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Does Cluster Hiring Enhance Faculty Research Output, Collaborations, and Impact? Results from a National Study of U.S. Research Universities

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Abstract For U.S. research universities, cluster hiring has become a popular means to add faculty members in university-defined priority fields. The expectation of advocates is that these faculty members will collaborate on high-impact research. Utilizing a national sample of 168 cluster-hire faculty members from eight U.S. research universities, we find statistically significant gains in research output, collaborations, and research impact from pre- to post-hire. However, these gains are not distributed equally. Some output and impact measures show greater gains for white and Asian researchers relative to under-represented minorities and for men relative to women. Significant gains in research output are associated with fields like advanced materials and health sciences for which generous external support is available. Significant research impact is associated with researchers located in wealthy, prestigious universities. The findings indicate that cluster hiring is no cure-all for fields that are disadvantaged in the competition for external funding or for non-elite universities that are disadvantaged in the competition for prestige.

Keywords Cluster hiring · Interdisciplinary initiatives · Research universities

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Introduction

Over the last three decades, cluster hiring programs have become a popular means for U.S. research universities to foster interdisciplinary collaboration and to align research faculty with federal funding priorities (Sá 2008a). These initiatives are typically based on the hiring of between three and eight faculty members into interdisciplinary teams, with the expectation that they will jointly pursue high-impact research. The University of Wisconsin-Madison launched the first large-scale cluster hiring program in the late 1990s (University of Wisconsin-Madison 2003). Since that time, at least 84 U.S. universities have implemented cluster hiring programs of varying size and scope (authors' calculation).

Funding agencies and professional organizations now emphasize the value of interdisciplinary collaborations in areas that require the skills and knowledge of many different types of specialists. This trend has encouraged the growth of faculty hiring programs that promote this style of collaboration, including cluster hiring initiatives (Bozeman and Boardman 2003; Corley et al. 2006; National Research Council 2015).[1] The existing empirical research provides some support for the idea that teams composed of specialists from different fields have greater potential for innovation. A key mechanism appears to be that these teams have greater access to diverse, relevant knowledge. This expanded knowledge base can provide fertile ground for innovation (Ruef 2002; Wuchty et al. 2007).

University administrators have lauded the capacity of cluster hiring initiatives to meet the "grand challenges" facing the United States and the world, such as adapting to climate change, mapping the brain, or ameliorating poverty (Hicks 2016). One campus website proclaimed that interdisciplinary hiring "underscores our commitment to innovation in the pursuit of solutions to some of the world's most pressing problems" (Arizona State University 2019). Another university webpage states that its cluster hiring program "echoes a nationwide movement through which universities are using their intellectual capital and research infrastructure to address 21st-century grand challenges" (University of Tennessee Knoxville 2018). Similarly, Lehigh University's website proclaimed, "Together (cluster hire) scholars can provide the critical mass necessary to cross new frontiers in teaching and research while addressing some of the world's most pressing problems" (Lehigh University 2019) and the University of Central Florida claimed that its cluster hire program "fosters the development of strong, interdisciplinary team focused on solving today's toughest scientific and societal challenges through teaching and research" (University of Central Florida 2019).

[1] The contemporary era of heightened interest in interdisciplinary organization dates to the mid-1980s when Congress, and both the National Science Foundation and the National Institutes of Health used augmented budgetary appropriations to initiate large-scale center grants, as well as many smaller-scale initiatives, such as NSF IGERTS (graduate student training grants). Although federal guidelines for these centers did not explicitly require interdisciplinary teams, these teams were widely considered to be important factors in successful applications (Bozeman and Boardman 2003; Brint 2005). At the state level, interest in the capacity of universities to contribute to state economic development goals was also heightened (Feldman et al. 2014).

Proponents of cluster hiring contrast it with the perceived narrowness of traditional, department-based hiring. They characterize departments as detached "silos" that are not well adapted to the contemporary research environment, contending that departments lack the nimbleness to innovate quickly and therefore slow the circulation of new perspectives and methods. They also cite a tendency of departmental faculty to reproduce their existing subfields rather than thinking creatively about the future (see, e.g., Association of American Universities 2005; National Academies 2005).

Despite the optimistic appraisals of the potential of cluster hiring, empirical evidence is scant to support the benefits advocates claim for it. The existing research has been based on work at a single (Dahlander and McFarland 2013) or pair of institutions (Sá 2008b) or as self-assessments by campus review committees (University of Wisconsin-Madison 2003). These studies have identified examples of successful collaborations, such as the agro-ecology (Patton 2015) and women's health (Greenberger 2002) clusters at the University of Wisconsin-Madison but they lack a comparative perspective both in terms of type of cluster and variation in institutional environment. One multi-site study exists, and it is based on interviews with administrators rather than a study of the experiences of faculty hired into clusters (Urban Universities 2015). Because the existing research is limited in scope, a broader investigation is required to evaluate the success of cluster hiring across demographic groups, cluster fields, and institutional environments.

Research Questions and Hypotheses

In this paper, we investigate the research output, collaborations, and research impact of cluster hire faculty at eight research university campuses as part of a U.S. national study of cluster hiring. We investigate one baseline and one more challenging question. The baseline question is whether the research output and collaborations of cluster hire faculty increase after they are hired into clusters. The second, more challenging question is whether researchers hired into clusters successfully pursue "high-impact" research. The latter question is more challenging to answer because no definitive criteria exist by which to identify "high-impact" research. In this paper we consequently develop criteria for measuring "high-impact" research.

Specifically, we investigate the following four research questions:

(1) Does the research output and do the collaborations of faculty researchers increase after their hire into clusters?
(2) Are increases in research output and collaborations concentrated in specific demographic groups, cluster fields, and institutions?
(3) Are cluster hire faculty more likely to engage in high-impact research after their hire into clusters?
(4) Are increased recognitions for research impact concentrated in specific clusters by demographic groups, cluster fields, and institutions?

We form our hypotheses on research output and collaborations from the optimistic expectations put forward by advocates of interdisciplinary research. We anticipate that the stimulation of new colleagues, the collaborative environment of clusters, and the advantages of recruitment into areas of institutional priority will, on average, lead to improvements in the research output and increased collaborations of faculty members hired into clusters.

H1: On average, faculty research output and collaboration will increase following hiring into clusters.
H2: On average, faculty recognitions for high-impact research will increase following hiring into clusters.

Advocates suggest that the benefits of interdisciplinary organization are widespread rather than distributed. They argue that all faculty members, regardless of rank or demographic characteristics, can benefit from the joining together of different specialists in the common pursuit of new knowledge (see, e.g., Crow and Dabars 2015; Klein 1990, 1996). We consequently also frame hypotheses regarding the distribution of outcomes from the optimistic expectations put forward by advocates of interdisciplinary research.

H3: Increases in research output and collaborations will be proportional across demographic groups and institutions.

H4: Increases in research impact will be proportional across demographic groups and institutions.

We note that the latter two hypotheses are inconsistent with findings of researchers who have studied inequalities in the professorial work force. This literature suggests that white males tend to be over-represented in leading positions in scientific disciplines, while women and minorities struggle to advance (Ceci and Williams 2011; Kao and Thompson 2013; Leslie et al. 2015). Moreover, some fields are better supported by external funders than others. These fields include advanced materials, big data, health sciences, neurosciences, and renewable energy sources (see Brint 2018: 214–226). Non-STEM fields have particular difficulty obtaining external funding (ibid.) The literature also shows that institutional environment has important implications for faculty careers. The advantages of leading universities due to resources, prestige, and peer stimulation are associated with both faculty productivity (Brint and Carr 2017) and career satisfactions (Clark 1987; Hermanowicz 1998). Although we form hypotheses from the optimistic assessments of advocates, we recognize the possibility that positive outcomes may be unequally distributed along demographic, cluster field, and institutional lines.

Data and Methods

Sample

We identified universities that had participated in cluster hiring via a web crawler that searched for higher education institutions in the United States whose websites listed any of the following terms: "cluster hire," "interdisciplinary cluster hire," "interdisciplinary hire," "transdisciplinary hire," or "thematic hire." In addition, we gathered the names of institutions from two other sources, Sá (2008a) and Urban Universities (2015). Through these efforts, we identified 84 institutions that had engaged in cluster hiring as of October 2017.

Bibliometric data are publicly available, but we also collected survey and interview data. We required institutional approval for collecting these latter types of data. Accordingly, we contacted the chief academic officer (CAOs) of each of the 84 institutions, requesting their participation in the study. 32 of the CAOs agreed to allow faculty members at their institutions to participate in the study. Private institutions constituted 25% (21) of the 84 institutions identified as having engaged in cluster hiring, but 19% (6) of those agreeing to participate in the study. We requested lists of faculty members who were hired through interdisciplinary cluster initiatives from the academic personnel offices of these 32 institutions. These requests yielded 509 names of individuals hired into clusters. We eliminated eight participating institutions whose cluster hiring programs were in their infancy. In addition, because we intended to compare the experiences of faculty members hired into the same fields at several different universities, we eliminated three universities whose cluster hiring programs focused on fields that were not represented at other participating institutions. Thus, 21 universities out of the original 32 were included in our final tally of participating institutions.

This study is based on a smaller subsample of individuals and institutions. To ensure that results reflected only those who had established a research record prior to their hiring into clusters, we selected a subsample of faculty members who were active as researchers at least 5 years prior to their hire into a cluster and for at least 5 years at the institution where they were hired into a cluster. All analyses in this paper are based on the individuals included in this subsample. The subsample includes 168 faculty members from eight research universities, six public and two private. We required that each cluster field and each institution have at least five researchers represented in the subsample.[2]

Table 1 provides an overview of the cluster fields and institutions represented in our subsample. The names of institutions are not reported so as to maintain confidentiality. Instead we group institutions by whether they are public or private-non-profits and by whether they are members of the Association of American Universities (AAU) or not. The AAU is an association of the 60 leading American research universities and includes also two Canadian member institutions. Table 1 confirms that cluster hiring is most often utilized to add faculty members in areas that the federal government has identified as research priorities, such as advanced materials, big

[2] Ideally, the study would have included a similar cohort of faculty members who were not part of cluster hires. We requested information from the participating universities on faculty members who were near-matches to those in the sample but were hired through traditional departmental means. Some institutions were unable to identify near matches. The remaining institutions submitted only a few names for matching. We conducted propensity score matching analyses, but could not find any faculty members at the participating institutions who were close enough on all potentially relevant dimensions to conduct comparative analyses of matched individuals.

Table 1 Cluster themes and types of institutions, productivity sample

	Freq.	Pct.	Cum. Pct.
A. Cluster type			
Advanced materials	19	11.3	11.3
Big Data	34	20.2	31.6
Climate/sustainability	6	3.6	35.1
Genomics	4	2.4	37.5
Health sciences	28	16.7	54.2
Microbiology	3	1.8	56.0
Neuroscience	18	10.7	66.7
New approaches to arts	10	5.9	72.6
Race/ethnic studies	11	6.6	79.2
Renewable energy	33	19.6	98.8
Security	2	1.2	100.00
Total	168	100.00	
B. Institution type			
AAU public research	68	40.5	40.5
Non-AAU public research	77	45.8	86.3
AAU private research	13	7.7	94.1
Non-AAU private research	10	6.0	100.00
Total	168	100.00	

data, health sciences, neuroscience, and renewable energy sources (see Brint 2018, chap. 6). Both AAU public universities and non-AAU public universities are well represented in the sample. The low representation of private universities is a limitation of the study.

Research Output and Collaboration Measures

To assess the influence of cluster hiring on faculty members' research output and collaborations, we collected data on all publications authored or co-authored by respondents, the number of citations each paper had received through 2018 in Clarivate Analytics' Web of Science, and the number of collaborators on each paper. For book publication and book citations we used Google Scholar as our data source, because books are not fully represented in the Web of Science.[3] We also collected data on the number of grants received each year and the size of these grants. We collected grant information through three methods: (1) by requesting data directly from

[3] Google Scholar is more generous than Web of Science in citation counts because it includes a larger source base and also includes citations from books. This would potentially introduce bias into the analysis. Because we do not analyze citation counts, we minimize the risk of bias with respect to citations. However, book writers may have a smaller number of publications and fewer collaborators than those who published only articles. This could bias statistics for book writers downward. Characteristics of the sample limit the potential for bias; only 5% of the individuals in the sample published any books during the period studied, and all of these individuals also published articles.

the Office of Research at each institution, (2) by gathering relevant grant information from cluster hire faculty members' curricula vitae, and (3) by inquiring directly to cluster hire faculty members. We obtained complete grant information from 82 of the 168 individuals whose careers spanned at least 5 years prior to and following their hire into clusters.[4] We included only externally-funded grants in these analyses.

Citation counts remain immature even 5 years after hire and citation trajectory varies by discipline, journal, topic, and other factors (Baumgartner and Leydesdorff 2013; Bornmann et al. 2014). It remains beyond the capacity of bibliometric scholars to accurately project citation trajectories from immature data. Our research output and collaboration analyses consequently exclude citation counts and are based on the following four measures: (1) publications per year, (2) grants per year, (3) grant dollars per year, and (4) collaborators per paper.

As Table 2 indicates, most of the individuals in our subsample were productive, highly collaborative researchers prior to their hire into clusters. They averaged nearly three publications per year and four co-authors per paper prior to being hired into clusters. Individuals with grants data averaged one half grant per year prior to hire, with an average grant value of approximately $280,000. Publications, numbers of co-authors, grant numbers and grant funding all increased on average after respondents were hired into clusters. Mean number of publications per year jumped to more than five, and co-authors per paper increased to nearly five. The average number of grants per year nearly doubled to just under one per year, and average grant amounts per year more than doubled to approximately $580,000, with a notably high standard deviation ($659,000).

Research Impact Measures

We categorized research impact using three measures:

(1) *National-level awards* are recognitions that researchers have made important advances. We included election to one of the national academies (including the American Academy of Arts and Sciences, the National Academy of Education, the National Academy of Engineering, the National Academy of Medicine, and the National Academy of Science); top national awards from professional associations, and, for younger scholars, NSF CAREER awards and Presidential Early Career Awards for Scientists and Engineers (PECASE), the two highest forms of recognition for early career scientists and engineers. We did not count disciplinary awards unless they were among the highest level awards the discipline had to offer. We collected award data from respondents' CVs, from their campus websites, and from news sources discussing the researchers' work.

(2) *Grants from federal agencies* for amounts of $2 million or more. Grants at this level represent less than 1% of NSF and NIH awards (authors' calculation from

[4] We initially attempted to collect all grants data from institutions. We were able to obtain only a small portion of the data from institutions. We subsequently contacted each person in the subsample three times with requests to provide grants data.

Table 2 Descriptive statistics

	N	Mean	SD
A. Independent variables			
Academic rank	168	2.5	1.34
AAU Ph. D. institution	167	0.68	0.47
Book authorship	167	0.05	0.23
Gender	168	0.72	0.45
Race/Ethnicity	168	1.43	0.63
Years since Ph. D.	165	18.8	10.3
B. Dependent variables			
Change in publications per year	166	3.6	4.3
Change in grants per year	86	0.78	0.89
Change in grant dollar amount per year (logged)	83	12.2	2.3
Change in collaborators per paper	165	3.6	4.3
Total research impact	168	0.76	1.2

Coding for variables is as follows: Academic rank: (1) Assistant professor, (2) Associate professor, (3) Full professor. AAU Ph.D. Institution: (0) non-AAU, (1) AAU. Book Authorship: (0) No books, (1) Authored book(s). Gender: (0) Female, (1) Male. Race/Ethnicity: (1) White, (2) Asian/Asian-American, (3) Under-represented minority

data provided by NSF and NIH). They are indicative of research programs of unusual performance and promise and include all large-scale center and training grants awarded by federal agencies. We collected grants data from respondents' CVs and from federal grant registries that allow for online searches.

(3) *"Other" recognitions* indicating high-impact research. We used the "other" codes primarily for press reports highlighting breakthrough research but also for such indicators as ISI recognitions of "essential" and "top cited" researchers. We also included a lead author of a report that formed the basis for the Paris climate accord, a researcher who had been recognized three times by his university for "breakthroughs of the year," researchers with five or more patents to their names, founders of sizable spin-off firms, and directors of research centers with budgets and endowments totally over $10 million. We collected these data from respondents' CVs, campus websites, and from news sources. A complete list of the "other" recognitions we coded is included as Appendix Table 7.

Awards and recognitions meeting the criteria we have set for high impact are comparatively rare events; fewer than 5% of the sample had received more than one major award or recognition either prior to or after their hire into clusters.[5] We

[5] In general, it is not more difficult for scholars who have won awards for their research to win additional awards; if, anything, the "Matthew Effect," (the notion that small differences in perceived status tend to result in benefits or disadvantages that subsequently lead to larger differences in status) (Merton 1968) still pertains in science (Bol et al. 2018; Perc 2014).

consequently did not use numerical counts but only counted whether or not the researcher had received a major award, very large grant, or "other" indicator of prominence either before hire, after hire, or both before and after. We coded "1" for awards and recognitions meeting these criteria and "0" when awards and recognitions were absent. Thus, we coded six possibilities for "1" counts: (1) major award(s) prior to hire, (2) very large grant(s) prior to hire, (3) other significant recognition(s) prior to hire, (4) major award(s) after hire, (5) very large grant(s) after hire, and (6) other significant recognition(s) after hire.

The members of the subsample were less likely to have received recognition for the impact of their work prior to their hiring into clusters than after their hiring into clusters. Altogether, 14% of the individuals in the subsample had received any of the recognitions we used to identify high impact research prior to their hire into clusters, while 40% achieved such recognitions after their hire into clusters (see Table 2).

Independent Variable Measures

Gender, race/ethnicity, and rank are the demographic variables most often discussed in the literature on the structure of inequality in academe (see Finkelstein et al. 2016: chaps. 8–9). Accordingly, we include gender, race/ethnicity, and academic rank in regression models. Gender is coded 0 for female and 1 for male. Race/ethnicity is coded 1 for white, 2 for Asian/Asian-American, and 3 for under-represented minorities. Academic rank is coded 1 for assistant professors, 2 for associate professors and 3 for full professors. We also measure whether members of the subsample received their doctorates from AAU or non-AAU institutions and the number of years since they received their doctorates. Doctoral institution is a potentially relevant measure of academic status. Seniority, as measured by years since doctorate, can lead to cumulative advantages for resource productive scientists (see Hermanowicz 1998). We control for those members of the sample who wrote books, because of the potential negative effect of book publication on research output and number of collaborators.

As Table 2 indicates, the subsample is composed primarily of men (72%) and whites (64%). Asian and Asian American researchers represent 28% of the sample. Under-represented minorities (African Americans, Hispanics, and Native Americans) represent just 8% of the subsample. The modal academic rank category was full professor (43%). Associate professors constituted 23% of the subsample and assistant professors 34%. Two-thirds of the members of the subsample obtained their doctorates from AAU institutions. The mean number of years since completing that doctorate was over 18, with a notably high standard deviation. Only 5% of the individuals in the subsample had authored or co-authored books.

We include the following eight cluster fields in regressions: (1) advanced materials, (2) big data, (3) climate/sustainability, (4) health sciences, (5) neuroscience, (6) new approaches to the arts, (7) race/ethnic studies, and (8) renewable energy, with race/ethnic studies as the reference category. The best represented fields in the subsample are big data (21%), renewable energy (21%), and health sciences (18%).

They are followed by advanced materials (12%), neuroscience (11%), race/ethnic studies (7%), new approaches to the arts (6%), and climate/sustainability (4%).

We include eight institutions in the regression models. These institutions include two public AAU member institutions, four public non-AAU member institutions; one private AAU member institution, and one private non-AAU member institution, with one of the non-AAU public universities as the reference category. The subsample is composed primarily of faculty members from non-AAU public universities (43%) and AAU public universities (41%). It includes 7% from the non-AAU private university, and 9% from the AAU private university (see Table 2).

Methods

To evaluate H1 and H2, we tested whether or not there were significant differences pre-hire to post-hire in research output, collaboration, and impact. We utilized t-tests to examine these differences. To evaluate H3, we utilized linear regression analysis to measure the degree to which observed changes in research output and collaboration pre-hire to post-hire were associated, net of covariates, with researcher demographic characteristics, cluster field, and institutional locations. We estimated models based on researcher demographic characteristics and cluster field regressions separately from those based on researcher demographic characteristics and institutional location. We opted to utilize separate regressions for these predictors to maximize the number of categories where the N is reasonable. We also sought to avoid overfitting the models due to adding more predictors than warranted by our sample size. To evaluate H4, we generated a count of our binary high-impact codes. This count ranges from 0 (i.e., no high-impact research) to 6 (i.e., high-impact research in all three categories, awards, grants, and other, both before *and* after hire). We opted to utilize this count in our regressions because the difference models (pre-to-post hire) lacked sufficient variation, as 68% of the sample had a score of zero on difference in research impact before to after cluster hire. When we investigated these scores conditional on several of our variables of interest, including cluster theme and institution, the lack of variation was even greater. Many of the categories of these two variables lack sufficient variation in outcomes with which to reasonably perform hypothesis testing. We utilized negative binomial regression, rather than Poisson, because our outcome's conditional variance exceeded its conditional mean in many categories of our predictor variables (Long and Freese 2006). For all of the regression analyses, we dropped any cluster field or institution that had an N of fewer than five.

Supplemental Interviews

To supplement the statistical analyses we conducted interviews with 12 administrators at six of the subsample universities. These interviews lasted between 30 and 60 minutes and were conducted by the senior author. We draw on these interviews to provide additional contextual information about the organization and outcomes

Table 3 T-tests of output and collaboration differences pre- to post-hire

Dependent variables	Pre-hire	Post-hire	Difference	Sig
Change in publications per year	2.8	5.3	2.5	***
Change in grants per year	0.48	0.90	0.42	***
Change in grant dollar amount per year (logged)	12.7	13.0	0.26	
Change in collaborators per paper	4.1	4.9	0.76	**

of cluster hiring at universities in the subsample. We also draw on interviews with administrators from one institution not included in the subsample. These latter interviews were particularly relevant for understanding why less prestigious universities may have difficulty mounting broadly successful cluster hiring programs (see Bloom et al. 2019).

Results

Research Output and Collaborations

In Table 3, we report the results of the t-tests we used to identify significant differences in mean publications per year, mean number of external grants per year, mean dollar amounts of external grants per year, and mean collaborators per paper prior to and after hire into clusters.

These results, on balance, support H1. In three of the four areas of research output and collaboration, we found a statistically significant positive gain post-hire. Gains in publications per year were in the order of +2.6 publications after hire, while gains in the number of grants per year were +0.42 grants after hire. We found average gains of approximately $300,000 post-hire for grant dollar amounts. We also found a small, but significant, boost (+0.76) in the number of collaborators per paper after hire. For grant dollars per year (logged), we did not find significant differences pre- to post-hire.

In Table 4, we report the research output regressions for pre-hire/post-hire differences in the research output and collaboration with cluster field included in the model as a predictor. The results show that researchers in fields that are well supported by external funders tend to receive larger boosts from joining clusters and that men also benefit disproportionately in relation to obtaining grants. Increases in collaboration were widespread across the subsample.

Column 1 provides the results for publications per year. Scholars working in the areas of advanced materials, renewable energy, and health sciences showed significant gains in publications per year compared to those working in race/ethnic studies. In column 2, we report the results for change in number of grants per year from pre-hire to post-hire. Here, we find additional evidence against H3 showing that the gains of cluster hiring programs are not equally distributed. Men showed significant gains in the number of grants per year. Column 3 provides results for grant dollar

Table 4 Regressions of research productivity on cluster hire demographics and cluster fields

	(1) Publications per year	(2) Number of grants per year	(3) Grant dollars (log) per year	(4) Collaborators per paper
Underrepresented minority	REF	REF	REF	REF
White	1.048	−0.187	−0.367	−0.0501
	(0.763)	(0.245)	(0.842)	(0.572)
Asian/Asian-American	0.121	−0.591	−1.206	0.982
	(1.017)	(0.329)	(0.972)	(0.618)
Male	−0.252	0.539**	0.729	−0.316
	(0.608)	(0.161)	(0.704)	(0.779)
AAU Ph. D. institution	0.690	−0.0203	0.493	−0.0780
	(0.587)	(0.173)	(0.666)	(0.634)
Years since Ph. D. granted	−0.0425	−0.00749	0.0491	0.0684
	(0.0538)	(0.0116)	(0.0316)	(0.0378)
Record has books	−1.300			−0.379
	(0.661)			(0.704)
Assistant professor	REF	REF	REF	REF
Associate professor	−0.00608	−0.197	−0.845	1.764
	(0.742)	(0.269)	(0.806)	(1.011)
Professor	1.094	−0.578	−0.996	1.392
	(1.407)	(0.402)	(0.777)	(1.089)
Advanced materials	2.451*	0.0143	4.999	1.288
	(1.108)	(0.409)	(2.666)	(0.911)
Big Data	1.028	−0.294	5.158	−0.552
	(0.875)	(0.400)	(2.676)	(0.688)
Climate/sustainability	3.130	0.341	4.131	1.833
	(1.876)	(0.673)	(3.321)	(0.965)
Health sciences	3.004***	0.316	5.995*	−0.188
	(0.861)	(0.332)	(2.555)	(0.692)
Neuroscience	1.524	−0.340	5.892*	1.860
	(0.958)	(0.412)	(2.573)	(1.188)
New approaches to arts	−0.692	0.155	1.654	−0.602
	(1.242)	(0.381)	(2.639)	(1.334)
Race/Ethnic studies	REF	REF	REF	REF
Renewable energy	2.123*	−0.368	5.044	1.823
	(0.944)	(0.454)	(2.711)	(1.049)
Constant	0.186	0.839	6.405*	−2.092
	(1.169)	(0.460)	(2.545)	(1.160)
Observations	148	76	77	152
R^2	0.143	0.346	0.314	0.190

Robust standard errors in parentheses, *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 5 T-tests of research impact difference pre- to post-hire

Dependent variables	Pre-hire	Post-hire	Difference	Sig
Any research impact	0.14	0.49	0.26	***
Award impact	0.07	0.26	0.19	***
Grant impact	0.08	0.23	0.15	***
Other impact	0.05	0.05	0.00	

amounts per year. Faculty working in health-or medicine-related clusters and those working in neuroscience showed significant gains in grant dollar amounts from pre- to post-hire, compared with those working in race/ethnic studies. Finally, Column 4 provides results for collaborators per paper. In this model, none of the coefficients are statistically significant. In this case, we fail to reject the null hypothesis related to H3.

We found only minor variation by institutions when we substituted institutional location for cluster fields in regressions on the research output and collaboration measures. In these regressions men continued to be disproportionately advantaged in obtaining grants post-hire and again we found broadly distributed benefits for increased collaborations.[6]

Research Impact

In Table 5, we report the results of t-tests we used to identify significant differences in research impact pre- and post-hire. We observed statistically significant gains in high-impact research post-hire, supporting H2. When we divided the impact measures, we found statistically significant gains in two of the three measures: (1) national awards and (2) grants of $2 million or more after hire.[7]

In Table 6, we present the results from the negative binomial regression of total research impact, a combined measure, on researchers' demographic characteristics. We include institution as a predictor. We find that institutional environment is an important factor in attracting and nurturing high-impact researchers. One institution – a wealthy, private AAU university – displayed a significant association with total research impact net of covariates. In addition, two other institutions showed sizable net associations with research impact, though one that did not quite reach statistical significance at $p < .05$. The results also show a significant effect related to years since Ph.D. was granted. White and Asian scholars also showed significantly greater research impact in this model than underrepresented minorities. Together, these results fail to support H4.

[6] These regressions are available in the online supplementary material associated with this paper.

[7] These included 35% of individuals in the subsample who had obtained major academic awards at any time during their careers, 27% who had obtained grants of $2 million or more, and 7% who had other recognitions for high-impact work. 19% of the subsample had obtained more than one of these three forms of recognition and 4% had obtained all three forms of recognition.

Table 6 Negative binomial regression of research impact on researchers' demographic characteristics and institutional locations

	(1) Total research impact
Underrepresented minority	REF
White	2.149*
	(0.782)
Asian/Asian-American	3.201**
	(1.353)
Male	1.017
	(0.198)
AAU Ph.D. institution	1.108
	(0.168)
Years since Ph.D. granted	1.049***
	(0.0119)
Record has books	0.262
	(0.258)
Assistant professor	REF
Associate professor	0.949
	(0.351)
Professor	1.112
	(0.445)
Northeast public	REF
Southwest public	1.084
	(0.611)
Southern public I	0.354
	(0.260)
Southern public II	0.775
	(0.566)
Northeast public AAU	1.555
	(0.759)
Midwest private	1.246
	(0.624)
West coast private AAU	4.154*
	(2.298)
Midwest public AAU	1.280
	(0.716)
Observations	149
Pseudo R^2	0.189

Exponentiated coefficients; Robust standard errors in parentheses, $*p < 0.05$; $**p < 0.01$; $***p < 0.001$

Bivariate analyses help to bring out the extent to which high-impact researchers are concentrated at elite universities. They indicate that a sizable proportion of the most eminent individuals are concentrated at four of the eight universities represented in the subsample. Faculty members from these institutions comprised

58% of the subsample but 75% of those who met at least one of the criteria for high impact. In each case, the proportion of high-impact researchers exceeded the proportion of faculty members in the subsample from these universities. As indicated in the regression, the most prestigious private university in our sample was particularly prominent, with nearly double the proportion of high-impact individuals as compared to its proportion in the subsample as a whole (8% of the sample but 14% who met at least one criterion of research impact.) Our interview with the vice president for research at the university indicated that cluster hiring was used there as a mechanism for recruiting very accomplished senior scholars. These exceptional individuals continued to make important contributions and to win prestigious awards following their appointments to positions at this prestigious private university. The other three notable institutions included two AAU public universities, both well known for research excellence, and one public university known as an up-and-coming innovator.

We found a scattering of high-impact achievements among researchers at the other institutions in our subsample. These included an important astrophysicist at a public research university in the South; an acclaimed terrorism expert at another public research university in the South; a well-recognized engineer working on solar cell technology at a small public research university in the Northeast; and a computer security specialist at a private university in the Midwest. However, a larger proportion of individuals at these non-core institutions failed to gain any marks of high-impact distinction, according to our criteria. They constituted 42% of the sample but only 25% of the researchers with high-impact distinctions.

When we substituted cluster field for institution, the results were less conclusive and weaker in explanatory power. Here too, years since Ph.D. was a significant predictor of research impact. No other demographic characteristics showed a statistically significant relationship with our research impact measure, and we found few significant net associations for cluster fields.[8]

Discussion

Interdisciplinary cluster hiring initiatives have become popular in the United States as a means to increase faculty output, collaborations, and research impact. Two important purported benefits of such practices are that (1) they create the conditions for stronger scholarly performance and more collaboration among those hired into clusters and that (2) they are especially important for the production of high-impact research that can help to solve the country's most pressing social and economic problems. In this paper, we subjected these claims to empirical scrutiny.

We found that cluster hiring is associated with significant gains, on average, in faculty research output, collaborator numbers, and research impact from pre-hire to post-hire. Faculty publications per year, number of grants per year, grant dollar amount per year, and number of collaborators per paper all increased significantly

[8] These regressions are available in the online supplementary material associated with this paper.

(and in the case of publications and grant amounts also sizably) after hire for those in our subsample. Increased productivity and impact during the course of the career are not uncommon among professors working at research universities (Way et al. 2017). Nevertheless, the consistency and the size of the changes post-hire for members of this cluster hire subsample are impressive. Another finding supportive of cluster hiring is the statistically similar, if modest, boost we found in collaborations post-hire across demographic groups, cluster fields, and institutions.

On most measures of output and impact, we found that certain groups benefitted more from being in a cluster. Men were more advantaged than women in obtaining grants after being hired into clusters. Whites and Asians were more likely to achieve markers of high-impact research than members of under-represented groups, and so were more senior scholars. Researchers in fields that are well supported by external funders showed stronger gains in publications and grant dollars post-hire. The fields that most consistently rose to the top in this study are advanced materials, health sciences, and neuroscience. Institutional location mattered more for research impact than research output. Wealthy and prestigious institutions were more likely to recruit and successfully nurture high-impact researchers.

The research suggests that faculty members in fields that face a resource rich funding environment will tend to fare better than those in fields poorly supported by external funders. We would characterize this finding as very nearly self-evident if not for the expansive claims for across-the-board gains made by advocates of cluster hiring. These findings suggest that universities that have chosen the strategy of employing cluster hiring broadly are in most cases trading off better targeted investments for the possibility of broader campus support.

Elite universities have multiple advantages for attracting and nurturing high-performing scholars, including those hired into clusters. Their ample resources, high-expectation cultures, and prestige make them attractive to talented faculty members they are interested in recruiting and enhance the likelihood that those appointed will continue to produce high-quality work (Brint et al. 2006). While other institutions in our subsample hired a few scholars recognized for the quality and significance of their work, they lack the resources and stature to hire and retain top researchers across more than a few fields. Our findings illustrate the continuing relevance of the "Matthew Effect" in science (Merton 1968).

Our interviews with administrators elicited some additional reasons why cluster hiring is unlikely to serve as a means to level the playing field among research universities.[9] One of the eight institutions represented in the subsample, the private AAU research university, is wealthy enough to "buy the best" in areas it has chosen to develop through cluster hiring. The hires are in the great majority of cases people who have already worked together and demonstrated a record of high-impact research prior to their appointments. The university is able to attract these individuals by offering higher salaries and usually also better facilities and equipment than were available to them at their previous institutions. A strong network of donors

[9] In this section we draw selectively on interview data also used in Bloom et al. (2019).

helps to facilitate these relocations by providing funds for new centers and state-of-the-art equipment.

Another of the eight universities, one of the AAU public research universities, has perfected mechanisms for recruiting talented junior faculty members and placing them in situations that can enhance their productivity and impact. These tools include recruitment of individuals who express an interest in collaborating with existing cluster members, seed grants for collaborative proposals, funding for seminars, explicit memoranda of understandings between organized research units (ORUs) and departments about expectations, joint funding of lines by ORUs and departments, and the purchase of expensive shared equipment as a locus for collaborative activity. Another high-performing university in the sample has built its clusters around veteran professors who know the university well and are highly regarded by their colleagues. Many are center directors. These individuals form clusters by recruiting junior faculty whose work is highly compatible with their ongoing activities and centers (see also Sá 2008b).

On the end of the spectrum, administrators at three of the eight institutions, and a fourth institution we use here for illustrative purposes, said they employed none of these mechanisms to encourage collaborations. Each of these four were non-AAU public universities. For these institutions, the campus level planning was largely limited to identifying cluster topics, planning for facilities' needs, and hiring individuals into clusters. The institutions seemed to lack the resources, and in some cases, the administrative competence to make the most of the opportunities afforded by cluster hiring.[10] Faculty pushback occurred at each of these universities.

> There were more losers than winners among the solicited proposals, which led to a lot of disappointment…The deans felt that the clusters took funding from their needs…They felt disenfranchised.
> - *Cluster lead, non-AAU public university*

> Instead of a deliberative process, we had a chaotic process in a rush to make major investments after (the campus) had announced a major initiative to hire hundreds of new faculty…Most of the hiring was to be done through clusters…. The deans eventually pushed back and got more control.
> - *Vice-chancellor for Research, non-AAU public university*

> I was surprised by the virulence of the opposition…If I were beginning all over, I would work harder at communicating what this was and what this wasn't. I would try to dispel the mythology that developed…
> - *Provost, non-AAU public university*

[10] One vice-president for research said that as many as 75 newly recruited faculty at his institution did not have labs available to them when they arrived on campus – or a timeline specifying when the labs would be ready. This was an extreme case, but not the only one demonstrating a failure to match hiring plans with facilities requirements.

Opaque processes for choosing successful proposals, no planned features to encourage collaboration, insufficient money to guarantee adequate facilities for newly recruited faculty, and no metrics by which to evaluate their impact were common in these initiatives.

> If we could start over, I would want a more transparent process to evaluate proposals with metrics for assessment purposes. I would have gone more slowly…. Because of a change in the budget model (that occurred simultaneously), the provost's office did not know what commitments were being made (by the colleges) for start-up packages, and we ended up overspending for start-ups.
> - *Provost, non-AAU public university*

> We were going to launch into the third round of cluster hiring when the financial crisis hit. We had to give back \$120 million to the state and that eroded some of the existing allocated dollars…This led to a lot of disappointed people.
> - *Cluster lead, non-AAU public university*

Several of these institutions also experienced disruptive leadership transitions. In one case, a president committed to cluster hiring left and was replaced by a new president with different priorities. In two other cases, provosts who led the initiatives were replaced after faculty pushback led directly or indirectly to their departures. New provosts scaled back the initiatives or ended them entirely.

In sum, we find evidence of increased output, broader collaboration, and more frequently recognized impacts post-hire for a sample of individuals hired into clusters. These findings amply demonstrate the promise of cluster hiring. But the findings also point to an unacknowledged feature of cluster hiring, lost in the hyperbole surrounding its presumed contributions – namely, that its benefits are unequally distributed across demographic categories and by field and institutional location. These findings should serve as a particular caution to university administrators at non-elite institutions who anticipate that large-scale cluster hiring initiatives can be used as a means for vaulting their institutions above the competition.

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Appendix

Table 7 "Other" recognition codes

Recognition type	Freq.
Director of institute with budget over $20m	3
Recognition as top-cited researcher	3
At least five patents	2
Founder of at least one business	2
Lead author on major international report	1
Founder of study resulting in hundreds of publications	1
Well known scholar with many media appearances	1
Total	13

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