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Understanding the Field of Public Affairs through the Lens of Ranked Ph.D. Programs in the United States

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The goal of this article is to understand the multidisciplinary field of public affairs. Based on data and text mining on the profiles and publications of all faculty members from a list of research-oriented U.S. public affairs programs, we describe the landscape of public affairs schools and scholars, identify 15 topics in public affairs research and discuss their trends of change between 1986 and 2015, and show the clustering and hiring networks of public affairs schools. Our results suggest a broader approach to understanding the field of public affairs than the public administration focus in the literature. Although public administration is highly visible in the field, which is evidenced by the journals most favored by public affair scholars, various specific policy areas (such as health, social, urban, environmental, global, and education policies) show strong representations based on our topical analysis of public affairs research.

KEY WORDS: public affairs, policy schools, text mining, topical analysis

本文目的是理解公共事务的多学科领域。针对以研究为导向的一系列美国公共事务计划的所有教职工简介及出版物，笔者进行了数据和文本挖掘，并描述了公共事务学校和学者概况，识别了*15*个公共事务研究主题，并探讨了*1986–15*年间这些主题的变化趋势，还展示了公共事务学校的集群网络和招聘网络。研究结果提出了一项相比起文献对公共管理的关注更为广泛的研究方法，用于理解公共事务领域。尽管公共管理在该领域是无法忽视的，这一点在公共事务学者最为推崇的相关期刊中有所证明，但基于笔者对公共事务研究的主题分析，不同的特定政策领域（例如卫生、社会、城市、环境、全球和教育政策）也展示了很强的代表性。

关键词：公共事务，政策学校，文本挖掘，话题分析

El objetivo de este artículo es comprender el campo multidisciplinario de los asuntos públicos. Sobre la base de datos y minería de textos en los perfiles y publicaciones de todos los miembros de la facultad de una lista de programas de asuntos públicos de EE. UU. Orientados a la investigación, describimos el panorama de las escuelas y académicos de asuntos públicos, identificamos 15 temas en la investigación de asuntos públicos y discutimos sus tendencias de cambiar entre 1986 y 2015, y mostrar las redes de agrupación y contratación de escuelas de asuntos públicos. Nuestros resultados sugieren un enfoque más amplio para comprender el campo de los asuntos públicos que el enfoque de la administración pública en la literatura. Si bien la administración pública es muy visible en el campo, como lo demuestran las revistas más favorecidas por los estudiosos de asuntos públicos, varias áreas de políticas

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específicas (como las políticas de salud, sociales, urbanas, ambientales, globales y educativas) muestran representaciones sólidas basadas en nuestra Análisis tópico de la investigación en asuntos públicos.

PALABRAS CLAVE: asuntos públicos, escuelas de políticas, minería de textos, análisis de temas

Introduction

Public affairs is a multidisciplinary field that covers a variety of topics related to public interest. Several social science fields, such as economics, psychology, political science, and sociology, often involve research that has public policy implications, but the field is best defined through the research and teaching in public affairs programs or schools. Public affairs schools have diverse concentrations. Some of the notable ones, such as at the Universities of Chicago and Michigan, are heavily economics-based. More often observed are those programs focusing primarily on public administration and management, such as at the Universities of Georgia and Kansas. Different from most of other public affairs programs, Indiana University Bloomington has a large and diverse faculty that includes a distinguishable number of environmental scientists. Therefore, even with an exclusive focus on public affairs schools, it is still quite difficult to understand the multidisciplinary field of public affairs.

Efforts have been made to understand a narrower version of public affairs, i.e., public administration, mostly through the lens of publications at major public administration journals (Lan & Anders, 2000; Miller & Jaja, 2005; Ni, Sugimoto, & Robbin, 2017). There are also a small number of studies trying to profile public affairs programs either through faculty/staff/student publications in major public administration journals (Douglas, 1996; Legge & Devore, 1987) or degrees offered (Koven, Goetzke, & Brennan, 2008). To our best knowledge, no research has examined the broader multidisciplinary field of public affairs that include not only public administration research, but also various other specific policy areas studied by scholars from public affairs programs. This article fills this gap.

We aim to understand the landscape of both public affairs schools and the multidisciplinary field of public affairs from a scientometric approach. This approach has both advantages and disadvantages. As summarized by Ni et al. (2017), "the value of scientometric methods is that they are relatively neutral: they provide lists of topics and authors without any bias. The limitation, however, is that scientometrics provides the *what* but not the *why*" (p. 497). Relying on data and text mining on the profiles and publications of all faculty members from a list of research-oriented public affairs schools, we describe the landscape of U.S. public affairs schools and scholars, identify the major topics in public affairs research and their trends of change between 1985 and 2015, and show the clustering and hiring networks of public affairs schools.

This research distinguishes itself from earlier field studies at least in three ways. First, we adopt a broader scope on public affairs beyond public administration. We examine all kinds of publication outlets by faculty in public affairs schools, not just public administration journals. Since public affairs schools are so diverse and those more policy analysis-oriented programs may naturally seek outlets beyond public administration journals, it is important to extend the scope for a better and more complete understanding of the multidisciplinary public affairs field. Second, using methods in big data/text mining, we provide an unbiased identification of topics in the field of public affairs, and based on that we show how different topics have evolved in public affairs research over the years. This approach has advantages over earlier topic identification efforts (Bingham & Bowen, 1994; Lan & Anders, 2000; Miller & Jaja, 2005) in terms of objectivity. Third, this research, to our best knowledge, is the only one that studies the clustering of U.S. public affairs schools based on research topics and hiring networks among them. This direction of efforts provides insights into the paradigm and interconnectedness of public affairs schools.

The article is organized as follows. After this introduction section, the methodology section justifies the list of public affairs schools in our sample, introduces the steps in faculty information collection, and explains methods for data analysis. The following section presents the results. The last section summarizes the research and discusses its limitations. Given its exploratory nature and similar to earlier field studies based on data mining (Koven et al., 2008; Ni et al., 2017), this article does not include a separate literature review. We have noted how this new study is distinct from earlier ones in the introduction.

Methodology

For a comprehensive examination of the landscape of public affairs schools in the United States, we start with a list of National Research Council (NRC) ranked programs in the field of Public Affairs, Public Policy, and Public Administration. With manual screening, we retrieved the information of the faculty in each of the departments hosting these programs, including their title; gender; graduating program and university; and, most importantly, publication records. Data collection were between January and March 2016. In this section, we introduce how we collect and analyze the data.

Selection of Policy Schools

The dataset includes 46 public policy, public administration, and public affairs schools/departments (hereafter policy schools) in the United States based on the list of NRC ranked Ph.D. programs (National Research Council, 2011). We rely on the NRC ranking instead of other rankings of public affairs (e.g., the ranking of master's programs in public affairs by *U.S. News and World Report*) because of our interests in faculty research and hiring networks. In the original listing, under the broad field Social and Behavioral Sciences and the field of Public Affairs, Public Policy, and Public Administration, there are 54 programs in 47 U.S. universities. Since the latest ranking was released in 2010, we validated the list based on the current information and generated an up-to-date list of schools that focus on policy research (Table

A1 in the Appendix). Specifically, we excluded (i) Florida International University's Social Welfare program in the School of Social Work; (ii) Johns Hopkins University's Health Policy and Management program in the Bloomberg School of Public Health; (iii) Northeastern University's Law Policy and Society program in the School of Law; (iv) University of Pennsylvania's Social Welfare program in the Wharton School; (v) University of Arkansas' Public Policy program, which is an interdisciplinary program without dedicated faculty members. We also replaced University of Arizona's Management program in Eller College of Management with its School of Government & Public Policy. It is worth noting that the NRC ranking is at the program level. For example, there are two ranked programs from Indiana University, one for public policy and the other for public affairs. However, this study focuses on formal academic units instead of programs. We therefore merged programs to the school level for (i) Indiana University; (ii) University of California at Irvine; (iii) University of Texas at Dallas. To account for a joint Ph.D. program by Georgia State University and Georgia Tech listed in the NRC ranking, we added Georgia State University's Department of Public Management and Policy in the Andrew Young School of Policy Studies (the policy school at Georgia Tech is already in NRC's list.)

Finally, we note that the final list is a mixture of schools, colleges, and departments. While it seems inconsistent at first sight, we argue that it is more reasonable to focus on the smallest academic units that aim at policy research. For instance, the Steven J. Green School of International & Public Affairs at Florida International University consists of eight departments. Only one of them, the Department of Public Administration, explicitly states its mission as providing a professional education in public sector and nonprofit management. The others, such as Religious Studies and History, have much less or even little connection with policy studies. Inclusion of such academic units would inevitably bring in noise.

Faculty Information Collection

For each of the 46 policy schools, we retrieved information for full-time faculty members, including their names, titles (full, associate, or assistant professors), graduating institutions and programs, and publication records from school and personal websites, as well as their LinkedIn profiles and CVs (if any). By full-time faculty members, we refer to those with titles full, associate, and assistant professors. Visiting, adjunct, teaching, or emeritus professors were excluded from the dataset.

Gender information was inferred by two software packages using first names: Sex Machine (Elmas, 2013) and Gender (Blevins & Mullen, 2015). Both Sex Machine and Gender give gender information with some extent of uncertainty. Specifically, the former only gives description (e.g., "mostly female" vs. "female"), whereas the latter one gives explicit probability (e.g., 95 percent of being female). For Sex Machine, we used the result only if it is certain about the gender; for Gender, we set the confidence level at 95 percent. If the desired confidence was not achieved, we marked this name as gender unknown, which was then searched manually. We performed manual search under two situations: (i) neither program gave certain gender information; (ii) two programs gave different answers to the same first name.

With both names and current affiliations as query keywords, we were then able to retrieve their author IDs using Scopus author search application programming interfaces (APIs). Scopus maintains researchers' publication profiles with unique identifiers for each author. However, due to name ambiguity and affiliation changes, there may exist more than one author ID for the same researcher, which were later merged into one. Among the results returned by the API, we manually excluded those who were clearly not a faculty member in our school list. With author IDs, we retrieved publication information for each author, along with their Scopus IDs, titles, publication types (journal/trade journal/book series/conference), dates, citation counts, and publication venues, etc. Abstract texts were then collected via abstract retrieval API.

Research Topics

Research topics were extracted from the abstracts of faculty publications from the sampled policy schools as mentioned above using latent Dirichlet allocation (LDA; Blei, Ng, & Jordan, 2003). LDA is a widely used topic modeling algorithm that aims at identifying latent topics of each document. Specifically, it takes a collection of documents as inputs, and generates two probabilistic distributions: (i) Each latent topic is represented as a multinomial distribution over words. Those words that have high probabilities associated with a topic are representative keywords for that topic. If a topic, for example, is composed of top keywords, including "urban," "city," "region," "planning," etc., we can interpret it as urban planning/policy. (ii) Each document is represented as a multinomial distribution over topics.

While it is possible to select the number of topics by quantitative measures (e.g., perplexity), such an approach often fails to produce human interpretable results (Chang, Gerrish, Wang, & Blei, 2009). Instead, we tested different numbers of topics k from 8 to 20 and picked 15, which produced the most interpretable and reasonable set of topics. In addition, there are two Dirichlet hyperparameters, α and β, that control the sparsity of document and topic representations. Lower values of the hyperparameters lead to more decisive associations between document-topic and topic-word distributions. In this article, we fit an LDA model with $\alpha = \frac{1}{k} = 0.05$ and $\beta = \frac{10}{V} = 2.7 \times 10^{-4}$ (Gerow, Hu, Boyd-Graber, Blei, & Evans, 2018). Detailed topic modeling results (i.e., the first probability distribution mentioned in the paragraph above) are listed in Table A2 in the Appendix. Note that interpretations were added manually based on the top keywords.

Clustering Policy Schools

Another interesting question relates to the possible groupings of policy schools, if there is any, so that schools that are similar to each other are placed in the same group. We applied hierarchical clustering based on the research profile of each school. A policy school is represented by the average topic distributions of all papers with at least one author from that school. Hence, the distances between clusters can be interpreted as the difference of research focuses between two schools. Specifically, we used agglomerative clustering with Ward's criterion (Ward, 1963), which aims at minimizing the sum of squared differences (i.e., variance) within clusters. Iteratively, we group individual schools into clusters until there is only one cluster that contains all the schools. The number of clusters is determined by a distance threshold—if distance between two clusters is above the threshold, we consider the merge invalid.

Hiring Network Analysis

A hiring network *G* was built for policy schools within the 46 institutions. Specifically, we manually inspected each faculty member's Ph.D. program and determined if they graduated from related programs instead of just the university. For example, a faculty member in the policy school at UC Irvine with a Ph.D. degree in history from the University of Pennsylvania would not be included in the network since her program was not public administration, public affairs, or public policy. In *G*, each node is a policy school. There will be an edge from *u* to *v* if *u* hires a Ph.D. graduate from *v*. The direction can be conceptualized as endorsement or recognition, because schools producing faculty to other schools are acknowledged as being able to produce competitive researchers (Hanneman, 2001). The weight of an edge is the number of Ph.D. graduates from the target node hired by the source node. Therefore, *G* is directed and weighted. The colors shown in Figure 10 indicate to which cluster each policy school belongs by maximizing modularity (Newman, 2006). Modularity is the fraction of edges within network communities minus the expected fraction of such edge. It is commonly used in quantifying the goodness of community structure in networks (Newman, 2006; Newman & Girvan, 2004). The higher it is, the more clear-cut the corresponding communities are. Policy schools clustered into the same community have tighter connection with each other and weaker with those in other communities, with respect to faculty hiring.

It is noteworthy that among all valid Ph.D. programs, there is a joint program in Public Policy by Georgia Tech and Georgia State. The weight from the source policy school will be split evenly to Georgia Tech and Georgia State (i.e., each gets 0.5.) Furthermore, four programs were only counted as *half* policy programs: (i) Public Policy and Economics; (ii) Statistics and Public Policy; (iii) Social and Decision Sciences and Public Policy from Carnegie Mellon; and (iv) Public Policy, Political Science from Indiana at Bloomington. Hiring a Ph.D. from such program was only counted as a 0.5 weight.

To find possible patterns, we compared the hiring network with three random graph models (Newman, 2003): Erdős-Rényi models (i) $G_{n,m}$; (ii) $G_{n,p}$; and (iii) the configuration model. The first two random graph models assumed that each edge in a network was added independently, and often lead to a tree-like structure. The configuration model, on the other hand, is more realistic by forcing nodes to have a given degree sequence, mimicking the degree distribution of a given network. The comparison between random graph models and a real-world network is used to test if the real-world network presents patterns that can hardly be generated just by chance.

Results

School Size

Among the 46 policy schools, we collected a total number of 1,065 full-time core faculty members, including 539 full, 277 associate, and 249 assistant professors (Table 1). Here we define senior faculty members to be those who are tenured (i.e., full and associate professors), and junior faculty members to be those on tenure-track positions (i.e., assistant professors). As a result, there are 816 senior (77 percent) and 249 junior (23 percent) faculty members, indicating a significant imbalance between professorship rankings. With respect to gender distributions, there are significantly more male (66 percent) than female (34 percent) faculty members. Controlling for seniority, such a huge imbalance disappeared when we only look at junior faculty (47 percent female vs. 53 percent male). This, to some extent, coincides with the general phenomenon of *leaky pipeline* in the scientific community (Shen, 2013). While a significant number of young female researchers enter the academy, male researchers still dominate senior positions (Etzkowitz, Kemelgor, Neuschatz, Uzzi, & Alonzo, 1994).

Looking at individual schools, we found significant inequality in school sizes, as represented by the number of full-time faculty members ($Gini = 0.45$; Figure 1). While departments are understandably smaller than schools, inequality still holds when we consider departments and schools separately ($Gini = 0.46$ for schools only; $Gini = 0.41$ for departments only).

Productivity

We limited our analysis to journal articles published up to the year 2015. Further, we only kept articles with abstracts available. In sum, we retrieved 16,834 papers by 995 out of 1,065 faculty members across all 46 institutions.[1]

Here we use the number of papers per year as a proxy for productivity. The number of papers grows steadily over time, with an average increasing rate of 21.2 papers per year (Figure 2A). Specifically, papers published in the past decade (i.e., 2006–15) account for 56 percent of all the papers since the 1960s. The peak of 1,176 papers was attained in 2015. The inequality of productivity, breaking into individual schools, is consistent with the sizes of schools. Intuitively, productivity of an institution will usually be higher if the institution has more faculty members. This is evidenced by their strong linear relationship (Figure 3). Such inequality persists when we control for seniority, gender, or both (all $Gini > 0.5$).

We note that the following time-trend analyses exclude earlier years (1962–85) due to the small number of papers in the annual record during that time period. The growing number of papers jumped from 135 in 1985 to 178 in 1986. The larger

Table 1. Faculty Composition

	Junior	Senior	Total
Female	117	248	365
Male	132	568	700
Total	249	816	1065

numbers of papers make statistical analysis results more reliable. We therefore focus on the 30-year time period between 1986 and 2015 for trend analyses thereafter.

At a more fine-grained level, seniority and gender both exert notable influence on the skewness of productivity. While the ratio between the numbers of senior and junior faculty members is 3.3 to 1, the senior group has 15,640 papers, 11.7 times as many publications as the junior group (1,333). This implies that senior members have accumulated much more time and resources than the newcomers so that they have dominated in the number of publications. Such imbalance between senior and junior members is consistent when we control for gender. Considering gender disparity, the number of publications by female is 4,239, merely one third of that by male (12,203), although the ratio between female and male populations is approximately 0.52. When we take a closer look into the evolving productivity for each gender, it is interesting to witness a gradually growing share of female-authored publications (Figure 4; from 8 percent to 35 percent). It is also clear that cross-gender collaboration is rare across time.

Finally, we show the top 15 popular journals with respect to the number of publications by policy school faculty members in Figure 5. The Lorenz curve along with $Gini = 0.52$ implies common preferences of journals. *Public Administration Review* (*PAR*), one of the best-known journals in public administration, tops the list of journals for policy scholars and contains 1.8 percent of the 16,834 papers. It is followed by another well-respected public administration journal: *Journal of Public Administration Research and Theory* (*JPART*). The top 15 journals contain 12.5 percent (i.e., 2,104) papers, whereas the remaining 87.5 percent were published in the other 3,131 journals.

Topics

Belonging to a highly multidisciplinary area, faculty members from different policy schools have various research interests. Based on a LDA analysis of faculty publications, we identify 15 topics in public affairs research, including (i) 10.73 percent policy development; (ii) 8.91 percent policy analysis; (iii) 8.89 percent public management; (iv) 8.75 percent health policy; (v) 8.15 percent public economics & finance; (vi) 6.64 percent social policy; (vii) 6.52 percent environmental management; (viii) 5.92 percent urban policy; (ix) 5.91 percent political system; (x) 5.91 percent public opinion; (xi) 5.45 percent environmental & energy policy; (xii) 5.18 percent global policy; (xiii) 4.99 percent education policy; (xiv) 4.88 percent health management; and (xv) 3.15 percent criminal justice (Table A2). The percentage ahead of each topic represents the proportion of the topic among all topics, showing the extent to which

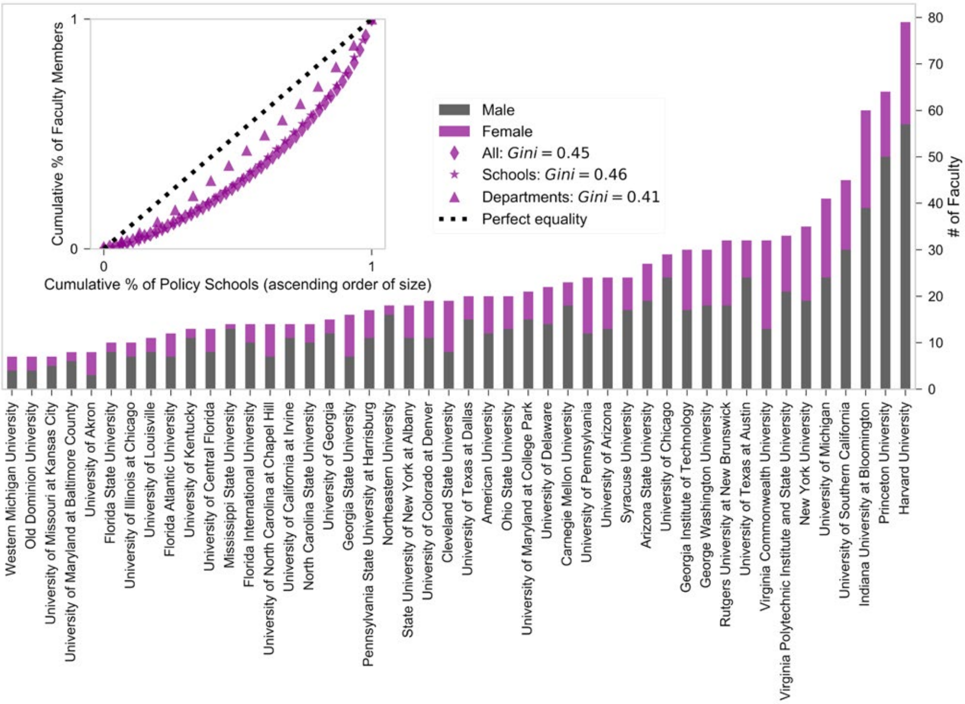

Figure 1. Sizes of Policy Schools. Schools are Ordered by the Number of Full-Time Faculty Members in the Dataset.
Note: Inset figure is the corresponding Lorenz curve.

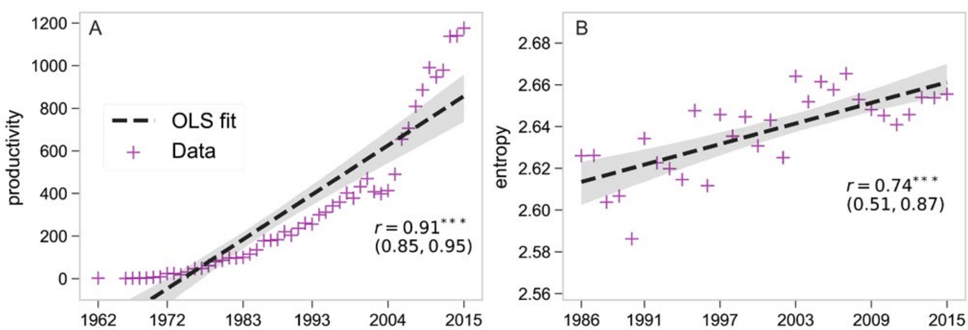

Figure 2. Productivity (A) and Topical Diversity (B) Over Time.

policy scholars have been interested in the topic. A first glimpse of the topic composition shows that policy researchers have broad interests. Using Shannon Entropy (Shannon, 1948) as an index of multidisciplinarity (higher value of entropy means a more even distribution, and thus more multidisciplinarity [Zuo & Zhao, 2018]), we observe consistent high entropy values across time (Figure 2B), with some small increase from early years. This provides empirical evidence on the multidisciplinarity of policy scholars. Such evolution coincides with the increasing rate of productivity

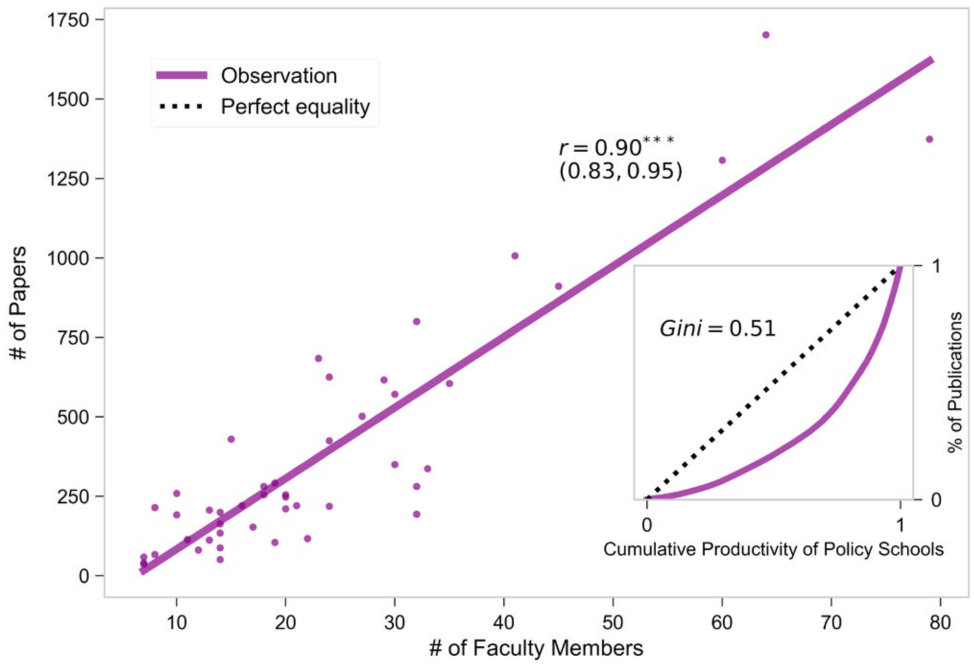

Figure 3. Relationship Between Institution Size and Productivity.
Note: Inset figure shows the Lorenz curve for productivity inequality across the 46 policy schools. Here we overuse Lorenz curve, where some papers may be counted more than once due to multi-authorship.

(Figure 2A). After all, it is likely that topics derived from more publications tend to be more diverse.

Individual topics exhibit various temporal trends. For each year from 1986 to 2015, we calculated the average topic proportions in all the papers published, as a proxy for topical prevalence (Figure 6). Specifically, there have been growing research interests in topics, such as public management, social policy, public opinions, and environmental and energy policy. By contrast, research in policy analysis, public economics and finance, environmental management, and political system shows declined importance among policy scholars. For the rest of the topics, the changes in their proportional importance during this 30-year time period are not significant and typically present some fluctuations. Regardless of the trends, in 2015, the most popular research topics are policy development and public management, both accounting for over 10 percent among 15 topics.

Research Impact

Despite its limitations, citations count is the most popular metric to quantify research impact. Here we retrieved annual citations up to 2015 for all the 16,834 papers. The citation distribution is highly skewed (Figure 7). The mean and median numbers of citations are 31 and 9, 90 and 300 times less than the highest citation

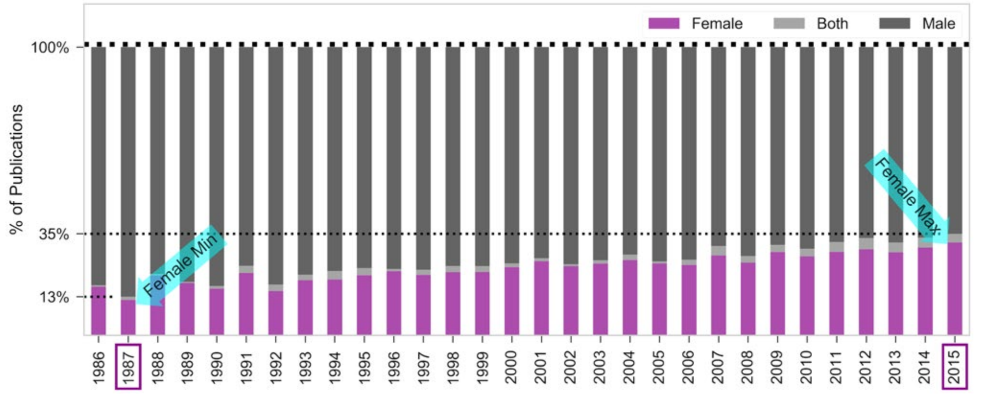

Figure 4. Annual Share of Publication Portion Between Female and Male.
Note: The lowest (except zero) and highest relative productivity of female faculty members are highlighted, as shown by two light dotted horizontal lines, respectively.

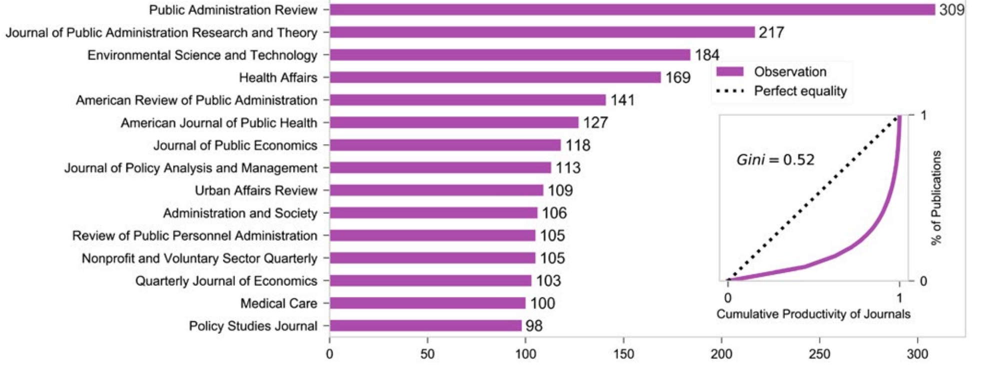

Figure 5. Top 15 Journals with Respect to the Number of Papers by Policy School Faculty Members.

count 2,713, respectively. Of all papers, 11.7 percent (i.e., 1,977) did not receive any citations, whereas 0.1 percent (i.e., 17) receive at least 1,000 citations. We define annual citation counts to be the total number of citations in that year, which contain citations to papers published before that. For the policy community, annual citation counts have increased rapidly to 6×10^4. This, obviously, is largely correlated with the cumulative number of published papers in each year ($r=0.97\in[0.95,0.98]$).

Based on the topic modeling results, we allocated each paper's citation counts proportional to their topic distributions (Figure 8). A paper with 150 citations, for example, with a uniform topic distribution (i.e., a paper whose topic probability is 1/15 for all the 15 topics), will correspondingly have a uniform topical impact distribution, with 10 citations distributed to each of the 15 topics. Topical citation is then the sum of proportional citations across all papers. It is reasonable to say that a topic with more citation counts is more *attractive* than those with lower citations.

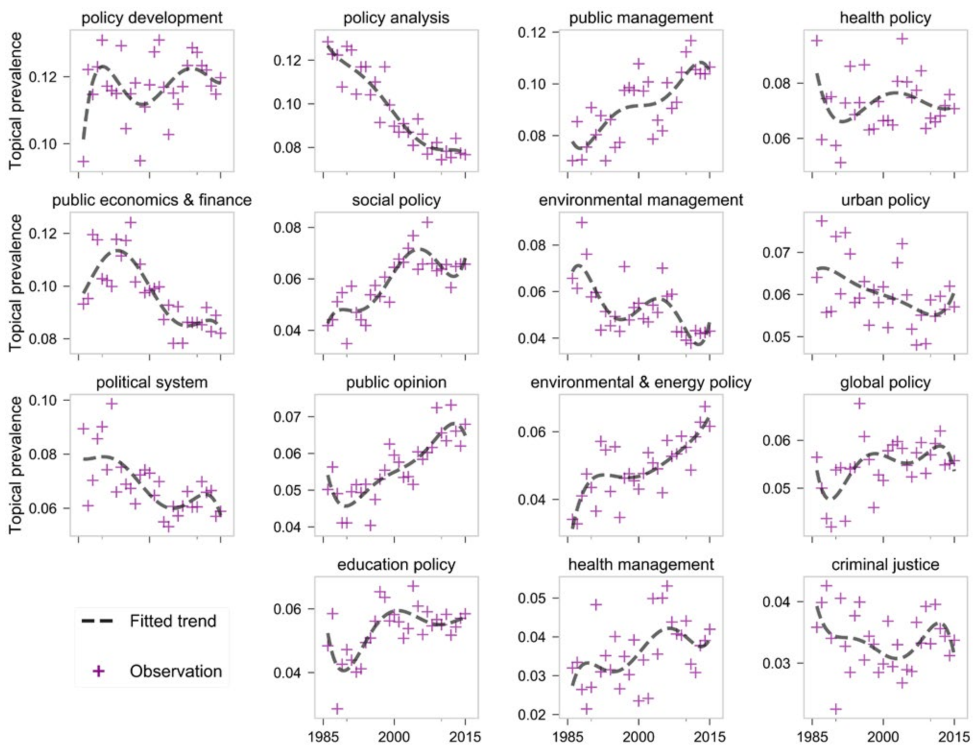

Figure 6. Prevalence of Topics Over Time.
Note: The trend is fitted by a polynomial interpolation with degree of 5.

A higher level of attractiveness of a topic could be a result of a higher proportion of the topic among all policy topics, or a greater impact when holding proportions constant, or both. As shown in Figure 8, policy analysis, policy development, and public economics & finance are the three most attractive topics. Two of them have actually experienced a substantial decline among policy scholars' research interests, as discussed earlier, but still maintain substantial proportions (around 8 percent in recent years, as shown in Figure 6), higher than most of other topics. At the other end, criminal justice is the least attractive topic. Indeed, only a few policy schools explicitly have a criminal justice concentration.

Clustering of Policy Schools

Figure 9 shows a complete dendrogram. See Tables A3 and A4 in the Appendix for lists of policy schools in each cluster when $k=3$ and $k=4$. A dendrogram is a useful tool to visualize the hierarchical clustering process and help determine the number of clusters. Specifically, vertical lines show which schools (or clusters at the higher level) are parts of the cluster merge indicated by horizontal lines, whose heights are the distances between schools (or clusters). For example, the vertical lines above the two schools on the right end—Levin College of Urban Affairs at Cleveland

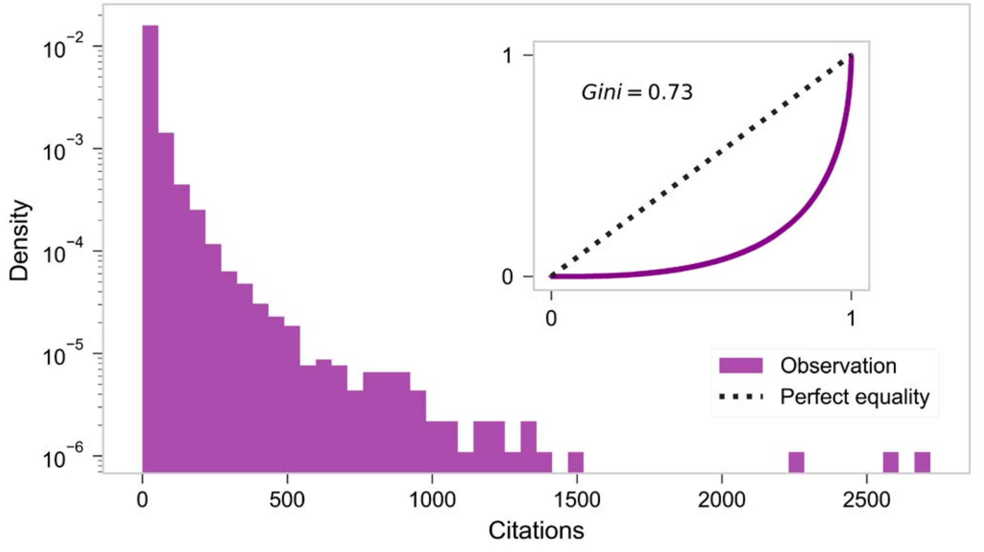

Figure 7. Distribution of Citation Counts at Paper Level.

State University and School of Public Policy & Administration at University of Delaware—indicate that these two policy schools are merged into the same cluster at a topical distance (measured by Euclidean distance) of less than 0.10 (i.e., the height value of the corresponding horizontal line). These two programs both have a strong focus on urban policy. As another example, University of Michigan's Ford School of Public Policy is most similar to University of Chicago's Harris School of Public Policy in terms of research topics. Faculty in these two programs overall have strong backgrounds in economic analysis. One notable observation from the dendrogram is that Indiana University Bloomington's School of Public and Environmental Affairs (SPEA), one of the best-known programs in the nation, is not merged into a cluster until a topical distance of 0.45. It shows that SPEA does not closely resemble any other policy schools in the nation. Overall, the policy schools can be divided into two broad clusters. Those on the left side of the dendrogram lean more toward public administration/management, and those on the right side are focused more on public policy analysis.

Hiring Networks

Figure 10 shows the hiring networks among policy schools. It is perhaps no surprise for policy scholars to see that policy schools in Syracuse, Georgia, Indiana, and University of Southern California supply the largest numbers of Ph.D. graduates who are on the faculty of all 46 policy schools considered in this research. Examples of strong hiring relationships include: Indiana and Georgia have observable reciprocal hires; American University hires Syracuse graduates heavily; Arizona State has substantial numbers of Georgia and Syracuse graduates on it faculty; University of

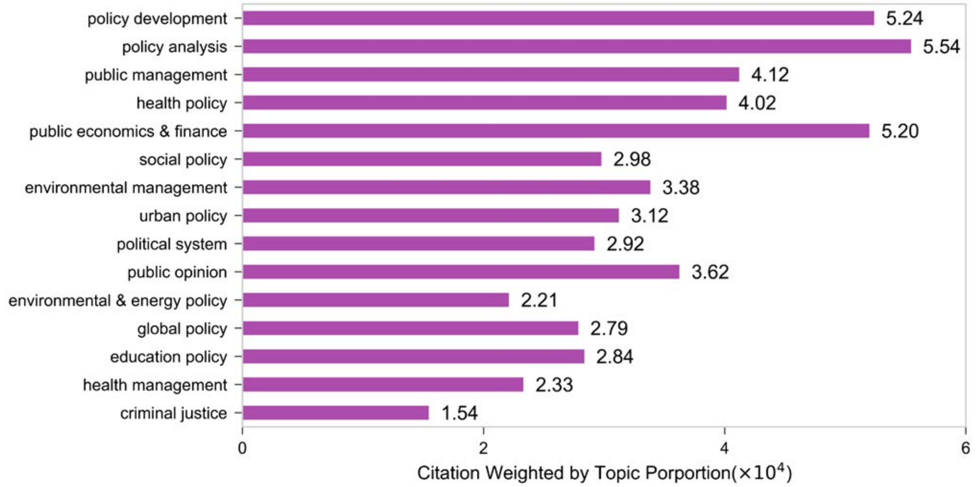

Figure 8. Topical Citations Distribution.
Note: For each topic, we aggregate citations from all the papers, proportional to their topic distributions. For example, a topic will receive 10 percent of a paper's citations if it has a 10 percent in this topic. The sum of such citations proportional to topic distributions is topical citation. Note that the scale is 10^4 on the *x* axis.

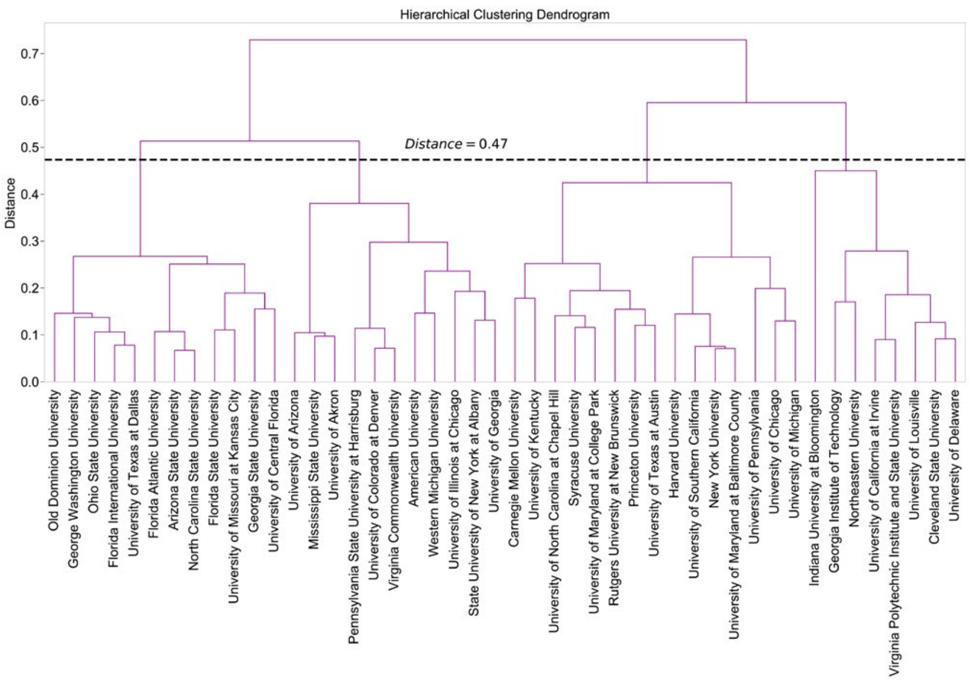

Figure 9. Hierarchical Clustering Dendogram of 46 Policy Schools.
Note: The black dashed line indicates the distance cutoff where we can obtain a four-cluster grouping.

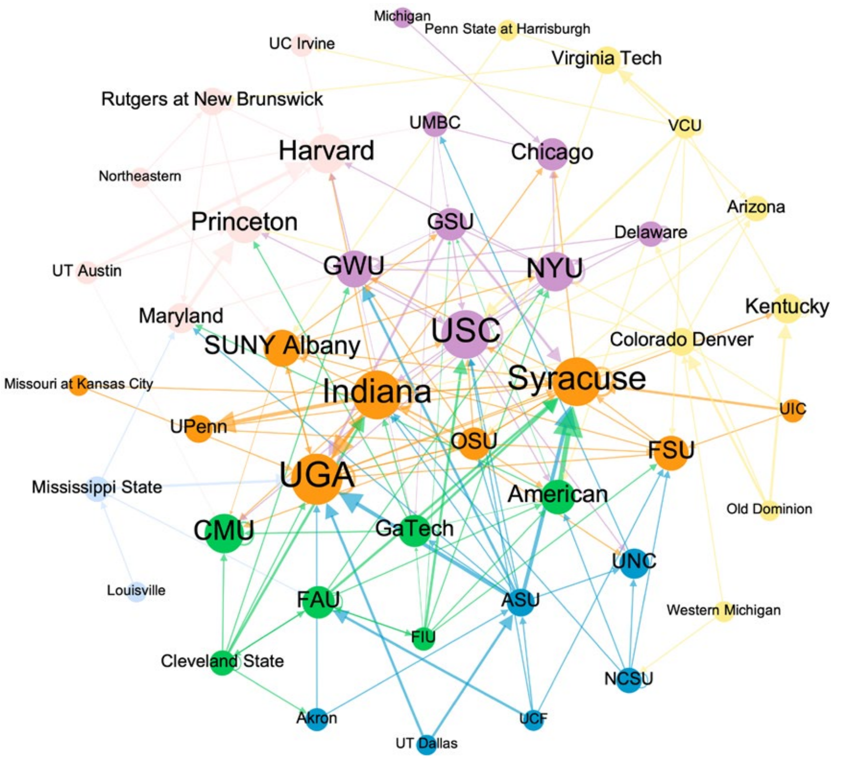

Figure 10. Hiring Network Between Policy Schools.
Note: Node size is proportional to the number of incoming edges (i.e., the number of Ph.D. hired by others); edge width is proportional to the number of Ph.D. flows.

Texas at Dallas has more than one faculty member who obtained their policy Ph.D. degree from Georgia and Arizona State; and graduates from two Ivy League policy schools—Harvard and Princeton—are favored by two state flagship universities, Maryland and University of Texas at Austin.

We calculated the following three network statistics (Table 2): (i) Percentage of self-loops. Self-loops quantify the extent to which schools hire their own graduates, also known as inbreeding. (ii) Modularity. The higher the modularity, the better the network can be clustered into well-separated subgroups. (iii) Reciprocity (the ratio between the number of reciprocal edges and the total number of edges). Self-loops do not count as mutual edge. Reciprocity implicitly contains information on mutual acknowledgement (Burris, 2004).

The same network statistics mentioned above are then calculated for 1,000 runs of random graph generations (Figure 11). All random graphs present lower rates

Table 2. Hiring Network Statistics

# of Nodes	# of Edges	% of Self-Loops	Modularity	Reciprocity (w/o Self-Loops)
46	176	0.12	0.34	0.04

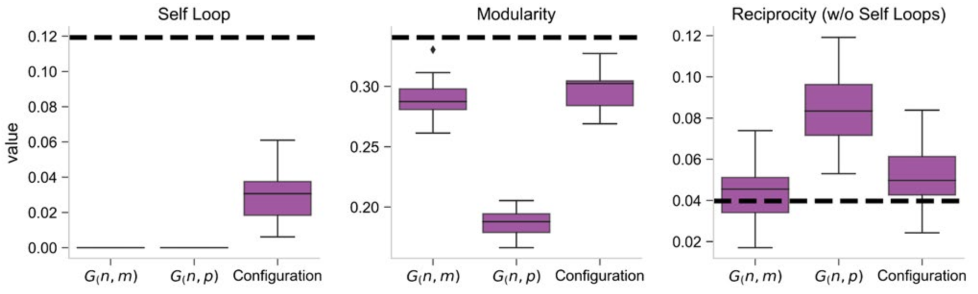

Figure 11. Comparison Between Self-Loop Rate, Modularity, and Reciprocity Between Random Graphs and the Empirical Hiring Network. The Dashed Line is the Value for the Empirical Hiring Network.

of self-loops, indicating that a policy school is more likely to hire Ph.D. graduates from itself as compared to by chance, though this may not be beneficial for productivity (Horta, Veloso, & Grediaga, 2010). With respect to topological structures, the empirical hiring network has a higher modularity compared to all random graphs and hence manifests a clear subcommunity structure. This may imply the existence of hiring circles within groups of policy schools. Different communities based on hiring circles are shown in Figure 10 with different colors. Not surprisingly, these differentiated communities to some extent mirror the topical clusters identified earlier. Reciprocity values in random graphs are slightly higher than the real dataset, showing that mutual acknowledgement is observed less than purely by chance. Although hiring decisions are not planned ahead, comparing the network statistics of the hiring network against randomly generated networks suggests that such bottom-up emergent behavior drives the clear-cut hiring structure within the policy school communities.

Summary and Limitations

In this research, we explored the landscape of the public affairs field through the lens of ranked Ph.D. policy schools in the United States. We summarized the faculty profiles of these policy schools, and more importantly, identified the focuses and topics of the multidisciplinary field of public affairs through faculty publications. Interestingly, though adopting a much broader scope than earlier studies that focus exclusively on publications in public administration journals, we found that publication administration journals, *PAR* and *JPART* in particular, are still the most popular outlets among public affairs scholars. It shows that public administration has been the most visible representation in the broader field of public affairs.

We identified 15 research topics in public affairs using a popular topic modeling algorithm. Different from adopting subjectively defined subfields in public administration or public affairs in the literature (Bingham & Bowen, 1994; Lan & Anders, 2000; Miller & Jaja, 2005), we let the publication text data speak for themselves, and therefore, the topics are more objectively derived. In addition, LDA allows each publication to simultaneously represent different topics in proportion to their relevance. The "one publication, one topic" approach in the past studies (Bingham & Bowen, 1994; Lan & Anders, 2000; Miller & Jaja, 2005) failed to take into account the interdisciplinary nature of public affairs research. For the topical results, it is no surprise to see that some of these topics overlap with the subfields of public administration discussed, for instance, in Lan and Anders (2000), as public administration is the key focus of a large number of policy schools and a key representation of the public affairs field as just discussed. These overlaps include policy development, policy analysis, public management, political system, and public opinion. New from our results are those specific policy areas that better define public policy schools than public administration departments, such as health policy, health management, environmental & energy policy, environment management, urban policy, global policy, and education policy. These area-specific policy topics justify our efforts to understand policy schools not simply from the perspective of public administration research.

Our work in clustering policy schools based on the research topics of faculty publications provides information on what policy schools are similar (or dissimilar) to each other. At the highest level, there is a distinction between the more public policy-oriented schools and the more public-administration-oriented schools. At the lower levels, schools are clustered based more on specific topic areas. It is perhaps to no one's surprise seeing that the clustering results to a large extent echoes the communities observed in the hiring network patterns we also identified. After all, schools are more likely to hire graduates from other schools with similar research concentrations. It however should be noted that our clustering and hiring network analyses are not intended to encourage schools to hire or collaborate more with similar schools. On the contrary, diversity is increasingly important especially in interdisciplinary research, such as public affairs. We simply present the patterns here and leave the interpretation part to policy school experts.

Although this research has advantages over earlier studies in terms of objectivity and neutrality, it has its own limitations, primarily in data quality. First, although it is ideal to consider all faculty publications for analysis, we cannot include those not digitally documented in Scopus. The publication record for earlier years is particularly biased when the digitalization practice in research was not as common as today. Second, we can only take into account faculty members who were affiliated with a policy school when our data were collected, i.e., between January and March 2016. Due to the interdisciplinary nature of the public affairs field, it is indeed common to see faculty moves between policy schools and other departments. Those public affairs scholars who had moved out of policy schools (including retirements and deaths) before our data collection period are not considered. Practically, there was no way we could find the faculty information of policy schools by year. Third, we only use the sample of NRC-ranked policy schools offering Ph.D. degrees because of our interests in hiring networks and to a lesser extent in faculty research. Although it is reasonable to assume higher research productivity by faculty from policy schools with Ph.D. programs, it certainly can be the case that non-Ph.D. policy schools are equally or even more active in faculty research. With these limitations in mind, it is our hope that this research helps us better understand the characteristics of policy schools and the multidisciplinary field of public affairs.

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Note

1. We cannot find any record for the rest in Scopus. They may have publications, but these are not reflected by our dataset because: (i) they wrote books/book chapters which were not included; (ii) they were not indexed by Scopus; and (iii) we could not match them due to name matching problems. Further, it may be the case where policy researchers publish professional articles or reports that are not indexed by bibliographic databases such as Elsevier.

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APPENDIX A1: List of Schools

Table A1. List of Policy Schools based on NRC Ranked Programs

University	Institution
American University	School of Public Affairs: Department of Public Administration & Policy
Arizona State University	School of Public Affairs
Carnegie Mellon University	School of Public Policy & Management
Cleveland State University	Maxine Goodman Levin College of Urban Affairs
Florida Atlantic University	School of Public Administration
Florida International University	Steven J. Green School of International & Public Affairs: Department of Public Administration
Florida State University	Askew School of Public Administration and Policy
George Washington University	Trachtenberg School of Public Policy and Public Administration
Georgia Institute of Technology	School of Public Policy
Georgia State University	Andrew Young School of Policy Studies: Department of Public Management and Policy
Harvard University	The Kennedy School of Government
Indiana University at Bloomington	School of Public and Environmental Affairs
Mississippi State University	Department of Political Science and Public Administration

University	Institution
New York University	Robert F. Wagner Graduate School of Public Service
North Carolina State University	Department of Public Administration
Northeastern University	School of Public Policy and Urban Affairs
Ohio State University	John Glenn College of Public Affairs
Old Dominion University	Strome College of Business: School of Public Service
Pennsylvania State University at Harrisburg	School of Public Affairs
Princeton University	Woodrow Wilson School of Public and International Affairs
Rutgers University at New Brunswick	Edward J. Bloustein School of Planning and Public Policy
State University of New York at Albany	Rockefeller College of Public Affairs & Policy: Department of Public Administration & Policy
Syracuse University	Maxwell School of Citizenship and Public Affairs: Department of Public Administration & International Affairs
University of Akron	Department of Public Administration and Urban Studies
University of Arizona	School of Government & Public Policy
University of California at Irvine	School of Social Ecology: Department of Planning, Policy and Design
University of Central Florida	College of Health and Public Affairs: School of Public Administration
University of Chicago	The Harris School of Public Policy Studies
University of Colorado at Denver	School of Public Affairs
University of Delaware	School of Public Policy and Administration
University of Georgia	School of Public and International Affairs: Department of Public Administration and Policy
University of Illinois at Chicago	College of Urban Planning and Public Affairs: Department of Public Administration
University of Kentucky	Martin School of Public Policy & Administration
University of Louisville	Department of Urban and Public Affairs
University of Maryland at Baltimore County	School of Public Policy
University of Maryland at College Park	School of Public Policy
University of Michigan	Gerald R. Ford School of Public Policy
University of Missouri at Kansas City	Henry W. Bloch School of Management: Department of Public Affairs
University of North Carolina at Chapel Hill	Department of Public Policy
University of Pennsylvania	School of Social Policy and Practice
University of Southern California	Sol Price School of Public Policy
University of Texas at Austin	Lyndon B. Johnson School of Public Affairs
University of Texas at Dallas	School of Economic, Political & Policy Sciences
Virginia Commonwealth University	L. Douglas Wilder School of Government and Public Affairs
Virginia Polytechnic Institute and State University	The School of Public and International Affairs
Western Michigan University	School of Public Affairs and Administration

APPENDIX A2: Topic Modeling Results

Table A2. Interpretation and Top Words of LDA Topics

Interpretation	Proportion	Top Keywords
Policy development	0.1073	0.0122*policy + 0.0111*social + 0.0093*development + 0.0092*process + 0.0085*knowledge
Policy analysis	0.0891	0.0433*model + 0.0208*data + 0.0146*estimate + 0.0118*analysis + 0.0112*measure
Public management	0.0889	0.0327*public + 0.0182*organization + 0.0173*government + 0.0166*service + 0.0163*management
Health policy	0.0875	0.0469*health + 0.0408*care + 0.0201*cost + 0.0188*patient + 0.0179*hospital
Public economics & finance	0.0815	0.0209*market + 0.0142*price + 0.0139*tax + 0.0136*economic + 0.0133*cost
Social policy	0.0664	0.0399*child + 0.0211*age + 0.0174*family + 0.0173*health + 0.0149*woman
Environmental management	0.0652	0.013*concentration + 0.0075*high + 0.0071*increase + 0.0067*water + 0.0065*temperature
Urban policy	0.0592	0.0266*city + 0.0225*urban + 0.0179*area + 0.0166*housing + 0.0135*neighborhood
Political system	0.0591	0.0508*state + 0.0452*policy + 0.0214*public + 0.0212*political + 0.0182*government
Public opinion	0.0591	0.0202*social + 0.0161*survey + 0.0136*group + 0.0102*individual + 0.01*attitude
Environmental & energy policy	0.0545	0.0254*environmental + 0.0173*energy + 0.0158*risk + 0.0157*climate + 0.0133*policy
Global policy	0.0518	0.0295*country + 0.0159*international + 0.0152*political + 0.0137*state + 0.0114*economic
Education policy	0.0499	0.0369*school + 0.0223*student + 0.0195*program + 0.0166*worker + 0.0159*work
Health management	0.0488	0.0226*patient + 0.0186*cancer + 0.0139*risk + 0.0118*rate + 0.0104*woman
Criminal justice	0.0315	0.0235*crime + 0.0203*violence + 0.0161*drug + 0.015*criminal + 0.0136*police

APPENDIX A3: Hierarchical Clustering Results (k = 3)

Table A3. Cluster Membership When k = 3

Cluster	Cluster Members
1	American University; Arizona State University; Florida Atlantic University; Florida International University; Florida State University; George Washington University; Georgia State University; Mississippi State University; North Carolina State University; Ohio State University; Old Dominion University; Pennsylvania State University at Harrisburg; State University of New York at Albany; University of Akron; University of Arizona; University of Central Florida; University of Colorado at Denver; University of Georgia; University of Illinois at Chicago; University of Missouri at Kansas City; University of Texas at Dallas; Virginia Commonwealth University; Western Michigan University
2	Carnegie Mellon University; Harvard University; New York University; Princeton University; Rutgers University at New Brunswick; Syracuse University; University of Chicago; University of Kentucky; University of Maryland at Baltimore County; University of Maryland at College Park; University of Michigan; University of North Carolina at Chapel Hill; University of Pennsylvania; University of Southern California; University of Texas at Austin
3	Cleveland State University; Georgia Institute of Technology; Indiana University at Bloomington; Northeastern University; University of California at Irvine; University of Delaware; University of Louisville; Virginia Polytechnic Institute and State University

APPENDIX A4: Hierarchical Clustering Results (k = 4)

Table A4. Cluster Membership When k = 4

Cluster	Cluster Members
1	Arizona State University; Florida Atlantic University; Florida International University; Florida State University; George Washington University; Georgia State University; North Carolina State University; Ohio State University; Old Dominion University; University of Central Florida; University of Missouri at Kansas City; University of Texas at Dallas
2	American University; Mississippi State University; Pennsylvania State University at Harrisburg; State University of New York at Albany; University of Akron; University of Arizona; University of Colorado at Denver; University of Georgia; University of Illinois at Chicago; Virginia Commonwealth University; Western Michigan University
3	Carnegie Mellon University; Harvard University; New York University; Princeton University; Rutgers University at New Brunswick; Syracuse University; University of Chicago; University of Kentucky; University of Maryland at Baltimore County; University of Maryland at College Park; University of Michigan; University of North Carolina at Chapel Hill; University of Pennsylvania; University of Southern California; University of Texas at Austin
4	Cleveland State University; Georgia Institute of Technology; Indiana University at Bloomington; Northeastern University; University of California at Irvine; University of Delaware; University of Louisville; Virginia Polytechnic Institute and State University