Idea Brokers: Twitter-based Social Networks for Policy Experts in D.C.

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Abstract

Think tanks, the "public-policy research analysis and engagement organizations that generate policy-oriented research, analysis, and advice,"[1] have profoundly influenced the ideological formation and policymaking process in the United States. Different from the social scientists in ivory-tower universities, policy experts in think tanks actively engage in politics: they work closely with policymakers in drafting policies, deliver testimonies in Congress, propose policy recommendations and evaluations, as well as publish policy-oriented op-eds and articles. However, previous studies disagree, from a qualitative perspective, on what constitutes the authority and reliability of these policy experts and their affiliated think tanks and how to characterize their interactions. In this paper, I propose to construct a Twitter-based social network based on about four hundred experts from three influential think tanks, the Brookings Institution (Brookings), the American Enterprise Institute (AEI), and the Heritage Foundation (Heritage). I argue that this network can be a nice proxy for the organizational structures of policy experts. Further, a comparison of different degree centrality measures implies that the ability to bridge among other non-friend experts (betweenness centrality) is more important in explaining how experts are different in their network influence than their direct connections with other influential experts (eigenvector centrality). Finally, an expert's influence on her inner-organizational network is uncorrelated with the academic citation index or tweeting sentiments but is statistically correlated with the number of followers from government agencies and elected officials. In all, the results imply that the U.S. policy experts, instead of advising policymakers individually, tend to leverage their social network influence through existing organizational structures such as their affiliated think tanks. Further, the gap between scholars focusing on peer-reviewed publications and policy experts focusing on unchecked books and testimonies is significant. The gap stresses more critical deliberation in interpreting expert opinions.

Keywords

Think Tanks, Policy Experts, Technocracy, Social Network Analysis, Centrality, Twitter

INTRODUCTION

Historically, policy experts in think tanks played an important role in shaping domestic and foreign policies as well as influencing public opinion in the U.S. For example, President Reagan implemented many of the proposals proposed by the Heritage Foundation (Heritage) in its three-thousand-page long publication *Mandate for Leadership*.[2] Policy experts from the Brookings Institution (Brookings), on the other hand, produced reports which blueprinted many major policy decisions including the Marshal Plan[3] and NASA's space programs[4].

Despite the profound influence of policy experts in shaping the current U.S. political context, quantitative academic research on how policy experts and think tanks gain their influence is limited. A particular challenge is the lack of consensus among scholars as to what constitutes a think tank because policy research institutions differ significantly in their funding measures and targeted audience. Kent Weaver identifies three major types of think tanks.[5] According to his widely cited theory, certain research scholars either prefer the "seclusion" of think tanks to teaching responsibilities or dislike the "overwhelmingly liberal"[6] environment in universities. "Universities without students" such as Brookings and AEI thus offer a refuge for them to conduct policy-oriented studies. RAND and the Urban Institute, instead, employ field-specific experts and serve specific needs of policymakers as government contractors. Thirdly, a new generation of policy institutes such as Heritage identify themselves as advocacy-oriented and ideological-driven, disregarding the conventional policy research principles of neutrality.[7]

This theory, however, poses two general questions I hope to focus on for this project. The first question regards its premise: Can we analyze policy experts from an organizational perspective at all? Does the concept of organizational affiliation affect the interactions among policy researchers who physically concentrate within only a few blocks in D.C. and hold a wide range of ideological differences *not* always demonstrated in the missions of their institutions? Furthermore, if policy experts in think tanks—at least some of them—still identify themselves as policy researchers, is academic reputation still valued in their social network? How is academia, i.e. a university, connected to "universities without students:" the industry of policy and political ideas, government contractors, and activists? If not, which factors determine an expert's influence over its network?

In this project, I try to answer these questions by proposing a computational method to analyze the social network of policy experts. Through web-scraping techniques, I construct a Twitter-based follower-following network that can cover about 70% of all policy experts in the three think tanks I chose to start with, i.e. Brookings, AEI, and Heritage. I argue that first, this network clearly shows the organizational structures of experts in the three think tanks. Further, using the Gini coefficient to compare the inequality of different degree centrality measures, it seems that the ability to bridge among other non-friend experts is more important in capturing experts' differences in network influence than their direct connections with other influential experts. Finally, an expert's influence on her inner-organizational network is uncorrelated with her academic citation index or sentiments in tweets. But the influence is indeed statistically correlated with the number of followers from government agencies and elected officials. In summary, the results imply that the institutionalization of expert networks transforms the role of policy experts from academic researchers to idea brokers[8] who transmit political ideas through networks to targeted audiences without necessarily producing supporting research evidence themselves. However, the conclusion is limited to only three think tanks. In further research, I will expand the research horizon to more think tanks.

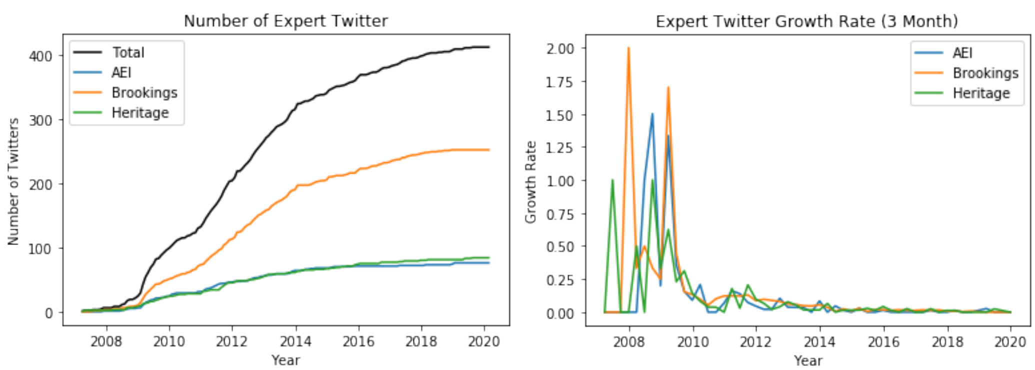
DATA COLLECTION

[Twitter Handles]

To start with, I obtained a complete list of policy expert full names by scraping the staff websites of the three think tanks, Brookings, AEI, and Heritage. Most of these experts published their twitter handles on the websites and I manually supplemented the rest of the Twitter handles through Google Search. To avoid the issue of name duplication which happens frequently, I matched an expert with a Twitter handle only when at least one of the following criteria was satisfied: 1) the Twitter account explicitly mentions the expert's institutional affiliation, such as a university, 2) the Twitter profile picture looks exactly like the expert's profile picture, and 3) the corresponding think tank directly refers to this Twitter account in a tweet.

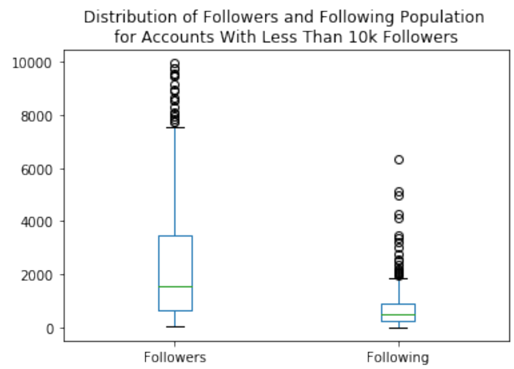
In summary, I gathered a total of 668 distinct expert names, including 119 experts from AEI, 424 experts from Brookings, and 124 experts from Heritage. The percentages of experts who can be matched to Twitter handles are consistent across the three policy think tanks at the level of about 70 percent (464 accounts in total). This suggests widespread use of Twitter among policy experts as a potential way to access news information, interact with political actors, and disseminate their research findings and opinions.

To interpret what motivated policy experts to start using Twitter, I scraped each twitter handle's profile information and obtained the joining time for each handle. It turns out that the number of twitter accounts grew rapidly before 2010 but almost stopped changing after 2014, suggesting that Obama's election campaign has significantly more influence than Trump's election campaign on policy experts' adoption of social media. President Obama, known as the first U.S. presidential candidate who successfully mobilized the general public online by using over fifteen social network sites[9], did leave an influential legacy of discussing political topics on social media. While President Trump does use Twitter more actively and frequently especially after assuming office in 2017, it seems that those experts who wanted to use social media have already gone online, and those who did not want to use social media feel no pressing pressure to change.



[Follower-Following Network]

To construct the follower-following networks, I exhaustively scrapped through all followers and following accounts for each policy expert handle. Among the 464 available Twitter handles, I excluded the 44 protected accounts for which scraping behavior is prohibited. Because it is computationally expensive to scrape through the follower-following accounts, I also excluded 28 accounts with more than 50,000 followers, including some of the well-known political-academic celebrities such as Ben Bernanke. In summary, 72 accounts were excluded, and 392 accounts were left. The population of followers and following displays great diversity, with an average of about 4950 followers and 925 following accounts. The graph below shows the distribution of followers and following population for accounts with less than ten thousand followers, so the averages are different.



[Account Identities]

To interpret the components of experts' followers and following accounts, I tried to classify the accounts by obtaining multiple datasets from Harvard Dataverse. The dataset collects twitter handles of "End of Term 2016 U.S. Government Twitter Archive"[10], 115th and 116th U.S. Congress Tweet Ids[11] [12], News Outlet Tweet Ids[13], and U.S. government tweet Ids.[14] According to Harvard Dataverse, almost all 100 senates and 435 house representatives in the 115th and 116th Congress have Twitter accounts, and one might have multiple accounts. The dataset provides 435 (House) and 102 (Senate) Twitter handles for the 115th Congress, as well as 433 (House) and 99 (Senate) Twitter handles for the 116th Congress. It also provides 3,897 active handles controlled by U.S. federal government agencies collected between January 20, 2017, and July 20, 2018, as well as 4,514 active handles controlled by news outlets including "everything from local U.S. newspapers to foreign television stations," collected between August 4, 2016, and May 12, 2020. These Twitter handles were collected from the GET statuses/user_timeline method of the Twitter API using Social Feed Manager.

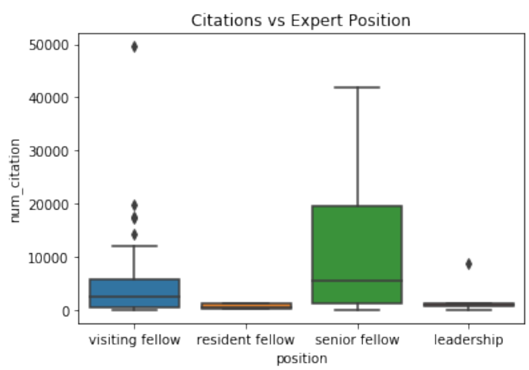
[Number of Citations]

Given that one of the policy analysts' central tasks is to conduct policy-related research, it is reasonable and common to assume that policy analysts establish their reliability largely based on their academic backgrounds. But if this assumption is true, then academic reputation should be an important predictor for policy analysts' influence. At the very least, this influence corresponds to whether their (potential) followers consider their comments informative and trustworthy. If academic reputation is indeed essential to a policy analyst's professional identity and her scope of influence, the number of accumulated citations should be a highly predictive factor of these measures.

To start, I automatically searched each expert's name on Google Scholar and scraped all search results with similar names. I then manually matched the names based on experts' university affiliations and fields of specialty, assuming that a public health expert would not publish papers on computer science journals. For this primary research, I preferred Google Citation to other publicly available citation metrics, because Google Citation provides the most complete similar-name search results. It is however important to note that Google Citation metric has multiple limitations: For example, an individual might be related to multiple variations of a name and the cited list covers materials such as "blog posts, syllabi, or anything else mentioned in a scholarly article."[15] For further research and the purpose of cross-validation, a more rigorous metric such as H-index might be preferred.

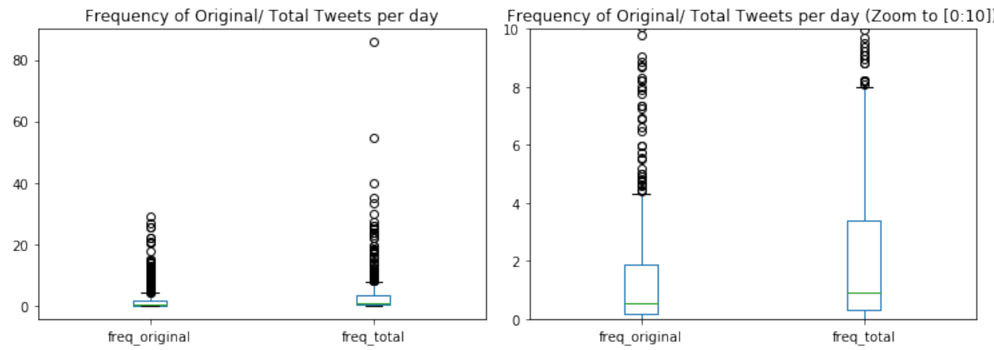
My primary data exploration shows an overwhelming gap of connection between the D.C. policy circle and academia. Out of all experts who have Twitter accounts, only 5 out of 160 experts from AEI and Heritage can be matched to the Google Citation index. Even for Brookings, the well-established policy think tank known for being not just an origination but an education institute[16], only about 30 percent of experts' publications can be found on Google Scholar. But citations do matter to Brookings, if anything, given that 22 experts in Brookings have more than 5,000 citations from Google Scholar. Due to the limitation in data scope, it is hard to conclude whether such a gap of connection is related to ideological-partisan differences.

Moreover, academic reputation seems to have no linear correlation with experts' job titles. The boxplots below indicate that resident fellows tend to have fewer academic publications, but researchers with more academic citations might be recruited as visiting fellows or senior fellows. Those in the leader board are not interested in academic research as well. This non-linear connection suggests that policy think tanks do not themselves produce, or even have the motivation to publish peer-reviewed articles. Congress testimonies, books, opinion articles, as well as, public lectures and interviews, are still more preferred—if not easier—ways to gain names and reputations.[17] This industry-academic intermarriage is saliently different from the industry-academic partnership common in the fields of Science, Technology, Engineering, and Math (STEM), where influential companies such as Google and Microsoft actively fund research teams dedicated to publishing on peer-reviewed journals.



[Frequency of Tweets]

I collected at most 300 pages of historical tweets for each expert account. I recorded whether each tweet is original or retweeted as well as its posted date. I calculated an account's frequencies of posting original and total tweets as "number of tweets / (today – earliest available tweet posting date)." As shown below, while the average frequency is about 2.25 original tweets and 3.72 total tweets per day, the variance is extremely high. Political analysts such as Sean Trende from AEI and Benjamin Wittes from Brookings posted over twenty original tweets per day in the past four months, mostly related to politics, while over forty experts – twelve of them have less than a hundred followers – posted on average one post per more than twenty days. Admittedly, the scraping strategy is not perfect and may pose potential questions on whether the current COVID-19 pandemic may skew the posting behavior: For example, public health experts might feel more necessity to share their knowledge and opinions. Therefore, further and more longitude research is needed. However, given that many of the most active accounts are not directly associated with public health, the pandemic may have already been so influential to all fields that the posting behavior is no longer skewed by specialty.



Identifying the political "opinion leaders" on Twitter as well as their posting patterns is itself an interesting research topic. Despite the wide use of Twitter as a means of communication, most academic research focuses on Twitter hashtags,[18] retweeting/ message-forwarding behaviors,[19] network structures [20], and automation detection[21] [22]. The only research that I found closely relevant so far is from the University of Michigan[23]. In their paper, the authors collected data from 507 active Twitter users from August 2010 to October 2011 and conducted longitudinal research. The research shows that 1) overuse of hashtags and undirected messages – messages without replies and mentions – will hinder audience growth, 2) directed communication is not a significant factor, 3) producing or passing along informational content predict more followers. However, it is not clear how the authors selected these Twitter users since most of the users are ordinary users rather than celebrities: "The majority of users have 176 to 949 followers," the authors write. Therefore, it is not clear whether the conclusions on ordinary 2010-2011 Twitter users can infer anything about how political elites use Twitter in the age of President Trump.

Given the data from over four hundred experts from three major think tanks, I found that first, those who have more followers and *less* following accounts tend to post original and total tweets more frequently. Those more active Twitter users also have significantly more followers from news outlets. These more active users also tend to follow more news outlets, but the correlation is not statistically significant. Interestingly, the number of followers from government agencies is not correlated to the frequency of original tweets but has a statistically significant and positive correlation with the frequency of total tweets. These regression results stated above suggest that first, experts who tweet more actively on Twitter—no matter in terms of original content or not—tend to receive more attention from the media. Second, U.S. federal government agency accounts seem to interact more with the experts who retweet more and do not care about whether the content of tweets is original or not.

Another potentially interesting topic is that the correlation between the frequency of total tweets and experts' position in the organization is negative and close to 0.05-level significance (p-value = 0.08). This might suggest an urge for lower-level experts to tweet more to gain more attention and media exposure. But this relation, if exists, is not strictly linear, or is disguised by our arbitrary measurement of position purely based on job titles within think tanks. I will discuss more about the limitations in quantifying job titles later.

Model: Y = Frequency of Original Tweets

OLS Regression Results

Dep. Variable:	freq_original	R-squared:	0.355
Model:	OLS	Adj. R-squared:	0.339
Method:	Least Squares	F-statistic:	21.73
Date:	Mon, 25 May 2020	Prob (F-statistic):	2.77e-32
Time:	10:33:44	Log-Likelihood:	-1089.2
No. Observations:	406	AIC:	2200.
Df Residuals:	395	BIC:	2244.
Df Model:	10		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1.1159	0.392	2.847	0.005	0.345	1.886
num_followers	3.3e-05	4.18e-06	7.897	0.000	2.48e-05	4.12e-05
num_following	-0.0001	2.77e-05	-5.176	0.000	-0.000	-8.88e-05
position	-0.2092	0.153	-1.371	0.171	-0.509	0.091
num_citation	-2.673e-05	3.97e-05	-0.673	0.501	-0.000	5.14e-05
gov_followers	0.0646	0.041	1.563	0.119	-0.017	0.146
congress_followers	-0.0824	0.055	-1.504	0.133	-0.190	0.025
news_followers	0.2435	0.045	5.452	0.000	0.156	0.331
gov_following	0.0130	0.017	0.766	0.444	-0.020	0.046
congress_following	-0.0145	0.012	-1.246	0.214	-0.037	0.008
news_following	0.0199	0.010	1.926	0.055	-0.000	0.040

Omnibus:	222.702	Durbin-Watson:	2.110
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1839.447
Skew:	2.215	Prob(JB):	0.00
Kurtosis:	12.440	Cond. No.	1.47e+05

Model: Y = Frequency of Total Tweets

OLS Regression Results

Dep. Variable:	freq_total	R-squared:	0.428
Model:	OLS	Adj. R-squared:	0.414
Method:	Least Squares	F-statistic:	29.57
Date:	Mon, 25 May 2020	Prob (F-statistic):	2.72e-42
Time:	10:34:13	Log-Likelihood:	-1291.9
No. Observations:	406	AIC:	2606.
Df Residuals:	395	BIC:	2650.
Df Model:	10		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1.3179	0.646	2.041	0.042	0.048	2.587
num_followers	4.948e-05	6.88e-06	7.188	0.000	3.59e-05	6.3e-05
num_following	-0.0002	4.56e-05	-4.657	0.000	-0.000	-0.000
position	-0.4420	0.252	-1.757	0.080	-0.936	0.052
num_citation	7.266e-06	6.54e-05	0.111	0.912	-0.000	0.000
gov_followers	0.2448	0.068	3.596	0.000	0.111	0.379
congress_followers	-0.1465	0.090	-1.622	0.106	-0.324	0.031
news_followers	0.4862	0.074	6.608	0.000	0.342	0.631
gov_following	0.0364	0.028	1.304	0.193	-0.018	0.091
congress_following	-0.0169	0.019	-0.883	0.378	-0.055	0.021
news_following	0.0305	0.017	1.789	0.074	-0.003	0.064

Omnibus:	255.029	Durbin-Watson:	2.079
Prob(Omnibus):	0.000	Jarque-Bera (JB):	3749.832
Skew:	2.403	Prob(JB):	0.00
Kurtosis:	17.092	Cond. No.	1.47e+05

[Sentiment Analysis]

To analyze whether experts' sentiments in tweets affect their influence over the social network, I scraped at most 200 pages of historical tweets for each expert. I then applied sentiment analysis using the Natural Language Toolkit (NLTK) package. An NLTK sentiment analyzer from Valence Aware Dictionary and sEntiment Reasoner (VADER) applies a lexicon and rule-based model to determine whether a piece of text is positive, negative, or neutral. According to its developers, the model is "specifically attuned to sentiments expressed in social media."[24] Primarily, it tokenizes a piece of unit text as a bag of words and calculates the percentages of positive and negative words. It generates negative, neutral, and positive scores for each piece of text. In most cases, the VADER model properly estimates the level of sentiment in tweets, but without a context, the model sometimes yields low accuracy. For example, in the response of the current Black Lives Matter movement, a 1.2-million-likes tweet writes "They'd rather arrest hundreds of American citizens then 3 of their own. Very telling." This is an angry and sarcastic tweet, negative in any means, but the model scores it 83% neutral and only 17% negative because the only somewhat negative word is "arrest." As a comparison, the tweet "It is important for advertisers to know what they are sponsoring. Their choices can encourage or discourage bad dangerous propaganda" scores 46% neutral and 37% negative. The latter tweet is perhaps also negative, but it is intuitively not as sentimental as the former tweet. Therefore, further research is needed for better classification.

[Summary]

Even with some primary data exploration, we can already conclude a few interesting points about policy experts' social media usage. I summarize three major takeaways here, which may help us better interpret the results and discussions I will present in the next section.

First, over seventy percent of policy experts have Twitter accounts. Most of them, despite ideological differences, started to use Twitter during and right after Obama's Election Campaign. Second, we can match only less than 20% policy experts to academic publications on Google Scholar. Regression results imply that academic reputation does not seem to have a linear correlation with experts' job titles. Finally, experts who tweet more frequently tend to receive more attention from media outlets and federal government accounts. The frequency of tweets is not significantly correlated with the number of followers from elected officials.

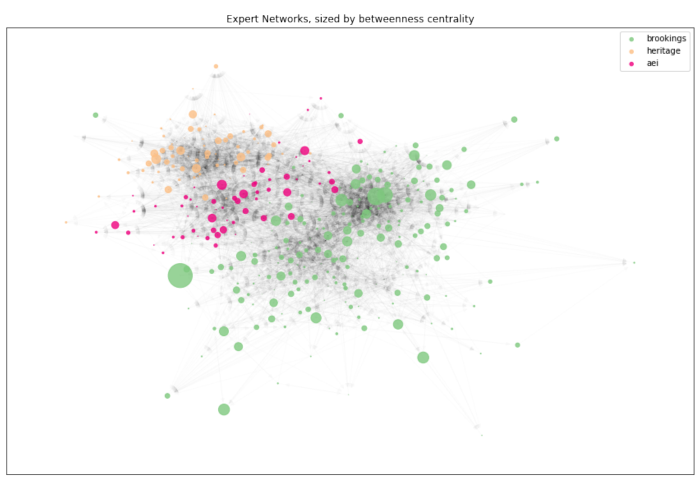
METHODS: Network Construction

Given the scraped data, we can construct follow-following networks for policy experts. That is, each expert is considered a node. If expert A follows expert B on Twitter, then A and B are connected with a directed edge from A to B. Before analyzing the structure of these networks, we need to discuss a set of prerequisite questions.

First, to which extent do the follow-following networks correspond to the organizational structures of policy experts from Brookings, AEI, and Heritage? A potential concern would be that, policy experts simply follow each other whimsically based on certain tweets they read by chance or do not care about managing their personal Twitter accounts at all. Another concern is that other factors such as ideology, field specialty, and work experience may override organizational factors, motivating experts to follow those whose opinion they agree more or identify more with, instead of their colleagues in the same office building.

These concerns might be valid at least to some of the experts, but as shown in the graph below (network displayed using Spring Layout, which positions nodes using Fruchterman-Reingold force-directed algorithm), the distribution of nodes displays an organizational structure. We can also observe a spectrum of ideological differences: The very conservative nodes from Heritage cluster closely at the top left, and the relatively diverse—but mostly liberal—nodes from Brookings spread out from the center of the graph to the bottom right.

More rigorous modularity measures would be helpful, but the messages are already promising: First, the Twitter follower-following networks can indeed represent certain inner-organizational network structures. Second, the distribution of betweenness centrality is relatively independent of the inter-organizational positions. In other words, the nodes which bridge different think tanks do not tend to have higher centrality than others. These messages suggest that social-media-based networks can be a nice proxy for the inner-organizational power structure.



Second, which centrality measure best captures the power structure of policy experts within an organizational network? Social network analysis (SNA) researchers have not yet reached a consensus on which centrality measures best predict inner-organizational network influence. More precisely, different centrality measures quantify different forms of power, ranging from a direct collection of follower attention to an implicit control of information flows. I compare different centrality measures with the Gini coefficient, one of the most commonly used measurements of wealth inequality.[25] In this section, I take the AEI network as a case study, use Gini coefficients to compare five common centrality measures, and discuss the implications of these centrality measures.

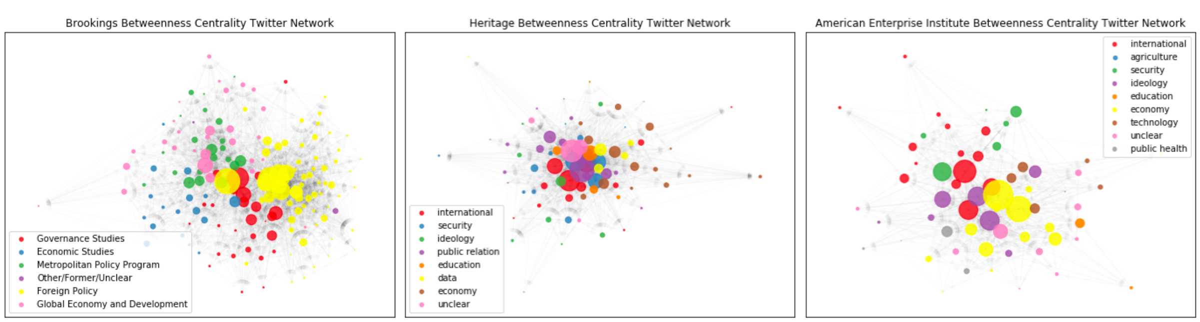
Among many other options, degree, closeness, eigenvector, and betweenness centrality are the most popular and intuitive options. Degree centrality is defined as the number of links that a node has. In our case, the in-degree centrality refers to the number of follower nodes a node has. Given that a Twitter user can not only see her total number of followers but the name of individual followers, in-degree centrality not only measures popularity and attention but might also imply a sense of explicit alignment, if not loyalty. Closeness centrality of a node is the average length of the shortest path between the node and all other nodes in the graph.[26] Defined originally as the reciprocal of the farness, closeness centrality measures how closely a node is connected to other nodes. Eigenvector centrality, instead, measures the influence of a node in a network. It assumes that those nodes that are connected to nodes with high scores should themselves be influential as well.[27] Google's PageRank, as a variation of eigenvector centrality, applies a similar algorithm in calculating centrality: It assigns relative scores to all nodes and updates node scores based on their connections to other nodes. Finally, betweenness centrality measures the number of times a node acts as a bridge along the shortest path between two other nodes.[28] In our case, it quantifies how important an expert is in terms of linking other experts together, i.e. making two experts who do not have direct follower-following relationships see each other's tweets.

For our case of the AEI network, different measures emphasize different power structures. The Gini coefficients are 0.34 for Indegree Centrality, 0.096 for Closeness Centrality, 0.38 for Eigenvector Centrality, 0.35 for PageRank Centrality (alpha = 0.85), and 0.66 for Betweenness Centrality. The inequality level for closeness centrality is extremely low, indicating that nodes are so closely clustered together that for most of the nodes, it does not take a long way to be connected to any other nodes. The inequality levels for indegree, eigenvector, and PageRank centrality are relatively high at about 0.3-0.4 but are not as high as that for betweenness centrality. An over 60 percent Gini coefficient suggests that the most powerful 20 percent nodes control 80 percent of all power, displaying a significant level of power inequality.

This difference between indegree, eigenvector (PageRank as one of its variations), and betweenness centrality measures imply important patterns in policy experts' social network structures. Eigenvector and PageRank centrality measures tend to yield higher unequal results because higher-scored nodes that cluster together tend to reciprocally add to each other's scores. But in our case, they are lower than betweenness centrality, probably because senior experts who are supposed to have higher scores do not follow each other closely on social media. They might be separated based on field specialty, subtle ideological differences, personal relationships, etc.

Most importantly, the unusually high level of inequality in betweenness centrality gives implications regarding how to interpret the forms of experts' inner-organizational power. Betweenness centrality measures a node's ability to control information flows: A node with high betweenness centrality plays a more essential role in facilitating the information communications among experts who are not friends on social media. This echoes Smith's description of think tank policy experts: Policy experts are "Idea Brokers," who leverage information among stockholders without necessarily producing innovative content, he writes.[29]

The third question is, are there certain salient sub-organizational factors that may affect the network structure? One hypothesis is that experts in the same think tank might cluster based on field specialty. For example, a health economist may tend to follow other economists rather than a denuclearization expert. More research needs to be done in this section, particularly because the boundary of each specialty is subject to ideological differences and framing strategies. For example, one might argue that healthcare is more of an economic topic for conservatives and more of a civil-right topic for liberals. Moreover, experts may have diverse experiences in different fields and specialties are highly related to each other. For example, almost all policy issues can be somewhat related to economic studies. Drawing a boundary among different specialties thus requests more detailed knowledge on each expert's experience and skills. Nevertheless, as shown in the graph, compared to experts in Heritage, those in Brookings and AEI tend to cluster in different groups, along the line of foreign policy, domestic policy, and economic studies. This is probably because both Brookings and AEI established multiple departments to address different policy issues, institutionalizing specialty differences into certain departmental structures. In other words, compared to specialties, formal institutional arrangements still better indicate the clusters of expert nodes.



RESULTS: What Explains the Variation in Experts' Centrality?

As discussed above, it is hard to quantify experts' job titles. For this project, I adopt a general assumption that more organizational involvement should indicate higher titles. Therefore, I rank titles as follows: Presidents, directors, board members, managers > senior or distinguished research fellows > resident scholars and fellows > visiting or non-resident scholars and fellows > research assistants. However, this ranking measure fails to capture many of the subtle power dynamics among experts with similar-level job titles, just like tenured professors in the same university may have a wide range of social reputation levels. Also, visiting scholars may be involved less in a think tank's managerial affairs, but they tend to hold other important positions in academia, politics, or industry, which may increase their social influence from a channel external to think tanks themselves. Therefore, centrality measures can serve as a better proxy for experts' inner-organizational influence.

In the regression models below, I focus primarily on in-degree centrality and betweenness centrality. In-degree centrality shows an explicit form of node popularity. Betweenness centrality, on the other hand, best captures the variation and inequality in experts' network influence and measures an important form of implicit power: the control over information and idea flows through connecting unconnected nodes. I summarize the key findings below:

	Total		**Heritage**		**AEI**		**Brookings**	
	In-Degree	BTN	In-Degree	BTN	In-Degree	BTN	In-Degree	BTN
Number of Followers	0.000***				0.000***		0.000***	
	(0.000)				(0.000)		(0.000)	
Number of Following	-0.000***			0.000*			-0.000***	
	(0.000)			(0.000)			(0.000)	
Government Followers								-0.0002*
								(0.000)
Congress Followers	0.0091***	0.0007***						
	(0.002)	(0.000)						
News Followers								
Government Following	0.0015***	0.0002***		0.0005***			0.0013***	0.0003***
	(0.001)	(0.000)		(0.000)			(0.000)	(0.000)
Congress Following								
News Following		0.000*					0.0005**	0.0001***
		(0.000)					(0.000)	(0.000)
Position	0.0458***	0.0029***	0.0303**		0.0464***	0.0050**	0.0281***	0.0035***
	(0.005)	(0.000)	(0.013)		(0.016)	(0.002)	(0.003)	(0.001)
Number of Citation								
Frequency of Original Tweets			0.0884***	0.0043**				
			(0.028)	(0.002)				
Frequency of Total Tweets			-0.0335**					
			(0.013)					
Negative Sentiment								
Positive Sentiment								
Neutral Sentiment					-1.1102**			
					(0.533)			
Adjusted R^2	0.458	0.290	0.582	0.677	0.405	0.092	0.535	0.357
F-statistic	23.70	11.98	8.607	12.43	4.64	1.541	19.72	10.04
N	404	404	83	83	76	76	245	245

* for P-value < 0.1, ** for P-value <= 0.05, *** for P-value <= 0.01
BTN: Betweenness Centrality

1) Our models tend to explain more variation in in-degree centrality (0.44 for total, 0.35 for AEI, and 0.48 for Brookings) than in betweenness centrality (0.29 for total, 0.09 for AEI, and 0.36 for Brookings). This is because an

expert with more followers (number of followers) almost certainly has more expert followers (in-degree centrality). That is, the number of followers is a strong predictor for in-degree centrality.

2) The models for Heritage explain a surprisingly high level of variation in both centrality measures: 0.58 for in-degree centrality and 0.68 for betweenness centrality. Existing literature has shown that, while Brookings and AEI prefer a public image of political neutrality, Heritage tends to involve more in explicit political advocacy and is, therefore, more motivated to influence public opinion and policymakers through social media.[30] Our quantitative result echoes this qualitative observation by suggesting that Heritage's institutional structure corresponds more to its virtual social media network structure. Moreover, the frequencies of original and total tweets are only significant for Heritage in predicting centrality, which again emphasizes Heritage's unique interest in advocating via social media.

3) In almost all models, position (job titles) is highly correlated with both centrality measures. It reconfirms our argument that both centrality measures are nice proxies for experts' influence on their organizational networks.

4) The models for AEI fail to explain most of the variations and the almost-only significant factor is position (job titles). This suggests that most of the factors that influence experts' centrality cannot be found in experts' social media usage or the number of citations. Another possible interpretation is that AEI might recruit a relatively more heterogeneous expert community. Visiting scholars who work primarily academia, former ambassadors and officials from international organizations, and residential research fellows interested in accumulating political capital and joining politics one day, may adopt distinct social media strategies to achieve their own goals.

5) Another interesting observation for AEI is that the increase in neutral sentiment scores significantly decreases an expert's in-degree centrality but does not significantly affect an expert's betweenness centrality. One possible explanation is that AEI, a think tank known for its anti-China, anti-Communist, strong national defense agenda, might cluster around its key expert figures who have a strong voice in the Sino-U.S. relations, supporting the Trade War and Hong Kong-related bills. That is, the key figures may use more positive words to describe themselves and negative words to describe foreign countries and therefore have less neutral sentiment scores. However, although these more sentimental experts have relatively higher in-degree centrality, they do not have higher betweenness centrality, suggesting that they do not necessarily have more informal organizational influence.

6) The overall models and the Brookings models further suggest that centrality levels may also be influenced by the components of followers and following accounts. We observe that experts with more followers controlled by Congress members, as well as more following accounts controlled by federal government agencies and news outlets, tend to have higher in-degree and betweenness centrality. That is, the experts who are more influential in their networks tend to be followed by more policymakers and keep closer track of the updates from government agencies and news outlets.

7) Google Scholar citation index fails to predict any of the centrality measures in any think tank. This suggests that the influence of policy experts in their network is not related to the number of their academic citations. As discussed before, out of all experts who have Twitter accounts, only 5 out of 160 experts from AEI and Heritage can be matched to the Google Citation index. Therefore, the non-linear correlation is almost solely about experts from Brookings. Either way, the message is clear: these think tanks either do not recruit any scholars at all or the academic citations a scholar does not necessarily bring her any network influence.

In summary, the main takeaways are that first, unlike Heritage, AEI and Brookings, the two more established and historical institutions see a higher correlation between institutional arrangements (job titles) and the informal influence over expert networks (betweenness centrality). Second, among the three think tanks, Heritage seems to show a stronger tendency to advocate in Congress through public outlets such as social media, and thus values the experts who follow more Congress members and publish more original content. Finally, the citation index and sentiments in tweets, in general, have low predictive power in all models. It implies that experts with higher academic reputation or more sentimental tweets do not tend to receive higher influence over expert networks.

DISCUSSION AND CONCLUSION

We need to note that there exist several limitations in this research regarding both internal and external validity.

In terms of external validity, the major problem is that we only have about four hundred experts from three think tanks in our data. As a comparison, Harvard Kennedy School reports more than 1,200 think tanks and research centers, suggesting that our results are by no means conclusive[31]. Unlike the major think tanks like AEI and Brookings which focus on a wide range of policy issues and a clear mission to improve governance, most of these think tanks are either academic institutes (e.g. Santa Fe Institute), professional associations (e.g. American Press Institute), or policy-specific think tanks (e.g. Environmental Law Institute). In further research, I plan to collect more data from each type of think tanks and obtain a better understanding of the general policy expert community which forms our current political knowledge.

In terms of internal validity, the model still misses some important factors. For example, in further research, I should incorporate the information about experts' previous work experience. Particularly, experts with prior experience in the military, industry, governments, and academia might have significantly different research approaches and (if any) lobbying agenda. Moreover, looking through expert profiles in these three think tanks, I hypothesize that there might be a "labor division" between research-based experts and political commentators even within the same think tank. The former gains the think tank a name of trustworthiness, while the latter advocates for political and financial support. Further research is needed to test this hypothesis.

Despite the limitations stated above, I believe that with more than four hundred experts in three of the most influential think tanks in the U.S., the research project indicates multiple important findings. First, it shows that Twitter-based social networks can be a nice proxy for related research on expert interactions. Second, it finds that the network influence of policy experts is not correlated with their academic reputation. In other words, there seems to be a trend of de-academization among at least major think tanks, where experts may still claim to be social scientists but do not truly establish their power and influence based on their research ability. Third, it suggests that policy experts, instead of lobbying on their own, have been organized and even professionalized into organizations such as think tanks to the extent that even their informal social network is highly institutionalized. If we can generalize the results and use it as an estimation of the whole policy research community, it seems that the information transactions among policy experts have been highly institutionalized and thus clustered, and their gap with academia significantly enlarged. In extreme cases, it might be that policy experts should be considered more as “orators”— ancient Athens define them as public speakers who may manipulate public opinions for partisan purposes[32], than as social scientists. This paper and its relevant future research thus call for more caution from policymakers and media when adapting or citing articles and research results from think tanks, and a more comprehensive retrospection on the roles of policy elites who have been shaping our political knowledge in the name of “scientific” research.

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