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Why Stars Matter

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Abstract

We use a rich longitudinal dataset on department-level productivity in a contemporary field of science to identify and decompose the causal impact of hiring a star on local knowledge production. Specifically, we estimate the relative roles of knowledge spillovers versus recruiting externalities as they affect co-located researchers who are related or unrelated to the star in idea space. Hiring a star does not increase overall incumbent productivity, but this aggregate effect hides offsetting effects on colleagues who are related (positive) versus unrelated (negative). Star hires improve subsequent joiner quality for both related and unrelated scientists, although the effect is significantly larger for related scientists. The overall positive impact of the star on department-level productivity is mainly due to joiner-quality effects. Furthermore, the productivity impact is more pronounced at mid- and lower-ranked institutions, suggesting implications for the optimal spatial organization of science and university strategies aimed at ascending departmental rankings.

Jelcodes:O31,J24

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JEL Classifications: O31, J24, I23.

Certainly in our own profession, the benefits of colleagues from whom we hope to learn are tangible enough to lead us to spend a considerable fraction of our time fighting over who they shall be, and another fraction travelling to talk with those we wish we could have as colleagues but cannot. We know this kind of external effect is common to all the arts and sciences - the "creative professions." All of intellectual history is the history of such effects.

Robert Lucas (1988)

1 Introduction

An influential strand of modern growth theory emphasizes the importance of combining existing ideas to produce new knowledge (Romer, 1990; Jones, 1995; Weitzman, 1998). As Mokyr (2002, p. 7) notes: "[w]hat makes knowledge a cultural entity . . . is that it is distributed to, shared with, and acquired from others; if that acquisition becomes too difficult, . . . knowledge will not be accessible to those who do not have it but are seeking to apply it." The challenges of accessing knowledge and cooperating to produce new knowledge highlight the importance of the spatial organization of science. However, in a modern market economy with free movement, the ultimate location of scientific activity is largely unplanned, resulting from individual utility-maximizing and firm/university recruitment decisions, raising questions about the efficiency of the spatial allocation of scientists.[1]

A well-known feature of science is that the distribution of output is highly skewed across scientists. Almost a century ago, Lotka (1926) observed that 6% of physicists produced more than 50% of all papers. 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). As our opening quote makes clear, however, the impact of stars on productivity goes well beyond their own publications. The presence of star scientists could directly affect their colleagues' productivity; their presence could also

[1]The efficient allocation is also likely to have changed over time. One reason is that the extent and nature of scientific collaboration is itself evolving. Benjamin Jones (2009) develops a "knowledge burden" theory that the depth and breadth of knowledge required to work at the outward shifting research frontier is increasing, raising the returns to collaboration. Agrawal et al. (2013) report data that support the knowledge burden hypothesis using the collapse of the Soviet Union as a natural experiment; the sudden shock to the knowledge frontier caused by the release of previously hidden research was more significant in some fields than others. They show that fields that undergo a greater outward shift in the knowledge frontier subsequently experience a disproportionate increase in collaboration. Furthermore, the rising knowledge burden may increase the importance of co-location since proximity facilitates collaboration. Pulling in the opposite direction, however, is evidence that evolving communications technologies reduce the distance-related costs of collaboration (Agrawal and Goldfarb, 2008; Kim et al., 2009). These forces have the potential to alter the spatial organization of science, including the tendency (and desirability) of leading scientists to concentrate at top departments.

affect subsequent recruitment through a desire of others to be near them for productivity, reputational, or consumption reasons.

It is surprising that limited evidence exists on the consequences of recruiting stars given their widely acknowledged importance in science. An exception is Waldinger (2012), who, utilizing the dismissal of scientists in Nazi Germany as a natural experiment, does not find evidence of productivity effects on peers. This is curious since the broader peer-effects literature documents significant productivity effects that are highly sensitive to the micro-geography of interactions (Sacerdote, 2001; Mas and Moretti, 2009).[2] Furthermore, Azoulay et al. (2010) and Oettl (2012) both report significant star-specific peer effects, utilizing data on unexpected star deaths as a natural experiment, although they both focus on coauthoring peers as opposed to co-located peers. Moreover, the broader research on spillovers emphasizes spatial relationships as a key determinant of knowledge flow patterns (Jaffe et al., 1993; Agrawal et al., 2006; Singh and Agrawal, 2011; Catalini, 2013), although the focus in these papers concerns the effect of co-location on the *direction* of research, as reflected in citation patterns as opposed to productivity.

In terms of recruiting externalities, the existing evidence is more uniform. Notwithstanding his earlier finding of an absence of peer productivity effects, Waldinger (2013) uncovers evidence of long-lasting effects on the quality of recruits of star dismissals in Nazi Germany. Roach and Sauermann (2010) report a strong preference of scientists to work with the best scientists possible.

Little is known, however, about the factors that influence the relative roles of these local knowledge spillovers and recruiting externalities. The distinction has important implications. For example, if recruiting externalities play a significant role, then a department with resources for further growth through additional hiring will enjoy higher returns from recruiting a star than an otherwise similar department that is not able to make additional hires and thus is unable to benefit from those externalities. However, these departments would experience similar returns from recruiting a star if the benefits are instead primarily due to knowledge spillovers.

Thus, we examine the question of *why* stars matter. We use a rich longitudinal dataset on incumbent and joiner productivity in a contemporary field of science to identify the causal impact of hiring a star

[2] Other studies focus on different benefits of stars, such as Zucker et al. (1998), who identify the location of star scientists as a key determinant of the timing and location of the birth of biotechnology firms.

on department-level productivity. We examine the effect of hiring a star on incumbent productivity, distinguishing between incumbents who are related and unrelated to the star in "idea space." We also examine the effect of the star hire on the quality of subsequent recruits, again distinguishing between related and unrelated joiners. Finally, we examine how the incumbent and joiner effects are mediated by the rank of the hiring institution. Taken together, these results allow us to look inside the black box of how the location of stars affects scientific knowledge production and to better understand the forces driving the spatial organization of science.

We base our productivity estimates on a sample of 255 evolutionary biology departments that published 149,947 articles over the 29-year period 1980 to 2008. We employ a difference-in-differences estimation approach, comparing the productivity of "treated" to "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. Importantly, we distinguish between incumbent versus joiner scientists in the department and also between those whose work is related versus unrelated to the star.

We find evidence of a large overall star effect. On average, department-level output increases by 54% after the arrival of a star. A significant fraction of the star effect is indirect: after removing the direct contribution of the star, department level output still increases by 48%. In terms of department-level productivity, which we estimate by controlling for department size, we observe a 26% increase after excluding the star's contribution. This implies that much of the observed indirect output gains are due to increasing department quality, not just size. The effect does not seem to diminish even by the end of our sample period, eight years after the arrival of a star.

We next turn our attention to composition and distinguish between incumbent scientists who are in the department prior to the star and new recruits (or "joiners") who join the department after the arrival of the star. We further decompose the samples of incumbents and joiners into those who conduct research related to the star versus those who do not. We find that related incumbents increase their productivity after the arrival of the star by 49%, whereas the effect on unrelated incumbents is negative, perhaps due to resource shifting (negative point estimate, but statistically insignificant at standard levels). The overall star effect on incumbent productivity (related and unrelated combined) is neutral.

Thus, we offer a first step towards reconciling the seemingly contradictory findings described above by reporting evidence that is on the one hand consistent with Waldinger (2012) (that is, no aggregate productivity effect on incumbents from hiring a star) and on the other hand consistent with others (Azoulay et al., 2010; Oettl, 2012) (that is, significant productivity effects on some) by disaggregating departments and distinguishing between co-located peers who are related versus unrelated to the star in terms of their position in idea space.

We then examine the impact of hiring a star on the quality of joiners. Since by definition joiners are not present in the department in the pre-star period, we shift our analytical approach to examining the quality of joiners (measured by the citation-weighted stock of their publications) who join the department in the years before versus after the arrival of the star. Overall, the quality of joiners jumps significantly (68%) after the arrival of a star. When we split the sample into related and unrelated joiners, the estimated increase in the quality of related joiners is a striking 434%. Interestingly, the quality of unrelated joiners also increases by 48%. Thus, although stars do not seem to generate production externalities (spillovers) for unrelated incumbents, they do appear to provide recruiting externalities for unrelated scientists that lead to attracting higher-quality joiners.

We also examine the extent to which the star effect on department-level productivity is correlated with department rank. We assume that a star's share of their department's knowledge stock is greater at lower ranked institutions and thus we expect the direct proportional productivity effect of hiring a star to be larger at lower-ranked institutions. Indeed, we find that the star effect is significantly greater at lower-ranked institutions.

Finally, we explore the role of star engagement. Some stars engage with their new colleagues significantly more than others through collaborative relationships. Does engagement level influence the externalities stars generate for their department's productivity, or is their presence alone enough? We find that engagement through collaboration explains most of the increase in incumbent productivity but only a much smaller fraction of the increase in quality of new recruits.

Our analysis is subject to identification concerns. For example, it is possible that stars are attracted to moving to departments that are on the rise, rather than stars arriving at a department and causing the rise in productivity (reverse causality). In addition, it is possible that 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), causes the department to both hire a star and increase its overall productivity in terms of both 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, there remains a concern that time-specific department-level shocks could lead to a misidentification of causal effects.

To complement our initial empirical approach, we take three additional steps that, while not fully ruling out alternative explanations, give us further confidence that the relationship between the arrival of a star and department productivity is indeed causal. First, we employ a spline regression analysis for all results reported above (main star effect, star effect with star output netted out, star effect on incumbents, star effect on joiners, star effect on related versus unrelated for both incumbents and joiners). In all cases, we find: 1) the main effect persists over time (throughout the eight years examined after the arrival of the star), and 2) no evidence of a pre-trend in increasing productivity prior to the arrival of the star. These results help to rule out the alternate explanation (reverse causality) that stars in our sample move to departments because they are on the rise.

Second, we add controls for department- and university-level shocks that may influence both the hiring of a star and non-star related output by controlling for changes in the size, quality, and presence of a star in another subfield within biology (developmental biology, which is distinct from our focal subfield of evolutionary biology) as well as two additional unrelated departments at the focal university: mathematics and psychology. These results help to rule out the alternate explanation (omitted variable bias) that university- or even department-level shocks that may be correlated with both the recruiting of a star as well as the productivity of incumbents and quality of joiners are driving our result.

Third, we employ an instrumental variable analysis based on a count of the number of stars at other institutions who are at risk of moving to the focal institution in any given year, which is a function of the star's career age and work history (based on prior interactions with researchers from the focal university's region). This instrument is correlated with the probability of department i hiring a star in year t but is not correlated with department-level output. Our main results are robust to each of these extensions. While none of these individual tests are fully conclusive with respect to identification, together they provide further evidence that is consistent with our causal interpretation and inconsistent with alternative explanations.

The paper proceeds as follows. We briefly sketch our theoretical framework in Section 2 and develop it fully in Appendix A. We describe our data in Section 3 and our empirical strategy in Section 4. We report and interpret our basic difference-in-differences results in Section 5. In Section 6, we provide further evidence for a causal interpretation. We conclude with a discussion of the implications of our findings in Section 7.

2 Theoretical Framework

To generate testable hypotheses, we develop a model of how the hiring of a star affects incumbent productivity and the quality of subsequent recruitment (formalized in Appendix A). We assume Romer-style, knowledge-production functions, where incumbent productivity depends on local knowledge stocks. The impact of these stocks is allowed to differ depending on whether the knowledge is related or unrelated to the research of an incumbent scientist.

Hiring a star has direct positive impacts on incumbent productivity, and these effects are assumed to be larger for related incumbents. The proportional direct impact is also larger for lower-ranked institutions since the star's knowledge stock is a larger proportion of the total local stock. Critically, however, the star's impact on incumbent productivity is also conditioned on the impact of the star hire on subsequent recruitment. We introduce the idea of a recruitment function to capture this recruitment channel. For a given research area, this function shows how the quality of the applicant pool depends on existing local knowledge stocks, as well as on the speed with which the quality of the marginal hire declines with the number of hires in a particular research area.

We show that the average quality of subsequent joiners in both related and unrelated areas rises as a result of hiring a star. However, the star hire also shifts the optimal composition of hiring towards scientists working in areas related to the star. Overall, it is possible for the productivity of unrelated incumbents to decline relative to a no-star-hire baseline, notwithstanding a direct positive impact on their productivity.

The model suggests a number of testable hypotheses. A star hire will: 1) increase the productivity of related incumbents; 2) increase or decrease the productivity of unrelated incumbents, depending on the balance of the direct effect of the star's knowledge stock and the indirect effect through the composition of subsequent hiring; 3) increase the quality of both related and unrelated joiners; and 4) have larger proportional effects on incumbent productivity and joiner quality in lower-ranked institutions.

3 Empirical Setting and Data

Our study focuses on the field of evolutionary biology, a sub-field of biology concerned with the processes that generate diversity of life on earth (e.g., the origin of species). Research in evolutionary biology consists of both theoretical and experimental contributions. While experimental evolutionary biology can be capital intensive due to the costs of running experiments in a lab, productivity within the discipline is not predicated on access to very specific facilities, as is the case in experimental particle physics and empirical astronomy. Evolutionary biology's mix of theoretical and experimental research activities makes it a good test subject for an initial exploration of the star effect on department growth.

3.1 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. A critical first step is to define the field of evolutionary biology. We impute department membership using the following approach:

- 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.* We focus on these four society journals since every article published here concerns evolutionary biology and is relevant to evolutionary biologists. This yields 15,256 articles.
- We next 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 will serve as the basis of evolutionary biology knowledge for the purposes of our study.

- We then 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).

3.2 Identifying Authors

We next attempt to 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 of the papers belonging 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.

3.3 Identifying Scientist Locations

Using the generated unique author identifiers for each evolutionary biology paper, we next 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 impute author location using reprint information that provides a one-to-one mapping between the reprint author and the scientist's affiliation. In addition, we take advantage of the fact that almost 57% of evolutionary biology papers are produced with only a single institution listing. We thus are able to directly attribute the location of all authors on these papers to the focal institution.

We note that this method of location attribution is more effective within evolutionary biology than many other science disciplines since article production within evolutionary biology is not characterized by large teams (2.55 average authors per paper).

3.4 Unit of Analysis

Our unit of analysis is the department-year. We include all evolutionary biology departments that had at least one scientist present in 1980 and at least one scientist present in 2008. This criterion ensures that we are not simply counting new entrants or other idiosyncratic details of the data. Furthermore, this ensures that for any given department-year, a department is at risk of hiring a star scientist. Two-hundred-fifty-five departments fit this criterion. As such, we have 7,395 department-year observations.

3.5 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) $IncumbentOutput_{it}$: the sum of the citation-weighted papers published by scientists present the year prior to the star's arrival 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.

We only use citations from articles published in the four evolutionary biology society journals that are made within five years of the focal paper's publication. In the majority of our specifications, we also exclude the publications of the arriving star.

3.6 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 (above the 90th percentile of citation-weighted stock of papers published up until year

$t-1$) joins department i and 0 otherwise. 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 Figure 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 ten years (1995-2005).

3.7 Descriptive Statistics

We provide summary statistics of our dataset in Table 1. The average department in our sample produces just over 80 citation-weighted publications per year. When we exclude the contributions of the star, this number is reduced to just under 77 citation-weighted publications per year. While it initially may appear that the star is not contributing much to the department, we should note that this is the mean across all department-years and as such includes departments that never receive a star as well as the output of departments prior to the arrival of a star. Just under 22 scientists are active in each department in a given year on average, and incumbent scientists produce fewer than 18 citation-weighted publications a year.

4 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:

$$E[Y_{it}] = \exp(\alpha Star_{it-1} + \beta \ln Scientists_{it} + \delta_t + \mu_i), \tag{1}$$

where Y_{it} is one of our three dependent variables. As previously mentioned, we remove the arriving stars contributions to Y_{it} in most specifications.

Of the 255 departments, 178 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. 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:

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

The leading indicators help discern the extent to which reverse-causality influences our coefficients; that is, whether changes in department output influence the likelihood of recruiting a star. The leading indicators also help to identify if there is an issue of omitted changes in department resources that precedes the recruitment of a star. Finally, the lagged indicators allow us to explore temporal dynamics, in particular the duration of the star effect.

5 Difference-in-Differences Results

5.1 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 2, Column 1) implies that after a star arrives, department-level output increases by 53.7%, on average, per year ($e^{0.430} - 1 = 0.537$). This is not surprising since the department now has a star who, by definition, is prolific. However, even after we remove the star's contribution, we still find a department-level increase in output of 48% per year on average (Column 2).

Recognizing that recruiting a star may coincide with an overall expansion of the department, we add a control for the number of scientists present in the department in the focal year. The estimated coefficient on *Star* indicates that a department's productivity (output per scientist) increases by 26%, on average, after the arrival of a star, still excluding the star's contribution to department output (Column 3). This estimate is both economically and statistically significant (1% level). Furthermore, this 26% increase corresponds to an approximate increase of just under 8 Citation-Weighted Publications.

We present the results from Columns 2 and 3 in graphical form in Figure 2 by estimating Equation 2. 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." Furthermore, when we remove the output of the star in Panel (b), 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. Moreover, 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, controlling for 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 (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 Figure 3. As can be seen there is no observable change in incumbent output either prior to the star's arrival nor after.

5.2 Star Effect on Joiner Quality

We turn next to examining joiners. We are not able to estimate joiner output the way we do for incumbents since by construction joiners have no output at the focal department prior to their arrival. Therefore, it is impossible to estimate a change in joiner 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. Significant variation exists in the quality of joining cohorts (mean = 37, standard dev. = 78, min. = 1, max = 2348, Table 1). Thus, we estimate the relationship between joiner quality (dependent variable) and the presence of a star (Table 3). 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 70% (Column 1). We once again observe no pre-trends in this specification when presented graphically (Figure 4). It is interesting to note that the increase in joiner quality commences one year after the star's arrival suggesting that the arrival of the star triggers an increase in subsequent recruits.

Next, we examine whether this boost in joiner quality applies across all levels of recruits (rookie, mid-career, senior). A number of studies document variation in productivity of scientists over their professional lifecycle (Lillard and Weiss, 1978; Levin and Stephan, 1991; Jones, 2010). Furthermore, Weinberg (2006) reports evidence that the extent to which a researcher is influenced by their co-located peers varies with age. To explore this issue in our setting in terms of how star impact on the quality of joiners varies with joiner vintage, we split the sample according to career age: 1) early-career (up to 10 years of publishing experience), 2) mid-career (10-20 years), and 3) late-career (more than 20 years). We report results in Columns 2, 3, and 4. The largest increase in quality appears to come from mid-career joiners, although the point estimates are not statistically distinguishable from those of early- and late-career.

5.3 Star Effect on Related Scientists

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_{0-1} and unrelated otherwise. We split the sample accordingly. On average, 9% of incumbents and an equal fraction of joiners (9%) 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 significantly greater increase in output than the unrelated portion (Table 4, Column 1 versus 3). In fact, after the arrival of a star, the output of related scientists increases by more than 126% compared to 11% for unrelated but where only the point estimate on the related scientists is statistically significant. Figure 5 plots the estimated coefficients from Equation 2 graphically. 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 49% 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 4). 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 2, Column 4) and consistent with the aggregate findings reported in Waldinger (2012). Figure 6 presents these results graphically. Both panels do not display any form of pre-trends. In addition, only panel (a), examining related incumbent output, reveals an increase in output after the star's arrival. This increase is only temporary with the largest increase occurring 4 years after the star's arrival.

5.4 Star Effect on Related Joiners

We combine our analyses on joiner quality and relatedness in the analysis we report in Table 5. We classify joiners as related or unrelated following the procedure described above. We split the sample according to relatedness and, following the procedure described in Section 5.2 above, we estimate the relationship between joiner quality and the presence of a star. 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: 434% compared to 48% (Columns 1 and 2, respectively). The differences are less stark when we calculate the effect size on joiner quality. The arrival of a star corresponds to an increase in related and unrelated joiner quality (stock) by 9.6, and 8 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.

5.5 Department Rank

Next, we examine the extent to which the star effect on department-level productivity is influenced by the rank of the institution. In Table 6, we report the point estimates of $Star_{it-1}$ for regressions using our three main dependent variables (*Output w/o Star*, *Incumbent Output*, and *Joiner Quality*) split by institutions in the top 25 at the time of the star's arrival versus not-top 25. The rank splits reveal large heterogeneity in effects across institution types. Top departments experience less of a gain after star arrival of their first star compared to institutions outside of the top 25. These results are robust to different cutoffs for top institutions (e.g., top 10, top 50).

5.6 Collaboration

To explore the possible channels through which the recruited stars affect new departments we examine the extent to which star engagement with their new colleagues is associated with the observed department-level productivity gains. We employ co-production of new knowledge (i.e., coauthorship) as a proxy measure for star engagement. We report the results in Table 7. 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 1.6% increase in overall department-level productivity but statistically insignificant. The effect is twice as large when we focus only on related peers (3.4%). Star engagement is not correlated with the productivity of unrelated peers.

Although star collaboration accounts for some of the variation in department-level productivity (as compared to the point estimates in Table 2, Column 3 and Table 4, Column 1) it does not fully account for the increase in productivity after the star's arrival. While co-production between stars and their department peers is important, it does not fully explain the productivity increase post-star arrival. That said, collaboration is only one channel through which stars may engage with their peers. However, star collaboration does seem to account for all of the productivity boost for incumbents (Columns 4-6). As with the results we report in Columns 1 through 3, more star collaboration is associated with a greater increase in incumbent productivity, but in contrast to Columns 1 through 3, in Columns 4 through 6 the inclusion of the collaboration variable causes the main effect of the star's arrival to disappear. 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 4, Column 2.

5.7 Robustness Checks

We present additional robustness to our main analysis in Appendix B. First, 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). The relationship between a star's departure and joiner quality is statistically insignificant highlighting the possible path-dependency of joiner quality once a star arrives. In addition, the positive relationship between star arrival and total output and joiner quality remain alleviating concerns that our results are inflated due to the departure of scientists at other institutions. Second, we further refine our star arrival variable by only considering the arrival of scientists that are members of the National Academies of Sciences (an even more illustrious sample). We observe that the arrival of a National Acadamies 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. Third, we explore what happens when an incumbent star scientist becomes a member of the National Academies of Science. For observe no statistically significant relationship between the appointment of a scientist to the National Academies of Science and our three main outcome measures.

6 Is the Estimated Star Effect Causal?

The previous section has documented an economically and statistically significant star effect on department productivity (excluding the output of the star), related incumbent productivity, and post-star joiner quality. However, the suspicion remains that these effects might not reflect the causal impact of the star. Star recruitment might just be a manifestation of a broader strategy to improve department size and quality (omitted variable bias). Moreover, the successful recruitment of the star might itself be the result of independently improving department performance (reverse causality bias). We adopt a three-strand approach to further support a causal interpretation of the Section 5 results.

First, we rely on the spline regressions and associated graphics presented in Section 5 to examine pre-trends in productivity and joiner quality. These figures allow us to examine whether the improvement in performance pre-dates the arrival of the star. The strong absence of any pre-trends help rule out a broader department-improvement strategy or reverse causality from performance to star recruitment. Second, we add controls for department- and university-level resource shocks that might influence both the hiring of a star and output. The controls help to mitigate concerns about resource shocks that are contemporaneous with the arrival of the star and thus not discernible in the pre-trends identified from the spline regressions. We add controls for changes in the size, quality, and presence of a star in another subfield within biology (developmental biology, which is distinct from our focal subfield of evolutionary biology) as well as two additional unrelated departments at the focal university: mathematics and psychology. Third, we introduce an instrument for star recruitment based on a time-varying measure of move risk for stars in evolutionary biology who have a well-defined pre-existing connection with the focal department.

6.1 Additional Department and University Controls

In Table 7, we control for department- and university-level shocks that may influence both the hiring of a star and department-level output. We do this by controlling for the presence of a star and the department size at the focal institution's developmental biology, mathematics, and psychology departments. We construct our developmental biology sample in a similar fashion to the one outlined in Section 3.1 by drawing upon all articles cited at least once in the following main developmental biology journals: *Development*, *Developmental Biology*, *Developmental Cell*, and *Genes & Development*. We construct our mathematics and psychology departments by drawing upon all articles published in journals classified as "Mathematics" or "Psychology" in the ISI Journal Citation Reports. Controlling for these effects only slightly diminishes the magnitude of the reported effects.

6.2 An Instrument for Star Recruitment

The splines and controls help to rule out strategies to improve evolutionary biology department performance and strategies that coincide with the recruitment of the star that are also present in other biology disciplines and the wider university. However, the recruitment of the star might still be coincident with a new strategy of department improvement that is specific to evolutionary biology. This suggests the use of an instrument for star recruitment that is plausibly uncorrelated with any change in departmental strategy.

A potential instrument for the successful recruitment of a star must incorporate both the movability of stars in year t (due to exogenous reasons) and the likelihood of moving to department i (due to pre-determined reasons). We incorporate these two components by interacting the number of star scientists that are in the career age of greatest mobility and have a pre-determined link to institution i. Explicitly we construct a variable $TotalStarMovers$ that cumulates the count of scientists who formed coauthoring relationships with scientists at department i in the first five years of the star's career and who have a career age between 6 and 9.[3] Appendix C presents evidence that these two assumptions have predictive power. This variable satisfies the exclusion restriction since the quality of coauthors at department i are controlled for with the department fixed effects included in all specifications and we have seen from the splines presented in Figures 2-6 that there were no productivity pre-trends.[4] Lastly, this variable is cumulative since our endogenous variable is a dummy that stays "on" once treatment has occurred.

Our instrument, $MoveRisk$, is a dummy set to 1 if the variable $TotalStarMovers_{it}$ is above the median value across all years and institutions, and 0 otherwise.[5]

Table 9 presents the two-stage least squares (2SLS) estimates instrumenting the arrival of a 90th percentile star with $MoveRisk$. Column 1 presents the results of the first-stage regression regressing $Star_{t-1}$ on the instrument, $MoveRisk_{t-1}$. The excluded instrument is both economically and statistically meaningful: when there are more than 4 scientists (above the median number of risk) at risk of moving to institution i in year t, institution i is 20% more likely to hire a star. As can be seen in the remainder of the specifications (Columns 2-5), the point estimates are qualitatively similar to those generated in earlier tables.[6] The point estimates are larger, but the differences are not statistically

[3] We only examine collaborations made in the first five years of the star scientist's career to avoid contaminating the sample. Results are also robust to using alternate career age windows (e.g., 5-10 years and 7-8 years).

[4] The lack of pre-trends helps rule out the concern that scientists in the first five years of their career were strategically coauthoring with scientists at departments on the rise.

[5] The median number of stars at risk of moving is 4.

[6] We log transform the dependent variables (ln +1) to allow for easier comparison with the log-linear poisson model we present

significant.

Table 10 presents instrumental variables (IV) results for our analysis of department-level output, incumbent output, and joiner quality by the scientist's topic-relatedness to the star. Once again, the IV results reaffirm the poisson results previously presented: the arrival of a star positively increases a department's output, incumbents' output, and joiner quality for scientists who work in related areas, is unrelated to aggregate department output and incumbent output of those working in unrelated areas but still increases joiner quality for scientists working in unrelated topic areas.

7 Discussion and Conclusion

We explore how the hiring of a star scientist affects incumbent productivity and the quality of subsequent recruitment. We find that the effects of star location are economically significant but subtle. To illuminate the causal channels, we apply a simple model that allows for both differentiated knowledge and recruitment spillovers. We base differentiation on the relatedness of work of the star to incumbents and potential joiners. 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 by the star with 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 also uncover evidence to support the model's prediction of larger proportional productivity and recruitment effects in lower-ranked institutions.

The main empirical challenge is to demonstrate that the observed star-related associations are at least in part causal. We adopt a three-part approach to support a causal interpretation: an examination of pre-trends (to rule out a pre-existing department-improvement trend), controls for university- and department-level shocks (e.g., surge in resources), and use of an instrument that is correlated with star recruitment but plausibly uncorrelated with broader department improvement strategies. While none

throughout.

of these approaches provides perfectly clean identification on its own, together they give evidence that is consistent with a casual explanation of the observed star effects and inconsistent with the plausible alternative explanations.

Reflecting on these results, we decompose the overall indirect star effect (26%) to determine the relative importance of production versus recruiting externalities. Overall, based on rough calculations that extrapolate from mean productivity changes in response to a star's arrival, we estimate that roughly 9% of this effect is due to a boost in related incumbent productivity, 0% is due to a boost in unrelated incumbent productivity, 38% is due to a quality increase in related joiners, and 53% is due to a quality increase in unrelated joiners.[7] The impact from unrelated joiners is high relative to related joiners, despite a significantly greater quality increase in related joiners, due to a larger average number of unrelated joiners.

What are possible normative implications of our findings on why stars matter? In general, our findings on the impact of stars on colleague productivity and the dynamics of recruitment suggest that the location decisions of stars are important for the spatial organization of science. However, the evidence that highly productive scientists are drawn to one another for reputational as well as productivity reasons raises a concern that there may be excessive positive sorting of scientists from an efficiency perspective at top-ranked institutions.

Such sorting might lead to missed opportunities for the development of strong clusters of related scientists to form around a star at less highly-ranked institutions. On the other hand, under certain conditions particular institutions should have a strong incentive to pursue star-focused strategies to ascend the rankings. Our findings suggest that star-recruitment strategies may be most effective where a cadre of related incumbents is already present and the department has a flow of new hiring slots sufficient to take advantage of the improved quality of potential new recruits. Our findings thus have

[7] These calculations are crude. The mean output value prior to a star's arrival for departments that receive a star is 31 citation-weighted publications. A 26% increase corresponds to an increase of 8 citation-weighted publications after the first star's arrival. We disaggregate this increase into the fractions from related versus unrelated peers. While the output of related scientists increases by 126% (exp(.815)-1), the mean is only 3 citation-weighted publications, corresponding to an increase in 3.7 citation-weighted publications, or 47% of the total 8 citation-weighted publications so we can attribute the remaining 53% to unrelated scientists. Since the output of unrelated incumbents does not increase after the star's arrival, unrelated joiners account for 47% of the total increase. Related incumbents, however, experience a 49% increase in output after the star's arrival from a baseline of 1.5 citation-weighted publications prior to the star's arrival or 0.7 citation-weighted publications. Thus, if 0.7 citation-weighted publications (9% of 8) can be attributed to related incumbents, then the remaining 3 (38% of 8) citation-weighted publications of the total 3.7 related scientist increase can be attributed to joiners.

possible lessons for public/private funding and endowment strategies for seeding dynamic research clusters.

Although a university department is a rather special local knowledge economy, our findings on the relative importance of knowledge- and recruitment-related externalities are also suggestive of a broader role of "stars" – scientists, CEOs, entrepreneurs, and the like – in the dynamics of local agglomeration and growth. We plan to extend our analysis of why stars matter to include these broader effects in future research.

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Figure 1: Number of Departments that Recruit their First Star (by year)

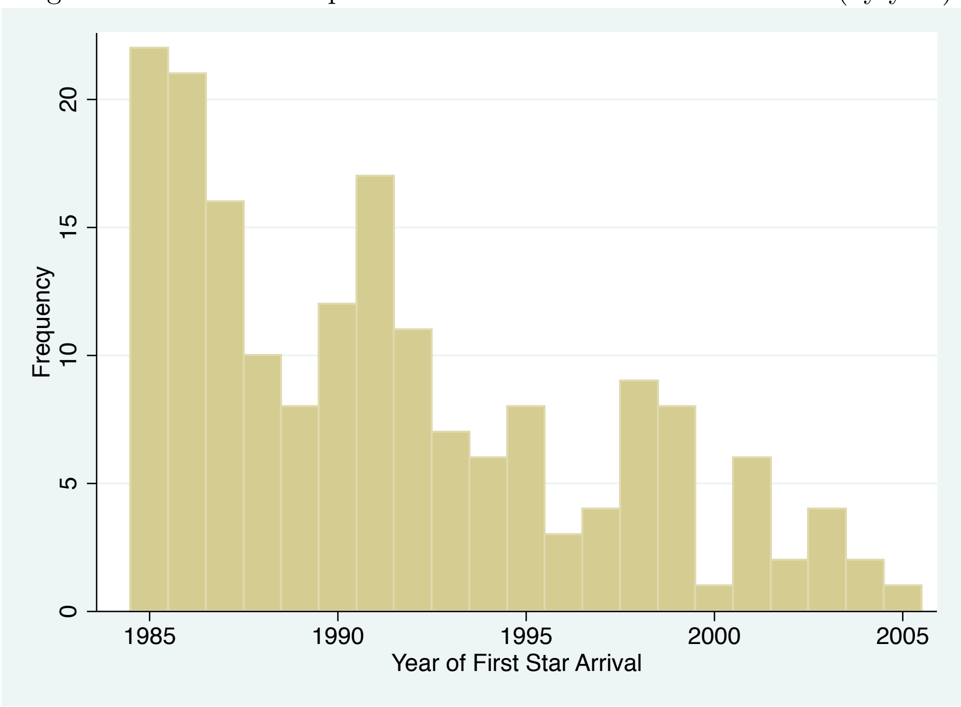
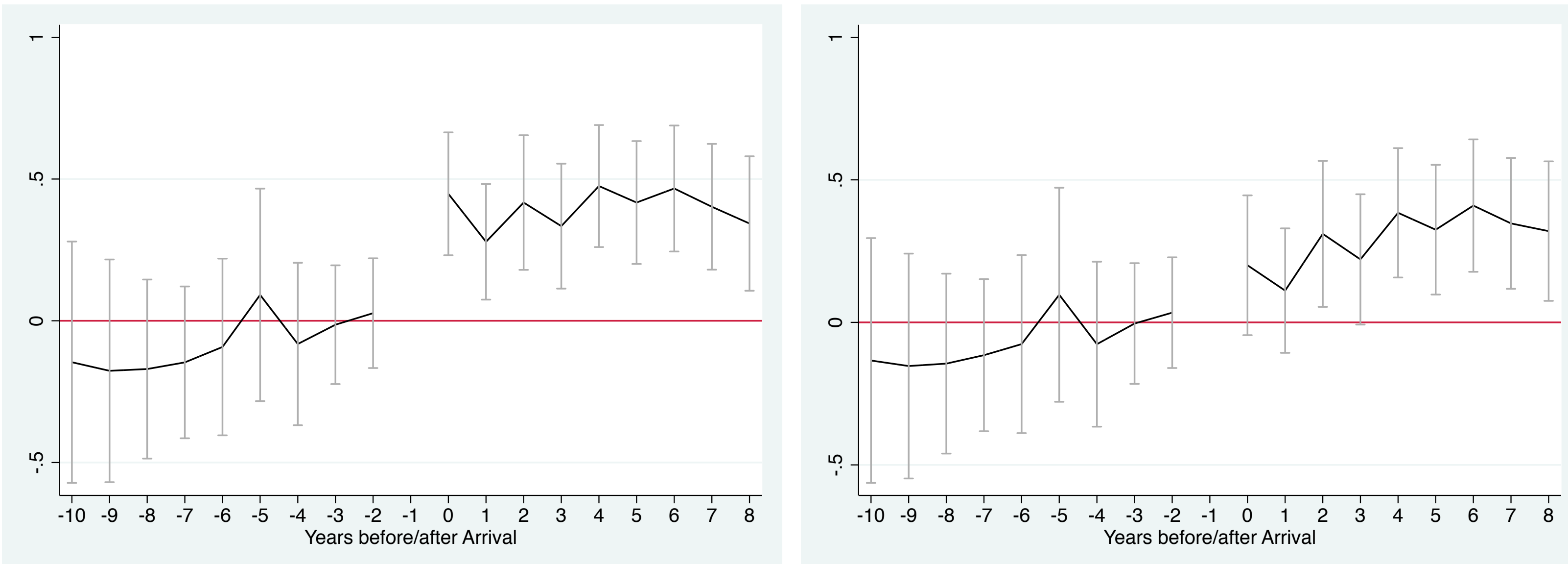


Figure 2: Department Output



(a) Including Star

(b) Excluding Star

Figure 3: Department Output – Incumbents Only

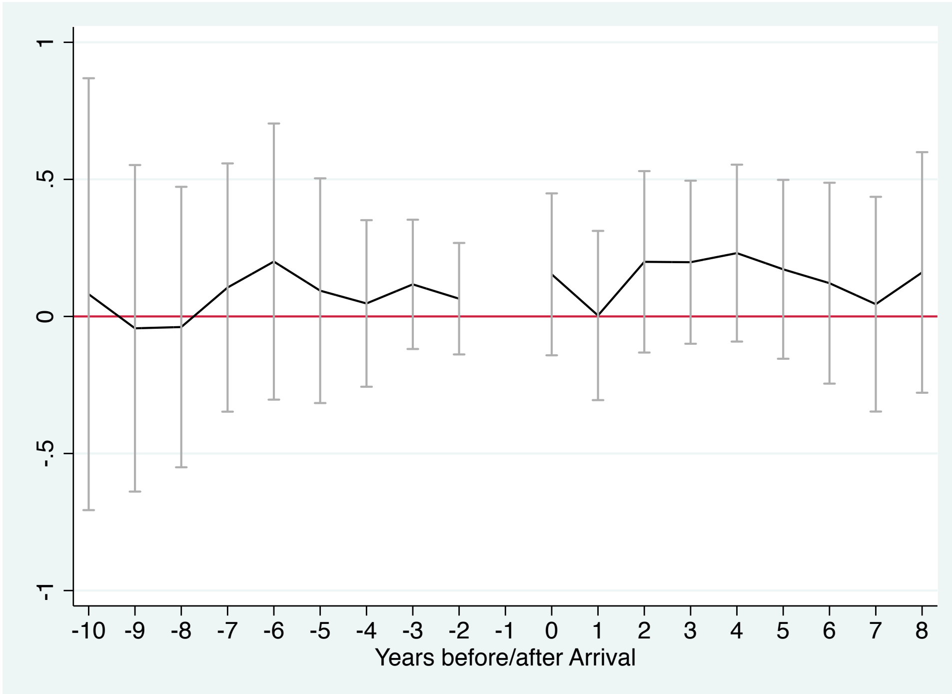


Figure 4: Joiner Quality

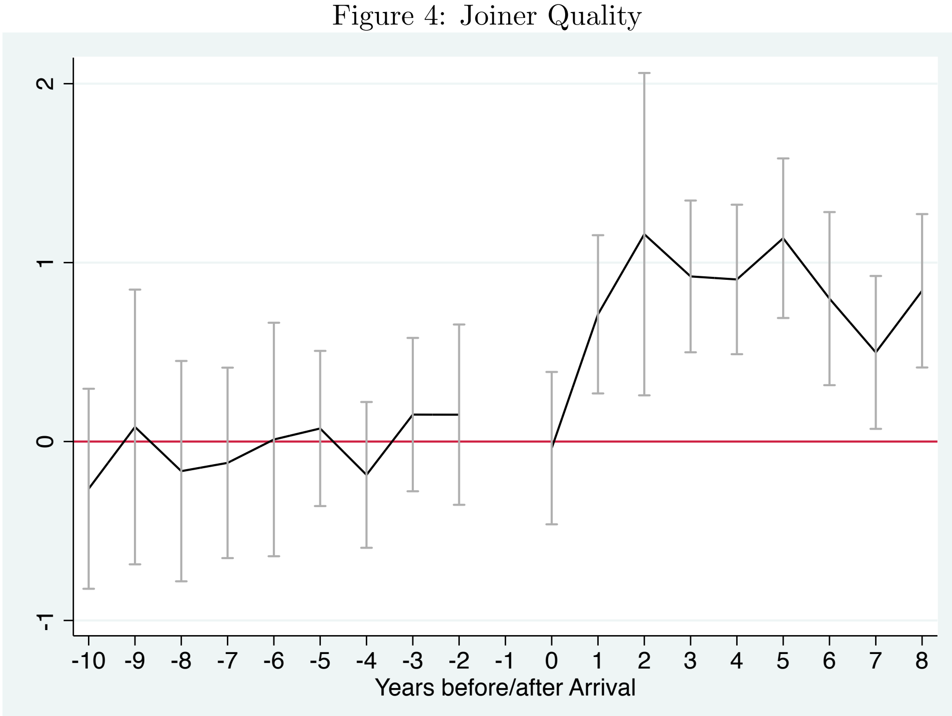
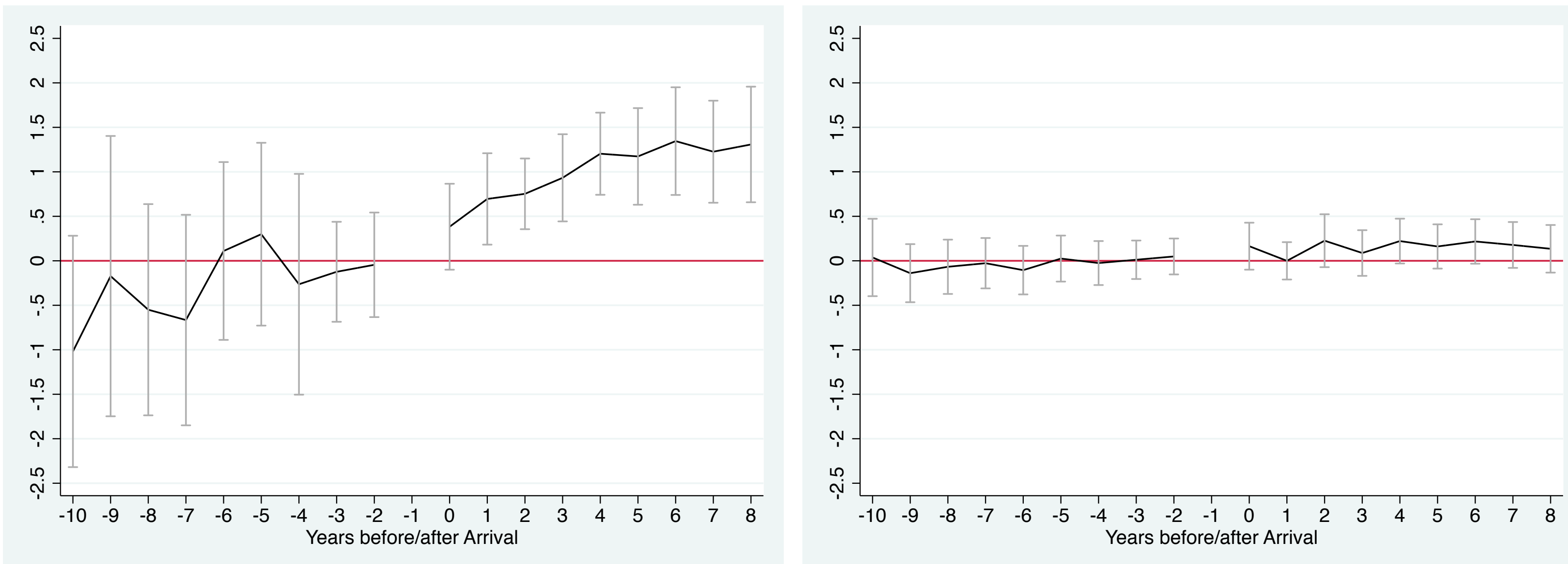


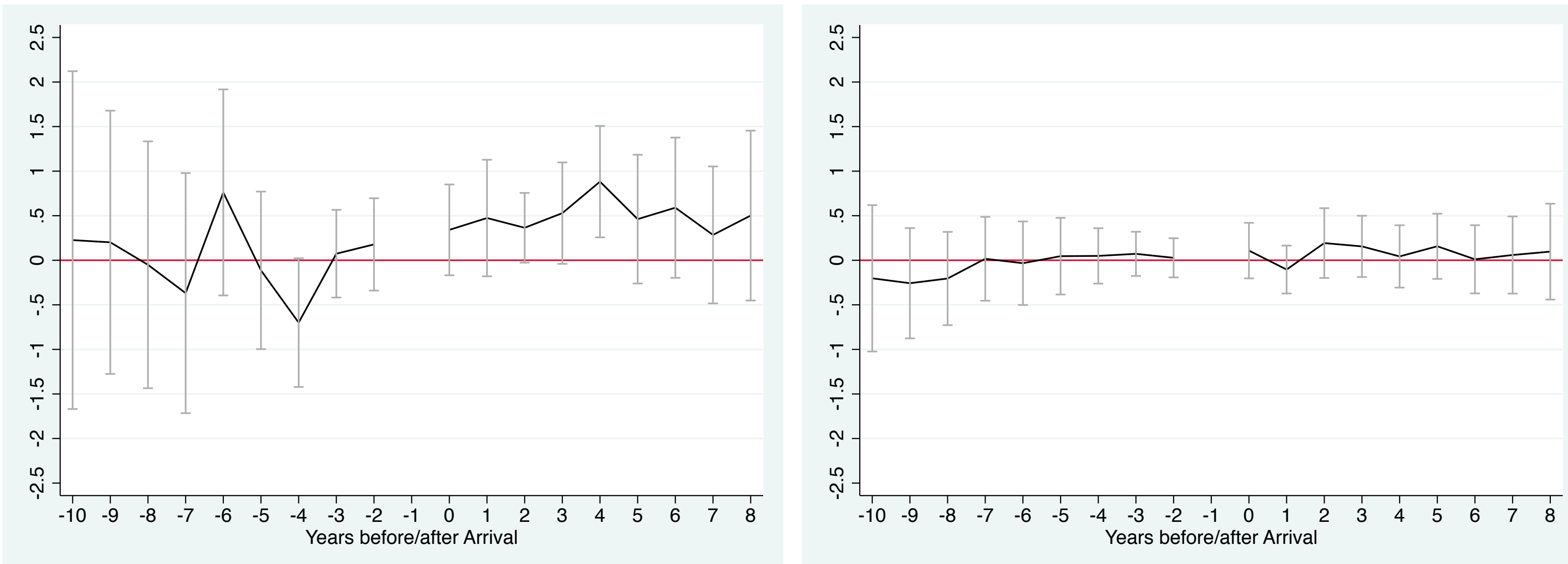
Figure 5: Department Output Excluding Star: Related versus Unrelated



(a) Related Scientists

(b) Unrelated Scientists

Figure 6: Department Output – Incumbents Only: Related versus Unrelated



(a) Related Incumbents

(b) Unrelated Incumbents

Table 1: Summary Statistics; N = 7,395

Variables	Mean	Median	Std. Dev.	Min.	Max.
Output	80.90	26	155.32	0	2500
Output w/o Star	76.75	24	151.60	0	2498
Scientists	21.67	14	24.23	1	175
Incumbent Output	17.61	2	53.83	0	1650
Incumbents	6.60	3	9.88	0	93
Star	0.43	0	0.49	0	1
Joiner Quality	36.53	14	78.34	1	2348
Joiner Quality - Early Career	27.97	11.5	56.16	1	1137
Joiner Quality - Mid Career	72.15	19	163.79	1	2925
Joiner Quality - Late Career	108.65	23	296.53	1	3242
Output w/o Star - Related	14.62	0	49.89	0	1687
Output w/o Star - Unrelated	62.13	20	127.91	0	2498
Incumbent Output - Related	3.93	0	18.61	0	719
Incumbent Output - Unrelated	13.68	1	48.96	0	1650
Joiner Quality - Related	21.21	0	94.29	0	1766
Joiner Quality - Unrelated	29.71	0	73.26	0	2348
MoveRisk	51.15	26	67.67	0	589

Table 2: Main Results

	(1)	(2)	(3)	(4)
Dependent Variable:	*Output*	*Output w/o Star*	*Output w/o Star*	*Incumbent Output*
Star_{t-1}	0.430**	0.392**	0.230**	0.045
	(0.077)	(0.082)	(0.077)	(0.084)
ln Scientists			1.274**	
			(0.092)	
ln (Incumbents +1)				1.230**
				(0.090)
Department Fixed Effects	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓
Observations	7140	7140	7140	4984
Number of Departments	255	255	255	178
Log-Likelihood	-155577	-151447	-122950	-48134
Pre-Star Mean of Dependent Variable:	30.87	30.87	30.87	13.24
Effect Size of $Star_{t-1}$ on Dependent Variable†	16.59	14.82	7.98	0.61

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

† 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.

Table 3: Characteristics of Joining Scientists

	(1)	(2)	(3)	(4)
Dependent Variable:	*Joiner Quality*	*Joiner Quality*	*Joiner Quality*	*Joiner Quality*
Sample:		*Early Career*	*Mid Career*	*Late Career*
Star_{t-1}	0.543^{**}	0.675^{**}	0.971^{**}	0.863^{+}
	(0.120)	(0.128)	(0.252)	(0.492)
Department Fixed Effects	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓
Observations	3629	3051	1539	735
Number of Departments	250	244	215	155
Pre-Star Mean of Dependent Variable:	17.99	15.68	27.02	34.71
Effect Size of $Star_{t-1}$ on Dependent Variable†	12.91	15.21	49.73	46.74

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

Table 4: Output by Topically Related and Unrelated Scientists

	(1)	(2)	(3)	(4)
Dependent Variable:		*Output w/o Star*		
Sample:	*All*	*Incumbents*	*All*	*Incumbents*
SubSample:	*Related*		*Unrelated*	
Star_{t-1}	0.815^{**}	0.401^{*}	0.105	−0.017
	(0.242)	(0.173)	(0.083)	(0.092)
ln Scientists	1.380^{**}		1.243^{**}	
	(0.278)		(0.090)	
ln (Incumbents +1)		1.049^{**}		1.304^{**}
		(0.175)		(0.089)
Department Fixed Effects	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓
Observations	4704	3472	7140	4984
Number of Departments	168	124	255	178
Pre-Star Mean of Dependent Variable:	2.97	1.48	27.90	11.76
Effect Size of $Star_{t-1}$ on Dependent Variable†	3.74	0.73	3.09	−0.20

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

Table 5: Joiner Quality by Topically Related and Unrelated

	(1)	(2)
Dependent Variable:	*Joiner Quality*	
SubSample:	*Related*	*Unrelated*
Star_{t-1}	1.676^{**}	0.390^{**}
	(0.378)	(0.120)
Department Fixed Effects	✓	✓
Year Fixed Effects	✓	✓
Observations	2663	3629
Number of Departments	151	250
Pre-Star Mean of Dependent Variable:	2.20	16.69
Effect Size of $Star_{t-1}$ on Dependent Variable†	9.56	7.96

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

† 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.

Table 6: Results Split by Rank

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	*Output w/o Star*		*Incumbent Output*		*Joiner Quality*	
Sample:	*Top 25*	*Non-top 25*	*Top 25*	*Non-top 25*	*Top 25*	*Non-top 25*
Star_{t-1}	0.021	0.156^{**}	0.089	-0.054	0.431	0.907^{**}
	(0.175)	(0.060)	(0.246)	(0.068)	(0.264)	(0.172)
ln Scientists	1.001^{**}	1.251^{**}				
	(0.216)	(0.063)				
ln (Incumbents +1)			0.990^{**}	1.060^{**}		
			(0.260)	(0.098)		
Department Fixed Effects	✓	✓	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓	✓	✓
Observations	2828	6468	672	4312	2772	6412
Number of Departments	101	231	24	154	99	229
Pre-Star Mean of Dependent Variable:	28.83	23.54	9.81	7.78	20.81	6.65
Effect Size of $Star_{t-1}$ on Dependent Variable†	0.61	3.97	0.91	-0.41	11.21	9.82

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

† 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.

Table 7: Star Coauthorships

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable		*Output w/o Star*			*Incumbent Output*	
Sample:	*Full*	*Related*	*Unrelated*	*Full*	*Related*	*Unrelated*
Star_{t-1}	0.199^{**}	0.735^{**}	0.098	-0.013	0.185	0.006
	(0.077)	(0.244)	(0.082)	(0.087)	(0.180)	(0.095)
Collaborations w/ Star	0.016	0.034^{*}	0.004	0.117^{**}	0.194^{**}	-0.075
	(0.010)	(0.016)	(0.011)	(0.040)	(0.053)	(0.049)
ln Scientists	1.268^{**}	1.363^{**}	1.242^{**}			
	(0.092)	(0.274)	(0.091)			
ln (Incumbents +1)				1.210^{**}	0.998^{**}	1.313^{**}
				(0.090)	(0.171)	(0.090)
Department Fixed Effects	✓	✓	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓	✓	✓
Observations	7140	4704	7140	4984	3472	4984
Number of Departments	255	168	255	178	124	178
Pre-Star Mean of Dependent Variable:	30.87	2.97	27.90	13.24	1.48	11.76
Effect Size of $Star_{t-1}$ on Dependent Variable†	6.80	3.22	2.87	-0.17	0.30	0.07

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

† 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.

Table 8: Main Results with Developmental Biology Controls

Dependent Variable:	(1) *Output w/o Star*	(2) *Incumbent Output*	(3) *Joiner Quality*
Star_{t-1}	0.227^{**}	0.065	0.511^{**}
	(0.071)	(0.079)	(0.123)
ln Scientists	1.290^{**}		
	(0.093)		
ln (Incumbents + 1)		1.231^{**}	
		(0.090)	
Devel. Biology Star_{t-1}	0.025	−0.065	0.105
	(0.113)	(0.137)	(0.176)
ln (Devel. Biology Scientists_{t-1} +1)	−0.187	0.020	−0.128
	(0.149)	(0.167)	(0.140)
Department Fixed Effects	✓	✓	✓
Year Fixed Effects	✓	✓	✓
Math and Psychology Controls	✓	✓	✓
Observations	7140	4984	3629
Number of Departments	255	178	250
Pre-Star Mean of Dependent Variable:	30.87	13.24	17.99
Effect Size of $Star_{t-1}$ on Dependent Variable†	7.87	0.89	12.00

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

† 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.

Table 9: Instrumental Variable Results

	(1)	(2)	(3)	(4)
Estimation:	*OLS*	*2SLS*	*2SLS*	*2SLS*
Dependent Variable:	$Star_{t-1}$	*Output w/o Star*	*Incumbent Output*	*Joiner Quality*
MoveRisk_{t-1}	0.201^{**}			
	(0.032)			
Star_{t-1}		0.421^{*}	−0.127	1.499^{**}
		(0.199)	(0.342)	(0.320)
ln Scientists	0.092^{**}	1.248^{**}		0.656^{**}
	(0.019)	(0.032)		(0.049)
ln (Incumbents +1)			1.299^{**}	
			(0.024)	
Department Fixed Effects	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓
Observations	7140	7140	4984	7140
Number of Departments	255	255	178	255
Angrist-Pischke F-test	202.85	202.85	89.53	202.85

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 10: Instrumental Variable Results - II

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*Output w/o Star*	*Incumbent Output*	*Joiner Quality*	*Output w/o Star*	*Incumbent Output*	*Joiner Quality*
SubSample:		*Related*			*Unrelated*	
Star_{t-1}	2.147^{**}	1.359^{**}	0.860^{**}	0.040	-0.259	0.497^{*}
	(0.248)	(0.340)	(0.219)	(0.202)	(0.345)	(0.225)
ln Scientists	0.365^{**}		0.074^{*}	1.238^{**}		0.123^{**}
	(0.036)		(0.033)	(0.032)		(0.034)
ln (Incumbents +1)		0.348^{**}			1.256^{**}	
		(0.028)			(0.024)	
Department Fixed Effects	✓	✓	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓	✓	✓
Observations	7140	4984	7140	7140	4984	7140
Number of Departments	255	178	255	255	178	255
Angrist-Pischke F-test	202.85	89.53	203.33	202.85	89.53	203.33

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$