Received: 10 March 2023 | Revised: 21 February 2024 | Accepted: 1 April 2024

DOI: 10.1002/asi.24895

RESEARCH ARTICLE

JASIST WILEY

To move or to be promoted: Examining the effect of promotions and academic mobility on professors' productivity and impact

Chaojiang Wu[1] | Erjia Yan[2] | Chaoqun Ni[3] | Jiangen He[4]

[1]Ambassador Crawford College of Business and Entrepreneurship, Kent State University, Kent, Ohio, USA

[2]College of Computing and Informatics, Drexel University, Philadelphia, Pennsylvania, USA

[3]Information School (iSchool), University of Wisconsin-Madison, Madison, Wisconsin, USA

[4]School of Information Science, University of Tennessee, Knoxville, Tennessee, USA

Correspondence
Erjia Yan, College of Computing and Informatics, Drexel University, Philadelphia, PA 19104, USA.
Email: ey86@drexel.edu

Abstract

Promotions and academic mobility are trajectory-altering events in a researcher's career. This paper compiles a unique large data set and investigates publication and citation differences between two groups of researchers: the ones who are mobile and their counterparts who stay at a university with a promotion. This paper finds that mobile researchers often have a lesser productivity increase than their post-promotion counterparts. The difference is largely driven by male professors in physical science and clinical health fields moving from more research-intensive to less research-intensive institutions. In contrast, the citational impact differences between the two groups are largely minimal.

1 | INTRODUCTION

Academic mobility is a fundamental element of the scientific workforce. Given the chance, scientists often choose to move to other institutions for a variety of career-, family-, or geopolitical-related reasons. They typically seek to move to institutions that offer better research resources, higher pay and provide clearer career advancement opportunities. Their family's well-being also plays an important role in the decisions that lead to scientists' mobility: stability and work-life balance are prioritized when making decisions about changing institutions.

The impact of an academic move on one's career manifests differently, predicated on disciplines, genders, and institutional elitism. Certain disciplines such as biology and physics tend to have higher concentrations of foreign-born scientists while scientists in some disciplines make significantly fewer moves (Laudel, 2005). Due to the common societal expectations of higher-level engagement for women in family life, women scientists are often hesitant to move because such an action would disrupt the family, especially those whose children attend secondary schools (Azoulay et al., 2017). Additionally, scientists from elite institutions tend to move to other elite institutions. However, for scientists from non-elite institutions, their upward moves are often fraught with obstacles (Hunter et al., 2009; Laudel, 2005).

There is a large body of literature on academic mobility, often centered on international academic moves and the consequences of regional brain drain. Methods including trend statistics and historical analysis have been employed to study the matter (Docquier et al., 2012; Ioannidis, 2004; Sugimoto et al., 2017; Velema, 2012). In the past few decades, studies have revealed a general intercontinental mobility pattern from the South to the North and the East to the West though more recently a reverse mobility pattern, particularly from the West to China (Marini & Yang, 2021). Countries that welcome international researchers and encourage cross-border collaboration tend to produce papers with high scientific impact (Wagner & Jonkers, 2017).

This research joins the literature on domestic mobility (e.g., Bernela et al., 2017; Dietz et al., 2000; He et al., 2019; Peng et al., 2023; Woolley & Turpin, 2009).

Our research focuses specially on domestic academic mobility within the United States. Our research setting is different from many prior studies where mobility was tracked at two different points of time using two geographic locations: postgraduate (i.e., PhD) institutions and current working institutions (e.g., He et al., 2019). Our method utilizes a large data set of researchers who exhibited mobility at any point of time in their careers and their counterparts who stayed throughout the observational duration. The publications and citations of mobile and promoted researchers are also retrieved. This unique dataset enables us to match and compare mobile researchers (i.e., those who changed institutional affiliations) and promoted researchers while controlling for possible differences in their gender, discipline, and institutional research intensity. While productivity and citation counts are expected to increase for both academic events, the use of carefully cleaned data and the distinction between move and promotion makes it possible to delineate confluence of the two major academic events.

2 | LITERATURE REVIEW AND RESEARCH QUESTIONS

2.1 | International academic mobility

Quantitative studies have described the general characteristics of global academic mobility. In a study of 1523 highly cited scientists, Ioannidis (2004) found that 31.9% of these scientists did not reside in the country where they were born, but great variability has been shown across developed countries and across different disciplines in the proportions of foreign-born scientists. In a large-scale study of 16 million scientists, results showed that 4% of scientists made international moves based on their publication affiliations (Sugimoto et al., 2017). Van Der Wende (2015) found that intercontinental mobility exhibited patterns in which scientists move from the South to the North and from the East to the West.

The United States is the top destination country for mobile scientists and is perceived as a destination for advancing one's research career (Bland & Van Noorden, 2012; Franzoni et al., 2015; Ganguli, 2015; Veugelers & Van Bouwel, 2015). A major reason individuals reported moving to train in the United States is the prestige of its programs and its bountiful career prospects (Stephan et al., 2016). However, foreign-born American scientists are likely to return to their home country when the country becomes more scientifically developed (Darby, 2014). Studies also suggested mobility is distributed unequally among disciplines (Cañibano et al., 2011; Laudel, 2005). For example, fewer Russian immigrants came from the field of chemistry and more from physics (Ganguli, 2015). In Italy, psychology is the discipline with the highest concentration of foreign scientists (Abramo et al., 2019).

There is a consensus that the international mobility of scientists is making human capital scarcer where it is already scarce and more abundant where it is already abundant (Docquier et al., 2012). Unsurprisingly, elite scientists migrated systematically towards nations with large research expenditures (Hunter et al., 2009; Kato & Ando, 2017) and mobility occurred more among emerging scientists rather than established elite researchers (Laudel, 2005). Elite scientists also tended to move from places with fewer peers in their discipline to places with more peers, which led to a geographic concentration of star scientists over time (Darby, 2014).

2.2 | Mobility and productivity

In the context of mobility and productivity, literature generally studies two kinds of mobility: one measures the "true" mobility from a working institution to another during a researcher's career and the other measures the mobility of researchers from postgraduate institutions to current working institutions. The former stream of research investigates general patterns of changing institutions during a researcher's career for a few disciplines. For instances, Allison and Long (1987) and Debackere and Rappa (1995) focus on prestige between universities; Rosenfeld and Jones (1986) studies mobilities of psychologists; Deville et al. (2014) documents the mobility of physicists among elite institutions and between elite and lower-rank institutions; Payumo et al. (2018) focuses on researcher affiliations variations for researchers of a research-intensive university during a 10-year period. The latter stream of research documents, measures, and explores mobility from graduating institutions for different disciplines in a country (e.g., Clauset et al., 2015; He et al., 2019; Peng et al., 2023; Zhu & Yan, 2017). This stream tended to use larger data sets and reveal more generalizable results. The work by Clauset and colleagues (Clauset et al., 2015; Lee et al., 2021) included more than 16,000 tenure-track or tenured faculty at 461 PhD-granting Business, Computer Science, and History departments in the United States and Canada. They found a steep hierarchical structure within the faculty placement and hiring network in which elite programs dominated the supply of talents in the three disciplines. A recent work by the team of authors significantly expanded the scope of the data by including more than a quarter million faculty members from all disciplines at close to 400 U.S. higher education institutions (Wapman et al., 2022). A similar observation was made that universal inequalities were found in faculty placement and hiring in which a small minority of elite universities supplied a large majority of faculty across fields.

Researchers with foreign work experience tended to publish more articles in high impact factor journals as first or last authors than their counterparts who have not been abroad (Jonkers & Cruz-Castro, 2013). Additionally, migrants performed at a higher level than domestic scientists with or without prior experience of international mobility (Franzoni et al., 2014; Halevi et al., 2016). However, Hunter et al. (2009) found the average productivity of elite movers is not different from that of elite stayers among highly cited physicists. In a study of 350 foreign scientists in Italy, their scientific performance is, on average, better than that of their domestic colleagues, but there are also notable shares of unproductive foreign professors or those with mediocre performance (Abramo et al., 2019). Cao et al. (2019) analyzed Chinese researchers who had overseas training and work experience. The study showed Chinese returnees published work with higher impact and continued to publish in more esteemed venues than their domestic counterparts. Among Chinese researchers returning home, researchers with more academic moves tended to have higher scientific outputs (Jonkers & Tijssen, 2008). Ejermo et al. (2020) also found that mobility across universities induces a long-lasting increase in a researcher's publications by 32% and that the positive effect of mobility applies to researchers in medicine, natural sciences, and engineering and technology. Mobile researchers who changed affiliations during their scientific career tend to have slightly higher publication and citation rates than other researchers (Aksnes et al., 2013). However, the number of institutions a researcher moved to did not make a significant difference (Halevi et al., 2016). Due to the limited sample size and the highly contextualized nature of these studies, no consensus was made on the effect of mobility on a professor's productivity. The effect of mobility on research productivity is often complicated by socio-epistemological factors such as career stage (Aksnes et al., 2013; Halevi et al., 2016), discipline (Ejermo et al., 2020), institutional profile (Clauset et al., 2015), and gender (Azoulay et al., 2017; Moskal, 2020; Sugimoto, 2022; Sugimoto & Larivière, 2023). To better control for these factors, our research compiles a distinctive dataset by uniquely identifying researchers using their ORCID and locating their associated publications and citations, then further identifies the differences in publications and citations between mobile researchers and their counterpart who stay with their institution with a promotion.

2.3 | Mobility and career advancement

In a study of 345 women scientists, McLean et al. (2013) found a positive relationship of geographic mobility that coincided with advancement in administrative positions. International research visits have been found to have a positive effect on promotion and reduce the waiting time for promotion in Japan (Lawson & Shibayama, 2015) and in Argentina (Jonkers, 2011). However, multiple mobility effects may delay career advancement (Ryazanova & McNamara, 2019) and was typically associated with subsequently lower earnings (Tohmo & Viinikainen, 2017).

Although a promotion in academic advancement may bring more research opportunities and resources, a promotion coupled with a move may not significantly increase the positive effects on research performance. In a study of Swedish researchers, movers who are simultaneously promoted do not show a statistically significant different publication rate than movers who are not promoted, which suggests that mobility itself explains the positive effect of mobility on productivity, not promotion (Ejermo et al., 2020). Another recent study of Italian researchers also suggested that the presence of concurrent promotion in an academic's move does not appear to impact their research performance (Abramo et al., 2022). Our general research questions are described below.

Given equal research productivity prior to moving events (a researcher changing institutions), how does the productivity of a mobile researcher differ from a non-mobile researcher who received a promotion? If there are any differences, are the differences between the two groups also heterogeneous across different disciplines, between genders, and across universities of different research intensities?

2.4 | Data

The 2018 version of ORCID data was collected through figshare (Blackburn et al., 2018). We limited researchers to U.S. tenure-track or tenured professors. We developed a rubric to identify tenure-track and tenured professorship in ORCID. Only profiles that were last updated in October 2016 or later were included. In total, 47,044 professors met the criteria; among them, 38,426 did not have a change in rank or organization and were not included in the current analysis. The remaining 8618 professors made 12,671 changes in rank or organization. After treating data anomalies, including missing employment starting or ending years and a lack of match between ORCID institution names and those from the Carnegie Classification of Institutions of Higher Education (CCIHE) (Yan et al., 2020), 10,656 position changes remained. We used

CCIHE to identify institutional profiles. The remaining 10,656 records are fully matched with CCIHE; among these, 4718 had only a rank change and 5938 had an organization change (2278 had both rank and organization changes and 3660 had only an organization change) and are included in this analysis. The data is accessible at figshare (Yan, 2020). Detailed data processing procedures can be found in Yan et al. (2020). To obtain professors' publication and citation data, we further linked the integrated intermediary data with Web of Science. We decided not to use the publication list readily on ORCID due to its limited completeness of professors' publication records.

Our team has access to a raw XML version of Web of Science, thus making it possible to measure the yearly numbers of publications and citations for any researcher between 1980 and 2020. However, many publications in Web of Science XML files are not linked to authors' ORCIDs. Retrieving their publications and citations by ORCIDs in the XML files would lead to an incomplete dataset. Thus, we used "researcher search"[1] offered by the Web of Science website to identify the list of publications of a professor. The researcher search enabled us to retrieve a researcher's publications, including the ones that are not explicitly linked to their ORCID. Using the researcher search, each professor was searched by their ORCID, and their publications' unique identifiers in Web of Science were extracted from the researcher search results. The publication identifiers were used to obtain professors' complete publication and citation data from the XML version of Web of Science.

To properly measure the effect of an intervention on the productivity and citation impact on a professor, we need sufficient pre- and post-intervention observational points. We set the threshold for the pre- and post-intervention years of employment to six to match with the general window of pre-tenure time span and the resulting number of records is 4348. In addition, to mitigate the oversized impact of the fluctuations of publication and citation numbers on the analysis, we only consider professors who had aggregated numbers of publications at 10 and set the aggregated number of citations at 100 for a professor during the 12-year span. This procedure resulted in a set of 2436 records which served as the final data in the logistic regression analysis. Among these records, 1490 have the same organizations (promotion only) and 946 have changed institutions (including 416 also with rank change). The arts and humanities observations were very limited, totaling only six so we removed them. The final data for analyses contain 2430 researchers, 1487 of which were promoted and 943 moved. Given 424 professors moved as full professors, there are no counterparts for them in the promoted group as full professor is the highest rank in academia. The ultimate sample for investigating differences of moved versus promoted professors includes only the professors without full professor status before the move. Without getting into the details of matching, which is described in the Methods section below, we simply state that there are a final identified sample of 519 moved professors. Table 2 below further describes the data summary of the included researchers, including distributions of disciplines, key variable differences of the two groups around promotion/move time.

2.5 | Methods

To compare the differential effects of move versus promotion, one could find a professor who stays within the university but otherwise has identical characteristics to the moved professor, such as discipline, gender, rank, employment year, and institutional characteristics (e.g., research intensity, public status, and minority-serving status). However, matching all characteristics over all the dimensions can be extremely difficult, if not impossible. We adopted an alternative method which aims to match the propensity score of a professor moving to another university. The propensity score matching method was developed by Rosenbaum and Rubin (1983) and is used in observational studies. In this study, the propensity score matching intends to find for a professor in the control group of professors a close match within the treatment group in the dimension of similar propensity to move, conditional on given multidimensional observable covariates. We used the moved group of professors as the treatment group and the promoted group as the control group. To implement the propensity score model, the following logistic regression model is used to estimate the propensity of a professor moving to another institution:

$$\Pr(\text{move}) = f\Big(\text{depvar}_{-5}, \text{depvar}_{-4}, \text{depvar}_{-3}, \text{depvar}_{-2}, \text{depvar}_{-1}, \text{control variabls}\Big), \tag{1}$$

where $f(\beta X) = \frac{\exp(\beta X)}{1+\exp(\beta X)}$ is the conventional transformation function of linear predictors for logistic regression and βX is the linear combination of the covariates; "depvar" is the dependent variable (number of publications or citations) used in the regression analysis after propensity score matching. All variables are defined in Table 1. The potential list of control variables includes individual characteristics such as gender, rank, discipline, and employment length of a professor, as well as institutional

TABLE 1 Variable descriptions.

Variable	Descriptions
Publications	Number of publications in a year
Citations	Number of citations in a year
Gender	Gender of professor: Male (1) or Female (0)
Discipline	Discipline of professor: Social, Physical, Life, Engineering, Clinical based on the Global Institutional Profiles Project (GIPP) mapping scheme (http://help.incites.clarivate.com/inCites2Live/indicatorsGroup/aboutHandbook/appendix/mappingTable.html).
Rank	Rank of professor: Assistant, Associate, Full
Employment year	Years since employment in current university
Class	Carnegie classification: R1, R2, Medical School, Other
Type	University public status: public (1) or private (0) based on CCIHE
msi	Minority Serving Institute Status: non-MSI (1) based on CCIHE

characteristics such as class, type, and minority serving status. We choose these control variables for the well-known factors that are associated with mobility and productivity of researchers. For instance, individual characteristics such as gender, discipline, and rank of a researcher are shown to be related to mobility (He et al., 2019), and productivity (Blanden, 2013; Hesli & Lee, 2011; Sandström, 2009). Beside individual characteristics, institutional characteristics also are shown to be related to mobility (Peng et al., 2023) and productivity (Bonaccorsi et al., 2021; Ryazanova & Jaskiene, 2022). Other potential drivers of mobility and/or productivity are not considered for the lack of available observations.

According to literature on propensity score matching, some variable selection prior to the matching process may help increase estimation efficiency by reducing variance while not increasing bias (Brookhart et al., 2006). It is suggested in Brookhart et al. (2006) that variables strongly related to propensity of treatment but weakly related to outcome should be excluded from the propensity estimation equation. We conduct variable selection to include only significant predictor variables in the regression of outcome variable (publications or citations). The variable selection procedure leads us to exclude two variables: the type of institution (private or public) and minority service status. The estimated probability using Equation (1) is the propensity score of a professor moving to another institution and close matches are found to be close in terms of the propensity to move for the two groups. Our main results are based on the one-to-one matching using the nearest neighbor method; that is, we find in the pool of promoted professors one closest (instead of multiple) match of propensity score for a moved professor. Additional choices on the matching process, such as one-on-one or one-to-many matches or different matching algorithms, are explored in the Robustness Checks Section. The matched samples should have similar distributions of the propensity score.

An adequate degree of covariate balance between treatment and control samples is necessary to properly account for confounding effects of observable explanatory variables. Moreover, balancing covariates may also highlight the potential issues in identification of treatment effects. To achieve covariate balance, one should expect to observe similar values of the observable covariates for both treatment and control groups. Table 2 shows the covariate balance results before and after the matching process for publications. Before matching, we observe a gradual change of productivity differences between the promoted group and the moved group. More specifically, while the initial differences are minimum, evidenced by the no-significant-differences in the 5-year prior publication numbers, the promoted group gradually outperforms their peers in the moved group, evidenced by the increased gap in publications and more significant p-values when getting close to promotion or move year.

While there are no gender, rank, or school classification differences between the two groups prior to promotion or move, there are differences in the distribution of disciplines and the employment duration is slightly shorter in the promoted group. As a special note on the rank of professors, there are many full professors in the moved group, though few in the stayed group. Therefore, the full professors are removed from the treated group for the lack of matches in the control group.

After the matching process, all covariates were balanced because there were no significant differences in each covariate for the moved and promoted groups. Figure 1 plots the distribution of the propensity scores before and after matching publications. In the unmatched sample, the treated group, on average, has a higher propensity score than the control group. One can see that the matching process greatly improved the balance of propensity scores because the distributions of the matched propensity scores are quite similar between the treated and Control groups. In sum, both propensity scores and covariates are balanced for the moved and promoted groups. The difference of promotion versus move on citational impact is largely minimum between the groups (Table A1 and Figure A1).

TABLE 2 Variable balance results for matched sample for publications.

	Before matching			After matching		
	Moved	**Promoted**	***p*-value**	**Moved**	**Promoted**	***p*-value**
n	519	1480		519	519	
5-year prior publications (mean (SD))	3.11 (3.58)	3.22 (3.84)	0.564	3.11 (3.58)	3.14 (3.70)	0.865
4-year prior publications (mean (SD))	3.23 (3.73)	3.53 (4.46)	0.167	3.23 (3.73)	3.26 (3.79)	0.875
3-year prior publications (mean (SD))	3.69 (4.06)	4.15 (4.99)	0.056	3.69 (4.06)	3.83 (4.35)	0.585
2-year prior publications (mean (SD))	4.08 (4.35)	4.58 (5.55)	0.065	4.08 (4.35)	4.04 (4.48)	0.888
1-year prior publications (mean (SD))	4.43 (4.34)	5.33 (7.10)	0.006	4.43 (4.34)	4.52 (4.32)	0.720
Gender = Male (%)	377 (72.6)	1085 (73.3)	0.811	377 (72.6)	371 (71.5)	0.729
Rank = Associate professor (%)	167 (32.2)	429 (29.0)	0.190	167 (32.2)	165 (31.8)	0.947
Major (%)			<0.001			0.964
Clinical health	153 (29.5)	241 (16.3)		153 (29.5)	152 (29.3)	
Engineering	33 (6.4)	146 (9.9)		33 (6.4)	34 (6.6)	
Life	210 (40.5)	678 (45.8)		210 (40.5)	219 (42.2)	
Physical	61 (11.8)	287 (19.4)		61 (11.8)	58 (11.2)	
Social	62 (11.9)	128 (8.6)		62 (11.9)	56 (10.8)	
Employment year (mean (SD))	21.96 (8.87)	20.55 (8.58)	0.001	21.96 (8.87)	22.17 (9.21)	0.708
Class (%)			0.063			0.960
Medical School	55 (10.6)	106 (7.2)		55 (10.6)	57 (11.0)	
Other	35 (6.7)	84 (5.7)		35 (6.7)	37 (7.1)	
R1	366 (70.5)	1103 (74.5)		366 (70.5)	358 (69.0)	
R2	63 (12.1)	187 (12.6)		63 (12.1)	67 (12.9)	

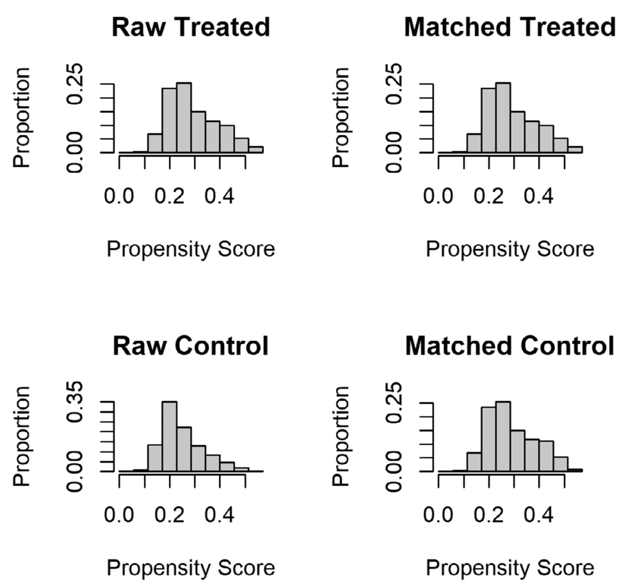

FIGURE 1 Histogram of propensity score of raw and matched samples of publications.

With the matched sample, one can estimate the effect of move compared to promotion using a difference-in-difference estimator. More specifically, the effect of move on publication productivity or citation impact can be estimated using the two group differences of before-after changes:

$$E(\Delta \text{depvar}|\text{move}) = E\left(\text{depvar}_{\text{moved, after}} - \text{depvar}_{\text{moved, before}}\right) - E\left(\text{depvar}_{\text{promoted, after}} - \text{depvar}_{\text{promoted, before}}\right), \quad (2)$$

where the Δdepvar is the change in either publication productivity or citation impact. This difference-in-difference can be implemented in a simple regression:

$$\text{depvar} = \beta_0 + \beta_1 \text{ move} + \beta_2 \text{ prepost} + \beta_3 \text{ move} * \text{prepost} + \epsilon,$$

where "move" is an indicator variable with 1 being moved and 0 being promoted; "prepost" is an indicator with 0 being pre-move and 1 being post-move.[2] Coefficient β_1 gives the estimate of before-move group differences; coefficient β_2 gives the estimate of the change in "depvar" from before to after for the promoted group of professors; coefficient β_3 gives the difference-in-difference estimator in Equation (2). For added robustness, we add back the two control variables that were previously omitted in the matching process: type of institutions and minority serving status. Because of the potential changing types and minority servicing status for the moved group, we add both before- and after-move variables in the estimation equation. In sum, the regression we use for estimation is as follows:

$$\begin{aligned}\text{depvar} = {} & \beta_0 + \beta_1\,\text{move} + \beta_2\,\text{prepost} + \beta_3\,\text{move} * \text{prepost} \\ & + \gamma_1 \text{type}_{\text{pre}} + \gamma_2 \text{type}_{\text{post}} + \gamma_3 \mathit{msi}_{\text{pre}} \\ & + \gamma_4 \mathit{msi}_{\text{post}} + \epsilon.\end{aligned} \tag{3}$$

3 | RESULTS

After the propensity score matching and the inspection of covariate balance, we can move forward with exploratory and regression analyses.

The average numbers of publications for moved and promoted professors before and after moving or promotion are shown in Figure 2. The moved group has, on average, about the same productivity in the number of publications as the promoted group. In addition, there is an increase in the number of publications for both groups after a move or promotion. Finally, the increase in productivity is slightly smaller in the moved group.

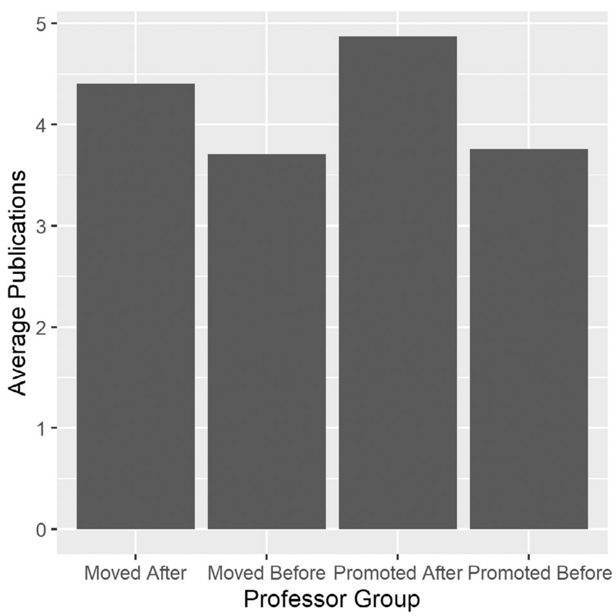

FIGURE 2 Average publications for moved and promoted professors before and after moving or promotion. The year in which the promotion or move took place is excluded from the calculations.

Table 3 presents the statistical test of the differences in the increase in publications after moving or promotion is presented. Column (1) of Table 2 estimates the overall difference of the moved and promoted groups before the move. The coefficient for *Move* is the pre-move or pre-promotion difference in the number of publications between moved professors and promoted professors. The near-zero coefficient of −0.104 means that, on average, the moved professors have about the same number of publications as the professors who stayed in the same institution. The results are expected since the matching has included the pre-move publications or citations. The coefficient of *After* is the change in publications from before to after for the promoted group of professors. The positive coefficient means that there is a positive change in the number of publications. The coefficient for the interaction term *Move* × *After* is the difference-in-difference estimate for the difference of the moved and the promoted groups. The productivity of moved professors does not increase as high as their counterpart: moved professors have a lower increase in their productivity post-move when compared with their counterpart who stays within the same institution with a promotion.

Because the norms of disciplines are different, one may expect a disciplinary differential effect of move versus promotion. The difference-in-difference estimates for the five disciplines are presented in columns (2)–(6) of Table 3. Each estimate for a discipline is based on a regression analysis of the matched sample, constructed via a separate matching process for all moved professors within that discipline. Overall, there is no significant difference between the two groups of professors in the increase of publications post-move or post-promotion except for Physical Science and Clinical Health. For professors in those two fields, the promoted group enjoys a higher productivity increase than their counterparts.

The regression analysis results for citations impact are presented in Figure 3 and Table 4. Figure 3 shows that moved professors received slightly lower citations before moving than their counterparts who received promotion within the same institutions. Both groups of professors received higher citations later; however, differences in the two groups are quite small for both before and after moving or promotion.

To test the statistical differences, a series of regressions are employed, and the results are shown in Table 4. Column (1) of Table 4 shows that when all disciplines are lumped together, there are no differences in citation for

TABLE 3 Regression results after propensity score matching for publications.

	Publications					
	All	Social	Physical	Life	Engineering	Clinical
	(1)	(2)	(3)	(4)	(5)	(6)
Move	−0.104 (0.137)	−0.083 (0.204)	−0.544 (0.732)	−0.117 (0.169)	0.571 (0.613)	−0.076 (0.294)
After	1.114*** (0.131)	0.389* (0.194)	2.702*** (0.698)	0.970*** (0.159)	1.459* (0.586)	2.231*** (0.280)
Move × After	−0.414* (0.185)	0.174 (0.274)	−2.028* (0.987)	−0.100 (0.225)	−1.017 (0.828)	−1.643*** (0.396)
Constant	3.788*** (0.255)	2.274*** (0.412)	1.705 (1.192)	2.770*** (0.340)	8.444*** (1.048)	5.062*** (0.601)
Observations	11,418	1364	1342	4620	726	3366
Public or private (before)	Yes	Yes	Yes	Yes	Yes	Yes
Public or private (after)	Yes	Yes	Yes	Yes	Yes	Yes
Minority servicing (before)	Yes	Yes	Yes	Yes	Yes	Yes
Minority servicing (after)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,418	1364	1342	4620	726	3366
R^2	0.013	0.014	0.026	0.029	0.108	0.037

$^*p < 0.05$. $^{***}p < 0.001$.

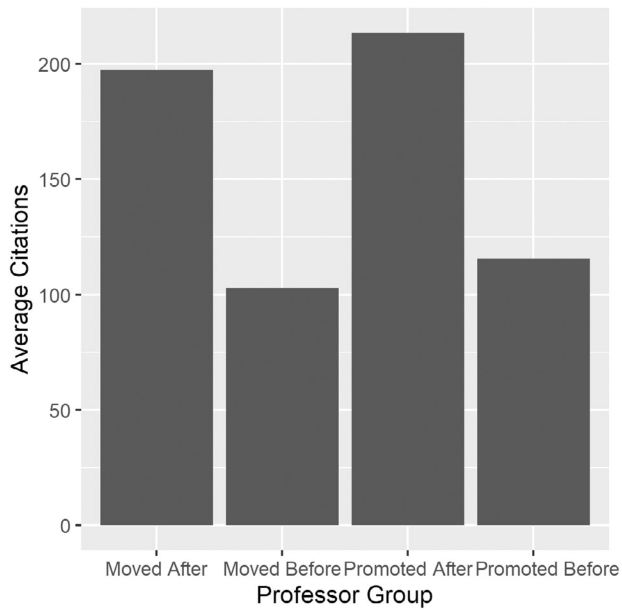

FIGURE 3 Average citations for moved and promoted professors before and after moving or promotion. The year in which the promotion or move took place is excluded from the calculations.

the two groups, either before or after move/promotion, evidenced by the statistically insignificant coefficients of *Move* and *Move* × *After*. The significant coefficient of *After* indicates there is an increase of citation after either move or promotion, which is expected. To investigate disciplinary differences, in a similar fashion as the publications, we find a closest match for each moved professor within each discipline, then conduct a series of regression analyses to estimate the difference in the increase of citation impact in the two groups. The results are presented in columns (2)–(6) of Table 4. Once again, the statistically insignificant coefficients of *Move* and *Move* × *After* show that there is no significant difference between the two groups for the five disciplines.

3.1 | Gender differences

This section studies gender differences in the differential productivity increase in moved and promoted groups. To investigate the gender difference of moved and promoted professors in their productivity increase, the propensity score matching is conducted separately. That is, the matching of moved versus promoted groups is conducted within the female and male group separately. The regression results after the propensity score matching are presented in Table 5. Column (1) shows that the overall difference of the moved group has lower publication increase after moving when compared to the promoted group. Columns (2) and (3) show that this difference is largely driven by the male group. That is, male professors, after move, have a larger productivity gap when

TABLE 4 Regression results after propensity score matching for citations.

	Citations					
	All	Social	Physical	Life	Engineering	Clinical
	(1)	(2)	(3)	(4)	(5)	(6)
Move	−16.935 (9.829)	6.549 (8.011)	85.762 (58.199)	−16.579 (11.474)	37.339 (25.036)	3.596 (7.581)
After	97.908*** (9.373)	53.197*** (7.655)	84.044 (55.482)	72.075*** (10.828)	68.799** (23.799)	104.975*** (7.234)
Move × After	−3.433 (13.255)	4.060 (10.826)	73.858 (78.463)	26.108 (15.313)	30.175 (33.656)	−26.766** (10.231)
Constant	136.764*** (18.858)	5.437 (13.564)	82.759 (95.036)	133.193*** (22.099)	164.303*** (37.013)	92.602*** (15.012)
Public or private (before)	Yes	Yes	Yes	Yes	Yes	Yes
Public or private (after)	Yes	Yes	Yes	Yes	Yes	Yes
Minority servicing (before)	Yes	Yes	Yes	Yes	Yes	Yes
Minority servicing (after)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,418	1364	1342	4620	726	3366
R^2	0.024	0.080	0.028	0.050	0.260	0.111

$^{**}p < 0.01$. $^{***}p < 0.001$.

TABLE 5 Regression results after propensity score matching for gender differences.

	Publications			Citations		
	All	Female	Male	All	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Move	−0.104 (0.137)	−0.047 (0.199)	0.041 (0.158)	−16.935 (9.829)	−0.894 (8.089)	4.411 (12.762)
After	1.114*** (0.131)	1.035*** (0.190)	1.217*** (0.150)	97.908*** (9.373)	80.805*** (7.723)	108.345*** (12.170)
Move × After	−0.414* (0.185)	−0.319 (0.268)	−0.523* (0.213)	−3.433 (13.255)	−19.075 (10.922)	−1.536 (17.211)
Constant	3.788*** (0.255)	3.057*** (0.352)	4.164*** (0.316)	136.764*** (18.858)	129.483*** (14.197)	106.624*** (23.867)
Public or private (before)	Yes	Yes	Yes	Yes	Yes	Yes
Public or private (after)	Yes	Yes	Yes	Yes	Yes	Yes
Minority servicing (before)	Yes	Yes	Yes	Yes	Yes	Yes
Minority servicing (after)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,418	3124	8294	11,418	3124	8294
R^2	0.013	0.028	0.018	0.024	0.063	0.021

$^{*}p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

compared with their counterpart who get promoted, whereas the female professors do not witness much difference from the moved and promoted groups. The results on citations, shown in columns (4)–(6), indicate that there is no significant difference between the moved and promoted groups in their citation impact and this null difference is consistent across genders.

3.2 | Institution research intensity

This section discusses the differences among the professors who moved or received promotion in institutions of varied degree of research intensity. We focus on the universities with Carnegie Classification of Doctoral Universities—Very High Research (R1) and Doctoral Universities—High Research (R2) because these are the universities with the most research intensity and are more likely to be included in the ORCID data. To compare the differences of the two groups in their productivity, we matched the propensity scores of professors, conditioned on professors' discipline, gender, rank, employment year, and more importantly, their institution's research intensity. The results are reported in column (1) of Table 6. Then, a separate matching process was conducted for professors working in R1 and R2 institutions separately. That is, the matching is guaranteed to have the same type of research intensity for the two groups before the mobility event. The regression results are presented in columns (2)–(3) in Table 6.

First, there is a significant productivity increase for both groups post-move and post-promotion. However, regardless of whether both R1 and R2 institutions are included in the analysis, or R1 and R2 institutions are matched separately, the difference of productivity increase between the two groups is not significant at the 0.05 level. The insignificance is caused by both the low difference-in-difference estimates and high standard deviation. The results for citations, presented in columns (4)–(6) of Table 6, show similar results. That is, despite the increase in citation impact after moving or promotion, there is no impact difference in the increase of citations between the two groups.

It is natural to ask whether moving to a more research-intensive institution helps gain research productivity and impact. To answer this question, we focus on the moved professors only. We compared the professors who moved across different categories of research intensity (i.e., from R1 to R2 or from R2 to R1) with those professors who moved within the same categories of institutions. The results for both publications and citations are presented in Table 7. Column (1) compares the difference in productivity increase of the two groups after moving to a new institution.

The negative and significant coefficient before *Cross Class* means that, on average, professors who moved to a

TABLE 6 Regression results after propensity score matching for varied degrees of research intensity.

	Pubs-All	Pubs-R1	Pubs-R2	Cites-All	Cites-R1	Cites-R2
	(1)	(2)	(3)	(4)	(5)	(6)
Move	−0.336* (0.168)	−0.239 (0.166)	0.223 (0.337)	−6.784 (13.787)	3.733 (14.965)	−77.406 (47.459)
After	1.080*** (0.160)	0.928*** (0.158)	1.023*** (0.307)	109.614*** (13.137)	105.042*** (14.221)	112.217** (42.342)
Move × After	−0.223 (0.227)	−0.077 (0.223)	−0.123 (0.435)	−3.539 (18.578)	6.689 (20.111)	−49.463 (59.880)
Constant	4.092*** (0.344)	5.136*** (0.326)	3.198*** (0.590)	164.282*** (26.279)	221.067*** (29.411)	136.751 (75.163)
Public or private (before)	Yes	Yes	Yes	Yes	Yes	Yes
Public or private (after)	Yes	Yes	Yes	Yes	Yes	Yes
Minority servicing (before)	Yes	Yes	Yes	Yes	Yes	Yes
Minority servicing (after)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7810	6908	902	7810	6908	902
R^2	0.024	0.020	0.087	0.020	0.021	0.029

$^*p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

TABLE 7 Regression results for moved professors.

	Pubs			Cites		
	Both	R1 to R2	R2 to R1	Both	R1 to R2	R2 to R1
	(1)	(2)	(3)	(4)	(5)	(6)
Cross class	−0.922*** (0.263)	−0.705* (0.347)	0.102 (0.642)	−50.063 (27.792)	−48.801 (38.224)	−42.578 (30.424)
After	0.989*** (0.157)	1.007*** (0.161)	0.444 (0.768)	120.690*** (16.590)	122.460*** (17.766)	66.222 (36.393)
Cross class × After	−0.679 (0.356)	−1.319** (0.470)	0.584 (0.870)	−75.196* (37.631)	−91.051 (51.755)	−4.443 (41.194)
Constant	3.992*** (0.116)	4.035*** (0.119)	2.667*** (0.567)	123.072*** (12.253)	123.374*** (13.121)	113.778*** (26.878)
Observations	3905	3454	451	3905	3454	451
R^2	0.024	0.022	0.017	0.020	0.018	0.039

*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

different category of research-intensive institutions had a lower number of publications before moving. This is mainly driven by the fact that most moves are downwards in terms of research intensity. The positive and significant coefficient before the term *After* means that typically the professors who moved across different classes of institutions are more productive post-move. However, when all moves are pooled together, there seems to be little difference between moving across categories and moving within the same categories. Interestingly, a move from a R1 institution to a R2 institution has more of a negative effect on the publication productivity than a move between two R1 universities. The lower increase in productivity in the cross-tier moves is manifested in the negative coefficient of the term *Cross Class* × *After* in column (2). The move from R2 to R1 is not significantly different from the moves from R2 to another R2 institution (column 3). Overall, the results suggest that staying within higher research-intensive institutions is beneficial for attaining higher productivity than moving to a less research-intensive institution. But starting with a lower research intensity institution, a researcher moving to a university with higher research intensity is not different from lateral moves in terms of research intensity.

The results of citation impact in columns (4)–(6) are slightly different from the results of publications. First, there is no significant difference in the citation before moving for cross-category moves or within-category moves. Second, both cross-category and within-category moves result in higher citation after moving. Moreover, moving across categories generally results in a lower impact increase than staying within the same tier. This result is mostly driven by the majority moves from higher research-intensive institutions to lower research-intensive institutions. This is due to the large, albeit insignificant, negative coefficient for R1 to R2 moves when compared with R1 to R1 moves. Again, moving up does not seem to result in much difference in research impact than staying within R2 institutions.

3.3 | Moving with a promotion

For moved professors, we would like to ask whether the productivity and impact are different when the move also resulted in a promotion. The results of the moves with and without promotions are presented in Table 8. Results in publication are shown in columns (1)–(2) and citations in columns (3)–(4). Columns (1) and (3) present the regression results without additional controls and columns (2) and (4) with additional controls of pre-move individual and institutional characteristics. These additional controls are considered because two types of promotions (Assistant to Associate and Associate to Full) are included, while samples with a promotion are compared with samples without a promotion without using matching processes. The added controls should not affect much of our estimates but are included for cautionary reasons. As expected, adding time-constant controls only change the estimates of publications or citations for coefficient of the Promotion variable, which captures the pre-move publications or citations differences between the groups with and without a promotion. The nonsignificant coefficient for the cross-term *Promotion* × *After* suggests that the publication increases after move are not significantly different between promoted and not-promoted professors. The results for citations suggest that moved professors with promotions tend to have higher citations

TABLE 8 Regression results for comparing promoted and not promoted in moved professors.

	Publications	Publications	Citation	Citation
	(1)	(2)	(3)	(4)
Promotion	0.879*** (0.212)	0.811*** (0.208)	39.017* (19.312)	31.201 (19.267)
After	0.306 (0.256)	0.306 (0.251)	51.620* (23.348)	51.620* (23.176)
Promotion × After	0.493 (0.287)	0.493 (0.281)	53.941* (26.148)	53.941* (25.956)
Constant	3.010*** (0.189)	2.535*** (0.379)	71.850*** (17.244)	−5.454 (34.985)
Rank	No	Yes	No	Yes
Gender	No	Yes	No	Yes
Carnegie classification	No	Yes	No	Yes
Public or private	No	Yes	No	Yes
Minority serving	No	Yes	No	Yes
Observations	5698	5698	5698	5698
R^2	0.018	0.058	0.019	0.035

*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

than moved professors without promotions. Alternatively, one may interpret the results to mean that professors with more impactful work are more likely to move with a promotion than those who move without.

The overall message of our analyses suggests that professors who moved to another institution experienced less productivity increase than their counterparts who received promotion. By isolating the differences in the analyses, we identified that the negative productivity of moved group is mostly due to male professors in physical science and clinical health fields moving from more research-intensive institutions (R1) to lower research-intensive institutions (R2).

3.4 | Robustness checks

This section presents the robustness check results. We have tried several variations of matching method including a different matching ratio and different best matching criteria. For our observed sample, the moved versus promoted professors are 519 to 1480 (1 to 2.85). It would be possible to have a 1:1 or 1:2 ratio matching if no replacement sampling is allowed. In addition to the 1:1 ratio matching, we have conducted 1:2 ratio matching, and the results are qualitatively the same. That is, the covariates can be balanced, and the difference-in-difference estimates are numerically similar and qualitatively the same. In addition to the nearest neighbor method for matching, we have also explored different matching algorithms. Exact matching, which is considered best if matching is possible, is not possible for our dataset as quite a few covariates are numerical. Coarsened exact matching is also inappropriate for our dataset because it is only able to match 273 out of 519 moved professors. We tried three more matching methods including optimal pair matching, optimal full matching, and genetic matching with a Mahalanobis distance. We presented the difference-in-difference estimation for the publication outcome with the main sample using different matching methods in the following table. For comparison purposes, we replicate the near neighbor method here. As one may see, the difference-in-difference estimates are all comparable to the main results in Table 3 except for the optimal matching. The optimal matching is optimal in the sense that it tries to choose matches that collectively optimize the sum of the absolute pair distances in the matched sample, which is no better than the nearest neighbor matching at yielding matched samples (Austin, 2014) (Table 9). We note here that using various matching algorithms also yields qualitatively the same results as the default nearest neighbor methods (Table A2).

4 | DISCUSSION

Despite the substantial effects that promotions and academic moves have on a researcher's career, most research examines their effects separately and there is scant research that compares their effects on a researcher's productivity and impact. Through a careful design of matching control and treatment sets, this study was able to identify for two groups of professors with similar pre-mobility research productivity or impact, promotions add more value to a researcher's career as their post-promotion productivity and citation impact is higher

TABLE 9 Comparisons of regression results after propensity score matching for different matching methods.

	Publications				
	Nearest neighbor, 1:1	Nearest neighbor, 2:1	Optimal	Full	Genetic
	(1)	(2)	(3)	(4)	(5)
Move	−0.104 (0.137)	−0.037 (0.114)	0.109 (0.121)	−0.510*** (0.144)	0.004 (0.131)
After	1.114*** (0.131)	1.119*** (0.089)	0.943*** (0.115)	1.122*** (0.099)	1.128*** (0.125)
Move × After	−0.414* (0.185)	−0.419** (0.154)	−0.243 (0.163)	−0.422* (0.193)	−0.428* (0.177)
Constant	3.788*** (0.255)	3.895*** (0.182)	4.057*** (0.220)	4.066*** (0.210)	3.316*** (0.239)
Public or private (before)	Yes	Yes	Yes	Yes	Yes
Public or private (after)	Yes	Yes	Yes	Yes	Yes
Minority servicing (before)	Yes	Yes	Yes	Yes	Yes
Minority servicing (after)	Yes	Yes	Yes	Yes	Yes
Observations	11,418	17,127	11,418	21,989	11,418
R^2	0.013	0.017	0.021	0.010	0.013

$^*p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

than one who had an academic move. There is less uncertainty or risk involved in promotions than academic moves. Promotions reaffirm and elevate professors' resources and human capital while the success of academic moves in the production of research deliverables and impact is largely dependent on the timing of such moves. While moving on the right occasions can be advantageous, moving at the wrong time can disrupt one's research program and weaken one's social ties. Our findings seem to suggest that, compared with their peers who received promotion, mobile professors who moved due to less productivity yielded low post-move productivity. Literature suggests that returnees to China at an earlier career stage would be more productive than those who move at a later stage (Zhao et al., 2020). Moving internationally during one's first post-PhD job undermines research productivity while moving between year 2 and year 7 post-PhD is more likely to yield higher productivity than moving later (Ryazanova et al., 2017).

Discipline differences are demonstrably evident in the effect of promotions or academic moves on research productivity and impact. Disciplines differ in the norm of making academic moves: mobility is considered as more desirable for job seekers in STEM disciplines than in social science and humanities (Herschberg et al., 2018). Disciplines also differ in their demand for research resources. An academic move in STEM disciplines would result in more disruptions than resource-light disciplines such as social science. Therefore, in resource-dependent disciplines such as clinical health or physical science, its promoted professors enjoy a higher productivity increase than mobile professors. Using the concept of pluralism, Bäker (2015) argued that the more pluralistic the discipline, the more likely that a professor will be confronted with different research methodologies post-move and thus resulting in a loss of productivity. This research confirmed this argument since clinical health employs more diverse research methods and is considered as more pluralistic than physical sciences or social sciences.

When gender is considered, women professors generally move less often (Børing et al., 2015; Welch, 1997). Academics with children in secondary schools are less likely to move because of the resistance to the disruption of their teenagers' schoolings (Azoulay et al., 2017). There is also an unequal cost of mobility between men and women professors: many developing countries favor mobile men professors due to cultural norms (Jayachandran, 2015). However, this study found that while both men and women professors have increased their publications, moved group male professors are much less productive when compared with the promoted group of male professors. The female group did not witness any differences for the moved and promoted groups. Studies also showed that women professors are less likely than men to receive tenure and the disadvantage varied in several empirical studies from around 8% in life sciences to more than 30% in economics (Ginther & Kahn, 2004, 2009; McDowell & Smith, 1992) when other factors are controlled for. The gap may be explained by the demand of childbearing because the gap disappeared when childless women academics were compared with men in getting tenure (Ginther & Kahn, 2009).

Institutions' research intensity also affects research productivity and impact. Prior research suggested that professors' intrinsic motivations can be used to explain an improved research productivity when moving up to a more prestigious institution. In the meantime, moving down can also be beneficial when professors from former elite institutions would likely acquire a star status in a less prestigious institution (Gibson & McKenzie, 2014). This paper used research intensity as a proxy for institutional prestige: for an institution, a R1 designation by CCIHE is considered as more prestigious than a R2 designation. It found that a move from a R1 institution to a R2 institution has more of a negative effect on the publication productivity than a move within R1 institutions. The results suggest that moving down did not seem to help professors from former prestigious institutions retain research resources or social ties. It is likely that moving down transpires not by choice but rather is due to subpar evaluations at R1 institutions which could negatively affect a moving professor's career at their new R2 institution. This paper did not collect data on reasons of move and therefore it cannot verify this assumption.

5 | CONCLUSIONS

This paper found that promotions add more value to a researcher's career as their post-promotion productivity increases while citation impact is the same. It also found that in resource-dependent disciplines such as clinical health, its promoted professors enjoy a higher productivity increase than mobile professors. Finally, it found that staying within higher research-intensive institutions is beneficial for attaining higher productivity than moving to a less research-intensive institution.

Limitations of this research include matching method and data limitations. For the method, the matching can only consider the measurables but cannot include factors not observed in our dataset. Future research in this area will benefit from supplementing quantitative results with in-depth interviews to reveal insights on the role of intrinsic motivations, social ties, and institutional support on post-move productivity and impact.

The dataset is also limited in its time span. Our analysis is limited to a 12-year span of the researchers. The differences in citations in the moved and promoted groups are essentially nonexistent in our analysis. This could be true in the short term but, in the longer term, we may see citational differences in the two groups. We hope future research can shed light on the long-term citation impact on researchers' career after mobility.

Finally, some may argue that the comparisons of citations for the two groups may be somewhat unfair, given that the comparisons are conducted between two groups, each of which lumps different research topics together. We do observe the relatively large variation in the difference-in-difference estimates which could be the results of lumping those different research topics together. Meanwhile, the statistical insignificance of the mean differences could also result from a relatively low degree of differences between the moved and promoted groups. The null difference in citations between the two groups could be due to either a small difference in the mean citations or large variations or both. Our data only allows for a split-sample analysis based on disciplines which can alleviate concerns on disciplinary differences but does not allow for analysis considering research-topic level differences. We hope future research will be able to distinguish such subtle differences.

ORCID

Erjia Yan https://orcid.org/0000-0002-0365-9340
Chaoqun Ni https://orcid.org/0000-0002-4130-7602
Jiangen He https://orcid.org/0000-0002-3950-6098

ENDNOTES

[1] https://webofscience.help.clarivate.com/en-us/Content/researcher-search.htm.

[2] For robustness purposes, all numbers in the year of move or promotion are excluded from analysis.

REFERENCES

Abramo, G., D'angelo, C. A., & Costa, F. D. (2022). The effect of academic mobility on research performance: The case of Italy. *Quantitative Science Studies*, *3*(2), 345–362.

Abramo, G., D'Angelo, C. A., & Di Costa, F. (2019). A nation's foreign and domestic professors: Which have better research performance? (the Italian case). *Higher Education*, *77*(5), 917–930.

Aksnes, D. W., Rørstad, K., Piro, F. N., & Sivertsen, G. (2013). Are mobile researchers more productive and cited than non-mobile researchers? A large-scale study of Norwegian scientists. *Research Evaluation*, *22*(4), 215–223.

Allison, P. D., & Long, J. S. (1987). Interuniversity mobility of academic scientists. *American Sociological Review*, *52*(5), 643–652.

Austin, P. C. (2014). A comparison of 12 algorithms for matching on the propensity score. *Statistics in Medicine*, *33*(6), 1057–1069.

Azoulay, P., Ganguli, I., & Zivin, J. G. (2017). The mobility of elite life scientists: Professional and personal determinants. *Research Policy*, *46*(3), 573–590.

Bäker, A. (2015). Non-tenured post-doctoral researchers' job mobility and research output: An analysis of the role of research discipline, department size, and coauthors. *Research Policy*, *44*(3), 634–650.

Bernela, B., Bouba-Olga, O., & Ferru, M. (2017). Spatial patterns of PhDs' internal migration in France, 1970–2000. *Journal of Innovation Economics & Management*, *1*, 25.

Blackburn, R., Brown, J., Buys, M., Calvo, M., Cardoso, A., Demain, P., Demeranville, T., Gopinath, P., Laurel, H., Harley, S., Hershberger, S., Krznarich, L., Meadows, A., Mejias, G., Montenegro, A., George, N., Olson, E., Perez, J., Paglione, L., … Wynne, A. V. (2018). ORCID public data file. https://doi.org/10.23640/07243.7234028.v1

Bland, S., & Van Noorden, R. (2012). Global mobility: Science on the move. *Nature*, *490*(7420), 326–329.

Blanden, J. (2013). Cross-country rankings in intergenerational mobility: A comparison of approaches from economics and sociology. *Journal of Economic Surveys*, *27*(1), 38–73.

Bonaccorsi, A., Belingheri, P., & Secondi, L. (2021). The research productivity of universities. A multilevel and multidisciplinary analysis on European institutions. *Journal of Informetrics*, *15*(2), 101129.

Børing, P., Flanagan, K., Gagliardi, D., Kaloudis, A., & Karakasidou, A. (2015). International mobility: Findings from a survey of researchers in the EU. *Science and Public Policy*, *42*(6), 811–826.

Brookhart, M. A., Schneeweiss, S., Rothman, K. J., Glynn, R. J., Avorn, J., & Stürmer, T. (2006). Variable selection for propensity score models. *American journal of epidemiology*, *163*(12), 1149–1156.

Cañibano, C., Otamendi, F. J., & Solís, F. (2011). International temporary mobility of researchers: A cross-discipline study. *Scientometrics*, *89*(2), 653–675.

Cao, C., Baas, J., Wagner, C., & Jonkers, K. (2019). Returning scientists and the emergence of China's science system. *Science and Public Policy Journal*, *47*(2), 172–183.

Clauset, A., Arbesman, S., & Larremore, D. B. (2015). Systematic inequality and hierarchy in faculty hiring networks. *Science Advances*, *1*(1), e1400005.

Darby, Z. (2014). Movement of star scientists and engineers and high-tech firm entry. *Annals of Economics and Statistics*, *115/116*, 125–175.

Debackere, K., & Rappa, M. A. (1995). Scientists at major and minor universities: Mobility along the prestige continuum. *Research Policy*, *24*(1), 137–150.

Deville, P., Wang, D., Sinatra, R., Song, C., Blondel, V. D., & Barabási, A. L. (2014). Career on the move: Geography, stratification, and scientific impact. *Scientific Reports*, *4*, 1–7.

Dietz, J., Chompalov, I., Bozeman, B., Lane, E., & Park, J. (2000). Using the curriculum vita to study the career paths of scientists and engineers: An exploratory assessment. *Scientometrics*, *49*(3), 419–442.

Docquier, F., Rapoport, H., Pregnancy, P. T., Fertility, T. I., Growth, F., Docquier, F., & Rapoport, H. (2012). Globalization, brain drain, and development. *Journal of Economic Literature*, *50*(3), 681–730.

Ejermo, O., Fassio, C., & Källström, J. (2020). Does mobility across universities raise scientific productivity? *Oxford Bulletin of Economics and Statistics*, *82*(3), 603–624.

Franzoni, C., Scellato, G., & Stephan, P. (2014). The mover's advantage: The superior performance of migrant scientists. *Economics Letters*, *122*(1), 89–93.

Franzoni, C., Scellato, G., & Stephan, P. (2015). International mobility of research scientists: Lessons from GlobSci. In *Global mobility of research scientists* (pp. 35–65). Academic Press.

Ganguli, I. (2015). Who leaves and who stays? Evidence on immigrant selection from the collapse of Soviet science. In *Global mobility of research scientists* (pp. 133–154). Academic Press.

Gibson, J., & McKenzie, D. (2014). The development impact of a best practice seasonal worker policy. *Review of Economics and Statistics*, *96*(2), 229–243.

Ginther, D. K., & Kahn, S. (2004). Women in economics: Moving up or falling off the academic career ladder? *Journal of Economic Perspectives*, *18*(3), 193–214.

Ginther, D. K., & Kahn, S. (2009). Does science promote women? Evidence from academia 1973–2001. In *Science and engineering careers in the United States: An analysis of markets and employment* (pp. 163–194). University of Chicago Press.

Halevi, G., Moed, H. F., & Bar-Ilan, J. (2016). Researchers' mobility, productivity and impact: Case of top producing authors in seven disciplines. *Publishing Research Quarterly*, *32*(1), 22–37.

He, Z., Zhen, N., & Wu, C. (2019). Measuring and exploring the geographic mobility of American professors from graduating institutions: Differences across disciplines, academic ranks, and genders. *Journal of Informetrics*, *13*(3), 771–784.

Herschberg, C., Benschop, Y., & Van den Brink, M. (2018). Selecting early-career researchers: The influence of discourses of nternationalization and excellence on formal and applied selection criteria in academia. *Higher Education*, *76*, 807–825.

Hesli, V. L., & Lee, J. M. (2011). Faculty research productivity: Why do some of our colleagues publish more than others? *Political Science & Politics*, *44*(2), 393–408.

Hunter, R. S., Oswald, A. J., Charlton, B. G., & Charlto, B. G. (2009). The elite brain drain. *Economic Journal*, *119*(538), F231–F251.

Ioannidis, J. P. A. (2004). Global estimates of high-level brain drain and deficit. *FASEB Journal*, *18*(9), 936–939.

Jayachandran, S. (2015). The roots of gender inequality in developing countries. *Annual Review of Economics*, *7*(1), 63–88.

Jonkers, K. (2011). Mobility, productivity, gender and career development of Argentinean life scientists. *Research Evaluation*, *20*(5), 411–421.

Jonkers, K., & Cruz-Castro, L. (2013). Research upon return: The effect of international mobility on scientific ties, production and impact. *Research Policy*, *42*(8), 1366–1377.

Jonkers, K., & Tijssen, R. (2008). Chinese researchers returning home: Impacts of international mobility on research collaboration and scientific productivity. *Scientometrics*, *77*(2), 309–333.

Kato, M., & Ando, A. (2017). National ties of international scientific collaboration and researcher mobility found in Nature and Science. *Scientometrics*, *110*(2), 673–694.

Laudel, G. (2005). Migration currents among the scientific elite. *Minerva*, *43*(4), 377–395.

Lawson, C., & Shibayama, S. (2015). International research visits and careers: An analysis of bioscience academics in Japan. *Science and Public Policy*, *42*(5), 690–710.

Lee, E., Clauset, A., & Larremore, D. B. (2021). The dynamics of faculty hiring networks. *EPJ Data Science*, *10*(1), 48.

Marini, G., & Yang, L. (2021). Globally bred Chinese talents returning home: An analysis of a reverse brain-drain flagship policy. *Science and Public Policy*, *48*(4), 541–552.

McDowell, J. M., & Smith, J. K. (1992). The effect of gender-sorting on propensity to coauthor: Implications for academic promotion. *Economic Inquiry*, *30*(1), 68–82.

McLean, M. R., Morahan, P. S., Dannels, S. A., & McDade, S. A. (2013). Geographic mobility advances careers: Study of the executive leadership in academic medicine (ELAM) program for women. *Academic Medicine*, *88*(11), 1700–1706.

Moskal, M. (2020). Gendered differences in international graduates' mobility, identity and career development. *Social & Cultural Geography*, *21*(3), 421–440.

Payumo, J. G., Lan, G., & Arasu, P. (2018). Researcher mobility at a US research-intensive university: Implications for research and internationalization strategies. *Research Evaluation*, *27*(1), 28–35.

Peng, C., Li, Z., & Wu, C. (2023). Researcher geographic mobility and publication productivity: An investigation into individual and institutional characteristics and the roles of academicians. *Scientometrics*, *128*(1), 379–406.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41–55.

Rosenfeld, R. A., & Jones, J. A. (1986). Institutional mobility among academics: The case of psychologists. *Sociology of Education*, *59*(4), 212.

Ryazanova, O., & Jaskiene, J. (2022). Managing individual research productivity in academic organizations: A review of the evidence and a path forward. *Research Policy*, *51*(2), 104448.

Ryazanova, O., & McNamara, P. (2019). Choices and consequences: Impact of mobility on research-career capital and promotion in business schools. *Academy of Management Learning and Education*, *18*(2), 186–212.

Ryazanova, O., McNamara, P., & Aguinis, H. (2017). Research performance as a quality signal in international labor markets: Visibility of business schools worldwide through a global research performance system. *Journal of World Business*, *52*(6), 831–841.

Sandström, U. (2009). Combining curriculum vitae and bibliometric analysis: Mobility, gender and research performance. *Research Evaluation*, *18*(2), 135–142.

Stephan, P., Franzoni, C., & Scellato, G. (2016). Global competition for scientific talent: Evidence from location decisions of PhDs and postdocs in 16 countries. *Industrial and Corporate Change*, *25*(3), 457–485.

Sugimoto, C. R. (2022). Narrow hiring practices at US universities revealed. *Nature*, *610*, 37–38.

Sugimoto, C. R., & Larivière, V. (2023). *Equity for women in science: Dismantling systemic barriers to advancement*. Harvard University Press.

Sugimoto, C. R., Robinson-Garcia, N., Murray, D. S., Yegros-Yegros, A., Costas, R., & Larivière, V. (2017). Scientists have most impact when they're free to move. *Nature*, *550*(7674), 29–31.

Tohmo, T., & Viinikainen, J. (2017). Does intersectoral labour mobility pay for academics? *Scientometrics*, *113*(1), 83–103.

Van Der Wende, M. (2015). International academic mobility: Towards a concentration of the minds in Europe. *European Review*, *23*, S70–S88.

Velema, T. A. (2012). The contingent nature of brain gain and brain circulation: Their foreign context and the impact of return scientists on the scientific community in their country of origin. *Scientometrics*, *93*(3), 893–913.

Veugelers, R., & Van Bouwel, L. (2015). Destinations of mobile European researchers: Europe versus the United States. In *Global mobility of research scientists* (pp. 215–237). Academic Press.

Wagner, C. S., & Jonkers, K. (2017). Open countries have strong science. *Nature*, *550*(7674), 33.

Wapman, K. H., Zhang, S., Clauset, A., & Larremore, D. B. (2022). Quantifying hierarchy and dynamics in US faculty hiring and retention. *Nature*, *610*(7930), 120–127.

Welch, A. R. (1997). The peripatetic professor: The internationalisation of the academic profession. *Higher Education*, *34*(3), 323–345.

Woolley, R., & Turpin, T. (2009). CV analysis as a complementary methodological approach: Investigating the mobility of Australian scientists. *Research Evaluation*, *18*(2), 143–151.

Yan, E. (2020). Professor academic mobility data merged from ORCID and CCIHE. https://doi.org/10.6084/m9.figshare.12642623.v1

Yan, E., Zhu, Y., & He, J. (2020). Analyzing academic mobility of US professors based on ORCID data and the Carnegie classification. *Quantitative Science Studies*, *1*(4), 1451–1467.

Zhao, Z., Bu, Y., Kang, L., Min, C., Bian, Y., Tang, L., & Li, J. (2020). An investigation of the relationship between scientists' mobility to/from China and their research performance. *Journal of Informetrics*, *14*(2), 101037.

Zhu, Y., & Yan, E. (2017). Examining academic ranking and inequality in library and information science through faculty hiring networks. *Journal of Informetrics*, *11*(2), 641–654.

How to cite this article: Wu, C., Yan, E., Ni, C., & He, J. (2024). To move or to be promoted: Examining the effect of promotions and academic mobility on professors' productivity and impact. *Journal of the Association for Information Science and Technology*, *75*(12), 1350–1367. https://doi.org/10.1002/asi.24895

APPENDIX A

TABLE A1 Variable balance results for matched sample for citations.

	Moved	Promoted	*p*-value	Moved	Promoted	*p*-value
n	1480	519		519	519	
5-year prior citations (mean (SD))	3.22 (3.84)	3.11 (3.58)	0.564	75.64 (168.99)	89.62 (167.89)	0.182
4-year prior citations (mean (SD))	3.53 (4.46)	3.23 (3.73)	0.167	88.80 (208.74)	102.02 (183.00)	0.278
3-year prior citations (mean (SD))	4.15 (4.99)	3.69 (4.06)	0.056	102.01 (239.36)	115.30 (202.47)	0.335
2-year prior citations (mean (SD))	4.58 (5.55)	4.08 (4.35)	0.065	115.31 (297.60)	127.39 (209.69)	0.450
1-year prior citations (mean (SD))	5.33 (7.10)	4.43 (4.34)	0.006	132.04 (321.04)	143.67 (233.82)	0.505
Gender = Male (%)	1085 (73.3)	377 (72.6)	0.811	377 (72.6)	368 (70.9)	0.581
Rank = Associate professor (%)	429 (29.0)	167 (32.2)	0.190	167 (32.2)	174 (33.5)	0.692
Major (%)			<0.001			0.640
Clinical health	241 (16.3)	153 (29.5)		153 (29.5)	147 (28.3)	
Engineering	146 (9.9)	33 (6.4)		33 (6.4)	23 (4.4)	
Life	678 (45.8)	210 (40.5)		210 (40.5)	225 (43.4)	
Physical	287 (19.4)	61 (11.8)		61 (11.8)	64 (12.3)	
Social	128 (8.6)	62 (11.9)		62 (11.9)	60 (11.6)	
Employment year (mean (SD))	20.55 (8.58)	21.96 (8.87)	0.001	21.96 (8.87)	22.30 (8.91)	0.537
Class (%)			0.063			0.958
Medical School	106 (7.2)	55 (10.6)		55 (10.6)	59 (11.4)	
Other	84 (5.7)	35 (6.7)		35 (6.7)	36 (6.9)	
R1	1103 (74.5)	366 (70.5)		366 (70.5)	358 (69.0)	
R2	187 (12.6)	63 (12.1)		63 (12.1)	66 (12.7)	

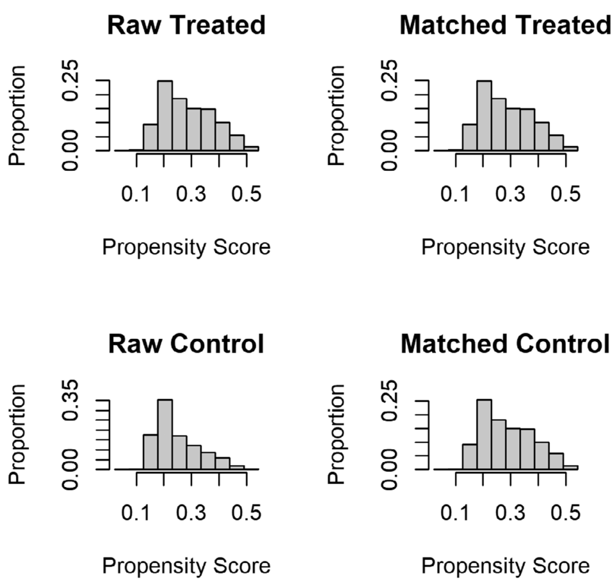

FIGURE A1 Histogram of propensity score of raw and matched sample for citations.

TABLE A2 Comparisons of regression results after propensity score matching for different matching methods.

	Citations				
	Nearest neighbor	**Nearest neighbor 2:1**	**Optimal**	**Full**	**Genetic**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Move	−16.935 (9.829)	−3.614 (7.719)	−5.013 (9.178)	−11.101 (8.008)	1.247 (9.263)
After	97.908*** (9.373)	94.155*** (6.004)	90.191*** (8.749)	101.137*** (5.493)	85.213*** (8.822)
Move × After	−3.433 (13.255)	0.320 (10.400)	4.284 (12.373)	−6.662 (10.780)	9.262 (12.476)
Constant	136.764*** (18.858)	124.174*** (12.707)	141.241*** (17.067)	124.288*** (11.700)	73.049*** (17.006)
Public or private (before)	Yes	Yes	Yes	Yes	Yes
Public or private (after)	Yes	Yes	Yes	Yes	Yes
Minority servicing (before)	Yes	Yes	Yes	Yes	Yes
Minority servicing (after)	Yes	Yes	Yes	Yes	Yes
Observations	11,418	17,127	11,418	21,989	11,418
R^2	0.024	0.024	0.023	0.022	0.021

*$p < 0.05$.**$p < 0.01$.***$p < 0.001$.