1+s)A_1 + \left(\frac{\phi_{12} - \phi_{22}}{\beta_1 + \beta_2}\right)A_2 + \left(\frac{\beta_2}{\beta_1 + \beta_2}\right)H. \tag{12}$$

We next identify the *change* in the number of type-1 hires that results from the hiring of the star. From (12), this change is given by:

$$\Delta_H H_1 = \left(\frac{\phi_{11} - \phi_{21}}{\beta_1 + \beta_2}\right) s A_1. \tag{13}$$

The change in type-1 hires will be positive, provided that $\phi_{11} > \phi_{21}$. This will be the case if a given improvement in the quality of type-1 scientists has a greater positive impact on the recruitment of type-1 scientists than type-2 scientists. We assume this condition holds.

Given the assumption of a fixed number of hiring slots, any increase in the hiring of type-1 scientists must be matched by an equal reduction in the hiring of type-2 scientists:

$$\Delta_H H_2 = -\left(\frac{\phi_{11} - \phi_{21}}{\beta_1 + \beta_2}\right) s A_1. \tag{14}$$

Thus, the hiring of the type-1 star will also shift the composition of subsequent hires towards type-1. In terms of Fig. 1, the hiring of the star shifts the department from point 1 to point 2.

The indirect effects of the hiring of the star on both type-1 and type-2 incumbents can be conveniently examined using Fig. 2. The induced change in the type-1 knowledge stock through higher quality subsequent hires is given by the area $X + Z$. The induced change in the type-2 knowledge stock is given by the area $Y - Z$. Thus, area Z represents a shift from type-2 to type-1 knowledge stocks due to the induced change in the composition of hiring in favor of type-1 scientists.

Both types of incumbents gain as a result of the increase in the knowledge stocks represented by areas X and Y in Fig. 2. For type-1 incumbents, given we have assumed that the marginal product of the type-1 knowledge stock is greater than the marginal product of the type-2 knowledge stock, it follows that type-1 incumbents gain from the shift in the composition of hiring; that is, they gain from the transfer of area *Z*. However, given that the opposite marginal product ranking is assumed for type-2 incumbents, they lose from the transfer of area *Z*. Thus, the indirect productivity effect from induced changes to subsequent hiring is positive for type-1 incumbents, thereby reinforcing the positive direct productivity effect from the star. However, both the indirect effect and the total effect are ambiguous for type-2 incumbents. Notwithstanding the improvement in the pool of applicants of both scientist types and the positive direct productivity effect of the star, type-2 incumbents still therefore could suffer an overall loss in productivity if the induced change in hiring towards type-1 scientists is large enough.

More formally, utilizing Fig. 2 and Eq. (8), the proportional indirect effect from the changed composition of subsequent hiring on type-1 incumbents is given by:

$$\frac{\Delta_H P_{1\iota}}{P_{1\iota}} \approx \left(\frac{\theta_{11}}{A_1}\right)(X+Z) + \left(\frac{\theta_{12}}{A_2}\right)(Y-Z)$$
$$= \left(\frac{\theta_{11}}{A_1}\right)X + \left(\frac{\theta_{12}}{A_2}\right)Y + \left(\frac{\theta_{11}}{A_1} - \frac{\theta_{12}}{A_2}\right)Z > 0. \tag{8$'$}$$

For type-2 incumbents, the proportional indirect effect is:

$$\frac{\Delta_H P_{2\iota}}{P_{2\iota}} \approx \left(\frac{\theta_{21}}{A_1}\right)(X+Z) + \left(\frac{\theta_{22}}{A_2}\right)(Y-Z)$$
$$= \left(\frac{\theta_{21}}{A_1}\right)X + \left(\frac{\theta_{22}}{A_2}\right)Y + \left(\frac{\theta_{21}}{A_1} - \frac{\theta_{22}}{A_2}\right)Z. \tag{9$'$}$$

Since the last term in (9′) is negative (i.e., the marginal product of type-1 knowledge stock is assumed to be lower than the marginal product of type-2 knowledge stock for type-2 incumbents), the indirect effect on type-2 incumbents is ambiguous.

3.3. Impact of hiring a star on the average quality of subsequent hires

We finally examine the impact of hiring a star on the *average quality* of subsequent hires. To determine the impact on average quality, we first note that the total quality of type-1 hires (measured by total citation-weighted publications) is given by:

$$A_{H1} = \int_0^{H_1} A_{j1} dj1 = \phi_{11}(1+s)A_1H_1 + \phi_{12}A_2H_1 - \frac{\beta_1}{2}H_1^2. \tag{15}$$

Note that s is equal to zero in the case where no star is hired.

The average quality of type-1 hires is then given by:

$$\frac{A_{H1}}{H_1} = \phi_{11}(1+s)A_1 + \phi_{12}A_2 - \frac{\beta_1}{2}H_1. \tag{16}$$

Using (13), the change in the average quality of type-1 hires due to the hiring of the star is then:

$$\Delta_H\left(\frac{A_{H1}}{H_1}\right) = \left(\phi_{11} - \frac{\beta_1}{2}\left(\frac{\phi_{11}-\phi_{21}}{\beta_1+\beta_2}\right)\right)sA_1$$
$$= \left(\frac{(\phi_{11}+\phi_{21})\beta_1 + 2\phi_{11}\beta_2}{2(\beta_1+\beta_2)}\right)sA_1 > 0. \tag{17}$$

Thus, the average quality of type-1 hires increases as a result of hiring the type-1 star. This result also can be seen intuitively using Fig. 1. The average quality of type-1 hires must increase given the upward shift in the recruitment function and recognizing that the quality of the marginal type-1 hire has increased as well.

The average quality of type-2 hires also increases as a result of hiring the type-1 star:

$$\Delta_H\left(\frac{A_{H2}}{H_2}\right) = \left(\phi_{21} - \frac{\beta_2}{2}\left(\frac{\phi_{11}-\phi_{21}}{\beta_1+\beta_2}\right)\right)sA_1$$
$$= \left(\frac{(\phi_{11}+\phi_{21})\beta_2 + 2\phi_{21}\beta_1}{2(\beta_1+\beta_2)}\right)sA_1 > 0. \tag{18}$$

This increase in average quality is the result of both an upward shift in the recruitment function for type-2 scientists and also a move up along the curve due to the reduced hiring (and consequently more selective recruitment) of these scientists, which increases the quality of the marginal type-2 hire (see Fig. 1).

3.4. Summary of testable propositions

The model yields a number of testable propositions:

- A type-1 star hire will increase the productivity of type-1 incumbents. This is the result of a positive direct productivity effect from the star and a positive indirect effect through a star-related reputation effect on hiring.
- A type-1 star hire has an ambiguous effect on the productivity of type-2 incumbents. This is the result of a positive productivity direct effect and an ambiguous indirect productivity effect.
- Hiring a type-1 star will increase the average quality of type-1 and type-2 hires relative to the no-star-hire baseline.
- The productivity effects will be larger at lower-ranked institutions; that is, the productivity effects are increasing in *s*, the star's citation weighted knowledge stock expressed as a share of the initial type-1 knowledge stock.

4. Empirical setting and data

Evolutionary biology has a long history as a subject in studies of the organization of science (see, for example, the classic work of Hull, 1988). For our empirical purposes, this subfield of biology also has the desirable feature that it is well defined by a particular set of journals that we describe below.

4.1. Defining evolutionary biology

We use bibliometric data from the ISI Web of Science to calculate output at the department level and to identify the locations of evolutionary biologists.[3] First, we collect data on all articles published in the four main society journals of evolutionary biology: *Evolution*, *Systematic Biology*, *Molecular Biology and Evolution*, and *Journal of Evolutionary Biology*. These are the primary journals of the Society for the Study of Evolution, Society for Systematic Biology, Society for Molecular Biology and Evolution, and European Society of Evolutionary Biology, respectively. We focus on these four society journals since every article published in each of these journals concerns evolutionary biology and is relevant to evolutionary biologists. This yields 15,256 articles.

Next, we collect all 149,947 articles that are referenced at least once by these 15,526 society journal articles. We call this set the corpus of influence since all of these referenced articles have had some impact on an evolutionary biology article. These 149,946

[3] We use the term "department" to refer to the invisible college of scholars working in the area of evolutionary biology at a particular institution. The individuals we attribute to the evolutionary biology department at a particular institution may actually belong to other departments at that institution, such as chemistry, physics, statistics, or computer science.

serve as the basis of evolutionary biology knowledge for the purposes of our study.

Finally, we weight this corpus of influence by how many times each article has been cited by an article published in the set of 15,256 evolutionary biology society journal articles within five years of publication. There are 501,952 references from the 15,256 society journal articles to the 149,946 corpus of influence articles. We use the 501,952 references to construct our citation-weighted publication measure.

The key benefit of this approach, as opposed to simply using the ISI Journal Citation reports field definitions, is that it allows us to include general journals that evolutionary biologists are likely to publish in, such as *Science*, *Nature*, and *Cell* among others.

4.2. Identifying authors

Next, we attribute the 149,946 articles in the corpus of influence to individual authors. One problem with the ISI Web of Science data is that until recently it listed only the first initial, a middle initial (if present), and the last name for each author. Since our empirical objective is to trace the movement of evolutionary biologists across departments, it is first necessary to disambiguate authors (that is, to distinguish J Smith from JA Smith). We rely on heuristics developed by Tang and Walsh (2010) to disambiguate between authors who share the same name. The heuristic considers backward citations of two focal papers. If two papers reference similar papers (weighted by how many times the paper has been cited, i.e., how obscure or popular it is), then the likelihood that the papers belong to the same author increases and we link the two papers to the same author. We repeat this process for all papers with authors who have the same first initial and last name. We exclude scientists who do not have more than two publications linked to their name. Our results are similar when we choose a different cutoff point, such as only those who publish four or more papers.[4]

4.3. Identifying scientist locations

We generate unique author identifiers for each evolutionary biology paper and then attribute each scientist to a particular institution for every year they are active. A scientist is active from the year they publish their first paper to the year they publish their last paper. Here again, we must overcome a data deficiency inherent within the ISI Web of Science data. Until recently, the Web of Science did not link institutions listed on an article to the authors. Instead, we find instances where the ISI defined "reprint" field (akin to the corresponding author) which provides a one-to-one mapping between a single author and that author's affiliation/address.[5] In addition, we take advantage of the fact that almost 57% of evolutionary biology papers are produced with only a single institution listing. As such, we use single-institution papers to produce a many-to-one mapping of multiple authors to the same institution in a given year. So, we generate an unbalanced panel of author-year observations where we know with high certainty where the authors were and then extrapolate the missing years. This method of location attribution is more effective for evolutionary biology than for many other science disciplines because the field is characterized by smaller teams (3.1 authors per paper on average).

We identify when scientists move locations by changes in the affiliation address listed on their publications.[6] The publication cycle in biology is relatively short, which is helpful for pinning down the year of the move. In our sample, evolutionary biologists publish 1.49 articles per year on average over their publishing careers. This includes stars as well as non-stars. Star scientists publish 2.35 articles per year on average.[7]

4.4. Unit of analysis

Our unit of analysis is the department-year. We define a "department" as the set of scientists at a given university working on evolutionary biology subjects as defined above. We include all universities in the United States and Canada that had at least one evolutionary biologist present in 1980 and in 2008. This criterion ensures that we are not simply counting new university entrants. Furthermore, this ensures that for any given year, a department is at risk of hiring a star. One-hundred-forty departments fit this criterion. As such, the sample contains 4,060 department-year observations.

4.5. Dependent variables

We use three key dependent variables: (1) $Output_{it}$: the sum of the citation-weighted papers published by scientists present at department i in year t; (2) $\frac{Incumbentoutput_{it}}{\#Incumbents_{it}}$: the ratio between the count of the Citation-Weighted Publications in year t by all scientists at department i who were present the year prior to the star's arrival and the number of scientists who were present the year prior to the star's arrival and who are present at department i in year t; and (3) $Joinerquality_{it}$: the mean citation-weighted stock of papers published up until year $t-1$ of all scientists who join department i in year t. All citation measures used in this paper are constructed by counting citations received from the four evolutionary biology society journals listed in Section 4.1 that are made within five years of

[4] Tang and Walsh (2010) demonstrate that this disambiguation method works quite well. Still, it is subject to error. Type 1 errors arise when the algorithm erroneously classifies different scientists with similar common names as being the same person. In this scenario, we bias the scientist's output upward. Type 2 errors occur when an individual has two (or more) very distinct research programs with no overlap in citations made. In this case, we may incorrectly identify a single scientist as two or more separate scientists. If so, then we undercount the scientist's output and bias our productivity estimate downward. Both error types result in measurement error and thus attenuation bias resulting in a downward bias of our estimates. Type 1 errors (incorrectly aggregating multiple scientists into one) will result in a higher probability of classifying a non-star as a star. To the extent that the arrival of a non-star has less effect on departmental productivity than the arrival of a real star, our estimates will be biased downwards due to Type 1 errors. To the extent that Type 2 errors (incorrectly attributing a single scientist's output to several scientists) result in a lower likelihood that we correctly classify a star scientist as a star, our estimates will again be biased downwards (the premium associated with a star's arrival is reduced because the true star is now part of the control). We collect the CVs for a random sample of 10 scientists from our data set. As expected, our method that focuses on evolutionary biology peer-reviewed publications only captures a fraction of each scientist's total scientific output across all fields and manuscript types (including books, literature reviews, popular press articles, etc.). When we compare the number of evolutionary biology publications per scientist generated from our disambiguation algorithm to the total number of publications listed on their CVs we find a correlation of 0.901 across these scientists. The disambiguation method seems to work reasonably consistently across different individuals.

[5] We identify institutions from the affiliation data listed in Web of Science, thus an affiliation such as `Univ Texas, Dept Microbiol, Austin, TX 78712` would simply be cleaned to `Univ Texas`.

[6] We deal with the possible issue of dual affiliations by looking at the set of institutions that a scientist is affiliated with in a given year and if there is no overlap with the set of institutions the scientists was at the previous then we count this as a move.

[7] The publication cycle (submitted → accepted → published) is much shorter in biology than in management and economics. We interviewed scientists in evolutionary biology who estimate the average publication cycle to be between 6 and 12 months. This is in line with the findings reported by Björk and Solomon (2013) in their study "The publishing delay in scholarly peer-reviewed journals" where they estimate the mean number of months (received to published) as 8.91 (standard deviation 7.30) for chemistry and 9.47 (standard deviation 5.18) for biomedicine, compared to a mean of 17.70 for management and economics (standard deviation 7.52). They do not report results for biology. Chemistry and biomedicine are the two fields closest to biology (natural science).

the focal paper's publication.[8] In the majority of our specifications, we exclude the publications of the arriving star.[9]

We estimate the effect of star arrival on each of our dependent variables based on the scientists that are present in a given year. Thus, we handle the entry and exit of incumbents and joiners by adjusting their inclusion in the aggregate counts of output and number of scientists at the institution.

4.6. Independent variables

Our key independent variable is $Star_{it-1}$, which equals 1 if the year is greater than or equal to the year a star scientist joins department *i* and 0 otherwise. We define a star in evolutionary biology as a scientist whose stock of citation weighted papers published up until year $t-1$ is above the 90th percentile.[10] Thus, our definition of "stardom" is a time-varying characteristic.[11]

To ensure we observe adequate pre-treatment observations, we only examine the arrival of stars starting in 1985. Furthermore, we only examine the impact of the first arrival of a star. We provide a histogram of the variation in year of first star arrival in Fig. B.1. As the figure illustrates, the timing of first star arrival varies significantly across institutions, with approximately two thirds of the universities that recruit a star doing so during the first 10 years (1985–1995) and the remainder doing so in the second 10 years (1995–2005).[12]

4.7. Descriptive statistics

We provide summary statistics of our dataset in Table B.1. The average department in our sample produces just over 101 citation-weighted publications per year. On average, stars are approximately six times more productive than non-stars. Stars produce 15.3 citations-weighted publications per year compared to 2.4 by non-stars (15.3/2.4 = 6.4). The average department has just over 26 scientists in a given year, just less than half of which are incumbents (scientists present prior to the arrival of a star).

5. Empirical strategy

We examine the relationship between the arrival of a star scientist and the subsequent output of the department. The main empirical model we estimate is:

$$E[Y_{it}] = \exp(\alpha Star_{it-1} + X'_{it}\beta + \delta_t + \mu_i), \tag{19}$$

where Y_{it} is one of our three dependent variables. We remove the arriving star's contributions to Y_{it} in most specifications.

Of the 140 departments, 106 receive a star. The departments that do not receive a star act as control departments, allowing us to perform a difference-in-differences type estimation. The traditional post-treatment and treated cross-sectional unit coefficients are subsumed by the time dummies (δ_t) and department fixed effects (μ_i), respectively. All identification of α arises from the staggered arrival of stars at the 106 departments (Fig. B.1) that receive a star due to the inclusion of time and department fixed effects.[13] X_{it} refers to a vector of control variables including a control for the number of scientists present at department *i* in year *t*. Since the dependent variable is a count variable, we estimate our key specification using poisson quasi maximum-likelihood methods and adopt "Wooldridge" robust standard errors clustered at the department-level, which allows for arbitrary serial correlation (Wooldridge, 1999).

We also estimate our main specification with a full set of leading and lagging indicators of the star arrival variable in the following form:

$$\begin{aligned} E[Y_{it}] = \exp(&\alpha_{-10}Star_{it-10} + \alpha_{-9}Star_{it-9} + \cdots + \alpha_{-2}Star_{it-2} \\ &+ \alpha_0 Star_{it} + \cdots + \alpha_8 Star_{it+8} + X'_{it}\beta + \delta_t + \mu_i). \end{aligned} \tag{20}$$

The leading indicators help discern the extent to which reverse-causality influences our coefficients (i.e., whether changes in department output influence the likelihood of recruiting a star). The leading indicators also help to identify whether omitted changes in department resources precede the recruitment of a star. Finally, lagged indicators allow us to explore temporal dynamics, in particular the duration of the star effect.

6. Results

6.1. Department output increases after the arrival of a star

We begin by examining the relationship between the arrival of a star and the productivity of the department. The estimated coefficient on *Star* (Table 1, Column 1) implies that, on average, after a star arrives, department-level output increases by 66.5% per year ($e^{0.510}-1$ = 0.665). This is not surprising since the department now has a star who, by definition, is prolific. Column 2 includes a control for the number of scientists present in the department in the focal year as a star's arrival may coincide with an overall expansion of the department. The star's arrival is still associated with a 46.7% increase in department-level output.

Of greater interest is department-level productivity without the star's contribution. The estimated coefficient on *Star* in Column 3 indicates that a department's productivity (output per scientist)

[8] We do this in order to avoid any types of bandwagon or article-level Matthew effects, wherein highly-cited articles continue to attract citations. Recent work (Wang et al., 2013) provides some evidence that the number of citations a paper receives in its first five years is a strong predictor for the number of citations an article will receive over its lifetime. So while truncating the citation window avoids potential large outliers it does not reduce the likelihood of identifying important work.

[9] We do not, however, exclude the output of work co-authored with the star as this would erroneously diminish the aggregate output of those incumbents or joiners. Since each scientist has a fixed amount of time, removing co-authored work (which carries with it some opportunity cost) would give the impression that these incumbents or joiners were less productive after the arrival of the star scientists. It should be noted, however, that our results are robust to utilizing fractional citation counts as an alternate construction of our dependent variables whereby the citations that an author receive on a paper is proportionate to the number of authors on the paper.

[10] Our results are qualitatively unchanged when stars are defined as being above the 95th percentile.

[11] Alternatively, one might define a star as a time invariant characteristic (high innate ability). Relative to this definition, our definition is more likely to classify individuals that are more established and with a greater reputation as stars. Thus, our estimates of the star effect will likely be more influenced by reputational effects relative to knowledge flow effects than if we employed an innate ability definition. Our estimated effect on incumbents relative to new recruits may be higher if we used a time-invariant characteristic to classify stars instead. However, although our classification of stars likely favors older versus younger stars compared to the innate ability approach, it is not obvious that this will affect the empirical results as we do not find a significant difference when we compare the effect of young versus old stars, measured by above versus below the median publishing age. In addition, we also generate estimates for an alternate definition of a star that is "ever a star" (ever previously in the 90th percentile or above) which is in contrast to our primary definition "currently a star." The results are qualitatively similar for both definitions of a star.

[12] We do not count the transition of scientists from non-star to star status as a star arrival event. We only count individuals who are currently classified as a star at the time they move to a new institution as a "star mobility event."

[13] While the control departments do not directly contribute to the estimation of α, they do aid in identifying β and δ, which may be correlated with α and thus influence the precision by which α is estimated. Estimating Eq. (19) with only treated departments yields results that are both economically and statistically similar.

Table 1
Main results.

Dependent variable	(1) Output	(2) Output	(3) Output w/o star	(4) $\frac{Incumbentoutput}{\#Incumbents}$	(5) Joiner quality
$Star_{t-1}$	0.510^{**}	0.383^{**}	0.377^{**}	−0.059	0.494^{**}
	(0.097)	(0.093)	(0.094)	(0.109)	(0.175)
ln scientists		1.160^{**}	1.164^{**}		
		(0.143)	(0.150)		
Department fixed effects	√	√	√	√	√
Year fixed effects	√	√	√	√	√
Observations	3920	3920	3920	2968	2170
Number of departments	140	140	140	106	136
Log-likelihood	−88675	−77083	−75075	−6165	−55054
Pre-star mean of dependent variable	47.59	47.59	47.59	2.02	7.79
Effect size of $Star_{t-1}$ on dependent variable[†]	31.66	22.21	21.79	−0.12	4.98

Notes: This table reports coefficients for three Poisson quasi-maximum likelihood (QML) regressions. Observations are at the department$_i$-year$_t$ level. *Output* refers to Citation-Weighted Publications. Column 2 removes the Output of the arriving star. $\frac{Incumbentoutput}{\#Incumbents}$ is the ratio between the count of the Citation-Weighted Publication of all scientists at department *i* who are present the year prior to the star's arrival and the number of incumbent scientists (who are present the year prior to the star's arrival) who are present at department *i* in year *t*. The independent variable *Star* is a value of 1 if the year is greater than or equal to the year of the star's arrival and 0 otherwise. The control variable, *ln scientists*, is the natural logarithm of the count of the number of scientists present at department *i* in year *t*. Robust standard errors clustered at the department are in parentheses.

† Effect size is calculated as $(\exp(\hat{\beta}) - 1) \times \bar{x}$, where $\hat{\beta}$ is the estimated coefficient of $Star_{t-1}$ and $\bar{x}$ is the mean of the dependent variable before the star's arrival.
+ $p < 0.10$.
* $p < 0.05$.
** $p < 0.01$.

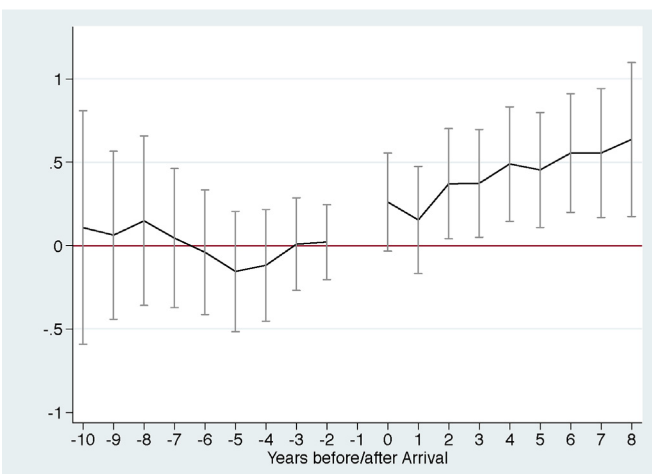


Fig. 3. Department output excluding star.
Notes: This figure plots point estimates from the specification in Eq. (20). The dependent variable is the output of department *i* in year *t*. The omitted category is one year prior to the star's arrival. The vertical bars correspond to 95% confidence intervals with department-clustered standard errors.

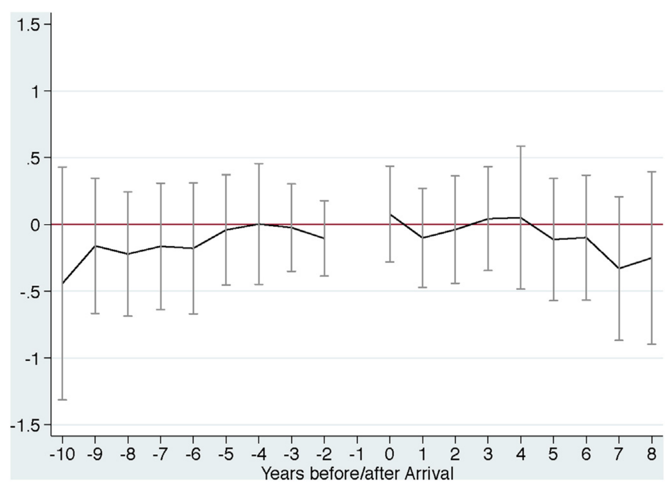


Fig. 4. Department output – incumbents only. *Notes*: This figure plots point estimates from the specification in Eq. (20). The dependent variable is the incumbent output of department *i* in year *t*. We define incumbents as scientists who are present in department *i* the year prior to the star's arrival. The vertical bars correspond to 95% confidence intervals with department-clustered standard errors.

increases by 45.8%, on average, after the arrival of a star. This estimate is both economically and statistically significant (1% level). This 45.8% increase corresponds to an approximate increase of just under 22 citation-weighted publications per year.

We present the results from Column 3 in graphical form in Fig. 3 by estimating Eq. (20). Department-level output remains reasonably constant in the years leading up to recruiting the star. Specifically, output in years t_{-10} to t_{-2} is statistically indistinguishable from output in the year prior to the star's arrival (t_{-1}), the omitted category. The bars correspond to 95% confidence intervals. Output increases sharply the year of the star's arrival relative to t_{-1}. Thus, we find no evidence of a pre-trend. In other words, stars do not appear to be moving in order to join departments "on the rise." We only observe an increase in post-arrival output two years after the star's arrival. This delay may be driven by new recruits who may be more likely to join due to the presence of the star. The increase in output relative to t_{-1} persists for the full period for which we have data (up to t_{+8}).

We next distinguish between incumbent scientists, who are in the department before the star arrives, and subsequent recruits ("joiners"). We begin by focusing on incumbents. Specifically, we drop joiners from the sample and estimate the prior equation based solely on incumbent data normalized by the number of incumbents (as defined by their presence the year prior to the star's arrival) present in year *t*. The arrival of a star does not seem to have an economically or statistically significant relationship with incumbent output (Table 1, Column 4). Since we define incumbents as scientists present the year prior to a star's arrival, we are only able to examine changes to incumbent output for departments that are "treated" by recruiting a star. We graphically present this non-relationship in Fig. 4. There is no observable change in incumbent output either prior to the star's arrival or after.

Next, we examine joiners. We are not able to estimate joiner output the way we do for incumbents because, by construction, joiners have no output at the focal department prior to their arrival. Therefore, it is impossible to estimate a change in joiner

Table 2
Output and quality of topically related and unrelated scientists.

Dependent variable	(1) Output w/o star	(2) $\frac{Incumbent output}{\#Incumbents}$	(3) Joiner quality	(4) Output w/o star	(5) $\frac{Incumbent output}{\#Incumbents}$	(6) Joiner quality
Subsample	*Related*			*Unrelated*		
$Star_{t-1}$	1.428**	0.673*	1.642**	0.212+	−0.173	0.425*
	(0.213)	(0.302)	(0.535)	(0.109)	(0.139)	(0.183)
ln scientists	1.222**			1.160**		
	(0.256)			(0.160)		
Department fixed effects	√	√	√	√	√	√
Year fixed effects	√	√	√	√	√	√
Observations	2800	1988	1690	3920	2968	2170
Number of departments	100	71	92	140	106	136
Pre-star mean of dependent variable	2.90	0.12	1.18	44.69	1.90	7.13
Effect size of $Star_{t-1}$ on dependent variable†	9.19	0.12	4.92	10.55	−0.36	3.78

Notes: Columns 1–3 only include scientists who are topically related to the arriving star (make at least one reference in their papers to the arriving star), while Columns 4–6 only include scientists who are topically unrelated to the star (do not make any references to the papers of the arriving star). Columns 1 and 4 include all scientists, Columns 2 and 5 include all incumbents present the year prior to the star's arrival, and Column 3 and 6 include joiners. Robust standard errors clustered at the department are in parentheses.

+ $p < 0.10$.
* $p < 0.05$.
** $p < 0.01$.

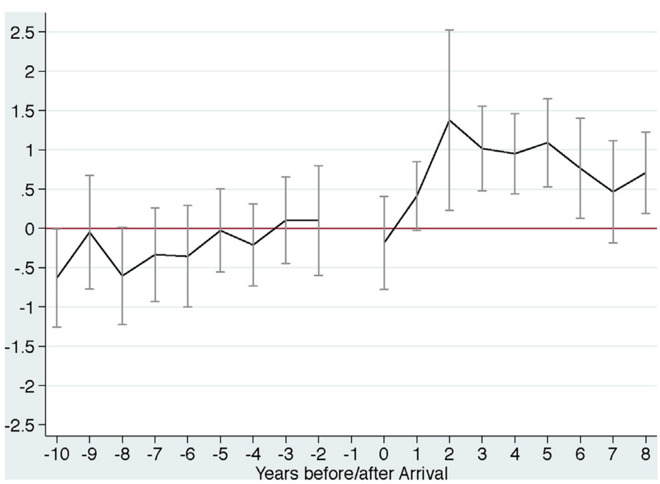


Fig. 5. Joiner quality. *Notes*: This figure plots point estimates from the specification in Eq. (20). The dependent variable is the mean quality of scientists who join department *i* in year *t*. The vertical bars correspond to 95% confidence intervals with department-clustered standard errors.

productivity between the periods pre- and post-arrival of the star using our prior approach. However, we are able to observe variation in the *quality* of joiners before versus after the arrival of a star. To do this, we calculate the mean annual citation-weighted stock of papers published during the period prior to year *t* for each scientist joining department *i* in year *t*. The quality of joiners varies significantly (mean = 45, standard dev. = 109, min. = 1, max = 2925). Thus, we estimate the relationship between joiner quality (dependent variable) and the presence of a star (Table 1, Column 5). As before, we use the department as the unit of analysis and employ both department and year fixed effects. The estimated coefficient on star indicates that after the arrival of a star, the mean quality of joining scientists increases by more than 63.9%. We once again observe no pre-trends in this specification when presented graphically (Fig. 5). The increase in joiner quality commences one year after the star's arrival, suggesting that the arrival of the star triggers an increase in the quality of subsequent recruits.[14]

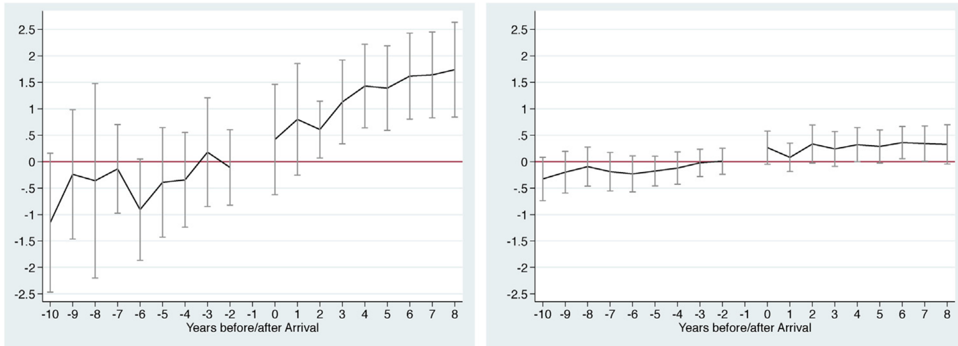
6.2. *Related scientists experience a greater increase in output than unrelated*

We further dissect our main result by examining the difference between scientists who are working on topics related to the star versus those who are not. We classify a scientist as related if they cite at least one of the star's papers in any year prior to t_{-1} and unrelated otherwise. We split the sample accordingly. On average, 9% of incumbents and 6% of joiners are related to the star. We find that the portion of the department that does research in areas related to that of the star experiences a proportionately greater increase in output than the unrelated portion (Table 2, Column 1 versus 4). In fact, after the arrival of a star, the output of related scientists increases by more than 317% compared to 24% for unrelated (statistically significant at the 1% and 10% levels, respectively). In Fig. 6, we plot the estimated coefficients from Eq. (20). Once again, we observe no pre-trends.

In contrast to our earlier "no effect" result on incumbents, we find that incumbents who are related increase their productivity by 96% on average (Column 2). This result is hidden in the aggregate result reported earlier concerning incumbents since related incumbents represent a small fraction of overall incumbents (9%). Furthermore, the arrival of a star may adversely affect the level of resources allocated to unrelated incumbents, shifting resources from unrelated to related areas (e.g., future hires, department funds), which may result in a decrease in their productivity. The negative, albeit insignificant at conventional levels, point estimate may reflect that (Column 5). The negative effect on unrelated incumbents counteracts the positive effect on related incumbents such that, in the aggregate, the overall effect on incumbents is neutral, as reported above (Table 1, Column 4), and consistent with the aggregate findings reported in Waldinger (2012).

We next focus our analyses on joiner quality and relatedness. Although the quality of both types of joiners increases after the arrival of the star, the increase is much greater for joiners who work in related areas of research: 417% compared to 53% (Columns 3 and 6, respectively). The differences are less stark when we calculate

[14] While a small fraction of these may be postdocs or graduate students, the majority of joiners are most likely faculty moving from other institutions. The median joiner in our sample joins the focal university after 9.7 years of publishing at a different university. We calculate this period as the time since first publication. It seems unlikely that a young scientist has been publishing for 9.7 years at another university by the time they arrive to begin graduate school or even to begin a postdoc. Three quarters of new arrivals join after at least 4 years of publishing at a different university and one quarter join after at least 13 years of publishing at a different university.



(a) Related Scientists

(b) Unrelated Scientists

Fig. 6. Department output excluding star: related versus unrelated. (a) Related scientists. (b) Unrelated scientists. *Notes*: This figure plots point estimates from the specification in Eq. (20). The dependent variable is the mean quality of scientists who join department *i* in year *t*. The vertical bars correspond to 95% confidence intervals with department-clustered standard errors. In Panels A and B, the dependent variable is the output of department *i* in year *t* of related, and unrelated scientists, respectively. The vertical bars correspond to 95% confidence intervals with department-clustered standard errors.

Table 3
Department rank.

Dependent variable	(1) Output w/o star	(2) $\frac{Incumbentoutput}{\#Incumbents}$	(3) Joiner quality
$Star_{t-1}$	−0.031	−0.622**	0.439^{+}
	(0.136)	(0.208)	(0.236)
$Star_{t-1} \times$ *Non-Top25*	0.595**	0.706**	0.716**
	(0.151)	(0.207)	(0.249)
ln scientists	1.099**		
	(0.142)		
Department fixed effects	√	√	√
Year fixed effects	√	√	√
Observations	3920	2968	3864
Number of departments	140	106	138
Log-likelihood	−73353	−6100	−99499

Notes: *Non-Top25* is an indicator variable set to 1 if the institution is outside of the top 25 and 0 otherwise. Robust standard errors clustered at the department are in parentheses.
$^{+}$ $p < 0.10$.
* $p < 0.05$.
** $p < 0.01$.

the effect size on joiner quality. The arrival of a star corresponds to an increase in related and unrelated joiner quality (stock) by five and four citation-weighted publications, respectively. Still, it is interesting to note that the quality of unrelated joiners increases after the arrival of a star, in contrast to the productivity of unrelated incumbents, which does not increase.

6.3. Non-top tier departments benefit more from the arrival of a star

Next, we examine the extent to which the star effect on department-level productivity is influenced by the rank of the institution. In Table 3, we interact our main independent variable (*Star*) with an indicator if the department is outside the Top 25 (as measured by aggregate research output the year prior to the star's arrival). These interactions reveal large heterogeneity in effects across institution types. Non-Top 25 departments experience more of a gain after the arrival of their first star compared to institutions inside the Top 25. These results are robust to different cutoffs for top institutions (e.g., Top 10, Top 50).

6.4. Collaboration may account for much of the productivity gains by incumbents

We examine the extent to which direct collaboration is the primary channel through which stars enhance the productivity of their new colleagues (Table 4). First, we focus on the sample that includes all scientists (Columns 1–3). The variable *Collaborations w/Star* is a count of the number of collaborations between the star and a colleague in the same department. An additional collaboration with the star is associated with a 2.5% increase in overall department-level productivity and is statistically significant at the 10% level. While the effect is largest when we focus only on related peers (3.5%), it is still statistically insignificant.

Although star collaboration accounts for some of the variation in department-level productivity, it does not fully account for the increase in productivity after the star's arrival. However, star collaboration does seem to account for much of the productivity boost for incumbents (Columns 4–6). As with the result reported in Column 1, more star collaboration is associated with a greater increase in incumbent productivity, but in contrast to Column 1, in Columns 4 and 5 the inclusion of the collaboration variable results in the point estimates of the star effect to diminish by more than half and lose significance. This stands in stark contrast to the large and statistically significant effect from the arrival of a star on related incumbent productivity that we report in Table 2, Column 2.

6.5. Robustness checks

In Appendix A, we present additional robustness to our main analysis. First, Table A.1 replicates Table 1 but also controls for department-specific time trends in addition to department and year fixed effects. The inclusion of these trends allows each department to follow different trends across our sample time period. The inclusion of these controls results in qualitatively similar but smaller point estimates providing some additional support for the validity of our difference-in-differences framework.

Second, we examine the effect of star departures in addition to star arrivals and find that the departure of a star has a negative effect on output (total output and incumbent-only output) and joiner quality (Table A.2). In addition, the positive relationship between star arrival, total output, and joiner quality remains, alleviating concerns that our results are inflated due to the departure of scientists at other institutions.

Third, we further refine our star arrival variable by only considering the presence of scientists who are members of the National Academy of Sciences (an even more illustrious sample). The arrival of a National Academy scientist at a non-Top 25 institution has a positive effect on total output, no effect on incumbent output, and a positive impact on joiner quality (Table A.3).[15]

[15] In addition, our main results are robust to the subsample restricted to only those institutions that receive a star. The results are both quantitatively and qualitatively similar between the treated-only sample and the treated with controls sample.

Table 4
Star coauthorships.

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
	Output w/o star			$\frac{Incumbent output}{\#Incumbents}$		
Sample	*Full*	*Related*	*Unrelated*	*Full*	*Related*	*Unrelated*
$Star_{t-1}$	0.330**	1.348**	0.183+	−0.147	0.267	−0.176
	(0.093)	(0.224)	(0.108)	(0.112)	(0.311)	(0.143)
Collaborations w/star	0.025+	0.035	0.016	0.230**	0.327**	0.015
	(0.014)	(0.025)	(0.015)	(0.033)	(0.049)	(0.067)
ln scientists	1.146**	1.175**	1.151**			
	(0.151)	(0.254)	(0.162)			
Department fixed effects	√	√	√	√	√	√
Year fixed effects	√	√	√	√	√	√
Observations	3920	2800	3920	2968	1988	2968
Number of departments	140	100	140	106	71	106

Notes: Robust standard errors clustered at the department are in parentheses.
+ $p < 0.10$.
* $p < 0.05$.
** $p < 0.01$.

Table 5
Triple difference – evolutionary biology and developmental biology.

Dependent variable	(1) Output w/o star	(2) $\frac{Incumbent output}{\#Incumbents}$	(3) Joiner quality	(4) # Scientists
Evolutionary biology $Star_{it-1}$	0.087	−0.054	−0.079	0.014
	(0.076)	(0.096)	(0.092)	(0.052)
Evolutionary biology $Star_{it-1}$ ×	0.339**	0.027	1.369**	0.068
Evolutionary biology $department_f$	(0.124)	(0.159)	(0.209)	(0.066)
ln $scientists_{ift}$	1.301**		0.353**	
	(0.086)		(0.122)	
Institution – field fixed effects	√	√	√	√
Year fixed effects	√	√	√	√
Observations	5880	5040	5880	5880
Number of departments	210	180	210	210
Log-likelihood	−122742	−26364	−124690	−21714

Notes: Observations are at the $institution_i$-$field/department_f$-$year_t$ level, where department is either evolutionary biology or developmental biology. The independent variable *Evolutionary Biology Star* is a value of 1 for both evolutionary biology and developmental biology departments if the year is greater than or equal to the year of the evolutionary biology star's arrival and 0 otherwise. This variable is also interacted with an indicator variable, *Evolutionary Biology Department* if the department is evolutionary biology and 0 if the department is developmental biology. All specifications include universities that never receive a star as control institutions in addition to university-department (e.g., a separate dummy for the University of Chicago's evolutionary biology department and Yale's developmental biology department) and year fixed effects. Robust standard errors clustered at the department are in parentheses.
+ $p < 0.10$.
* $p < 0.05$.
** $p < 0.01$.

7. Is the estimated star effect causal?

We adopt a three-strand approach to further support a causal interpretation of these results. First, the absence of pre-trends found via the regressions with leading and lagging star arrival indicators and associated graphics presented in Section 6 helps to rule out an overall department-improvement strategy or reverse causality. Second, we estimate a triple difference model that reveals the star effect where we expect it to be and not where we do not. Third, the results are robust to adding controls for NSF grants.

7.1. Triple difference

The main identifying assumption of our difference-in-differences strategy is that untreated departments and departments that will be but have not yet been treated serve as appropriate controls. We extend this framework by expanding the data to include an additional dimension, developmental biology output, to estimate a triple difference (DDD) regression. As such, we shift our unit of analysis from the department-year to the institution-subfield-year. Developmental biology is an appropriate control field as it is administratively similar to evolutionary biology (similar department head, etc.) but intellectually distant, wherein the presence of a star in one field is unlikely to have much impact on the productivity of the other, *ceteris paribus*. If a funding shock that results in the hiring of an evolutionary biology star is also associated with more funding and resources in general, then we should see an increase in developmental biology output as well. The DDD framework allows us to net out this effect. We estimate the following equation:

$$E[Y_{ift}] = \exp(\alpha_1 EvolutionaryBiologyStar_{it-1} + \alpha_2 EvolutionaryBiologyStar_{it-1} \times EvolutionaryBiologyDept_f + X'_{ift}\beta + \delta_{ft} + \theta_{if}) \quad (21)$$

where i indexes the institution, f indexes the department type (Evolutionary or Developmental), and t indexes the year.[16] If α_1 is

[16] The variable *Evolutionary Biology* $Star_{it-1}$ is defined at the institution-year level and is set to 1 for all f if institution i received an evolutionary biology star in years $t-1$ or later. This variable is then interacted with the variable $EvolutionaryBiologyDept_f$ which is set to 1 if f is indexing the evolutionary biology covariates and 0 otherwise (that is, it is indexing the developmental biology covariates), while δ_{ft} is a vector of field-year dummies and θ_{if} is a vector of institution-field dummies.

Table 6
Main results with NSF grant control.

Dependent variable	(1) Output	(2) $\frac{Incumbent output}{\#Incumbents}$	(3) Joiner quality
$Star_{t-1}$	0.383**	−0.063	0.510*
	(0.106)	(0.132)	(0.199)
ln scientists	1.145**		
	(0.159)		
ln NSF grant $	−0.002	0.006	0.018
	(0.006)	(0.011)	(0.014)
Department fixed effects	√	√	√
Year fixed effects	√	√	√
Observations	3444	2576	1907
Number of departments	123	92	119
Log-likelihood	−68188	−5329	−50437

Notes: *ln NSF Grant* $ is the sum of NSF grants awarded to the focal institution in year *t* from the NSF's Division of Environmental Biology (the main directive for evolutionary biology research funding). Robust standard errors clustered at the department are in parentheses.
+ $p < 0.10$.
* $p < 0.05$.
** $p < 0.01$.

positive and significant, then hiring a star in evolutionary biology is associated with an increase in developmental biology output. If α_2 (the DDD estimator) is positive and significant, then hiring an evolutionary biology star is associated with an increase in output for the evolutionary biology department above and beyond the effect this star has on developmental biology's output.

We report the estimated coefficients for Eq. (21) in Table 5. Across our three main specifications, the hiring of an evolutionary biology star is not associated with a change in department-level output, incumbent output, or joiner quality at developmental biology departments. However, mirroring the results presented throughout, the arrival of an evolutionary biology star is associated with evolutionary biology departmental-level output and evolutionary biology joiner quality. It is still not associated with an increase in incumbent output.

7.2. NSF controls

In Table 6, we re-run our main specifications with the inclusion of the natural log of amount-weighted NSF grants awarded to the focal institution in year *t*.[17] One potential omitted variable is that a star's arrival is associated with the department's ability to win NSF grants and to consequently increase departmental productivity. Thus, funding is the main mechanism by which star arrival and departmental productivity are associated. The inclusion of this control does not change the magnitude of our core values in a meaningful way, reducing the concern that grant monies are driving our results.

8. Discussion and conclusion

The effects of star location are economically significant but subtle. The model's prediction that related incumbents should benefit from a star hire is strongly supported in the data, with the effect being strongest where there is evidence of actual collaboration between the star and incumbents. For unrelated incumbents, the model shows how a star hire can actually harm incumbent productivity through hiring composition effects, despite positive direct knowledge spillovers. Empirically, we find evidence of modest negative adverse impacts, which also explains the failure to find evidence of productivity effects for incumbents in the aggregate. The model's prediction that a star will improve the quality of both related and unrelated joiners also finds strong support in the data. Finally, we present evidence to support the model's prediction that lower-ranked institutions will experience larger proportional productivity and recruitment effects from the arrival of a star.

We adopt a two-part approach to support a causal interpretation of our findings: (1) an examination of pre-trends (to rule out a pre-existing department-improvement trend) and (2) controls for university- and department-level shocks (e.g., surge in resources). While these two approaches provide support for a causal explanation of our findings, concerns remain about the possible endogeneity of the arrival of a star at a department. Our findings should thus only be viewed as suggestive of the size and nature of star arrival effects.

A causal interpretation is still open to various mechanisms. For example, not only might the arrival of a star attract higher quality subsequent recruits, but a star might negotiate with the department to create specific slots or even an agreement to hire particular people, resulting in the effect we observe of an increase in the quality of joiners. Indeed, we estimate a change in the rate of recruiting by comparing the number of joiners in the three years prior to hiring the first star to the number in the three years following and find that there is a 2.8% increase in the number of recruits in the post-star period, which, although only a small increase, is consistent with the idea that some stars may bring joiners with them.

In terms of the existing literature, our findings support the relative importance of recruitment over individual productivity effects (see, e.g., the findings in Waldinger, 2012, 2016). Our findings also highlight the importance of the relationship of the star to incumbents in mediating any direct productivity effects, with unrelated incumbents potentially harmed by the arrival of the star. The importance of the "relational star" (Grigoriou and Rothaermel, 2014) is further underlined by the importance of direct collaboration with the star as a source of incumbent productivity gains.

What are the potential management and public policy implications of our findings? They suggest that star arrivals can have significant impacts on organizational and broader innovation system performance, with the impact of the quality of subsequent recruits being of particular importance. The findings also point to the conditions under which the hiring of a star will be most potent: a significant cadre of incumbents working in areas related to the star and a significant number of available hiring slots following the arrival of the star. A degree of flexibility in the filling of hiring slots to take advantage of the ability of the star to draw in related scientists is also important so as to take full advantage of the star's recruitment draw.

Our findings raise the question of why stars have the effect they do. We begin to address this question with our results on collaboration. However, this only scratches the surface. A well-placed star who sits on editorial boards and grant committees could improve funding, publications, and citations for colleagues at the same institution (Brogaard et al., 2014). Indeed, there are many attributes of stars (influence, capital, knowledge, relationships) that likely influence how they impact the departments they join. We do not unpack the differential effects of these attributes in this paper. Instead, our objective is to compare the relative effect of hiring a star on incumbents compared to joiners. However, a clearer understanding of the mechanisms underlying the star effect will enhance the managerial and public policy usefulness of this line of inquiry. In subsequent research we plan to explore the relative importance of different attributes to different channels.

Another unanswered question is whether the star effects are changing over time due to improvement in communication

[17] We match NSF grant data to institutions on an annual basis. We downloaded annual NSF award data from https://www.nsf.gov/awardsearch/download.jsp. We then extracted all grants from the Division of Environmental Biology and matched them to each institution on an annual basis. We created a name-mapper/crosswalk to normalize between our Web of Science names and those reported in the NSF data.

technologies. Such improvements could increase the outward orientation of the star's collaborative networks, reducing their value to co-located colleagues (see, for example, Kim et al., 2009; Agrawal et al., 2015). Some preliminary work suggests that the star effects may indeed be declining. In future research, we plan to extend the work presented here with a careful examination of how (and why) star effects are changing over time.

Appendix A. Robustness checks

We conduct three additional robustness tests for our main results. First, we first show robustness of our main results to the inclusion of department-specific year trends. We report the results of our three main dependent variables in Columns 1–3 in Table A.1. The point estimates decrease slightly in magnitude compared to those presented in Table 1 but remain statistically significant at conventional levels (other than Incumbent output, which is still statistically insignificant). The dependent variable in Column 4 is the number of scientists. Interestingly, after the arrival of a star, there is no increase in the number of scientists (after controlling for department innate characteristics and trends), lending some support to the proposition that, on average, departments are not drastically growing after the star's arrival.

Second, we report the results for our three main dependent variables when a star leaves in Table A.2. Not surprisingly, star departures are associated with a decline in department output, while the arrival of a star continues to be positively associated with an increase in department output. Perhaps more surprisingly, the negative effect on incumbent productivity of star departures is larger in magnitude than the positive effect of star arrival. A possible explanation is that departing stars have developed relationships with incumbents (e.g., collaborations, mentoring, or simply knowledge exchange) leading to adverse impacts on the productivity of those left behind. As Agrawal et al. (2006) emphasize, relationship capital built during periods of co-location endures, at least in part, post separation. Nonetheless, prior co-location is likely to be less effective in supporting incumbent productivity than current co-location. The final column in Table A.2 shows a negative effect of star departure on the quality of subsequent hires. The loss of a star appears to be associated with a decrease in the subsequent ability to attract high-quality scientists.

Third, we examine the robustness of our results to an alternative method of identifying stars. Rather than identifying stars based on their ranking in the distribution of citation-weighted

Table A.1
Department-specific time trends.

Dependent variable	(1) Output w/o star	(2) $\frac{Incumbent output}{\#Incumbents}$	(3) Joiner quality
$Star_{t-1}$	0.199*	−0.106	1.031**
	(0.081)	(0.097)	(0.260)
ln scientists	1.360**		0.884**
	(0.120)		(0.218)
Department fixed effects	√	√	√
Department-year trends	√	√	√
Year fixed effects	√	√	√
Observations	3920	2968	2170
Log-likelihood	−61513	−5860	−89042

Notes: This table reports coefficients for three Poisson quasi-maximum likelihood (QML) regressions. Observations are at the department$_i$-year$_t$ level. *Output w/o star* is the Citation-Weighted Publications in year *t* net of the star's contributions. $\frac{Incumbent output}{\#Incumbents}$ is the ratio between the count of the Citation-Weighted Publication of all scientists at department *i* who are present the year prior to the star's arrival and the number of incumbent scientists (who are present the year prior to the star's arrival) who are present at department *i* in year *t*. *Joiner quality* is the mean stock of all scientists hired by department *i* in year *t*. The independent variable *Star* is a value of 1 if the year is greater than or equal to the year of the star's arrival and 0 otherwise. The control variable, *ln scientists*, is the natural logarithm of the count of the number of scientists present at department *i* in year *t*. Robust standard errors clustered at the department are in parentheses.
+ $p < 0.10$.
* $p < 0.05$.
** $p < 0.01$.

Table A.2
Star departure results.

Dependent variable	(1) Output w/o star	(2) $\frac{Incumbent output}{\#Incumbents}$	(3) Joiner quality
Star $Arrive_{t-1}$	0.217**	0.170	1.171**
	(0.081)	(0.143)	(0.283)
Star $Depart_{t-1}$	−0.181*	−0.236*	−0.605*
	(0.088)	(0.106)	(0.270)
ln scientists	1.331**		
	(0.111)		
Department fixed effects	√	√	√
Department-year trends	√	√	√
Year fixed effects	√	√	√
Observations	3920	1876	3920
Number of departments	140	67	140
Log-likelihood	−63088	−4350	−87418

Notes: This table reports coefficients for three Poisson quasi-maximum likelihood (QML) regressions. Observations are at the department$_i$-year$_t$ level. *Output w/o star* is the Citation-Weighted Publications in year *t* net of the departing star's contributions. $\frac{Incumbent output}{\#Incumbents}$ is the ratio between the count of the Citation-Weighted Publication of all scientists at department *i* who are present the year prior to the star's departure and the number of incumbent scientists (who are present the year prior to the star's departure) who are present at department *i* in year *t*. *Joiner quality* is the mean stock of all scientists hired by department *i* in year *t*. The two key independent variables *Star Depart* and *Star Arrive* are set to 1 if the year is greater than or equal to the year of the star's departure or arrival, respectively, and 0 otherwise. The control variable, *ln scientists*, is the natural logarithm of the count of the number of scientists present at department *i* in year *t*. Robust standard errors clustered at the department are in parentheses.
+ $p < 0.10$.
* $p < 0.05$.
** $p < 0.01$.

Table A.3
Alternate star definition: National Academies Scientist (NAS) results.

Dependent variable	(1) Output w/o star	(2) $\frac{Incumbent output}{\#Incumbents}$	(3) Joiner quality
NAS $scientist_{t-1}$	−0.074	−0.077	0.040
X Top 25	(0.149)	(0.230)	(0.235)
NAS $scientist_{t-1}$	0.211*	−0.252	1.807**
X Non-Top 25	(0.101)	(0.178)	(0.664)
ln scientists	1.481**		
	(0.199)		
Department fixed effects	√	√	√
Department-year trends	√	√	√
Year fixed effects	√	√	√
Observations	1036	1036	1036
Number of departments	37	37	37
Log-likelihood	−29169	−2209	−36109

Notes: This table reports coefficients for three Poisson quasi-maximum likelihood (QML) regressions. Observations are at the department$_i$-year$_t$ level. *Output w/o star*, is the citation-weighted publications in year *t* net of the arriving star's contributions split by the characteristics of the scientist. $\frac{Incumbent output}{\#Incumbents}$ is the ratio between the count of the Citation-Weighted Publication of all scientists at department *i* who are present the year prior to the star's arrival and the number of incumbent scientists (who are present the year prior to the star's arrival) who are present at department *i* in year *t*. *Joiner quality* is the mean stock of all scientists hired by department *i* in year *t*. The independent variable, *NAS scientist*, is a value of 1 if the year is greater than or equal to the year of the arrival of a scientist who is a member of the NAS or the year a scientist became a member of the National Academies and 0 otherwise. This variable is interacted with two indicators each set to 1 if the department the scientist arrives at is a Top 25 department (at the year of arrival) or a non-Top 25 department (at the year of arrival). The control variable, *ln Scientists*, is the natural logarithm of the count of the number of scientists present at department *i* in year *t*. Robust standard errors clustered at the department are in parentheses.
+ $p < 0.10$.
* $p < 0.05$.
** $p < 0.01$.

Table B.1
Summary statistics.

Variables	*N*	Mean	Median	Std. dev.	Min.	Max.
Panel A: Unit of analysis: institution-year						
Output	4060	101.58	36	178.17	0	2500
Output w/o star	4060	97.04	33	174.71	0	2498
Scientists	4060	26.50	17	28.02	1	175
Incumbent output	3074	31.16	9	76.92	0	1650
Incumbents	3074	11.13	7	12.24	0	93
Star	4060	0.48	0	0.50	0	1
Output w/o star – related	4060	14.90	0	44.23	0	719
Output w/o star – unrelated	4060	82.14	29	155.93	0	2498
Incumbent output – related	3074	6.03	0	23.27	0	719
Incumbent output – unrelated	3074	25.13	7	71.82	0	1650
Panel B: Unit of analysis: institution						
Knowledge stock of institution in year before star arrival	106	704.70	449.0	739.8	112.0	4634.00
Knowledge stock per incumbent in year before star arrival	106	29.34	23.0	19.9	9.6	118.82
Knowledge stock of star in year before arrival	106	130.77	100.5	91.6	36.0	499.00
Share: knowledge stock of star/ Knowledge stock of institution year before arrival	106	0.29	0.3	0.2	0.0	0.83
Output per star in year of arrival	106	23.99	12.5	35.5	1.0	219.00
Output per incumbent in year of arrival	106	2.83	1.4	5.2	0.0	38.37
Panel C: Unit of analysis: scientist-year						
Output per star scientist	11655	15.33	4	36.49	0	1364
Output per non-star scientist	95936	2.44	0	7.88	0	274
Output per related scientist	5067	4.45	1	11.74	0	196
Output per unrelated scientist	90869	2.32	0	7.59	0	274
Joiner quality	5131	21.45	8	80.30	1	2603
Joiner quality, related	272	78.67	27	224.45	1	2349
Joiner quality, unrelated	4859	18.25	7	61.68	1	2603

cumulative output, we do so based on their membership in the National Academy of Sciences (NAS). The advantage of this method is that it is not directly related to any measures of output that we use as dependent variables in our regressions. A disadvantage is that it reduces the number of observed star arrivals in our data from 178 to 37 scientists. We report estimated coefficients on indicator variables for the presence of an NAS scientist at a Top 25 and non-Top 25 institution in Table A.3. The results indicate that the presence of an NAS scientist at a Top 25 institution is statistically unrelated to all of our main output measures, while the presence of an NAS scientist at a lower-ranked institution is positively related to an increase in department-level output and an increase in the quality of subsequent joiners but is unrelated to any changes in incumbent productivity.

Appendix B. Additional figures and tables

See Fig. B.1.

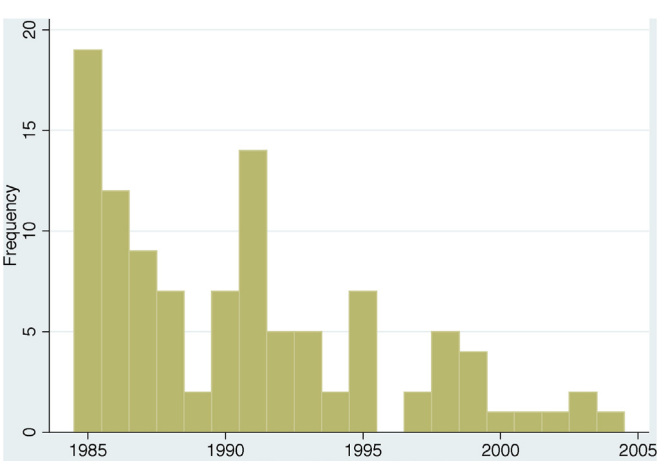


Fig. B.1. Number of departments that recruit their first star (by year). *Notes*: The above histogram displays the year in which departments recruit their first star.

References

Agrawal, A., Cockburn, I., McHale, J., 2006. Gone but not forgotten: knowledge flows, labor mobility, and enduring social relationships. J. Econ. Geogr. 6 (5), 571–591.

Agrawal, A., McHale, J., Oettl, A., 2015. Collaboration, stars, and the changing organization of science: evidence from evolutionary biology. In: Jaffe, A.B., Jones, B.F. (Eds.), The Changing Frontier: Rethinking Science and Innovation Policy. National Bureau of Economic Research Conference Report. The University of Chicago Press.

Ali, A., Gittelman, M., 2016. Research paradigms and useful inventions in medicine: patents and licensing by teams of clinical and basic scientists in academic medical centers. Res. Policy 45 (8), 1499–1511.

Azoulay, P., Graff Zivin, J., Wang, J., 2010. Superstar extinction. Q. J. Econ. 125 (2), 549–589.

Azoulay, P., Stuart, T., Wang, Y., 2013. Matthew: effect or fable? Manag. Sci. 60 (1), 92–109.

Bercovitz, J., Feldman, M., 2011. The mechanisms of collaboration in inventive teams: composition, social networks, and geography. Res. Policy 40 (1), 81–93.

Björk, B.-C., Solomon, D., 2013. The publishing delay in scholarly peer-reviewed journals. J. Informetr. 7 (4), 914–923.

Brogaard, J., Engelberg, J., Parsons, C.A., 2014. Networks and productivity: causal evidence from editor rotations. J. Financ. Econ. 111 (1), 251–270.

Conti, A., Liu, C.C., 2015. Bringing the lab back in: personnel composition and scientific output at the MIT department of biology. Res. Policy 44 (9), 1633–1644.

Ernst, H., Leptien, C., Vitt, J., 2000. Inventors are not alike: the distribution of patenting output among industrial R&D personnel. IEEE Trans. Eng. Manag. 47 (2), 184–199.

Grigoriou, K., Rothaermel, F.T., 2014. Structural microfoundations of innovation the role of relational stars. J. Manag. 40 (2), 586–615.

Groysberg, B., Lee, L.-E., 2009. Hiring stars and their colleagues: exploration and exploitation in professional service firms. Organ. Sci. 20 (4), 740–758.

Groysberg, B., Lee, L.-E., Nanda, A., 2008. Can they take it with them? The portability of star knowledge workers' performance. Manag. Sci. 54 (7), 1213–1230.

Higgins, M.J., Stephan, P.E., Thursby, J.G., 2011. Conveying quality and value in emerging industries: star scientists and the role of signals in biotechnology. Res. Policy 40 (4), 605–617.

Hohberger, J., 2016. Does it pay to stand on the shoulders of giants? An analysis of the inventions of star inventors in the biotechnology sector. Res. Policy 45 (3), 682–698.

Hull, D.L., 1988. Science as a Process. An Evolutionary Account of the Social and Conceptual Development of Science. The University of Chicago Press, Chicago and London.

Jones, B.F., 2009. The burden of knowledge and the 'death of the renaissance man': is innovation getting harder? Rev. Econ. Stud. 76 (1), 283–317.

Kehoe, R.R., Lepak, D.P., Bentley, F.S., 2016. Let's call a star a star. J. Manag.

Kehoe, R.R., Tzabbar, D., 2015. Lighting the way or stealing the shine? An examination of the duality in star scientists' effects on firm innovative performance. Strateg. Manag. J. 36 (5), 709–727.
Kim, E.H., Morse, A., Zingales, L., 2009. Are elite universities losing their competitive edge? J. Financ. Econ. 93 (3), 353–381.
Lotka, A.J., 1926. The frequency distribution of scientific productivity. J. Wash. Acad. Sci. 16, 317–325.
Lu, S.F., Jin, G.Z., Uzzi, B., Jones, B., 2013. The retraction penalty: evidence from the web of science. Sci. Rep. 3, 3146 EP.
Mas, A., Moretti, E., 2009. Peers at work. Am. Econ. Rev. 99 (1), 112–145.
Merton, R.K., 1968. The matthew effect in science. Science 159 (3810), 56–63.
Narin, F., Breitzman, A., 1995. Inventive productivity. Res. Policy 24 (4), 507–519.
Oettl, A., 2012. Reconceptualizing stars: scientist helpfulness and peer performance. Manag. Sci. 58 (6), 1122–1140.
Rosen, S., 1981. The economics of superstars. Am. Econ. Rev. 71 (5), 845–858.
Sacerdote, B., 2001. Peer effects with random assignment: results for dartmouth roommates. Q. J. Econ. 116 (2), 681–704.
Simcoe, T.S., Waguespack, D.M., 2011. Status, quality, and attention: what's in a (missing) name? Manag. Sci. 57 (2), 274–290.
Tang, L., Walsh, J.P., 2010. Bibliometric fingerprints: name disambiguation based on approximate structure equivalence of cognitive maps. Scientometrics 84 (3), 763–784.
Waldinger, F., 2012. Peer effects in science: evidence from the dismissal of scientists in Nazi Germany. Rev. Econ. Stud. 79 (2), 838–861.
Waldinger, F., 2016. Bombs, brains, and science – the role of human and physical capital for the creation of scientific knowledge. Rev. Econ. Stat. 98 (5), 811–831.
Wang, D., Song, C., Barabási, A.-L., 2013. Quantifying long-term scientific impact. Science 342 (6154), 127–132.
Wooldridge, J.M., 1999. Distribution-free estimation of some nonlinear panel data models. J. Econom. 90 (1), 77–97.
Wuchty, S., Jones, B.F., Uzzi, B., 2007. The increasing dominance of teams in production of knowledge. Science 316 (5827), 1036–1039.