Standing on the Shoulders of Giants?—Faculty Hiring in Information Schools

Zhiya Zuo[a], Kang Zhao[a,*], Chaoqun Ni[a]

[a] *University of Iowa, United States*

Abstract

The past three decades have witnessed the tremendous growth of the number of information schools (a.k.a., iSchools) and the size of their faculty bodies. However, there is little empirical evidence in faculty hiring patterns within the community. Analyzing hand-curated data of 81 junior and 485 senior faculty members from 27 iSchools in the United States and a total of 41,981 journal and conference proceeding publications, we investigate the effects of collaboration experience on placement quality, controlling for other well studied factors including gender, scholarly performance, and prestige of degree-granting programs. In particular, we find that strong ties in collaboration, as measured by PhD advisors' academic achievements, have little correlation with placement quality fixing other factors. On the other hand, weak ties, manifested by coauthors excluding advisors, are found to be beneficial. Providing a better understanding of hiring practice in iSchools, the results highlight the importance of "standing on the shoulders of giants" for junior information science researchers wishing to find high-quality faculty job. Finally, our findings lay the foundation for future investigations, where stakeholders and administrators can assess the effectiveness of existing hiring strategies, which in turn provide managerial and policy implications for iSchools to adapt to the fast growing landscape of information science.

Keywords: Information schools, Hiring networks, Collaboration, Strength of weak ties

1. Introduction

Information science is an ever-growing scientific discipline that conducts interdisciplinary research on the triad among people, information, and technology. iSchools, academic institutions that host information science educators and researchers, have gradually gained popularity since the first iConference at Penn State University in 2005. From the pioneer schools "Gang of Three" (Pittsburgh, Syracuse, and Drexel) in 1988 to the "Gang of Ten" in 2003, the iSchool community (Larsen, 2009; Olson and Grudin, 2009) has witnessed enormous growth, with over eighty members from all over the globe.

Featuring a multidisciplinary research agenda, iSchools have a tendency to hire faculty members from diverse backgrounds besides library and information sciences, including communication, computing, education, humanities, management and policy, science and engineering, and social and behavioral studies (Wiggins and Sawyer, 2012; Zhang et al., 2013; Zuo et al., 2017). At the

*Corresponding author

Email addresses: `zhiya-zuo@uiowa.edu` (Zhiya Zuo), `kang-zhao@uiowa.edu` (Kang Zhao), `chaoqun-ni@uiowa.edu` (Chaoqun Ni)

same time, an increasing share of iSchool faculty members have doctoral degrees from the field of information science (Zuo et al., 2017), indicating a more established and independent identity of iSchools in academia.

Important for both institutions and individuals, faculty hiring in the academia is one of the essential building blocks for the production and diffusion of knowledge. Successful hiring decisions contribute to better research and education outcomes, which would lead to higher prestige and more resources for institutions. In the meantime, individuals who get hired by top tier institutions could enjoy higher institutional reputation and better institutional resources. Therefore, accumulative advantages will be given to advantageous entities, leading to further inequality, which is also referred to as the *Matthew effect* (Merton, 1968).

Given the importance of faculty hiring, we believe it is a timely contribution to investigate the recruitment practice among iSchools. Specifically, from the perspectives of young academics hoping to become a faculty member, we analyzed factors that might impact the placement quality. We hope the findings can also provide empirical evidence on the big picture of talent acquisition in this emerging area, help stakeholders better understand the *iSchool movement* and its developing identity, and offer new insights to the future of faculty search.

2. Related Work

2.1. The Landscape of Information Schools

As a unique emerging area in the scientific community, iSchools feature rapid growth in both education and research. With continuous adjustments to addressing the identity issue (Cronin, 2005), iSchools are aiming at human and social good by interdisciplinary approaches with information and technology. Past research has documented the development and evolution of iSchools in different aspects. While Subramaniam and Jaeger (2011) called for more courses on diverse topics, Wu et al. (2012) found that iSchools in fact had diverse program structures based on core course design. More recently, Song and Zhu (2017) presents an education framework for iSchools to embrace the big data era. In addition to curriculum design, doctoral dissertations were examined to study the Library and Information Science doctoral education (Shu and Julien, 2018; Sugitmoto et al., 2009) and the evolution of iSchool research landscape (Shu and Mongeon, 2016; Sugimoto et al., 2011).

Meanwhile, faculty members are vital to the intellectual prospect of an iSchool. Education backgrounds (i.e., PhD degree programs) are commonly used to measure the diverse composition of iSchools. Empirical evidence has shown that there are very diverse faculty bodies within iSchools based on their education backgrounds, including communication, computing, education, humanities, information, library, management and policy, science and engineering, and social and behavioral studies. Among these, most faculty members obtained their degree in computing (including computer/mathematical science and electrical/computer engineering; Luo, 2013; Wiggins and Sawyer, 2012; Wu et al., 2012; Zuo et al., 2017). Meanwhile, they all point out that there is an increasing share of faculty from the information field (including information science/studies/transfer and informatics.) Regarding the gender of iSchool faculty, Zuo and Zhao (2017) finds an even distribution of female faculty in computing, information, and library sciences, whereas many of their male counterparts obtained their degrees in computing.

Education backgrounds, while simple and straightforward, are too coarse-grained and may not align with faculty members' current research areas, especially in iSchools (Wiggins and Sawyer, 2012; Zhang et al., 2013). Numerous studies (Holmberg et al., 2013; Wu et al., 2012; Zhu et al., 2016) collected iSchool faculty members' online profiles and find diverse topics such as human-computer interaction, digital libraries, data mining, health informatics, social network analysis, etc., where the first two are dominant. By manually coding journal publications with the *People-Information-Technology-Management* scheme, Zhang et al. (2013) confirms iSchools' research focus on the triangle of people, information, and technology. More recently, Zuo et al. (2017) applied topic modeling techniques onto titles and abstracts of journal and conference proceeding articles by iSchool faculty for a finer-grained topical extraction over time. They find that topics including information technology for communication and collaboration, social network analysis, and user interface and experience are on the rise, whereas typical computer science areas such as algorithms, programming languages, and software engineering have been declining. Further, iSchools are found to be more cohesive and homogeneous with respect to their overall similarity in research topics. While male and female faculty have different research focuses based on their publications, such gender difference is smaller for among junior faculty members (Zuo and Zhao, 2017).

Finally, there are a few studies focusing on the faculty hiring within the information (and library) school community. Wiggins et al. (2008) compared the hiring practices between computer science (CS) departments and iSchools. The results imply that iSchools were more loosely coupled than CS departments and had more diverse hiring sources. In addition, hiring network statistics in both disciplines can explain the variance in US News and World Report with $R^2 > 0.7$. Investigating the faculty recruitment inequality of library and information science (LIS) schools, Zhu and Yan (2017) suggests that prestige hierarchy within the LIS community is manifested by (i) the size of downward placements and (ii) the dominant roles of highly ranked LIS schools. From a different perspective, Zuo et al. (2017) compared the assortativity mixing patterns (Newman, 2003) in iSchool hiring networks based on senior and junior faculty members on education backgrounds and research topics. They discover that iSchools tend to hire from similar peer schools. Meanwhile, the hiring network of junior faculty has a lower level of assortativity, implying that iSchools may have been trying to acquire talents that can complement their existing faculty body. Together with the increasing share of faculty members with doctorate degrees in information and more similar research topics, past studies have painted a comprehensive picture indicating a more cohesive and independent identity of iSchools.

2.2. Faculty Hiring

Past research has revealed two aspects affecting the hiring decisions in the academia: (i) universalism and (ii) particularism (Long and Fox, 1995). Universalism indicates that candidates are assessed based on their academic achievements, whereas particularism involves factors that are independent of scholarly merit such as social ties, ethnicity, and gender. Various studies have shown that particularistic factors including institutional prestige (Bedeian et al., 2010; Bedeian and Feild, 1980; Burris, 2004; Hadani et al., 2012; Hanneman, 2001; Katz et al., 2011; Zhu and Yan, 2017) and gender (Foschi et al., 1994; Reuben et al., 2014; Sheltzer and Smith, 2014) appear to dominate the final hiring decision, shaping a steep hierarchy in talent exchange networks (Clauset et al., 2015; Way et al., 2016).

While the vast literature has systematically examined the effects of institutional prestige and gender on hiring outcome, two social network factors could also provide a better understanding of academic job market—advisors and collaborators. Indeed, it is possible that past collaboration experience with prestigious researchers may benefit one's job search. Specifically, mentorship is one of the strongest ties as well as the most important aspects of PhD training. Past studies have shown the significant role of mentorship in various aspects, such as productivity (Hollingsworth and Fassinger, 2002; Johnson, 2008; Paglis et al., 2006; Tenenbaum et al., 2001; Williamson and Cable, 2003), future career planning (Cho et al., 2011; Curtin et al., 2016; Russo, 2011), and career satisfaction (Kammeyer-Mueller and Judge, 2008; Kay and Wallace, 2009). Indeed, PhD advisors not only advise students scholarly, but, more importantly, provide social capital that significantly help junior researchers expand their relatively limited social connections (Hezlett and Gibson, 2007). Specifically, Cable and Murray (1999) collected candidates' dissertation committee chairman eminence by surveying opinions from Editorial board members of Academy of Management Journal and Academy of Management Review. They found that this variable is significantly and positively correlated with the number of job offers, as well as their quality (i.e., prestige of offering institutions). However, Judge et al. (2004) finds no significant contributions from candidates' committee members' publication success to the prestige of job offers. The evaluation of committee (members and chairmen measured separately) was done by questionnaires to a random sample of 300 active members of the Society of Industrial and Organizational Psychology. Both studies utilized qualitative measures on mentorship prestige which can be hard to reproduce and lack objectivity. Hadani et al. (2012), on the other hand, measured PhD advisors' academic credentials by their publication records. They find little effect of these variables on the prestige of institutions that hired PhD students. More recently, Godechot (2016) discovers that the chance of a faculty candidate will be doubled if one of the search committee members is her PhD advisor. Such conflicting results suggests that the effect of advisors on academic placement may vary in different areas. This therefore necessitates further studies on the importance of mentorship on PhD students' academic career in the emerging field of information—because of the lack of well-accepted program prestige, a natural and intuitive hypothesis is the more important role of PhD advisors.

Another research gap is the lack of investigation on the importance of weak ties (Granovetter, 1973) that may potentially lead to better job placement. Past research has, in fact, shown that social ties have significant impact on academic careers (Bu et al., 2018; Pezzoni et al., 2012; Zinovyeva and Bagues, 2015). While dissertation committee members, especially chairmen (i.e., PhD advisors), can provide significant and direct assistance in student's future academic career, weaker social ties (e.g., infrequent but eminent collaborators in the past) may also bring in new perspectives and contribute to job placements. In particular, within a multidisciplinary area such as information science, collaboration is the key to integrate diverse knowledge source to achieve interdisciplinary research (Zuo and Zhao, 2018). As such, we propose that collaborators, especially those with high standing, may play a significant role in the future career of PhD graduates.

To bridge these gaps, we ask the following research question: *How do (i) PhD advisors and (ii) coauthors (excluding advisors) contribute to the faculty placement within the iSchool community?* The answers to the two questions provide empirical evidence on the current hiring practice, which is useful for stakeholders as well as administrators to review the current talent acquisition strategies, which in turn inspire managerial and policy implications for the future of faculty search. Additionally, we hope such findings can also help junior researchers who want to pursue faculty position in iSchools.

3. Methods

3.1. Data Collection

Our dataset is based on 27 iSchool members in the United States at the time of 2014 (Zuo et al., 2017). Specifically, we retrieve information for full time tenured and tenure-track faculty members, including their names, title (full/associate/assistant), PhD schools and programs, and current affiliations. It is noteworthy that we focus on the hiring of junior faculty members (i.e., assistant professor), whereas senior (i.e. associate and full professors) hiring data would be used to quantify placement quality (see Section 3.2.) Note that we only consider within-iSchool faculty hiring–an instance of faculty hiring must be about a faculty member who was employed up to the year of 2014 and obtained her PhD from one of the 27 iSchools. For example, if an iSchool faculty member has a PhD degree in history, her hiring by an iSchool would not be included as an instance of iSchool faculty hiring in our analysis. For the hiring of junior faculty members, we further collected gender, the year they joined their current schools, and doctoral dissertation advisors[1]. There are a total number of 566 faculty members, including 81 junior and 135 senior within-iSchool hiring instances, as well as 350 senior faculty members with doctorate degrees from outside iSchools.

Given the names and affiliations of a faculty member, we are able to retrieve her publication profile using Scopus APIs[2]. To eliminate the problem of author name ambiguity, we manually inspected each author profile ID in Scopus before using them to retrieve publication lists. A total number of 22,665 journal and conference proceeding papers published up to the year of 2014 were obtained from the API for the 566 iSchool faculty members. We also retrieved papers by PhD advisors and coauthors of the 81 junior faculty members. In summary, our publication dataset includes 41,984 papers, along with their annual citation counts.

3.2. Ranking iSchools

As an emerging and young discipline, there is no well-accepted ranking for iSchools. Instead, we constructed iSchool *attractiveness* scores via two data-driven approaches based on past faculty hires: one based on scholarly achievement, and the other based on hiring networks. We note that scores for each school in this context should be interpreted as *attractiveness* scores other than rankings—hiring decisions are mutual selections, where departmental standing is only part of the consideration.

3.2.1. Achievement-based Attractiveness Scores

Research achievement is one of the most important dimensions of academic departmental prestige. One commonly adopted metric to quantify research success is h-index (Hirsch, 2005): a researcher has an h-index of h if h of her published articles have at least h citations, which captures both productivity and citation impact.

To measure the attractiveness of an iSchool based on scholarly achievement, we defined a score for each iSchool as the median of all belonging senior faculty members' h-index, no matter whether

[1] Gender information was collected based on faculty profile pages as well as pronoun used in websites referring to the faculty members; Year of hire was found based on CVs or faculty profile pages; Advisors were identified via ProQuest Dissertations & Theses Global.

[2] We used Scopus Search and Citation Overview APIs. For more details, please refer to `https://dev.elsevier.com/api_docs.html`.

their PhDs were obtained from iSchools or not, based on their publications up to the year of a specific candidate's hire. For example, if a junior faculty member was hired by an iSchool in the year of 2011, the h-index of the iSchool for that hiring would be the median h-indices for all of its senior faculty's publications till 2011. The higher this value is, the more attractive an iSchool is with respect to research achievement.

3.2.2. Prestige-based Attractiveness Scores

Institutional attractiveness is also attributed to past hires which have been accumulating reputation. Thus we adopted another "ranking" of the 27 iSchools based on the hiring of *senior* faculty members. A hiring network (Figure 1) was constructed—each node is an iSchool, whereas directed edges represent the flow of PhD graduates, from an iSchool that granted a faculty member's PhD to the another iSchool that hired the faculty member. Note that only the 135 within-iSchool hiring of senior faculty members were included in this network.

Specifically, we used two network-based ranking methods: (i) minimal violation ranking (MVR; Clauset et al., 2015), which aims at minimizing edges from lower to higher ranked nodes. We ran MVR repetitively for 100 times, with 10,000 iterations as the burn-in window and 1,000 samples; (ii) PageRank (Page et al., 1998), which assigns high scores to nodes with incoming links from others with high scores. To calculate the PageRank scores, we reverse the edge direction of PhD flow—an iSchool A that hires another iSchool B' PhD graduate as a faculty member will have an edge from B to A, implying the direction of endorsement or acknowledge (Burris, 2004; Katz et al., 2011; Zhu and Yan, 2017). We repeated PageRank with 1,000 different damping factors ranging from 0 to 1. For both algorithms, we took the average as the final scores. It is worth noting that while an iSchool is more attractive with higher PageRank scores, it is less attractive with higher MVR scores. To make it consistent, we will be using negative MVR scores throughout this paper.

3.3. Measuring the Reputation of Collaborators

Given junior faculty members publication records, we retrieved a list of coauthors before they were hired by their current institution. We considered two types of collaborators for a junior faculty candidate: strong-tie collaborator(s) would be her dissertation advisor(s) while the other non-advising coauthors would be weak-tie collaborators. To measure the reputation of a faculty candidate's strong-tie collaborators, we used the h-index of her dissertation advisor[3] up to the year the candidate was hired as a junior faculty member. Similarly, the reputation of a candidate's weak-tie collaborators is the median of her weak-tie collaborators' h-indices up to the year the candidate was hired as a junior faculty member. Note that to reduce collinearity introduced by the nature of coauthorship, coauthored papers with a junior faculty candidate were excluded when calculating h-indices for the candidate's collaborators. Finally, we also counted the distinct number of weak-tie collaborators as an additional variable to measure one's past collaboration experience. However, this count is highly correlated with candidates' scholarly performance (0.78 with productivity and 0.74 with h-index; Figure 3). A more detailed description of variable selection can be found in Appendix A.

[3] In the case of co-advising, we used the average of both advisors' h-index as the reputation of strong-tie collaborators.

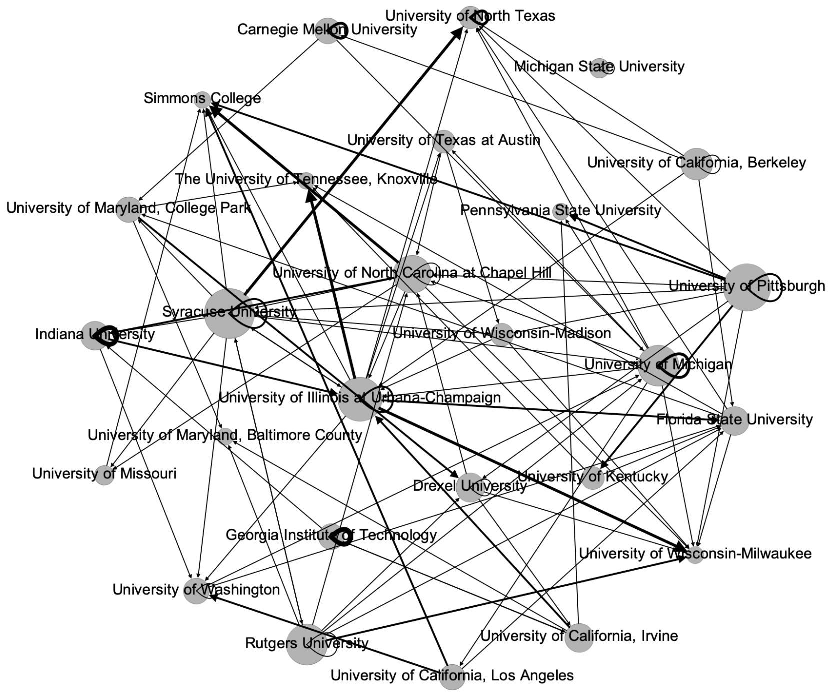


Figure 1: Hiring network of senior faculty members between the 27 iSchools. Node (i.e., iSchool) size is proportional to her out-degree (i.e., faculty members produced.) Edge width is proportional to the number of hires between the two end nodes.

3.4. Other Variables

Based on the literature, we included three variables which have been shown to affect faculty hiring in general:

(i) Gender of candidates (e.g., Way et al., 2016). It is encoded as a binary variable, where female is 1 and male is 0.

(ii) Faculty candidates' scholarly performance (e.g., Bertsimas et al., 2015; Burris, 2004; Kim and Kim, 2015; Way et al., 2016). While a candidate's h-index can approximate her scholarly performance, we decided to use productivity (i.e., the number of publications up to the year of hire) instead for two reasons: First, citations manifest various patterns such as delay, citation aging, or, more rarely, "sleeping beauties" (Wang, 2013). Therefore, productivity can also quantify the scholarly competency for junior researchers, when it is difficult to accumulate citations during the relatively short time span of doctoral studies. Second, compared to h-indices, the productivity of candidates is less correlated with h-indices of their strong-tie and weak-tie collaborators (Figure 3), and can thus help to reduce multicollinearity in our subsequent regression models.

(iii) Quality of the doctoral-degree-granting program (e.g., Bedeian et al., 2010; Burris, 2004; Hanneman, 2001; Way et al., 2016). The quality of a candidate's doctoral program is approximated by the attractiveness score of the iSchool from which she obtained her PhD degree.

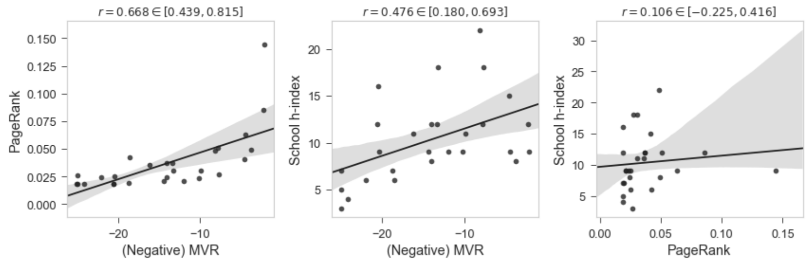
3.5. Regression Setup

To investigate the effect of collaboration ties on placement quality (i.e., the attractiveness scores of hiring iSchools) controlling for all other related factors, we conduct step-wise linear regression analysis. Specifically, we first enter the control variables, including candidate gender, productivity, alma mater attractiveness score. In the second and third step, we include the two variables of interest, the reputation of strong-tie collaborators (i.e., advisors) and weak-tie collaborators (i.e., coauthors excluding advisors), respectively. We also present the correlation matrix and the variance inflation factors to demonstrate that there is no collinearity issue.

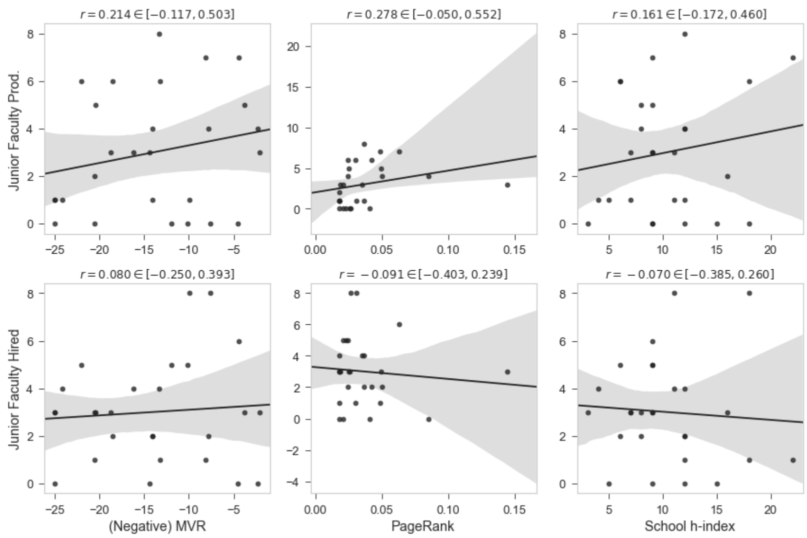
4. Results

As discussed in Section 3.2, each iSchool has three *attractiveness* scores based on senior faculty's scholarly achievement (i.e., school h-index) and historical hiring outcomes of senior faculty (MVR and PageRank scores). There are only low to moderate correlations between each pair of the three metrics (Figure 2a and first three elements in Figure 2c), indicating that these scores indeed capture an iSchool's reputation or quality in different ways. In addition, these three scores have low correlations with the number of junior faculty members produced or hired by each iSchool (Figure 2b and the last two rows in Figure 2c). Given that iSchools are multidisciplinary with faculty members from different disciplines, we believe that the number of faculty members one iSchool trained for or hired from other iSchools are not necessarily good indicators of the iSchool's overall attractiveness. After all, the hiring network is only among iSchools—some iSchools hire faculty members from outside the iSchool community, while some iSchools produce faculty members that are hired by other areas. Finally, we note that there is little multicollinearity in the dataset (Figure 3 and VIF columns in Tables B.1 to B.3).

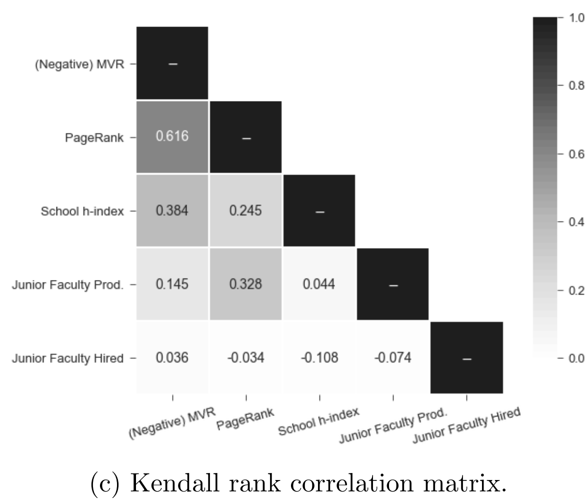
Figure 4 shows the standardized regression coefficients in the three different models with each of the three iSchool *attractiveness scores* as the dependent variables. Standardized coefficients enable us to compare various factors which are originally in different scales since the changes in both dependent and independent variables are in the units of standard deviations. For both achievement- and prestige-based attractiveness scores controlling for the well-studied variables, we find that (i) there is no strong correlations between the reputation of strong-tie collaborators and placement quality; (ii) the reputation of weak-tie collaborators ties on placement quality is shown to be beneficial. At the same time, other factors exert no significant regression coefficients, even though some are significantly correlated with placement quality based only on bivariate zero-order correlations (Figure 3). An exception is the positive and strong coefficient on PhD iSchool standing when the attractiveness score is based on school level scholarly achievement. Appendix B lists detailed regression outcome.



(a) Scatter plots between attractiveness scores.



(b) Scatter plots of the number of junior faculty members produced vs. attractiveness scores.



(c) Kendall rank correlation matrix.

Figure 2: Correlation between attractiveness scores as well as the number of junior faculty produced by the 27 iSchools: (a) & (b) Dots are observed scores while the solid black lines are fitted straight lines. Shaded areas are the 90% confidence intervals; Titles in each scatter plot show the Pearson correlation as well as the 90% confidence intervals. (c) Since attractiveness scores are inherently rankings, we also show Kendall's τ rank correlation coefficients.

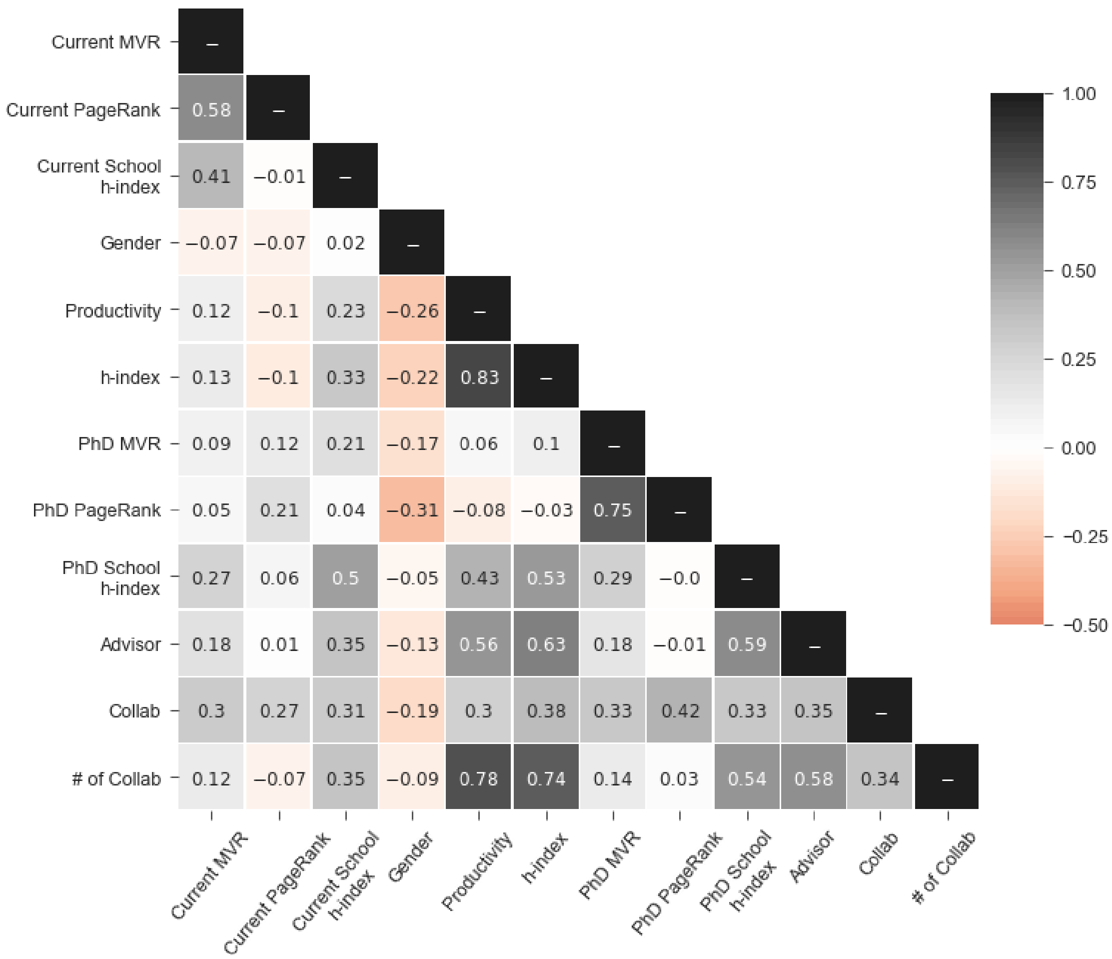
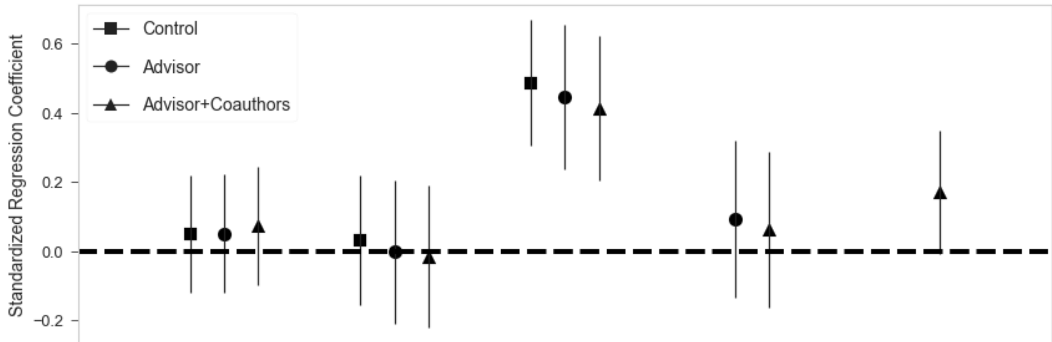
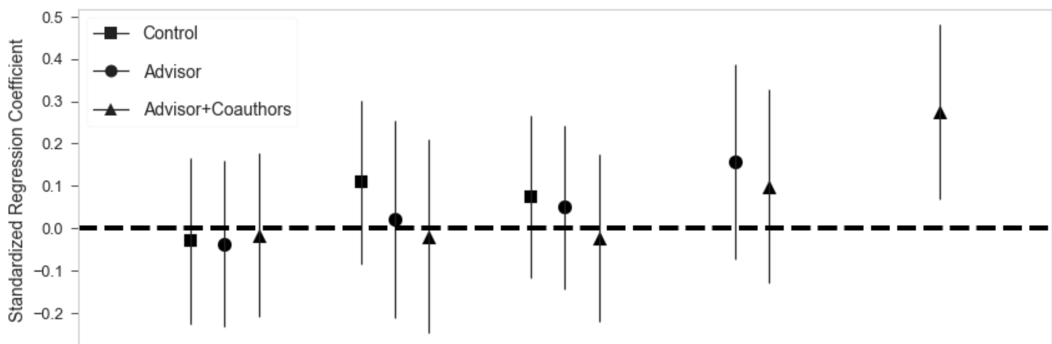


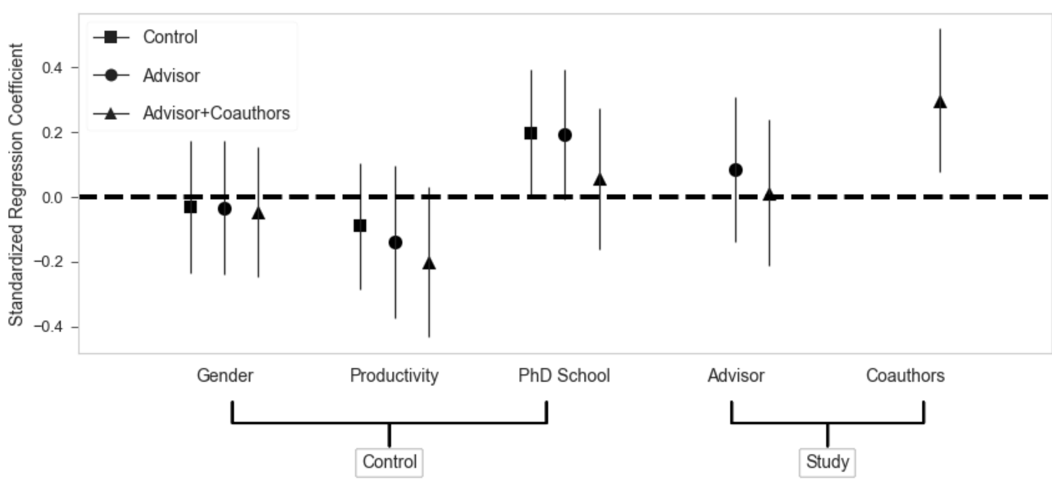
Figure 3: Pairwise zero-order Pearson correlation between all variables. More black-ish colors indicate positive correlation coefficients, whereas red-ish indicate negative ones. h-index and the number of weak-tie collaborators is included to show the superiority of excluding the latter and using productivity for reducing multicollinearity.



(a) School h-index as attractiveness score



(b) (Negative) MVR score as attractiveness score



(c) PageRank score as attractiveness score

Figure 4: Standardized regression coefficients for (a) achievement-based and (b) & (c) prestige-based attractiveness scores. Each solid symbol (square/circle/triangle) is the point estimate of a regression coefficient. The error bars are 90% confidence intervals. The further away the confidence intervals are from zero (the dashed horizontal reference line), the stronger the effects are on placement quality.

5. Discussion and Conclusion

Using hand-curated and large-scale bibliometric and educational data, we measured the *attractiveness scores* of iSchools using three different measures. We also constructed candidate profiles for iSchool junior faculty members, including their gender, scholarly performance, prestige of degree-granting iSchool, and reputation of both strong-tie and weak-tie collaborators.

By examining the effects of these factors on junior faculty's placement quality, we revealed some interesting findings. First, while correlated with the rest competency variables, gender has little to do with faculty placement quality in the iSchool community. Although gender disparity is not a serious issue among iSchools, we would like to call for attention to not overlook this non-uniformity risk that can potentially hinder diversity and inclusion in the community (Cole, 1987; Way et al., 2016). Looking at bivariate zero-order correlations, all proposed factors excluding gender have positive correlations with placement quality. Nonetheless, reputation of weak-tie collaborators is the only factor that stands out across three different iSchool attractiveness scores when controlling for the other factors. Such findings highlight the importance of *standing on the shoulders of giants* especially those who are not academic advisors, and *the strength of weak ties* (Granovetter, 1973), in finding faculty jobs in the iSchool community.

There are several limitations in our study. First, as mentioned before, iSchools have diverse hiring sources. By limiting the investigation on "within-iSchool hires", we cannot capture what affect faculty recruitment from outside the iSchool community. Second, our analysis inevitably suffers from specification errors. In particular, there are many important factors that can affect the final placement, such as personality (e.g., easy-going or not), academic potentials that can hardly be captured by publication profiles (e.g., communication skills), faculty recruiting criteria (e.g., focusing on a specific research area), characteristics of the target school (e.g., location and weather), and family issues, etc. Lastly, we note that quantifying university and institutional reputation is very difficult, if not impossible. The three proposed measures only capture some of the "attractiveness" characteristics, among others, that contribute to the reputation of an academic unit.

In closing, we also suggest exciting future research directions to advance the understanding of talent exchange within the iSchool community. Specifically, hires from other disciplines will be a significant step to boost our understanding of what directions iSchools have been heading towards. As pointed by the theory of Learning-by-Hiring (Song et al., 2003), iSchools, as an emerging and fast growing area, are constantly gaining new perspectives to study the triad of people, information, and technology by acquiring experts from outside the community. We believe that the study on how inclusion of "outsiders" contribute to the evolution of iSchools will not only help individual scholars understand the faculty job market in iSchools, but also, more importantly, provides insights into the evolving identity of information as a field. Another promising extension is to more systematically define strong- and weak-tie collaborators. While advisors are crucial to PhD students' future career, some of the non-advising collaborators, even when they may not be the most frequent co-authors, may be equally, or even more, important by providing strong guidance, mentorship, and reference in one's job search and career. Such identifications of the most significant chaperones among one's co-authors would need more fine-grained analysis of one's career history, such as the trajectories of research topics and impact. Finally, our findings lay the foundation for future investigations, where stakeholders and administrators can assess the effectiveness of existing hiring strategies, which in turn provide managerial and policy implications for iSchools to adapt to the fast growing landscape of information science.

Appendix A. Variable Selection for Measuring Collaborator Reputation

We evaluated various measures that quantify the reputation of strong- (i.e., advisors) and weak-tie collaborators (i.e., coauthors excluding advisors), including h-index, citation counts and productivity. Since there may be multiple collaborators for one junior faculty[4], we used maximal, mean, and median values to capture the top and central tendency of collaborators' reputation. In addition to research output, the number of weak-tie collaborators was also calculated to quantify the size of collaboration networks. For both types of collaborators (Figures A.1 and A.2), all research output metrics (h-index, productivity, and citation counts, including their maximum, mean and median) are highly or moderately correlated. For weak-tie collaborators, the count is moderately correlated with research output metrics. Therefore, we first selected median h-index for both strong- and weak-tie collaborator reputation. The number of weak-tie collaborators is also selected. However, we decided not to include this variable in the final regression model due to its high correlation with candidates' productivity as well as h-index (Section 3.3).

[4] 78 out of 81 junior faculty members have one single advisor, whereas 3 have co-advisors; the median and mean number of weak-tie collaborators are 15 and 13, respectively.

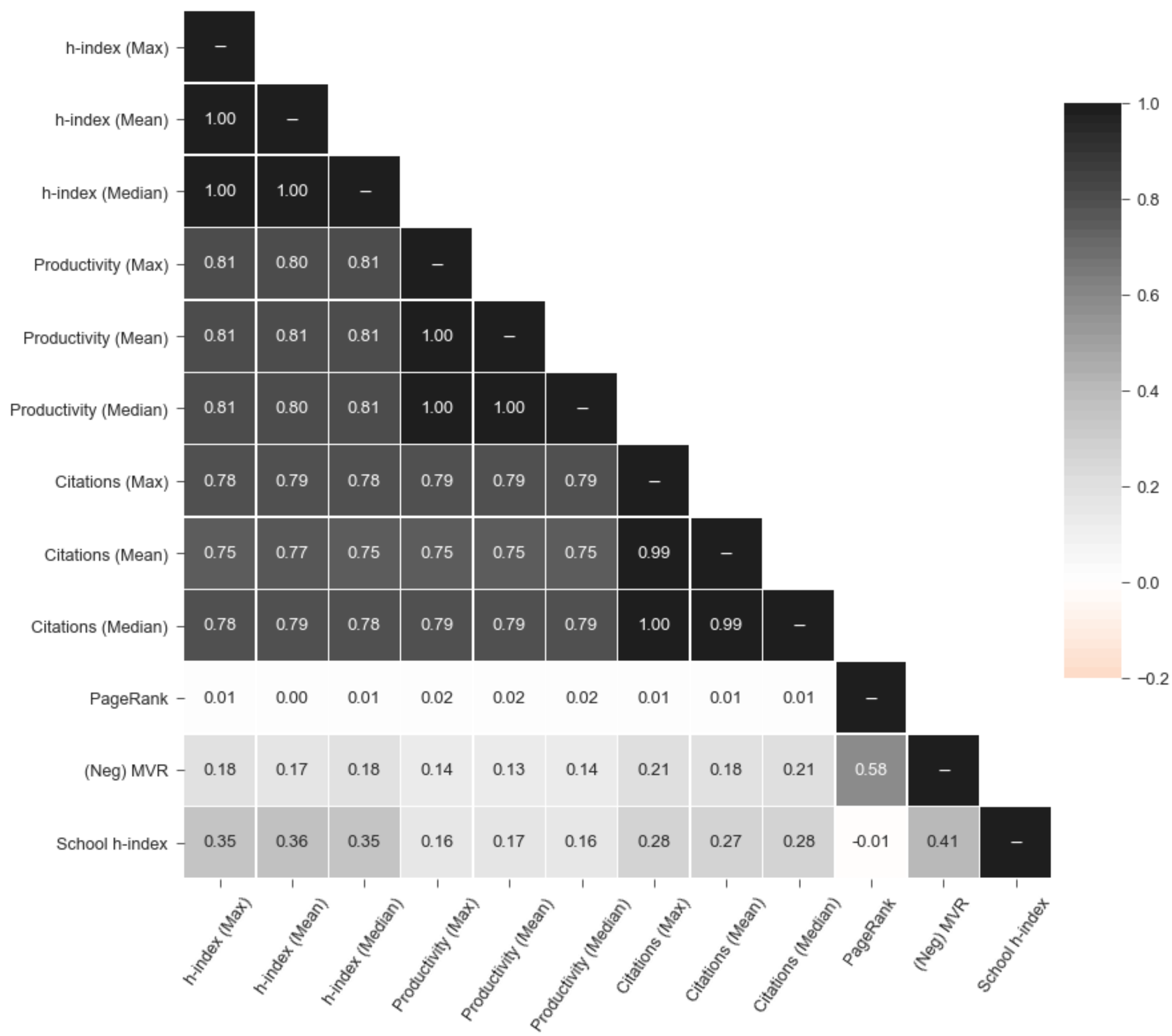


Figure A.1: Pearson correlation matrix among the candidate variables for strong-tie collaborator reputation and hiring iSchools' attractiveness scores (i.e., target variables).

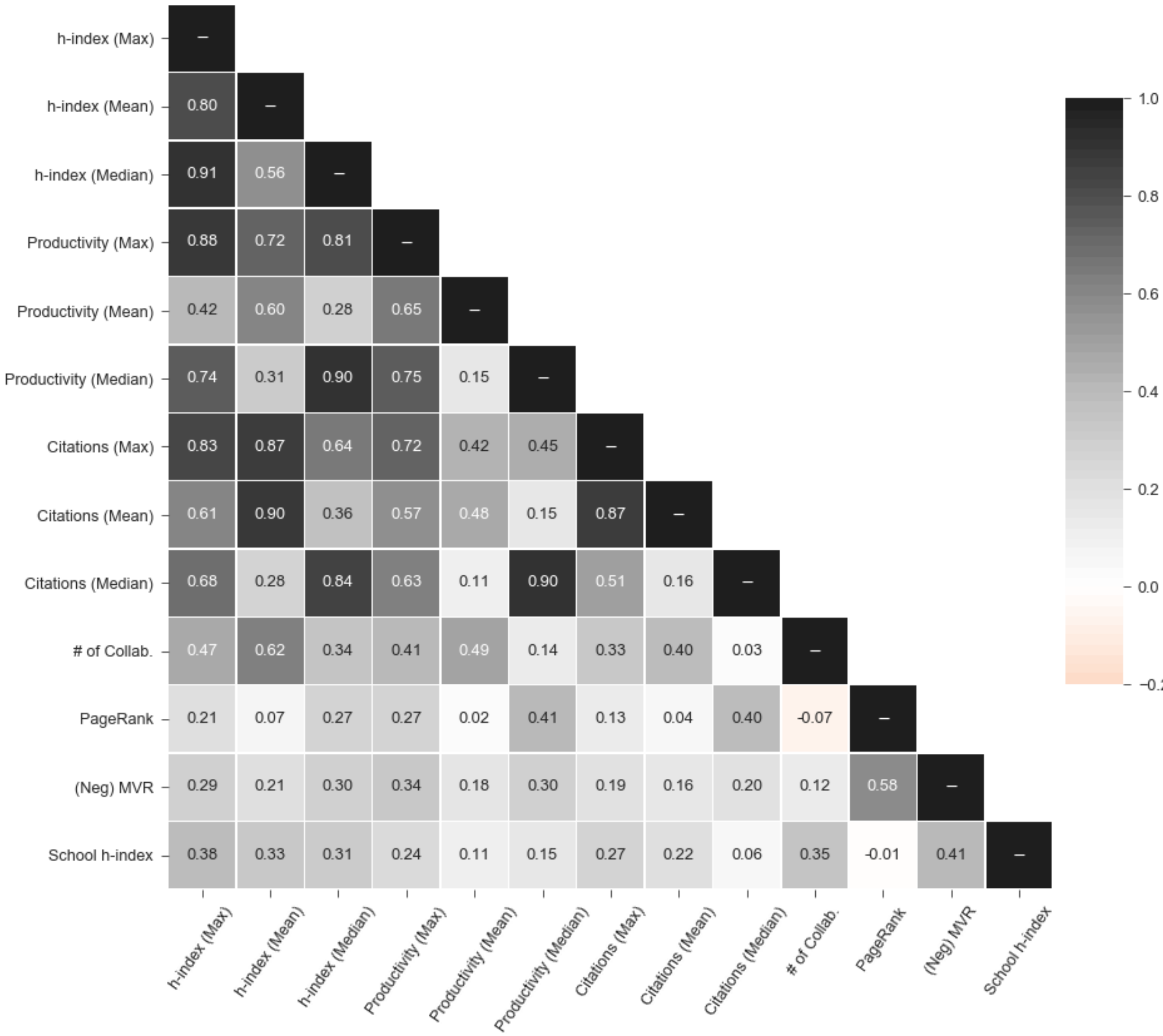


Figure A.2: Pearson correlation matrix among the candidate variables for weak-tie collaborator reputation and hiring iSchools' attractiveness scores (i.e., target variables).

Appendix B. Regression Results

In this section, we present the detailed results of our regression analyses, including the standardized regression coefficients and 90% confidence intervals (Tables B.1 to B.3). The variance inflation factors (VIF) in the full models (i.e., "Advisor+Coauthors") are also reported —all of them are lower than 2, indicating little multicollinearity.

Table B.1: Regression results for achievement-based attractiveness scores: h-index.

	Variable	Control		Advisor		Advisor+Coauthors		
		Coef.	90% Conf. Int.	Coef.	90% Conf. Int.	Coef.	90% Conf. Int.	VIF
Control	Gender	0.049	(-0.121, 0.220)	0.051	(-0.121, 0.222)	0.073	(-0.098, 0.244)	1.1
	Productivity	0.032	(-0.156, 0.221)	-0.002	(-0.209, 0.205)	-0.016	(-0.222, 0.189)	1.58
	PhD School	0.486	(0.304, 0.668)	0.446	(0.238, 0.653)	0.414	(0.205, 0.622)	1.629
Study	Advisor	—	—	0.092	(-0.134, 0.319)	0.063	(-0.163, 0.289)	1.917
	Coauthors	—	—	—	—	0.171	(-0.009, 0.350)	1.208

Table B.2: Regression results for prestige-based attractiveness scores: MVR.

	Variable	Control		Advisor		Advisor+Coauthors		
		Coef.	90% Conf. Int.	Coef.	90% Conf. Int.	Coef.	90% Conf. Int.	VIF
Control	Gender	-0.03	(-0.227, 0.167)	-0.036	(-0.233, 0.161)	-0.016	(-0.209, 0.177)	1.113
	Productivity	0.109	(-0.086, 0.303)	0.02	(-0.213, 0.253)	-0.019	(-0.248, 0.211)	1.573
	PhD School	0.074	(-0.116, 0.265)	0.05	(-0.143, 0.244)	-0.023	(-0.220, 0.174)	1.158
Study	Advisor	—	—	0.157	(-0.072, 0.387)	0.099	(-0.129, 0.327)	1.563
	Coauthors	—	—	—	—	0.274	(0.068, 0.481)	1.277

Table B.3: Regression results for prestige-based attractiveness scores: PageRank.

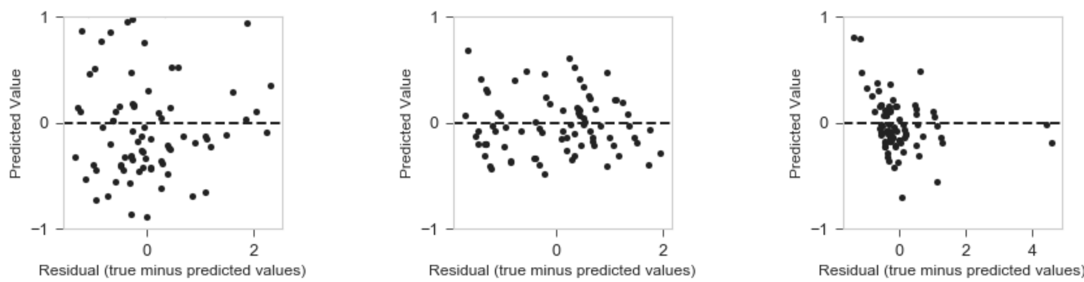
	Variable	Control		Advisor		Advisor+Coauthors		
		Coef.	90% Conf. Int.	Coef.	90% Conf. Int.	Coef.	90% Conf. Int.	VIF
Control	Gender	-0.032	(-0.236, 0.172)	-0.034	(-0.239, 0.171)	-0.048	(-0.248, 0.153)	1.227
	Productivity	-0.092	(-0.286, 0.103)	-0.14	(-0.373, 0.094)	-0.202	(-0.434, 0.030)	1.65
	PhD School	0.195	(-0.002, 0.393)	0.192	(-0.007, 0.390)	0.056	(-0.162, 0.274)	1.459
Study	Advisor	—	—	0.085	(-0.139, 0.308)	0.012	(-0.213, 0.237)	1.548
	Coauthors	—	—	—	—	0.298	(0.077, 0.518)	1.493

Appendix C. Checking Assumptions for Regression Models

The validity of linear regression results depends on three assumptions: (i) linearity: the relationship between independent and dependent variables should follow a *linear* relationship; (ii) homoscedasticity: the variance around the regression line is independent of the values of independent variables; (iii) normality: the residuals (i.e., error terms) are normally distributed. In this appendix, we test these assumptions for our regression models reported in Section 3.5.

Linearity and Homoscedasticity

First, we visualized the relationship between predictions and residuals (i.e., prediction errors) in Figure C.1. The reasonably random distribution of the residuals in Figures C.1a and C.1b indicate that linearity and homoscedasticity are valid in both regression models. While there are a couple of outliers in Figure C.1c, the majority of the residuals are reasonably random (data points in the left concentrated areas betwee 0 and 2 on the x-axis.) To supplement the visual diagnostics, we applied rainbow test (Utts, 1982) and failed to reject the null hypothesis of linearity with p-values of 0.490, 0.151, and 0.207 for all three attractiveness measures respectively. In addition, there is inadequate evidence to reject homoscedasticity with the Breusch-Pagan Lagrange Multiplier test (Breusch and Pagan, 1979) with p-values of 0.723, 0.744, and 0.754.

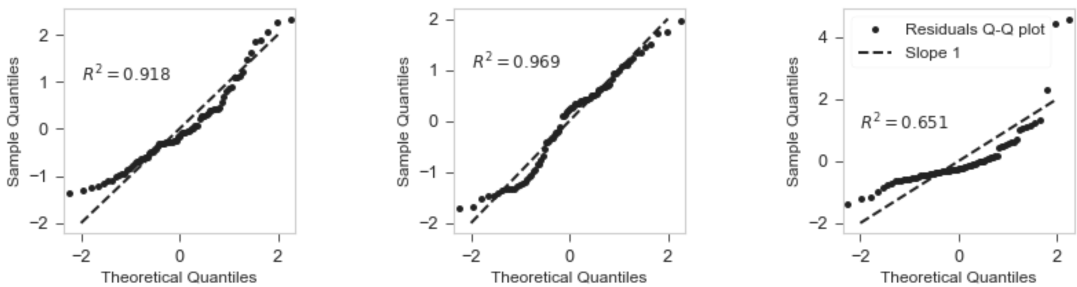


(a) h-index (b) MVR (c) PageRank

Figure C.1: Scatter plot of predictions vs. residuals for (a) achievement-based and (b) & (c) prestige-based attractiveness scores.

Normality

Quantile-Quantile (Q-Q) plot is employed to examine normality of the residual scores (Figure C.2). The better the Q-Q scatter points fall on the straight line, the closer the samples are to normal distribution. Strong linear relationships in Figures C.2a and C.2b ($R^2 > 0.95$) are found between the sample and theoretical (i.e., normal distribution) quantiles. For PageRank attractiveness scores, we only found a moderate linear trend ($R^2 = 0.651$) Nonetheless, past studies have shown that sample sizes of 40 (Barrett and Goldsmith, 1976) or 80 (Ratcliffe, 1968) are large enough to diminish the departure from normality for inference. Our sample size is 81, which is large enough for conducting effective statistical inference. Moreover, the literature generally recognizes that violation of normality assumption does not necessarily affect the validity of linear regression (Lumley et al., 2002).



(a) h-index (b) MVR (c) PageRank

Figure C.2: Q-Q plot for (a) achievement-based and (b) & (c) prestige-based attractiveness scores.

References

Barrett, J. P. and Goldsmith, L. (1976). When is n sufficiently large? *American Statistician*, 30(2):67–70.

Bedeian, A. G., Cavazos, D. E., Hunt, J. G., and Jauch, L. R. (2010). Doctoral degree prestige and the academic marketplace: A study of career mobility within the management discipline. *Academy of Management Learning and Education*, 9(1):11–25.

Bedeian, A. G. and Feild, H. S. (1980). Academic Stratification In Graduate Management Programs: Departmental Prestige and Faculty Hiring Patterns. *Journal of Management*, 6(2):99–115.

Bertsimas, D., Brynjolfsson, E., Reichman, S., and Silberholz, J. (2015). OR ForumTenure Analytics: Models for Predicting Research Impact. *Operations Research*, 63(6):1246–1261.

Breusch, T. S. and Pagan, A. R. (1979). A Simple Test for Heteroscedasticity and Random Coefficient Variation. *Econometrica*, 47(5):1287.

Bu, Y., Ding, Y., Xu, J., Liang, X., Gao, G., and Zhao, Y. (2018). Understanding success through the diversity of collaborators and the milestone of career. *Journal of the Association for Information Science and Technology*, 69(1):87–97.

Burris, V. (2004). The Academic Caste System: Prestige Hierarchies in PhD Exchange Networks. *American Sociological Review*, 69(2):239–264.

Cable, D. M. and Murray, B. (1999). Tournaments versus sponsored mobility as determinants of job search success. *Academy of Management Journal*, 42(4):439–449.

Cho, C. S., Ramanan, R. A., and Feldman, M. D. (2011). Defining the ideal qualities of mentorship: A qualitative analysis of the characteristics of outstanding mentors. *American Journal of Medicine*, 124(5):453–458.

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

Cole, J. R. (1987). *Fair Science: Women in the Scientific Community*. Columbia University Press, New York, 1st edition.

Cronin, B. (2005). An I-dentity crisis? The information schools movement. *International Journal of Information Management*, 25(4):363–365.

Curtin, N., Malley, J., and Stewart, A. J. (2016). Mentoring the Next Generation of Faculty: Supporting Academic Career Aspirations Among Doctoral Students. *Research in Higher Education*, 57(6):714–738.

Foschi, M., Lai, L., and Sigerson, K. (1994). Gender and Double Standards in the Assessment of Job Applicants. *Social Psychology Quarterly*, 57(4):326.

Godechot, O. (2016). The chance of influence: A natural experiment on the role of social capital in faculty recruitment. *Social Networks*, 46:60–75.

Granovetter, M. S. (1973). The Strength of Weak Ties. *American Journal of Sociology*, 78(6):1360–1380.

Hadani, M., Coombes, S., Das, D., and Jalajas, D. (2012). Finding a good job: Academic network centrality and early occupational outcomes in management academia. *Journal of Organizational Behavior*, 33(5):723–739.

Hanneman, R. (2001). The prestige of Ph. D. granting departments of sociology: A simple network approach. *Connections*, 24(1):68–77.

Hezlett, S. A. and Gibson, S. K. (2007). Linking Mentoring and Social Capital: Implications for Career and Organization Development. *Advances in Developing Human Resources*, 9(3):384–411.

Hirsch, J. E. (2005). An index to quantify an individual's scientific research output. *Proceedings of the National Academy of Sciences of the United States of America*, 102(46):16569–72.

Hollingsworth, M. A. and Fassinger, R. E. (2002). The role of faculty mentors in the research training of counseling psychology doctoral students. *Journal of Counseling Psychology*, 49(3):324–330.

Holmberg, K., Tsou, A., and Sugimoto, C. R. (2013). The Conceptual Landscape of iSchools: Examining Current Research Interests of Faculty Members. *Information Research*, 18(3).

Johnson, W. B. (2008). Student-Faculty Mentorship Outcomes. In *The Blackwell Handbook of Mentoring*, chapter 12, pages 189–210. Blackwell Publishing Ltd, Oxford, UK.

Judge, T. A., Kammeyer-Mueller, J., and Bretz, R. D. (2004). A longitudinal model of sponsorship and career success: A study of Industrial-Organizational Psychologists. *Personnel Psychology*, 57(2):271–303.

Kammeyer-Mueller, J. D. and Judge, T. A. (2008). A quantitative review of mentoring research: Test of a model. *Journal of Vocational Behavior*, 72(3):269–283.

Katz, D. M., Gubler, J. R., Zelner, J. L., Bommarito II, M. J., Provins, E., and Ingall, E. (2011). Reproduction of Hierarchy? A Social Network Analysis of the American Law Professoriate. *Journal of Legal Education*, 61(1):76–103.

Kay, F. M. and Wallace, J. E. (2009). Mentors as social capital: Gender, mentors, and career rewards in law practice. *Sociological Inquiry*, 79(4):418–452.

Kim, K. and Kim, J. K. (2015). Trends in determinants of entry into the academic career: The case of South Korea, 1980-2010. *PLoS ONE*, 10(10).

Larsen, R. (2009). History of the iSchools. *Encyclopedia of Library and Information Sciences*.

Long, J. S. and Fox, M. F. (1995). Scientific Careers: Universalism and Particularism. *Annual Review of Sociology*, 21(1):45–71.

Lumley, T., Diehr, P., Emerson, S., and Chen, L. (2002). The importance of the normality assumption in large public health data sets. *Annu. Rev. Public Health*, 23:151–69.

Luo, L. (2013). Being Interdisciplinary: A Look into the Background and Experiences of iSchool Faculty Members. *Libres*, 23(2):1–20.

Merton, R. K. (1968). The Matthew Effect in Science. *Science*, 159(3810).

Newman, M. E. J. (2003). Mixing patterns in networks. *Physical Review E*, 67(2):026126.

Olson, G. M. and Grudin, J. (2009). The information school phenomenon. *interactions*, 16(2):15.

Page, L., Brin, S., Motwani, R., and Winograd, T. (1998). The PageRank Citation Ranking: Bringing Order to the Web. *World Wide Web Internet And Web Information Systems*, 54(1999-66):1–17.

Paglis, L. L., Green, S. G., and Bauer, T. N. (2006). Does adviser mentoring add value? A longitudinal study of mentoring and doctoral student outcomes. *Research in Higher Education*, 47(4):451–476.

Pezzoni, M., Sterzi, V., and Lissoni, F. (2012). Career progress in centralized academic systems: Social capital and institutions in France and Italy. *Research Policy*, 41(4):704–719.

Ratcliffe, J. (1968). The Effect on the t Distribution of Non-Normality in the Sampled Population Author. *Journal of the Royal Statistical Society*, 17(1):42–48.

Reuben, E., Sapienza, P., and Zingales, L. (2014). How stereotypes impair women's careers in science. *Proceedings of the National Academy of Sciences*, 111(12):4403–4408.

Russo, G. (2011). Graduate students: Aspirations and anxieties. *Nature*, 475(7357):533–535.

Sheltzer, J. M. and Smith, J. C. (2014). Elite male faculty in the life sciences employ fewer women. *Proceedings of the National Academy of Sciences*, 111(28):10107–10112.

Shu, F. and Julien, C.-A. (2018). Does advisors' disciplinary background affect LIS doctoral students' publishing productivity and quality? *Proceedings of the Annual Conference of CAIS / Actes du congrès annuel de l'ACSI*, 0(0).

Shu, F. and Mongeon, P. (2016). The evolution of iSchool movement (1988-2013): A bibliometric view. *Education for Information*, 32(4):359–373.

Song, I.-Y. and Zhu, Y. (2017). Big Data and Data Science: Opportunities and Challenges of iSchools. *Journal of Data and Information Science*, 2(3):1–18.

Song, J., Almeida, P., and Wu, G. (2003). LearningbyHiring: When Is Mobility More Likely to Facilitate Interfirm Knowledge Transfer? *Management Science*, 49(4):351–365.

Subramaniam, M. M. and Jaeger, P. T. (2011). Weaving diversity into LIS: An examination of diversity course offerings in iSchool programs. *Education for Information*, 28(1):1–19.

Sugimoto, C. R., Li, D., Russell, T. G., Finlay, S. C., and Ding, Y. (2011). The shifting sands of disciplinary development: Analyzing North American Library and Information Science dissertations using latent Dirichlet allocation. *Journal of the American Society for Information Science and Technology*, 62(1):185–204.

Sugitmoto, C., Russell, T., and Grant, S. (2009). Library and Information Science Doctoral Education: The Landscape from 1930-2007. *Journal of Education for Library and Information Science*, 50(3):190–202.

Tenenbaum, H. R., Crosby, F. J., and Gliner, M. D. (2001). Mentoring Relationships in Graduate School. *Journal of Vocational Behavior*, 59(3):326–341.

Utts, J. M. (1982). The rainbow test for lack of fit in regression. *Communications in Statistics - Theory and Methods*, 11(24):2801–2815.

Wang, J. (2013). Citation time window choice for research impact evaluation. *Scientometrics*, 94(3):851–872.

Way, S. F., Larremore, D. B., and Clauset, A. (2016). Gender, Productivity, and Prestige in Computer Science Faculty Hiring Networks. In *Proceedings of the 25th International Conference on World Wide Web - WWW '16*, pages 1169–1179, New York, New York, USA. ACM Press.

Wiggins, A., McQuaid, M. J., and Adamic, L. A. (2008). Community Identity: Peer Prestige and Academic Hiring in the iSchools. In *iConference*.

Wiggins, A. and Sawyer, S. (2012). Intellectual diversity and the faculty composition of iSchools. *Journal of the American Society for Information Science and Technology*, 63(1):8–21.

Williamson, I. O. and Cable, D. M. (2003). Predicting early career research productivity: The case of management faculty. *Journal of Organizational Behavior*, 24(1):25–44.

Wu, D., He, D., Jiang, J., Dong, W., and Vo, K. T. (2012). The state of iSchools: An analysis of academic research and graduate education. *Journal of Information Science*, 38(1):15–36.

Zhang, P., Yan, J. L. S., and Hassman, K. D. (2013). The intellectual characteristics of the information field: Heritage and substance. *Journal of the American Society for Information Science and Technology*, 64(12):2468–2491.

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

Zhu, Y., Yan, E., and Song, M. (2016). Understanding the evolving academic landscape of library and information science through faculty hiring data. *Scientometrics*, 108(3):1461–1478.

Zinovyeva, N. and Bagues, M. (2015). The role of connections in academic promotions. *American Economic Journal: Applied Economics*, 7(2):264–292.

Zuo, Z. and Zhao, K. (2017). Systematic investigation of sex disparity in multidisciplinary institutions a case study of U.S. iSchools. *Proceedings of the Association for Information Science and Technology*, 54(1):857–858.

Zuo, Z. and Zhao, K. (2018). The more multidisciplinary the better? The prevalence and interdisciplinarity of research collaborations in multidisciplinary institutions. *Journal of Informetrics*, 12(3):736–756.

Zuo, Z., Zhao, K., and Eichmann, D. (2017). The state and evolution of U.S. iSchools: From talent acquisitions to research outcome. *Journal of the Association for Information Science and Technology*, 68(5):1266–1277.