The Organizational Impact on Individual Experts at D.C.: How Residency Affects the Expert Network

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Introduction

The role of expertise in the policy-making process has long been studied. However, most literature focuses either qualitatively on individual experts or, methodologically, on how experts manage or fail to gain trust from clients given overconfidence and asymmetry of knowledge (see, for example, Battaglini, 2004). From this individualistic perspective, if experts' influence does rely primarily on their personal reputation, it seems natural to believe that they need to build credibility through rigorous, independent research.

But the experts in the current United States do not truly play this game alone. Think tanks, broadly defined as non-for-profit research institutes on public policy, fund experts' research, connect them to concerned parties, amplify their voices through well-trained marketing teams, and sometimes even cultivate future experts through education programs. Experts' influence thus depends largely on their organizational affiliations. On the other hand, think tanks often operate with business principles and have ideological missions, producing opinions and marketing research products in the so-called marketplace of ideas. Their "products"—policy proposals and evaluations—often result from group projects. Even for the relatively independent projects, the organizational charts may institutionalize experts—and their idea-generation process—in a hierarchical structure of who can talk to who. The competition for donations and attention, along with waves of progressive and rightwing movements, further give the think tanks salient reasons to keep uniting their members and fostering more collective voices. As Andrew Rich (2010) shows through surveys and historical research, think tanks have "generally evolved from producing painstaking research and objective writing to pursuing ideological agendas with far-reaching impact in the war of ideas."

In all, the individualistic and the organizational perspectives of experts in think tanks both seem to omit important factors. The hidden, organizational influence on individual experts in forming and communicating political ideas may significantly affect the political polarizing process. This research gap motivates the following research project.

Hypothesis

In this project, I evaluate the causal effect of resident experience in think tanks on a policy expert's influence within and across the expert community. Because it is hard to compare think-tank and non-think-tank experts without forcing an arbitrary boundary on the population of policy experts, I focus instead on whether a think tank expert is a resident scholar. A resident scholar has a physical office in the organization, interacts with colleagues on a daily and causal basis, and is directly exposed to various dimensions of office culture, from rumors to food in the dining hall. Those in the control group, on the other hand, are non-resident scholars and visiting scholars who also serve the think tanks but live elsewhere, often working at a university or a non-profit organization. Like the resident scholars, they accept the think tank's mission and share many research interests. But away from this collective life experience, they may find their organizational affiliation more of a conceptual figure that provides funds than a real part of life. The opportunities to socialize with other colleagues are also much limited. Thus, they may be less embedded in the social and information network their resident colleagues share and develop.

Despite the benefits of residency mentioned below, I hypothesize that such benefits are limited within the organization. Compared to a non-resident scholar, a resident scholar may gain more influence within the organization. But suppose she has been so much labeled as, say, a scholar from the Heritage Foundation instead of being known for her research reputation. In that case, she might lose influence across the expert community outside of the organization. However, this negative effect might be moderated because so many think tanks are located close to each other in D.C. She may increase her external influence by socializing with experts from other think tanks: many of D.C.'s Friday happy hours gather experts from multiple respected think tanks to facilitate such interactions.

Given the discussion below, I propose two hypotheses. First, *being a resident scholar increases an expert's internal influence (network centrality within the organization).* Second, *being a resident scholar decreases an expert's external influence (network centrality among the experts outside of the organization), but this effect may be mitigated if the external experts are also geographically close to the organization.*

Here I use the concepts "influence" and "centrality" interchangeably due to the nature of my data. For dependent variables, I calculate in-degree centrality from a directed Twitter follow network which describes how think tank experts follow each other. Theoretically, in-degree centrality refers to the number of connections one has on the network, but influence emphasizes more of one's ability to inform and even persuade others through these connections. By interpreting centrality as an influence, I make two potentially problematic assumptions: first, these experts pay attention to their Twitter feeds; second, the Twitter ties estimate the experts' substantive connection. In a word, they do not simply follow others randomly on Twitter. I argue that this is likely true because the network is composed of very active nodes and highly reciprocal ties. About 87% of these expert users tweeted, retweeted, or replied to tweets more than ten times in the first half of the year 2020. 58% of the directed edges between experts are mutual, much higher than the 42% average for the general Twitter network (Myers et al., 2014). Admittedly, it might still take a leap of faith to say that this is a social network in the sense that Twitter follow relationship represents substantive friendship. But we can at least conclude that experts do pay attention to managing this online network, such that if one posts something, her followers are likely to see it. We can thus consider this Twitter follow network an information network, and centrality estimates one's influence on this network.

Data Collection and Preprocessing

After Twitter's updates in August 2020, the new API version has not yet permitted access to friendship data. Therefore, I could only use an existing dataset I gathered in mid 2020, which includes the Twitter networks for four major think tanks in D.C., namely the Brookings Institution (Brookings), the American Enterprise Institute (AEI), the Center for American Progress (CAP), and the Heritage Foundation (Heritage). CAP does not specify whether an expert is a resident or not, so it is excluded from this study. The three remaining think tanks are comparable in that, first, they are located close to each other, allowing informal interactions across the organization to happen daily or weekly. Second, they focus on a broad range of policy issues on international, national, and local levels. Finally, they are close to balancing left and right-leaning, and research- and advocacy-oriented think tanks.

All three think tanks list their experts on their organization websites. I scraped a complete list of their experts and obtained each expert's profile. I then extracted the following information from each expert's profile: full name, job title, Twitter account (if any), and education level through the profile links. By keyword searching on job titles, I coded if an expert 1) is a senior or distinguished scholar, 2) holds leadership positions, including directors, chairs, and presidents, 3) holds managerial positions, including being an editor, and 4) is a research assistant or associate. 1) is a proxy for the expert's reputation for her expertise; 2) tells us the expert's status in the organizational hierarchy, and 3) differentiates communications for managerial affairs from the spontaneous, less structured, and perhaps research-related interactions. For 4), research assistants and associates are often listed as "experts," but they are mostly predoctoral students and interns without a long-term contract with the organization. I excluded all of them from the analysis.

By keyword searching, I coded if an expert 1) has a doctoral degree, not including Doctor of Medicine (MD) or Doctor of Law (JD), and 2) has a degree in Law, including JD and LLM. These two variables are proxies for an expert's academic training. I then used a Python package called sexmachine[1] (Michael, 2007) to detect gender from experts' first names. This algorithm takes in a first name and returns its best guess (male, female, mostly male, mostly female, unknown). For the "mostly male," "mostly female," and "unknown" names, I manually coded gender based on the pronouns used in their profiles.

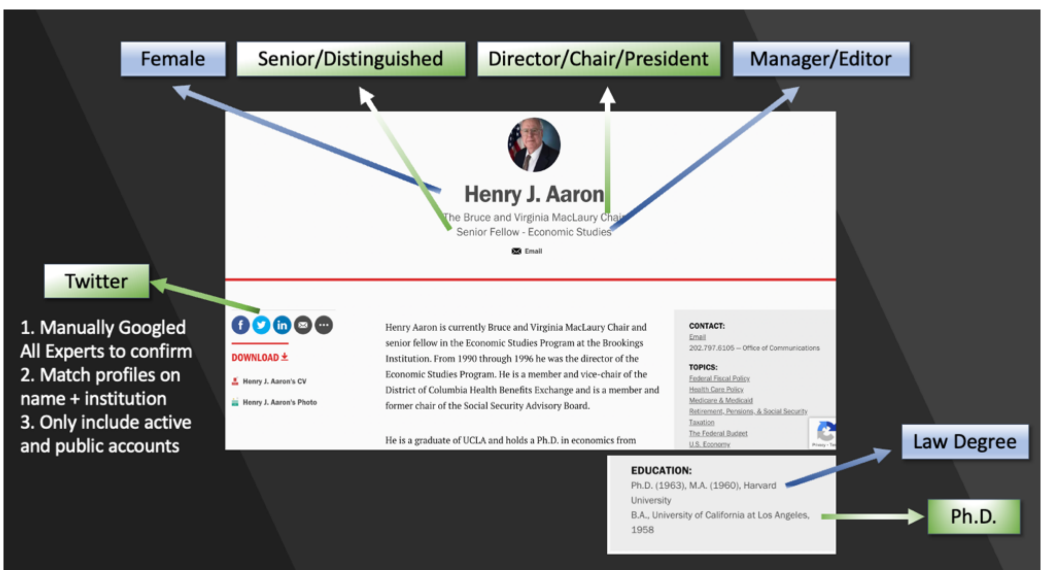

Figure 1

More than half of the experts reported their Twitter accounts, but some did not. Thus, I manually searched their names to check if they did use Twitter. Only when 1) a Twitter account explicitly mentions the expert's affiliated think tank or refers to the articles or events of this think tank, or 2) the account's profile photo is the same as the expert's photo on her think tank website

[1] https://pypi.org/project/gender-guesser/

(or LinkedIn), did I match this account to the expert. I then scraped and obtained a complete list of each expert's followers and the accounts she follows, through which I extracted a subgraph that includes only experts as nodes—an expert follow network.

Data Summary

I hope to focus on current experts who hold long-term careers in policy research. Thus, I excluded former experts, research assistants and associates (interns who haven't yet committed to this career), and non-research staff members such as a video designer from the dataset. The remaining dataset includes 126 experts in AEI, 401 in Brookings, and 109 in Heritage. About 70% of the experts have active Twitter accounts, a percentage much higher than the average Americans. This again suggests that experts actively utilize their Twitter account for professional purposes. I then excluded experts without Twitter accounts, leaving 86 experts from AEI, 279 from Brookings, and 83 from Heritage in the final dataset.

It is interesting to note the different compositions of personnel, which reflect different organizational strategies. Almost 90% of the experts at the Heritage are resident scholars, and only 20% have doctoral degrees. AEI also has much more resident scholars than Brookings. The large proportion of resident scholars in the conservative think tanks and the small proportion of Ph.D.'s in the Heritage echoes conservatives' long-standing mistrust of the university system. Meanwhile, Brookings names over 70% of its experts as senior or distinguished scholars. Given Brookings' deep-rooted connection with academia and engagement in the revolving door, this might be a strategy to keep influential university professors and politicians listed in the organization at least nominally. In all, the discussion above suggests that because organizations' different strategies and philosophies are reflected through their personnel management, the causal effect of residency should be measured separately by each organization.

Institution	Twitter	Resident	Senior	Director	Manager	Ph.D.	Law	Female
AEI	68.25%	61.11%	7.94%	15.08%	1.59%	59.52%	10.32%	18.25%
Brookings	70.07%	36.41%	70.82%	15.71%	1.00%	66.58%	9.98%	30.17%
Heritage	77.06%	88.99%	38.53%	36.70%	9.17%	20.18%	10.09%	27.52%

Figure 2 visualizes the Twitter follow network, and the nodes are sized by in-degree centrality. While network visualization could be misleading, it is still evident from eyeballing that experts cluster by organizations—most of the connections exist within the organization. Also, the moderate conservative AEI seems to connect the radical conservative Heritage and the moderate liberal Brookings. The relative locus of organizations on a network of individuals indicates that one's network position is influenced by both her own traits and her organization's traits.

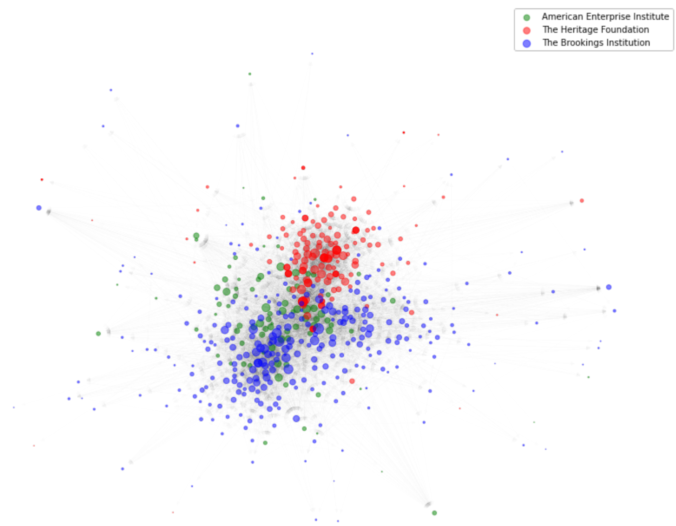

Figure 2

Model

I evaluate the average treatment effect on the treated (ATT) of residency on experts' network centrality with Inverse Propensity Score Weighting regression. Propensity scores are used as weights to account for treatment assignment differences between treatment and control groups. Compared to matching, using propensity scores allow us to include all the units for evaluation. Also, King and Nielson's (2019) criticism that propensity score matching is suboptimal compared to other matching methods does not apply to propensity score weighting. ATT is evaluated, instead of the average treatment effect (ATE), because the focus here is to compare the resident scholars with those nonresident scholars who could have been residents.

As mentioned in the two hypotheses, the dependent variables are 1) an expert's number of internal followers within the organization and 2) an expert's number of external followers from the other two organizations. The dependent variables are normalized to a scale from 0 to 1 to compare effect sizes. The treatment variable is whether an expert is a resident scholar (1) or not (0). Covariates include gender, organizational status, leadership positions, management positions, academic training, and organization affiliation. Since all the covariates are binary, the model does not assume linearity. The regression model is thus as follows:

$$
\begin{aligned}
Y_i = \alpha + \beta_1(AEI\ and\ Resident)_i + \beta_2(Brookings\ and\ Resident)_i \\
+ \beta_3(Heritage\ and\ Resident)_i + \gamma_1 Female_i + \gamma_2 Law_i + \gamma_3 PhD_i \\
+ \gamma_4\ Leadership_i + \gamma_5 Management_i + \gamma_6 Senior_i + \epsilon_i
\end{aligned}
$$

To validify the common support assumption, I started with exact matching to show that propensity scores rebalance our data relatively well. As shown in Figure 4, before adjustment, resident scholars are much more likely to hold leadership and management positions and much less likely to be academically recognized. Also, as we discussed before, right-leaning think tanks have more resident scholars. These imbalances are mostly adjusted with propensity scores.

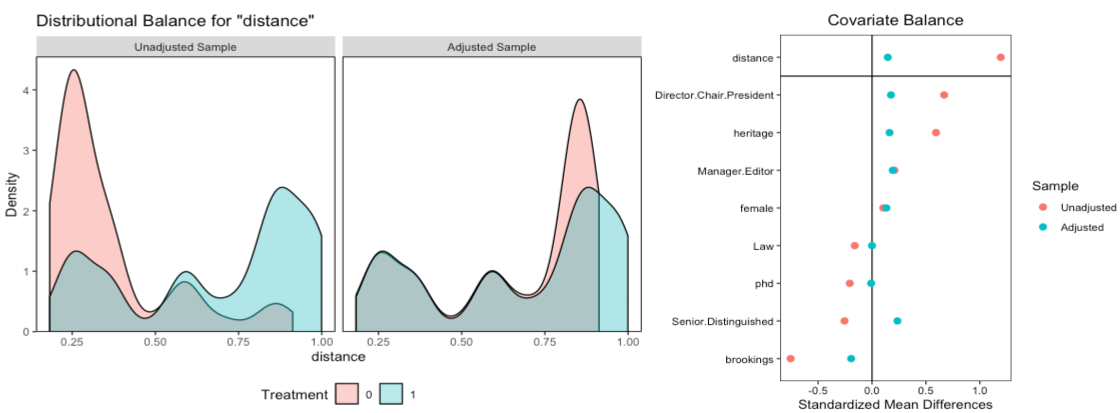

Figure 3 and 4

Results

The regression result is shown on the last page. HC2 robust standard error is used and clustered on organizational affiliation. The four dependent variables are 1) the number of followers within the organization and 2) outside the organization, 3) the number of experts an expert follows within the organization and 4) outside the organization. The first two dependent variables are the outcomes of interest. I included 3) and 4) as a reference point: the number of experts one follows may suggest a willingness to engage in this expert network and develop it. This willingness might be an alternative pathway to explain how residency affects network centrality. If you follow your colleagues, they are likely to follow back for politeness even though they might not know you personally. Since resident scholars may be more willing to cultivate this local expert network by following more people, they may harvest more followers regardless of their reputation. But including 3) and 4) in our model creates biases because, as post-treatment variables, they are not on any back-door paths.

The regression results show that resident scholars have significantly more internal followers in all three organizations. But although residency in Brookings and Heritage significantly increases an expert's internal influence, its effect on external influence is negative and not significant. The effect for Brookings is not significant probably because over half of our data points are from Brookings. There are not many external experts for Brookings, and all the external ones are from conservative organizations. Including more moderate and liberal think tanks might increase the significance level. The effect for Heritage is negative and not significant probably because its image as an explicitly partisan and biased research institute might reduce its external reputation among the expert community. This negative effect is strong despite the efforts of the resident scholars at Heritage to follow significantly more external experts. On the opposite, being a resident scholar at AEI increases both internal and external influence, and the effect on external influence is even larger than that on internal influence. Being the broker between Brookings and Heritage, AEI seems to enjoy certain advantages from the structural-hole position, receiving attention from both sides.

A sadly not surprising observation is that women are less embedded in this local network—they are less followed and follow fewer people. However, it seems that the negative effect of gender is only significant outside of the organization. A possible explanation is that women are less active in cross-organizational social events—such as conferences, testimonies, and happy hours. Or, based on my personal experience, women are more likely to be seen as irrelevant event-organizing staff members or the partners of some male experts in these social events.

Another noteworthy observation is that lawyers and Ph.D.'s are also less embedded in this network, although the effects are not very significant. The slightly negative effect of academic training on expert influence might echo a widely known dilemma for think tanks: those with higher academic credibility are often those who are less influential.

Conclusion

In conclusion, the first hypothesis is confirmed: Being a resident scholar increases an expert's internal influence. The second hypothesis could be true, but the effect is insignificant and varies by organization. Being a resident scholar sometimes decreases an expert's external influence, but the effect may depend on organizational reputation. Further, we need to include think tanks outside of D.C. to decouple the effects of being a policy expert in D.C. and being a resident expert, which might offset each other.

It is important to note some other limitations of this research. First, potential confounders such as race and age are not included in the model because it is hard to extract these data from websites. Religion might be another missing confounder that interacts with other factors.

Second, the sample is by no means randomly selected, and the units are not independent of each other. This violation reduces the model's internal and external validity. However, in the sense that residency status is not likely to have any spillover effect or be influenced by our outcome of interest—a Twitter network, I believe that the internal validity can be defended. Still, a potential criticism is that the physical presence of some experts with exceptional personalities may significantly promotes or disturbs office dynamics, such that the residency of one may have a spillover effect on the productivity of others.

Another possible criticism is that network centrality depends on the sample: if we include more think tanks, centrality distribution might be completely different. As a robustness check, I included experts from CAP to construct a new network and recalculate centrality. CAP was excluded because it does not label resident and non-resident scholars on its websites, but the Twitter data for CAP experts were collected through the same procedure. The result is the same and even further confirms our conclusion: being a resident scholar now significantly increases the external influence of a Brooking's expert and significantly decreases the external influence of a Heritage expert. However, this more significant effect is probably a result of including a radically liberal organization that allies with Brookings and considers Heritage its direct threat. Therefore, we might need to include even more think tanks to validify the robustness. But given Heritage's level of extremeness—and how much it is proud of itself for being an explicit advocate for conservatism and a challenger of the think tank's tradition of value neutrality—I believe that the conclusion will still be the same with the increase in sample coverage.

Myers, S. A., Sharma, A., Gupta, P., & Lin, J. (2014). Information network or social network? *Proceedings of the 23rd International Conference on World Wide Web - WWW '14 Companion*. https://doi.org/10.1145/2567948.2576939

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Rich, A. (2010). *Think tanks, public policy, and the politics of expertise*. Cambridge University Press.

Battaglini, M. (2004). Policy advice with imperfectly informed experts. *The B.E. Journal of Theoretical Economics*, *4*(1). https://doi.org/10.2202/1534-5963.1100

Gary King and Richard Nielsen (2019). "Why Propensity Scores Should Not Be Used for Matching." *Political Analysis*, 27, 4, Pp. 435-454

Table 1: Without CAP

	Dependent variable:			
	inside_followed	outside_followed	inside_following	outside_following
	(1)	(2)	(3)	(4)
Resident × AEI	0.083***	0.203***	0.036*	0.131***
	(0.018)	(0.037)	(0.021)	(0.031)
Resident × Brookings	0.183***	0.017	0.166***	0.033**
	(0.024)	(0.013)	(0.026)	(0.017)
Resident × Heritage	0.190***	−0.023	0.139***	0.102***
	(0.026)	(0.017)	(0.028)	(0.029)
Director.Chair.President	0.059***	0.012	0.046*	0.006
	(0.022)	(0.016)	(0.024)	(0.018)
Senior.Distinguished	0.029*	−0.004	−0.024	−0.047***
	(0.018)	(0.013)	(0.020)	(0.016)
Manager.Editor	0.199***	0.055	0.172**	0.056
	(0.055)	(0.047)	(0.068)	(0.042)
female	−0.023	−0.036***	−0.002	−0.046***
	(0.017)	(0.013)	(0.018)	(0.016)
Law	−0.052**	−0.019	−0.037	−0.042*
	(0.025)	(0.023)	(0.028)	(0.022)
phd	−0.013	−0.017	−0.017	−0.001
	(0.018)	(0.017)	(0.019)	(0.017)
Constant	0.096***	0.073***	0.128***	0.118***
	(0.018)	(0.023)	(0.022)	(0.020)
Observations	448	448	448	448
R^2	0.379	0.230	0.255	0.164
Adjusted R^2	0.366	0.214	0.240	0.147
Residual Std. Error (df = 438)	0.144	0.135	0.153	0.152
F Statistic (df = 9; 438)	29.725***	14.536***	16.686***	9.576***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 2: With CAP

	Dependent variable:			
	inside_followed	outside_followed	inside_following	outside_following
	(1)	(2)	(3)	(4)
Resident × AEI	0.083***	0.196***	0.036*	0.132***
	(0.018)	(0.038)	(0.021)	(0.033)
Resident × Brookings	0.183***	0.049***	0.166***	0.071***
	(0.024)	(0.018)	(0.026)	(0.021)
Resident ×Heritage	0.190***	−0.043**	0.139***	0.084***
	(0.026)	(0.020)	(0.028)	(0.029)
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Manager.Editor	0.199***	0.105	0.172**	0.089
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female	−0.023	−0.040**	−0.002	−0.047***
	(0.017)	(0.016)	(0.018)	(0.018)
Law	−0.052**	−0.007	−0.037	−0.031
	(0.025)	(0.027)	(0.028)	(0.027)
phd	−0.013	−0.019	−0.017	0.001
	(0.018)	(0.019)	(0.019)	(0.018)
Constant	0.096***	0.082***	0.128***	0.127***
	(0.018)	(0.025)	(0.022)	(0.020)
Observations	448	448	448	448
R^2	0.379	0.194	0.255	0.126
Adjusted R^2	0.366	0.178	0.240	0.108
Residual Std. Error (df = 438)	0.144	0.153	0.153	0.169
F Statistic (df = 9; 438)	29.725***	11.730***	16.686***	7.016***
Note:				*p<0.1; **p<0.05; ***p<0.01