#polisci Twitter: A Descriptive Analysis of how Political Scientists Use Twitter in 2019*

James Bisbee†, Jennifer M. Larson‡, Kevin Munger§

October 7, 2019

Abstract

Knowledge creation is a social enterprise, especially in political science. Sharing new findings widely and quickly is essential for progress. Scholars can now use Twitter to rapidly disseminate ideas, and many do. What are the implications of this new tool? Who uses it, how do they do so, and does all research shared on Twitter have an equal chance of reaching a large audience? We construct a novel dataset of all 1,236 political science professors at PhD-granting institutions in the United States who have a Twitter account in order to answer these questions. We find that female scholars and those on the tenure track are more likely to use Twitter, especially for the dissemination of research. However, we consistently find that research by men shared on Twitter is more likely to be passed along further by men than research by women.

Preliminary and incomplete. Please do not circulate without authors' permission

*The authors would like to thank Jessica Preece, Kristin Michelitch, Macartan Humphreys, Andy Guess, Pablo Barbera, Ryan Weldzius, and John Holbein, along with participants at the APSA 2018 Diversity Hackathon, particularly the panel on "What Can Men Do?"

†Postdoc, Princeton Niehaus. jhb362@nyu.edu. Corresponding author.

‡Associate Professor, Vanderbilt. jennifer.larson@vanderbilt.edu

§Assistant Professor of Political Science and Social Data Analytics, Pennsylvania State University. kevinmunger@gmail.com

Introduction

Science is a social enterprise. Sharing new findings allows researchers in the field to build on the work of others. Disseminating ideas widely and quickly is essential for progress. This is especially true for fields that focus on complex social phenomena such as political science. When there are many unknowns, the more researchers can rely on the work of others to pin down some of the complications, the more illuminating any new study will be. And of course, sharing ideas beyond academia allows them to have greater political and social impact. Sharing results widely is good for individual researchers within the field of political science as well: more attention tends to mean more citations; better chances at jobs and promotions; and access to collaborators, grants, and affiliations that can facilitate more impactful future research.

Over time, technology has broadened the options for sharing ideas with the rest of the field. Face-to-face conversations and in-person presentations were joined by long-distance conversations and remote presentations made possible by telephones, email clients, and teleconferencing services. More recently, scholars have been turning to online social media, especially Twitter, as an even lower cost method of sharing ideas with a large audience quickly. Twitter is free to use, messages ("tweets") sent on Twitter are quick to compose, and any tweet can be passed along from user to user, with the potential of reaching a very large audience (with over 120 million active Twitter users daily). Political scientists even have a guide to help them navigate this new space (Searles and Krupnikov, 2018).

In principle, Twitter could be a tool that substantially increases the reach of all political science research. Moreover, since it requires no travel funds and little time commitment to use, it may be an equalizing force, giving all research the opportunity to be broadcast. On the other hand, just how widely any one tweet about research spreads depends on how others interact with it. Only those tweets shared ("retweeted") by many others will ultimately reach a large audience. Whether Twitter functions as an equalizing or centralizing force within political science is an open empirical question.[1]

We construct a new dataset that allows us to systematically study the adoption and use of Twitter by political scientists. We first identify all 1,236 tenure-line political science professors at US-based PhD-granting institutions who have a Twitter account

[1] And related to other studies of how aggregate behavior within fields ultimately promotes certain ideas over others, or privileges certain scholars over others. See, for example, Hindman (2008) for a study of blogs and Hindman (2018) for a study of online media as examples of centralizing forces at work.

as of January, 2019 and compare them to the 2,903 other political science professors at these institutions who do not. This allows us to characterize who uses Twitter.[2] Then we collect up to 3,200 of each of these users' most recent tweets, also as of January, 2019. With these data, we can examine how political scientists are choosing to use Twitter and whether they broadcast research using this medium.

Of course, whether any tweet about research reaches many others depends on whether others who see the tweet retweet it. The potential reach of a message on Twitter is due to the networked structure of users– some are connected to others who are connected to others who are connected to others, and so on. We focus on who retweets whom in order to understand not only who uses Twitter, but who succeeds at disseminating research widely. Finally, we look specifically at who retweets whom when the tweet contained a link to research.

We start with a descriptive analysis of #polisci Twitter writ large, examining who is on Twitter, what schools they teach at, and how active they are on the platform. We show that women and tenure-track scholars are more likely to be on Twitter, but that tenured faculty have more followers. School characteristics such as rank, graduate enrollment, and average tuition (in 2017) are not prognostic of whether their faculty are on Twitter. However, scholars at schools with more graduate students tend to have more followers.

We then turn our attention to #polisci Twitter directly, separating our analysis into two frameworks. The first examines the *experience* of being a scholar on #polisci Twitter and tests whether gender, ideology, and position are correlated with these experiences. We show that network-level measures such as community membership and centrality are correlated with position, with tenure-track scholars being more central, particularly when we define network ties by tweets and re-tweets that share research. We also find evidence of homophily across gender, ideology, and position in terms of user experience, with mentions by a co-identity constituting a greater share of a scholar's mentions.

The second framework examines the *behavior* of scholars on #polisci Twitter and asks whether gender, ideology, and position predict an individual's choices about who to engage with on the platform. Here we find conflicting results depending on how

[2] With the exception of a list of the top-50 most retweeted entities by political scientists on Twitter, we report only aggregate results. Although we are using exclusively public data, our analyses combine this information in non-trivial ways to, for instance, estimate political ideology a la Barberá (2015), and so we err on the side of individual privacy.

we define user behavior. When we look at mentions of one scholar by another, we again find strong evidence of homophily by gender and ideology. But if we focus only on engagements with users who tweet about research, these patterns disappear with the exception of male scholars. Men are disproportionately more likely than women to re-tweet research shared by other men, whereas there is no difference when examining re-tweets of research shared by women. This finding is consistent with research by Usher, Holcomb and Littman (2018) who demonstrate similar patterns among male and female journalists.

Our data are complete for a very specific slice of the field of political science on Twitter – professors at PhD-granting institutions in the United States – and at a particular point in time – early 2019. That users of Twitter and their behavior can change easily is a key virtue of the platform. Rather than lament that future research may find different results from ours, we are hopeful that our research may help spark changes in Twitter, both in who opts to use it, and how users treat research that they encounter on the platform. Knowing what #polisci Twitter is like at one point in time helps to make that possible.

Our study suggests many reasons for optimism about the use of Twitter within the field of political science. We observe strong evidence of scholars engaging with one another and with one another's research on Twitter, with little evidence of firm divisions between junior and senior faculty, or between those with ideologies that we estimate to be different. We also find that the differences in behavior between men and women – specifically in the lower likelihood of a male political scientist sharing research tweeted by a female political scientist – has little impact on the ultimate reach of research that women and men tweet. These findings suggest that merely bringing to light a difference in engagement may be sufficient to close this gap.

1 Twitter and Academia

The emergence of Twitter as the central hub was caused by a combination of the specific technological affordances of Twitter and other, contextual factors. Twitter is intrinsically public-facing; unlike Facebook, the default setting on Twitter is for anyone to be able to see what you tweet. The character limit (combined with the capacity to share links) also encourages pithy communication, rewarding the ability to summarize ideas and results clearly and easily. This comes at the cost of inhibiting deliberation;

Jaidka, Zhou and Lelkes (2018) finds that the 2017 switch from a 140 to a 280 character limit produced a healthier political conversation.

Twitter is also over-represented in research *about* communication on social media. Tufekci (2014) discusses the reasons why Twitter has come to serve as the "model organism" for this kind of research, not all of which are ideal for understanding the dynamic of online communication in general. Just like Twitter itself, Twitter's API (the system through which researchers can request large amounts of data) is open, and easy to work with. And Twitter is *fast*—just as the short-lived fruit fly is an ideal test animal for certain biological interventions, Twitter provides rapid and frequent examples of information spreading throughout an online network. As a result, then, much of the research about the connection between sharing academic research on social media and outcomes of interest to academics (downloads, citations) was conducted on Twitter (Eysenbach, 2011; Ortega, 2016; Peoples et al., 2016).

Still, Twitter adoption is far from uniform across academic disciplines. Results using both survey methodologies (Mohammadi et al., 2018) and large-scale tweet analysis (Ke, Ahn and Sugimoto, 2017) find that social scientists are disproportionately likely to use Twitter. The latter approach estimates that social scientists comprise 21% of the "scientist" workforce but 48% of the "scientists" on Twitter. The composition of the links shared by different types of "scientists" offers a hint as to why this is the case. Links shared by natural scientists are far more likely to be to scientific domains than are links shared by social scientists. Among the ten disciplines studied by Ke, Ahn and Sugimoto (2017), political scientists are *least* likely to share links to scientific domains.

The likely reason for this tendency is the nexus of (political) journalists, policymakers and political scientists who use Twitter to share and discuss the news of the day. The speed of information dissemination makes Twitter an absolute necessity for political journalists (Kreiss, 2016; Mourão, 2015) and provides an opportunity of academic political science research to inform and influence the public discourse.

Twitter may also influence the career trajectories of academics themselves, which is the motivation for this paper. Twitter is not, as far as we know, explicitly used when considering hiring and promotion decisions within political science departments. Nevertheless, these decisions are based on citations, publications, and the respect for an academic's work among her peers. By exposing new research, participating in online discussions, and generally curating a recognizable online identity, Twitter may have important effects on who advances in the academic political science discipline. This analysis is fundamentally concerned with identifying who these people are, and how

Twitter amplifies or mutes under-represented voices in academia.

Indeed, "networking" has recently been identified as a crucial contributing factor in the underrepresentation of women in the top political science journals. Breuning et al. (2018) find little evidence of gender-based inequity in publication conditional on journal submission to the *APSR*. This concords with Barnes and Beaulieu (2017)'s argument that women with improved networking opportunities are more likely to submit to top journals.

Thus, although there are structural issues that can only be addressed by years of concerted effort (Sen, 2018), efforts to improve the visibility of female scholars can begin to counteract the implicit bias that limits their access in the discipline (Beaulieu et al., 2017). Analysis of Twitter sharing patterns can also complement analysis of gendered citation patterns (Dion, Sumner and Mitchell, 2018). The fact that Twitter accouts are all "solo authored" affords analytical purchase on the extent to which co-authorship trends are driving observed gendered citation patterns (Esarey and Bryant, 2018).

Although each of these tendencies is intrinsically linked, another important angle on equity in the discipline is institutional prestige. Beyond the sizable inequality in resources, prestige plays a role in paper acceptance rates, although this varies by journal and editorship (Breuning et al., 2018). To make an apples-to-apples comparison, we restrict our data collection to include only faculty at US PhD-granting institutions—scholars at smaller or teaching-focused institutions face distinct incentives.[3]

The centrality of news, journalism and political commentary to the popularity of #polisci Twitter raises the salience of ideological divisions within the discipline. Each person on Twitter has a number of distinct identities that become active when different topics are discussed (Munger, 2017), so the prominence of political news on the platform has the effect of frequently activating partisan identities. The question of ideological diversity in political science is an active and important one, and the topic of a recent symposium in *PS: Political Science and Politics* (Rom, N.d.).

Gray (N.d.) argues that the unequal ideological distribution of political scientist can create "blind spots" in the types of research questions that we ask and our intuitions about the plausibility of findings. It is possible that Twitter use could exacerbate these trends: the dissemination and public discussion of political science research might be

[3]This approach is not without drawbacks. As we discuss below in Figure 1, several of the most central nodes in the #polisci Twitter network are faculty from schools absent from our data.

especially inflected by ideology in a forum where partisan identities are often activated.[4]

2 Data

The list of 131 PhD-granting institutions in the US was taken from the "For Students" page on APSA's website. This list includes multiple institutions within the same university; for example, it treats Harvard University and the Harvard Kennedy School as distinct entities.

In December 2018, a research assistant was instructed to search each institution's Faculty web page and record the name, title, and gender of each faculty member.[5] They then searched for that person on Twitter and recorded whether an account could be located and, if so, that person's Twitter username.

The final list was spot-checked for completeness, and while we cannot be completely sure, we believe the process was thorough. We found (and recorded) a number of Twitter accounts that appeared to belong to a given faculty member which had very few followers and/or had not tweeted for years. Once we had identified these accounts, we accessed the Twitter REST API to scrape the account information and record the 3,200 most recent tweets from each user, the maximum allowed by Twitter.[6]

Given the self-imposed constraint of only examining faculty at PhD-granting institutions, we do not have Twitter accounts for several of the most central actors in our network. The top-50 most mentioned accounts are summarized in Figure 1 and are shaded green if we include these accounts in our #polisci dataset. The top 50 accounts contain many media outlets, presumably reflecting the intersection between political science and real-world politics. This list also contains several political scientists, in-

[4]The distinction between *ideological* and *partisan* diversity in political science is worth noting. As Wilson (N.d.) points out, conservative political scientists tend to be more focused on fiscal restraint and national defense, a strain of conservatism that is not exactly in ascent in the Republican party. Additionally, as Atkeson and Taylor (2019) demonstrate, voter registration from states with public voter files produces strong evidence of a Democrat/Republican ratio of around 7/1.

[5]We follow Usher, Holcomb and Littman (2018) in our construction of the gender variable: "Each Twitter account was manually coded for gender and assessed via normative social constructions of gender: by name, by gender presentation in profile photos, and by secondary information"—here, information on their faculty page that might include gendered pronouns. Again following Usher, Holcomb and Littman (2018), we define gender as a binary variable, and acknowledge the issues inherent in assigning gender based on the limited information available We do note that the most recent APSA report indicates that 99.88% of APSA members report their gender as either male or female.

[6]This represents the entire Twitter history for a solid majority of our sample. We identified a total of 264 who tweeted more than 3,200 times, or 21% of the sample.

cluding a handful that are not included in our dataset since they were employed in December of 2018 at non-PhD granting institutions. These omissions reflect an inherent limitation of our analysis but one that we don't believe significantly undermines our conclusions.

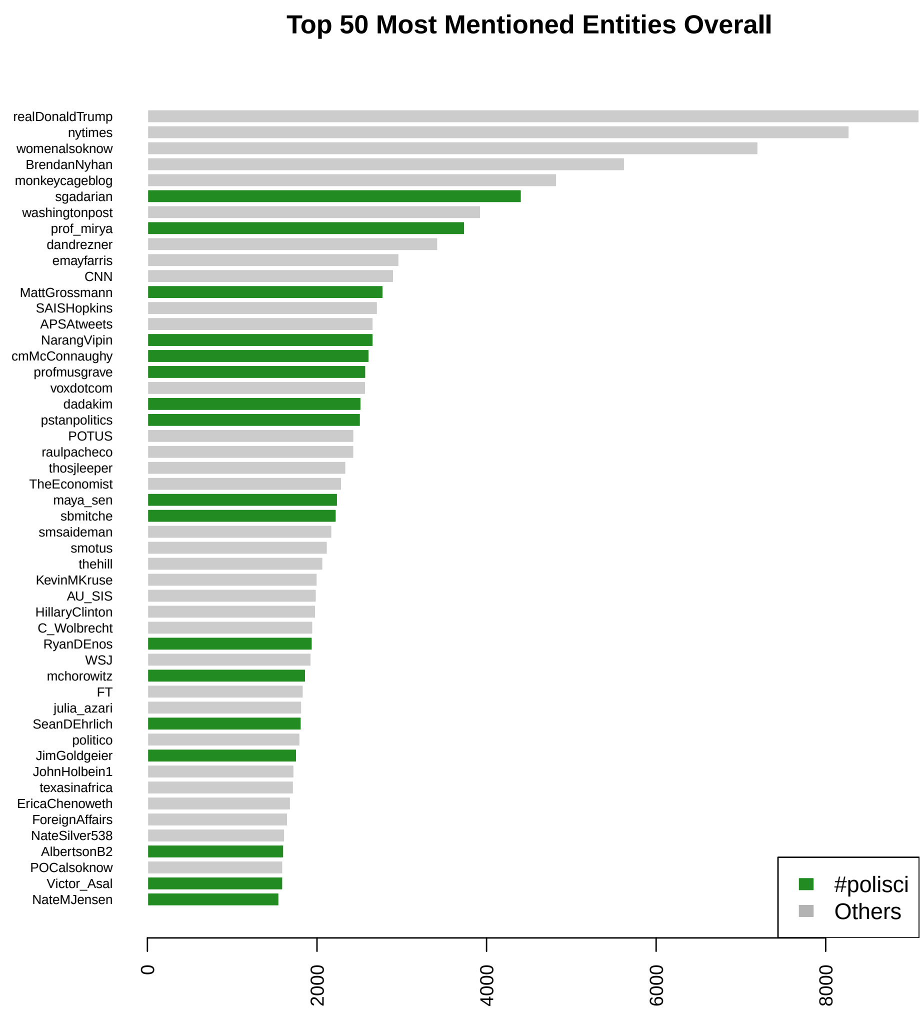

Figure 1: Top 50 Twitter accounts mentioned by #polisci Twitter. Green bars indicate accounts that are included in our #polisci Twitter dataset.

One additional caveat is that we only have access to the tweets that had not yet been deleted. A small group (one that includes some of this manuscript's authors) uses a program to automatically delete tweets that are more than 90 days old. The motivation behind this decision is to prevent old tweets from being brought up out of context. Twitter is often used for immediate, topical conversation, a use case that is at odds with the affordance of a permanent, public, searchable archive (Marwick and Boyd, 2011). By finding users who had fewer recorded tweets in April than in January, we identified 13 users who we believe are auto-deleting their tweets. This is likely an underestimate of the true number, but it suggests that the bias introduced by this behavior is not large enough to seriously skew our results.

We also matched the institutions in our sample with other datasets to characterize how adoption varies with institutional type. Objective measures include official designations as public or private institution as well as the total tuition and fees associated with undergraduate enrollment in 2018, total undergraduate enrollment, and total graduate enrollment. We also include two measures of institutional reputation; each of these is subjective and imperfect. First, we matched with the list of "Research-1" universities identified by the Carnegie Classification System as having "very high research activity." Second, we took the departmental ranking from the US News 2018 list.

All of the figures reported in this manuscript are based on the April 17 scrape. Given Twitter's fluid nature, along with our discipline's evolving use of the platform, we do not expect our findings to persist long into the future. Nevertheless, we believe our contribution is valuable for two reasons. First, characterizing the current state of #polisci Twitter can help political scientists find better ways to disseminate novel research, communicate important academic findings with the public, and improve and expand the range of voices that are heard on the platform. Second, insofar as online social media platforms like Twitter reflect core tendencies in human behavior, our analysis should also shed light on broader trends in how political scientists elevate and sideline research in general (Bisbee et al., 2017).

3 Descriptive Analyses

We organize our analyses as a funnel, starting with the broadest overview of who is on #polisci Twitter. We then examine the *experiences* and *behavior* of those scholars who are on #polisci Twitter.

3.1 Who is on Twitter and Where?

Table 1 displays basic summary statistics of #polisci Twitter. We identified a total of 1,236 Twitter users out of the 4,139 faculty on department websites, or 30%. However, this number is a moving target. In between the time we collected the data and when we scraped Twitter (January 3, 2019), one of 1,236 was no longer active. When we re-scraped the dataset (April 17, 2019), an additional 12 accounts were no longer active.

Table 1: Summary Statistics based on Twitter Use

	Twitter Users	Non-Users	Total
Number	1,236	2,903	4,139
% Female	36%	31%	32%
% Tenure-Track	28%	16%	19%
% Tenured	50%	59%	57%
% R1 Inst.	87%	82%	83%
Avg. Rank	62.6	67.2	65.8
Avg. Tuition	$37,791	$38,198	$38,380

Table 2 describes the summary statistics of Twitter users. In general, women were slightly more likely than men to use Twitter (33% versus 28%). Tenure-track professors were significantly more likely to use Twitter than tenured professors (43% versus 27%). As is the case with most Twitter data, the volume of tweets and followers is highly skewed, with the median number of tweets and followers around 650 while the mean values were above 3,000.[7]

Table 2: Summary Statistics of Twitter Users

	Median	Mean
Tweets	655	3,317
Followers	632	3,146
Following	386	666
Account Age (years)	7	6.7
Female	-	33%
Male	-	28%
Tenure-Track	-	43%
Tenured	-	27%

To characterize the ideology of the Twitter users in our dataset, we implemented the Bayesian Spatial Following model developed by Barberá (2015). This model estimates the ideology of each user based on which political actors they follow. We caution that this measure may be less accurate for political scientists who, depending on their research interests, might follow certain accounts that influence their ideology score

[7]Although we only have access to the most recent 3,200 tweets for content analysis, we are able to measure the total number of lifetime tweets for accounts.

without reflecting their true political beliefs. The ideological distribution of our data is presented in Figure 2. As illustrated, the overall distribution is skewed to the left, with liberals (defined as ideology scores less than -0.5) representing 55% of our data, and moderates (defined as ideology scores between -0.5 and +0.5) and conservatives (defined as ideology scores above 0.5) constituting about 22% of the data each.[8]

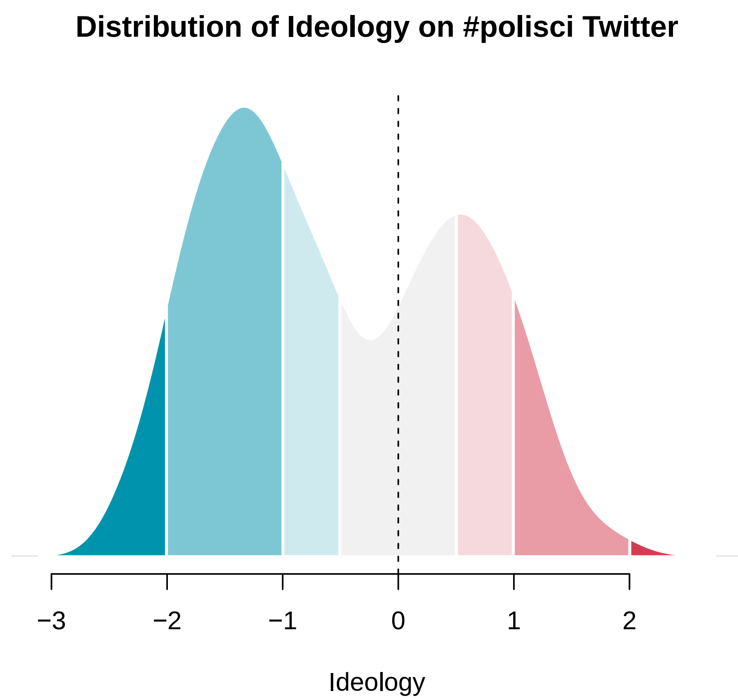

Figure 2: Density of ideology scores among 1,236 political scientists with active Twitter accounts. Ideology scores estimated according to Barberá (2015). Color shades represent substantive bins defined by the authors, ranging from very liberal (dark blue, ideology less than -2) to very conservative (dark red, ideology more than +2) with the range between -0.5 and +0.5 defined as moderate.

Figure 3 plots the rate of Twitter adoption by gender at different levels of career advancement. Again, we see the greatest adoption among tenure-track faculty and some evidence that female political scientists are more likely to be on Twitter than males. These differences by gender are driven by tenure-track and tenured scholars, with no difference among directors/deans/chairs/provosts or the other category. For the remainder of the analysis, we group tenured and higher positions (directors, deans,

[8] We also use a different method developed by the Social Media and Political Participation Lab (SMaPP Lab) at NYU that defines ideology using shares of news outlet links. Our substantive results do not differ across these measures, despite the distributions of ideology being only weakly correlated.

chairs, and provosts) together as "tenured" faculty and lump tenure-track with all others (adjuncts and lecturers) as "tenure-track".

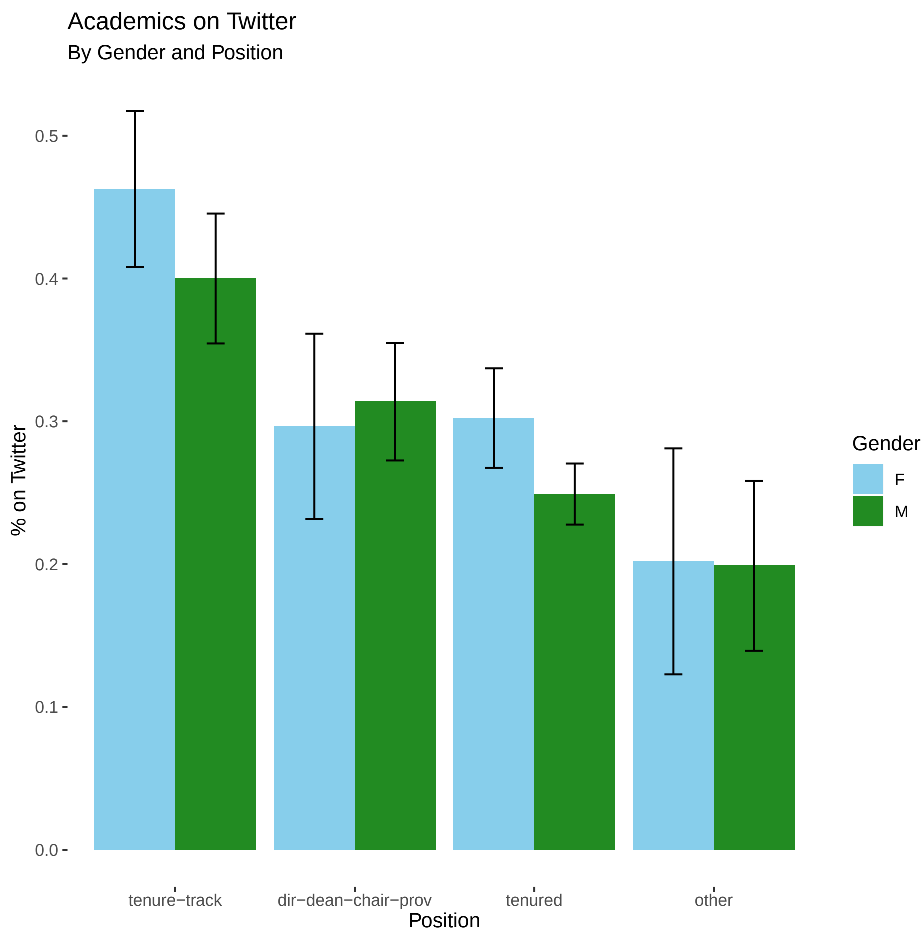

Figure 3: Gendered Adoption by Career Level. Bars indicate the share of each subgroup that is on Twitter out of the total number of academics at each level of their career (x-axis).

We explore Twitter activity by regressing the logged number of followers and the logged number of tweets on individual and school-level characteristics via multilevel model with academics nested within schools:

$$
\begin{aligned}
&Y_i = \beta \mathbf{X}_i + \gamma \mathbf{U}_s + \alpha_s + \varepsilon_{i,s} \\
&\alpha_s \sim N(0, \sigma_s^2)
\end{aligned}
$$

where $\mathbf{X}_i$ include gender, tenure status, ideology, and Twitter account age for individual i, and $\mathbf{U}_s$ include school s's rank, undergrad tuition, R1 status, undergraduate enrollment, and graduate full-time enrollment.

Figure 4 displays the results of these regressions with Y_i measured as either logged tweets or logged followers. The most statistically robust finding serves as something of a sanity check: professors at schools with higher graduate enrollment tend to have more Twitter followers. This suggests that a non-trivial amount of Twitter following behavior is within a given academic institution. Other face-valid results relate to career stage. Tenured professors and deans, chairs, provosts, directors have a statistically significantly higher number of followers but no more tweets compared to tenure-track professors and others.

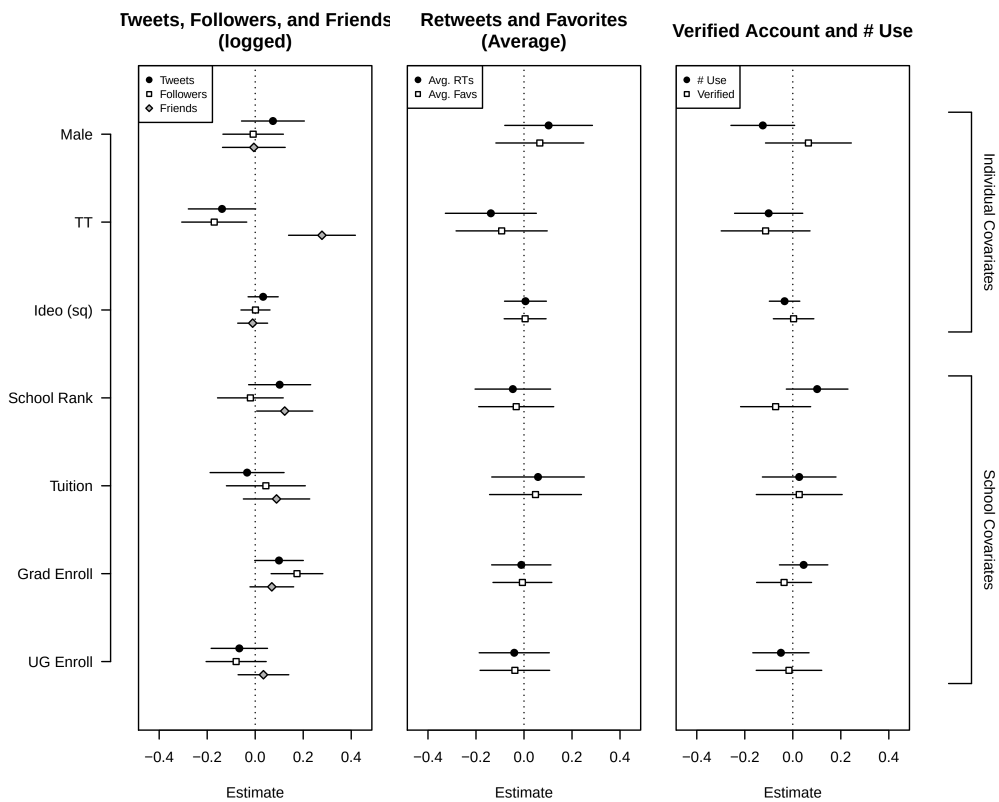

Figure 4: Regressions of number of followers and number of tweets (both logged) on individual-level and school-level covariates. Multilevel regression nests scholars within schools.

4 Network Analysis

The preceding analyses were purely descriptive, tracing the empirical patterns of who is on Twitter and how active they are. But there is more that we can do with these data. In the following sections, we explore the network characteristics of the political science Twitter network. To do so, we must define what constitutes a "link" between two "nodes" – or users– in our data. We define links in five ways, ordered from most general to most specific:

- Follows: the underlying follower network is built on directed unweighted links of who follows who in our network.
- All mentions: a directed weighted link, capturing re-tweets, @-mentions, replies, and quotes.
- Re-tweets: a directed weighted link between two users.
- Common URLs: if two users share the same URL, either independently or via a quote or re-tweet, we count this as an undirected weighted link.
- Common research: for the subset of URLs that link to scholarly research, we identify who originally shares the URL and then define directed weighted links as those tweets who share the tweet via re-tweets, replies, or quotes.

We define the underlying network as the follower network since this precedes any type of mentioning, re-tweeting, or other types of behavior that we observe in our period of analysis. Put more concretely, a user's decision about who to follow defines which tweets they are likely to come into contact with.

The full follower network is visualized in Figure 5, where users are colored by gender and tenure status, with directed links reflecting follows. Nodes are sized by the logged number of tweets associated with each account. The full network contains many scholars – roughly 11% of the Twitterverse – who do not follow other political scientists. We drop these nodes for visual clarity but emphasize that these are not dormant accounts. Rather, these scholars are online and active but not connected to our #polisci Twitterverse.

4.1 Experiences: Communities on #polisci Twitter

To operationalize these data, we focus on three measures of the network that capture how connected political scientists are. First, we estimate communities using a label propagation community detection algorithm, and measure each user's membership across these communities (Raghavan, Albert and Kumara, 2007).[9] We identify the

[9] We replace the community detection algorithm with alternatives in the SI, finding substantively similar patterns.

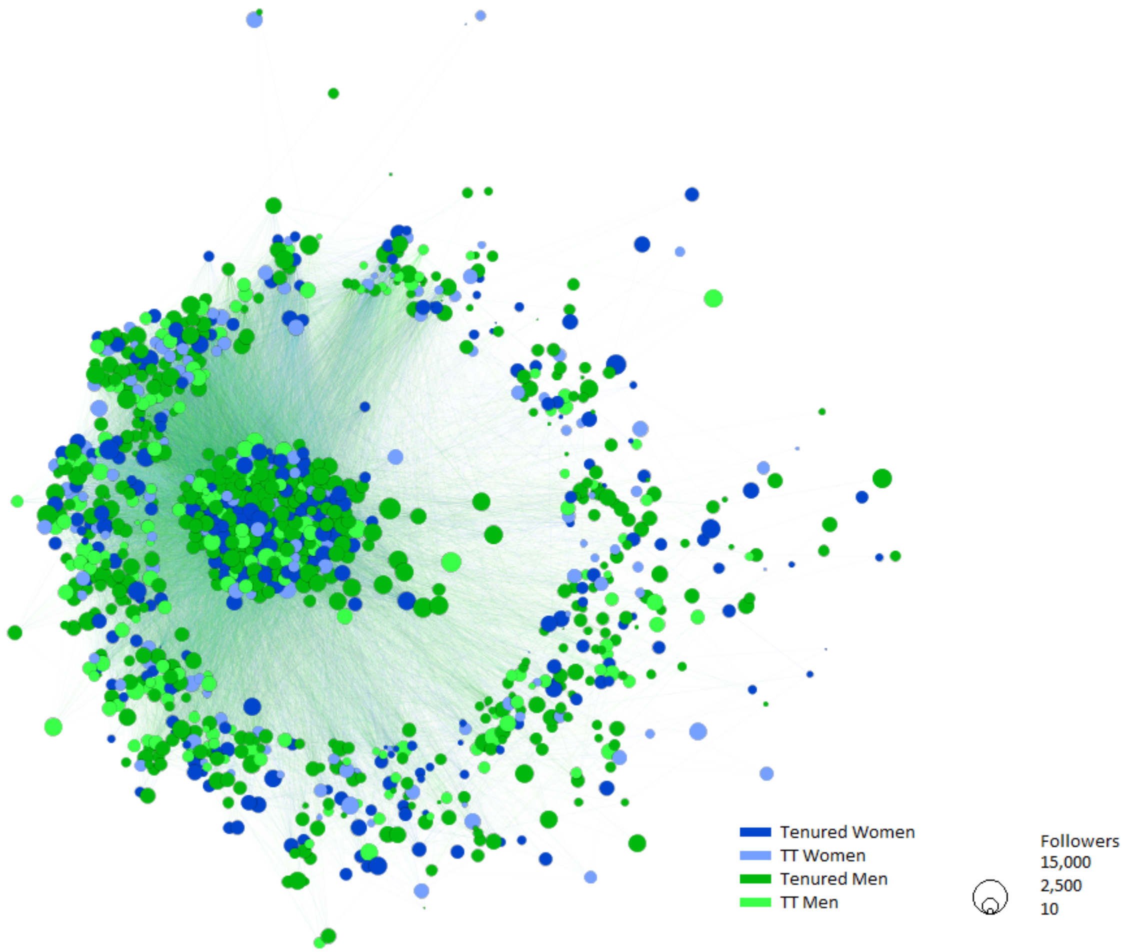

Figure 5: Full #polisci Twitterverse, as of April 2019. Nodes are size according to logged tweets as of April 2019. Nodes are colored to reflect male and female scholars (green and blue respectively) in tenure-track and tenured positions (light and dark shades respectively).

substantive content of these communities by calculating the most frequent terms found in the Twitter bios of their users that are infrequently found in other communities – a measure known as term frequency, inverse-document frequency, or TF-IDF. As illustrated in Figure 6, there are 8 main communities with more than 20 members based on mention networks. The two largest of these correspond to researchers studying international political economy (38% female, 24% tenure-track, 62% liberal), and researchers studying what is most likely American political behavior, with a focus on immigration (40% women, 48% tenure-track, 80% liberal).

Our descriptive findings are facially valid: the gendered breakdown of research topics mirroring those found by Key and Sumner (2018) in an analysis of dissertation abstracts, and the ideological breakdown mapping neatly onto the standard left-right

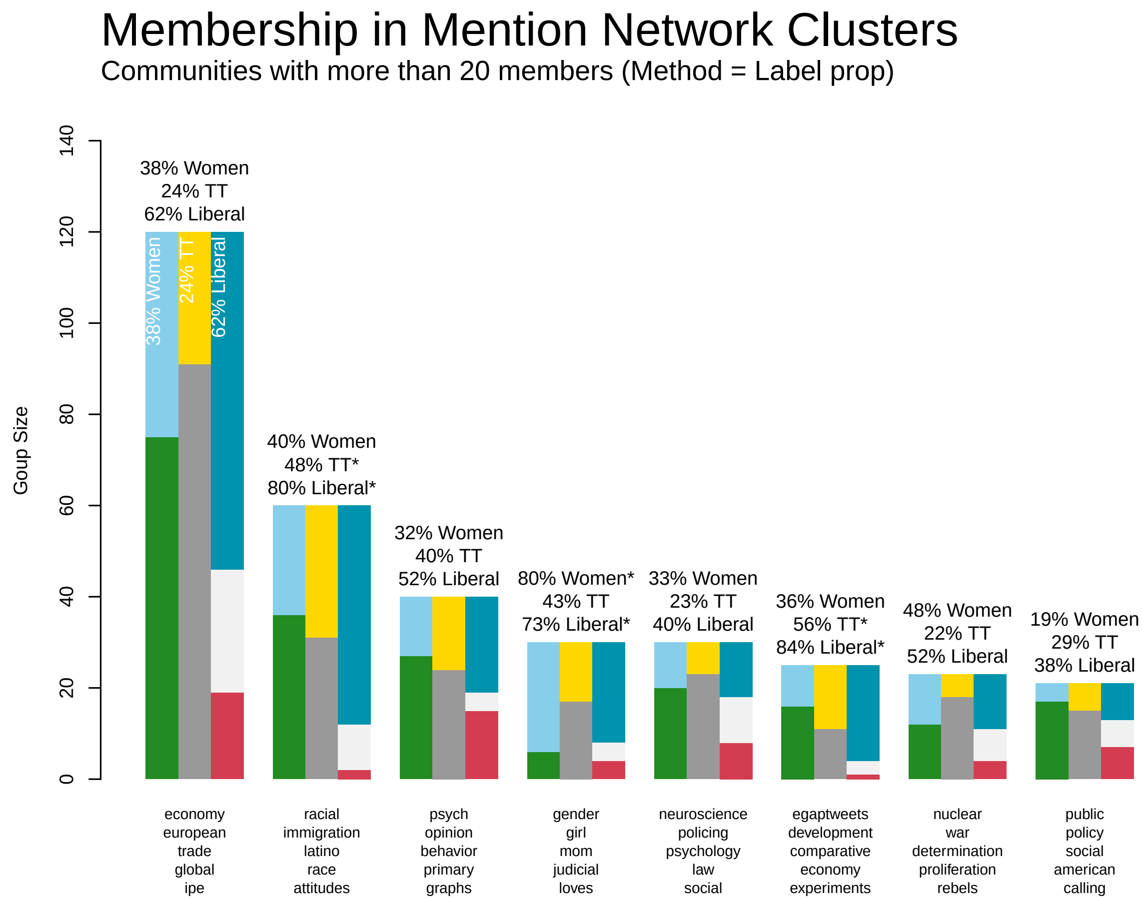

Figure 6: Communities from Network Analysis. Bars indicate the number of accounts assigned to each community where links are defined by mentions using the majority label proportion algorithm. Bars are colored according to the share of each community that is female (blue) and male (green), tenure-track (gold) and tenured (gray), and by ideology. Communities are labeled by the top five discriminating words (TF-IDF) based on text analysis of the concatenated Twitter bios of all members.

issue space. However, when reviewing these communities, it is important to keep the underlying shares of each group on #polisci Twitter (and the general population of PhD-granting institutions) in mind. While women and tenure-track scholars only comprise 38% and 24% of the largest community and liberals dominate at 62%, these shares are actually very close to the sample itself (36% female, 28% TT, and 55% liberal). We ran t-tests comparing the density of women, tenure-track, and liberal scholars in each community compared to their overall presence in #polisci Twitter and indicated shares that significantly diverged (at the 95% confidence level or greater) with a star. The most striking differences between the share of these groups in the general population and their representation in these communities are found in communities #2 and #4. Specifically, the community organized around race and immigration politics is disproportionately liberal (80%) and the gender-oriented community is disproportionately female (80%). In addition, we highlight the substantial participation in the comparative politics community (# 6) by tenure-track scholars. In sum, across all of the largest communities, the nominal representation of women and tenure-track scholars is either commensurate to their shares in the overall population or greater. We believe this is good news for #polisci Twitter in the sense that it may offset the underlying under-representation among political scientists writ large.

4.2 Experiences: Who are the most central users?

To determine who are the most important users in our network, we calculate three measures reflecting the centrality of each user in the overall network: betweenness centrality, degree centrality, and eigenvector centrality. These measures capture different dimensions of what it means to be an important node in this social network. Degree centrality is the simplest measure, merely counting the number of links each node has. With directed networks, this measure can be separated into "in-degree" (the number of links to a node) and "out-degree" (the number of links from a node). Betweenness centrality captures how important a given node is to the flow of information across a network and is calculated by measuring the shortest paths between any two nodes in the network. A node has high betweenness centrality if it lies along a considerable fraction of these shortest paths. Finally, eigenvector centrality captures the centrality of a node's neighbors, assigning a higher centrality score to those nodes who are connected to relatively central nodes.

We regress these centrality measures on individual and school-level covariates, again employing the multilevel specification described above. Figure 7 plots these estimates for a selection of individual- and school-level covariates, defining links as either all mentions, as retweets, or as follows. As illustrated, tenure-track scholars are much more central in terms of both out-degree centrality and eigenvector centrality for followers, highlighting that they are linked with more nodes in the network and that the nodes they are linked to are themselves more central. However, these scholars are less central in the sense that they are less likely to lie on the shortest path between two other nodes, suggesting that tenure-track scholars are less crucial to the information flow across the network. There is also marginally significant results indicating that school characteristics such as tuition and enrollment are prognostic of centrality.

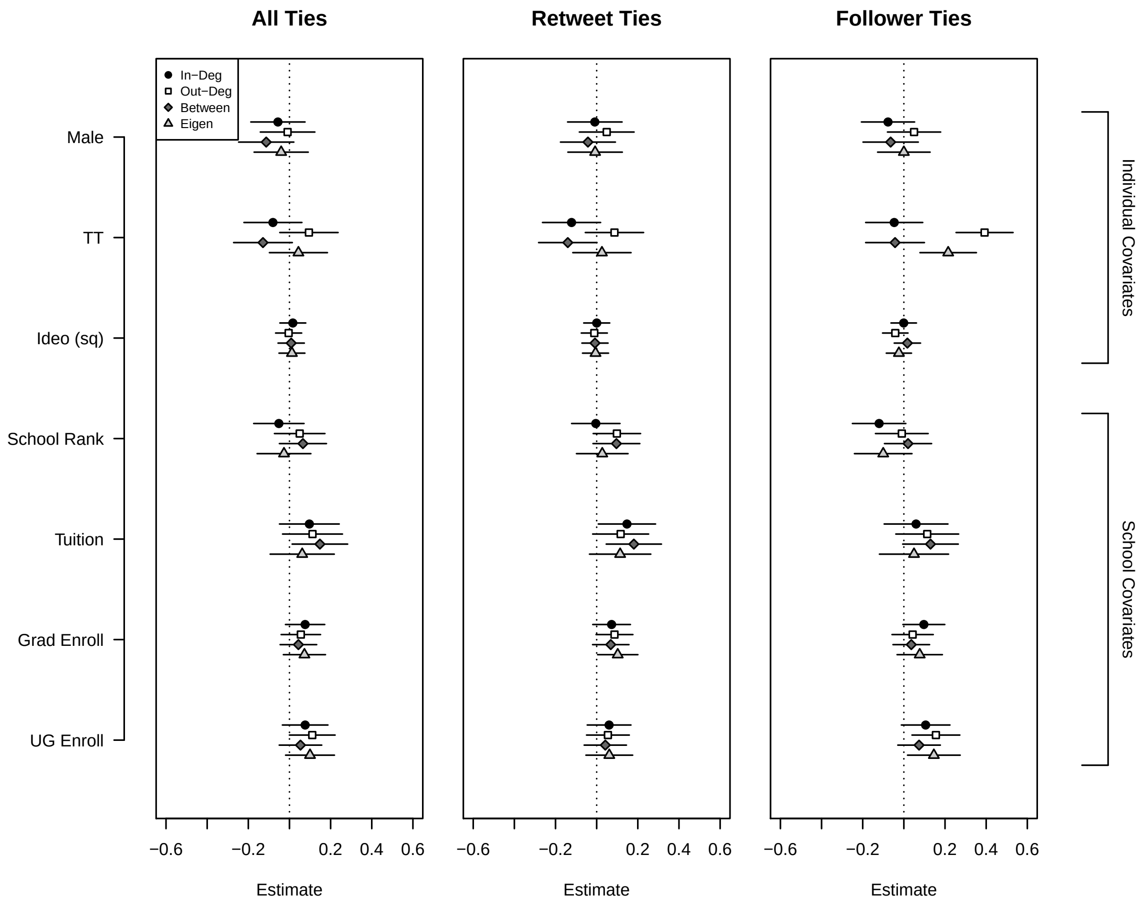

Figure 7: Centrality by Link Type. Coefficients (points) and two standard errors (bars) based on multilevel regression of centrality measure on individual-level and school-level covariates (y-axis). Different centrality measures calculated based on in-degree centrality (solid circles), out-degree centrality (hollow squares), betweenness centrality (dark gray diamonds), and Eigenvector centrality (light gray triangles). Links defined according to panel titles.

4.3 Experiences: Who benefits most from #polisci Twitter?

While it is interesting to learn which users are most central in the network, this doesn't actually tell us much about who benefits most from the exposure Twitter can provide. And while membership in a community does capture an aspect of access to #polisci Twitter, it does not illuminate how the choice of engaging with another user plays out. These engagements (we use "mentions" to capture retweets, quotes, replies, and @'s) elevate the profile of a scholar by exposing either their tweet or even just their account to a much broader audience.

To understand who benefits more or less from the opportunities provided by #polisci Twitter, we calculate the share of total times each user is mentioned by liberals, moderates, and conservatives; men and women; and tenured or tenure-track users in the network. Figure 8 plots these vectors as histograms for each ideological pair, with columns defining the group that is being mentioned, and rows defining the group that is doing the mentioning. Again, given the underlying percentages of each group in the data, we should not expect each group to be evenly divided across mentions. Instead, in the absence of ideological sorting, we would expect liberals to represent approximately 55% of mentions, and moderates and conservatives to represent approximately 22% of mentions. The significant stars indicate whether a simple t-test between the average share of mentions by a group (solid vertical line) is different from the population average of that group (dashed vertical line). As illustrated, liberals are significantly more likely to be mentioned by liberals than what the population share of liberals would suggest (68% versus 55%, top-left plot). Conversely, liberals are significantly less likely to be mentioned by moderates or conservatives (15% versus 22%, and 17% versus 22%, middle and bottom-left plots respectively). Meanwhile moderates are mentioned by liberals, moderates, and conservatives almost exactly in line with the underlying shares of the population. Finally, conservatives are also more likely to be mentioned by liberals (62% versus 55%, top-right plot) and marginally less likely to be mentioned by moderates.

We combine the dimensions of gender and position to examine the flow of mentions in Figure 9. This diagram visualizes who does the mentioning on the left and who is mentioned on the right. As illustrated, 65% of the those mentioned by tenured men are themselves tenured men. Again, we see strong evidence of homophily, with three out of the four groups being most likely to mention others in their group. The one exception to this pattern is among tenure track men who primarily mention tenured male scholars (43%). There is also strong evidence of scholars experiencing homophily with each group constituting the majority of mentions of others in their group (62% of mentions of tenured men come from other tenured men, 45% for tenured women, 42% for tenure track men, and 36% for tenure track women).

4.4 Behavior: Who is driving homophily on #polisci Twitter?

The preceding descriptive results suggest that there is a fair amount of homophily among political scientists on Twitter, with men and tenured scholars both being the

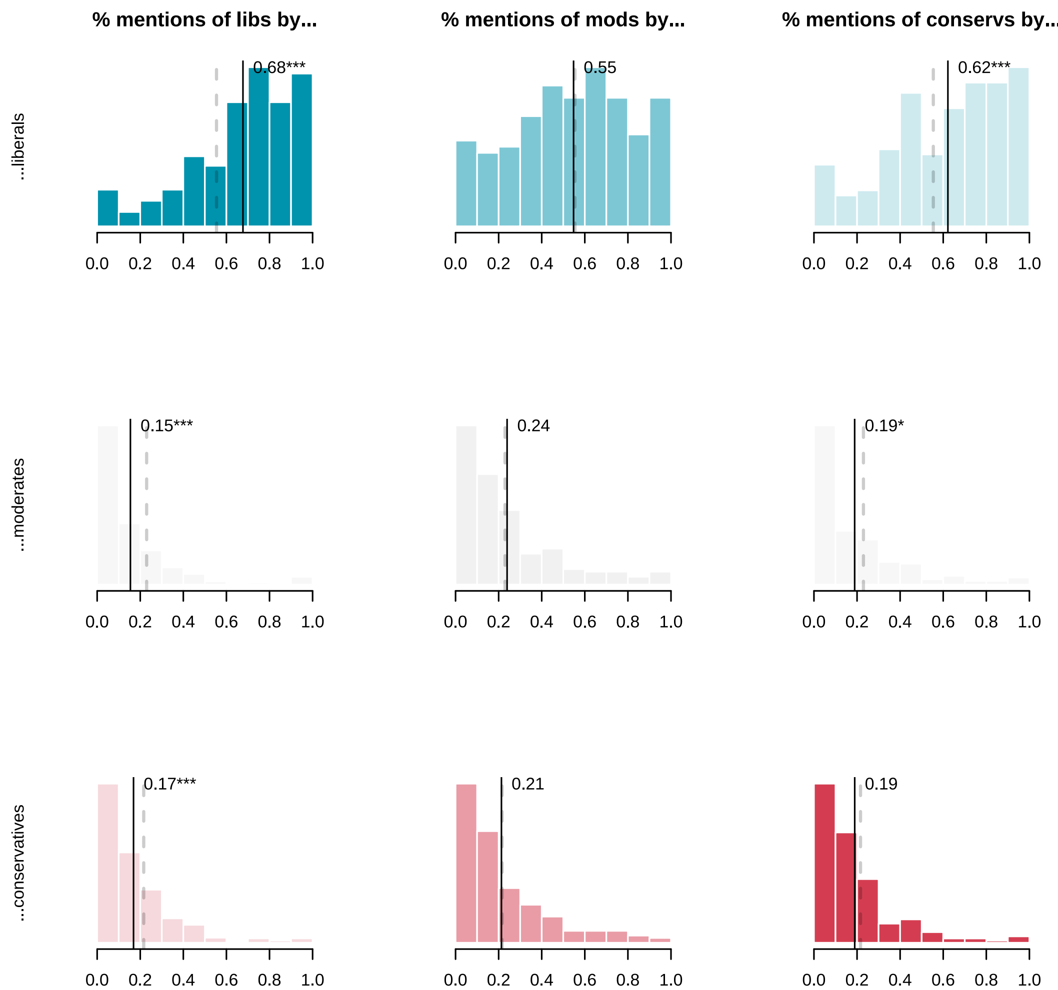

Figure 8: Mentions by ideology. Histograms reflect distribution of share of a user's mentions that come from other users of a given ideology. Columns indicate the ideology of the mentioned users. Rows indicate the ideology of the mentioning user. Vertical solid lines capture the mean of the distribution, given by the black text. Vertical dashed lines indicate the share of the group in the overall data. Significance stars indicate whether a simple t-test difference between the distributions mean and the share of the group in the overall data is significant at conventional levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

most active in terms of mentions and receiving the most mentions as a result. But to what extent are these descriptive patterns significant? And which dimensions of an "ego" (one who mentions) and an "alter" (one who is mentioned) are most prognostic of homophily? To explore these questions, we build a dyadic dataset and predict the probability of a user mentioning another user as a function of their gender, ideology, and position, along with school characteristics. Specifically, we run an interacted regression

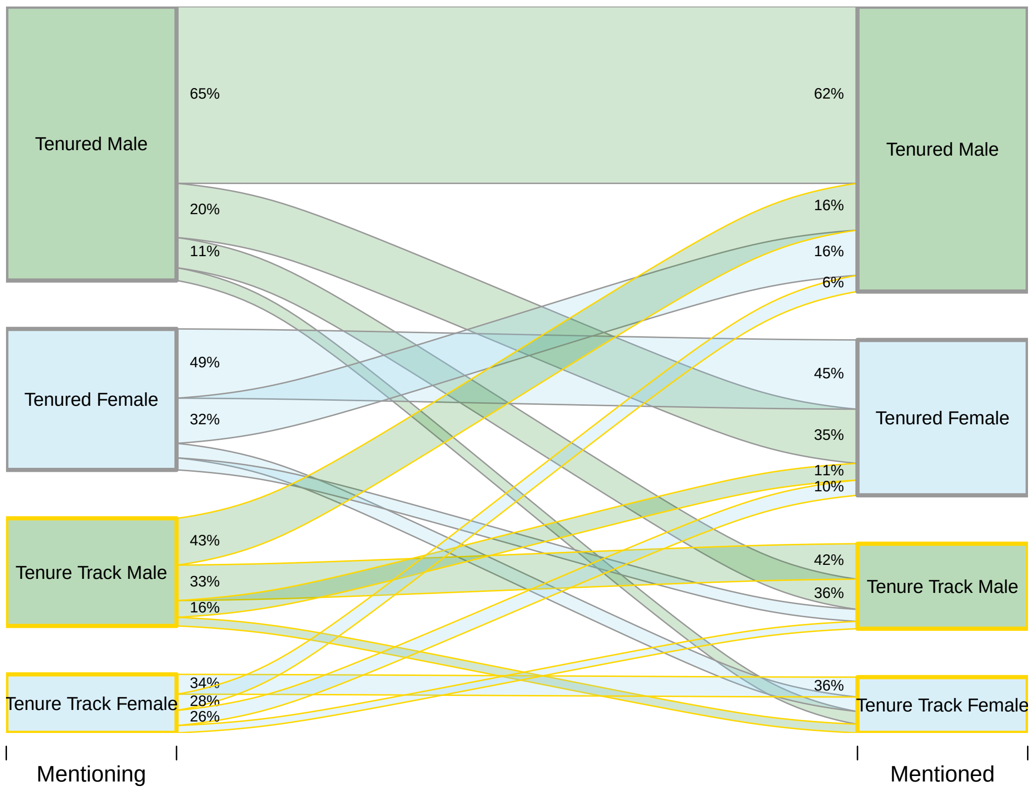

Figure 9: Mentions by position and gender. The left column describes the mentioning behavior by different groups, with the flows charting who they mention.

with the following specification:

$$
\begin{aligned}
m_{i,j} = \beta_0 + \beta_1 G_i + \beta_2 G_j + \rho_1 G_i \times G_j + \\
+ \beta_3 T_i + \beta_4 T_j + \rho_2 T_i \times T_j + \\
+ \beta_5 I_i + \beta_6 I_j + \rho_3 I_i \times I_j + \mathbf{S}_{i,j} + \epsilon_{i,j}
\end{aligned}
\tag{1}
$$

where $m_{i,j}$ is the number of mentions of alter j by ego i, G is a gender indicator, T is a tenure indicator, and I is an ideology indicator. $\mathbf{S}_{i,j}$ is a vector of school-level measures (tuition, enrollment, rank) that are measured as the absolute difference between ego i's school and alter j's school. The main coefficients of interest are the ρ's which capture the interaction effect of sharing an identity with another scholar. We implement dyad cluster-robust standard errors via multiway decomposition, as described in Aronow, Samii and Assenova (2015).

These results are summarized in Figure 10, which plots the marginal effects of the ego's gender, position, and ideology across values of the alter's identity in the left panel, and the interaction coefficient in the right panel. In the left panel, the y-axis summarizes the moderator values and the x-axis indicates the estimated "effect" of the ego's attribute on her decision to mention the alter in their tweets. To take liberals as an example, the plot suggests that liberal scholars are significantly more likely to mention other liberals than non-liberal scholars. But they are no different from non-liberals when it comes to mentioning other non-liberal scholars.

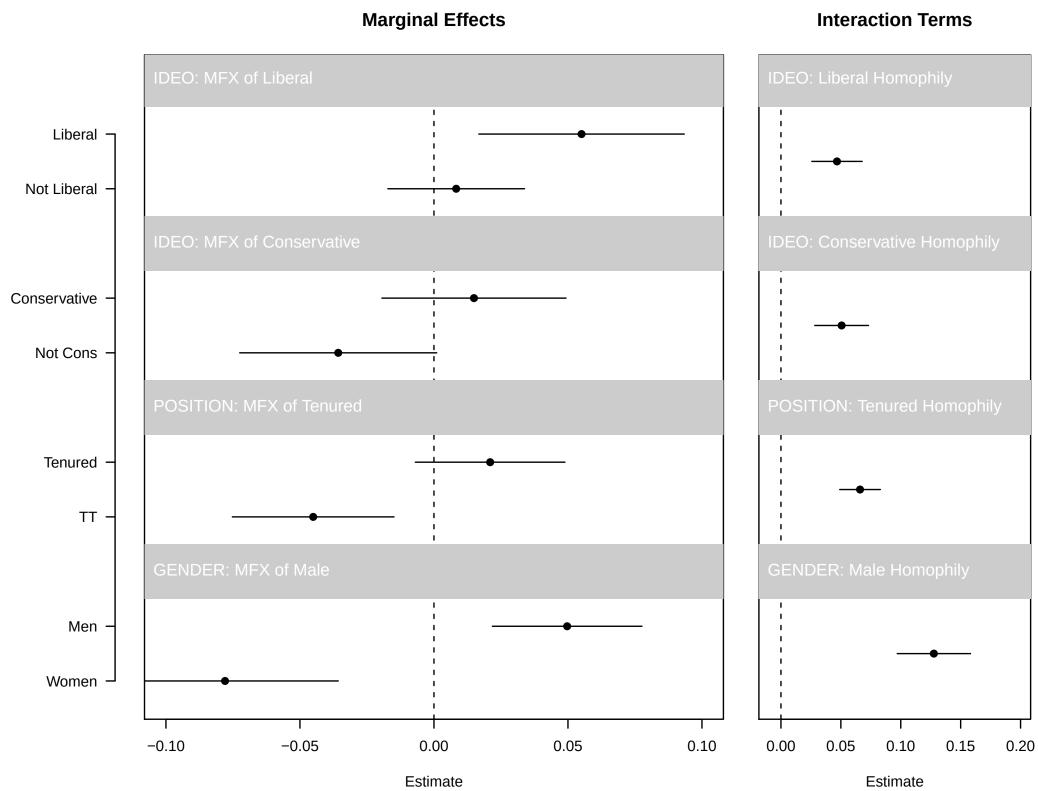

Figure 10: Interaction marginal effects (left panel) and interaction terms (right panel) estimated using dyadic data. Bars indicate two dyad-robust standard errors calculated via multiway decomposition (Aronow, Samii and Assenova, 2015).

Conversely, we find significant evidence of both men and women preferring to mention members of their same gender in the bottom-left panel of Figure 10. Specifically, men are much more likely to mention other men than women are. But unlike the liberal analysis summarized above, men are much *less* likely to mention women, compared to other women. The coefficient on the interaction term (bottom-right panel) is highly statistically significant, revealing strong evidence of homophily by gender. Indeed, all interaction terms are significant across the right panel. But the marginal effects for tenure-versus-tenure track scholars suggest that these differences are marginal. Furthermore, the despite having a significant interaction term, neither of the marginal effects on the difference between conservative and non-conservative scholars is significantly different from zero.

These results confirm the descriptive findings discussed above in that we find significant evidence of homophily across all three of the dimensions we analyze, with the strongest results for gender. But we are still unable to determine whether these patterns are driven by day-to-day choices about who to mention, or rather reflect underlying in-group biases in a scholar's antecedent choice of who to follow. To analyze this question, we restrict our attention to scholars with similar friend profiles, re-running the regressions above on subsets of the data for which each ego follows similar alters. Specifically, we bootstrap sample our egos and calculate the Euclidean distance between their vector of friends and the friend vectors for every other ego in the data. We then subset the data to the bottom quartile of these Euclidean distances and estimate the same interacted regression described above in Equation 1. We save the coefficients for both the interaction terms and the marginal effects and plot the confidence distribution (Shen, Liu and Xie, 2018) of these parameters in Figure 11. As illustrated, homophily in mentions and retweets persists even when we are comparing individuals who follow similar scholars, with the strongest correlations obtaining for gender. Specifically, male scholars are no more or less likely to mention or retweet other men compared to female scholars. But they are significantly less likely to mention or retweet other women.

5 Research Dissemination

The results summarized thus far suggest that #polisci Twitter exhibits certain types of homophily commonly found in social networks. The normative implications of these types of homophily for an individual's scholar career trajectory require research into how hiring and promotion decisions are influenced by Twitter – research that is beyond the scope of this paper. However, we are able to use our data to address one seemingly crucial implication of these findings: the dissemination of research and knowledge across the network. If the discipline's stated goal is to improve how it communicates its research with the larger world, these forms of homophily might be counter-productive. In the following section, we attempt to characterize how research itself – that is, tweets containing links to research – are disseminated and shared across the network.

To do this, we begin by identifying all tweets that contain links to research by parsing

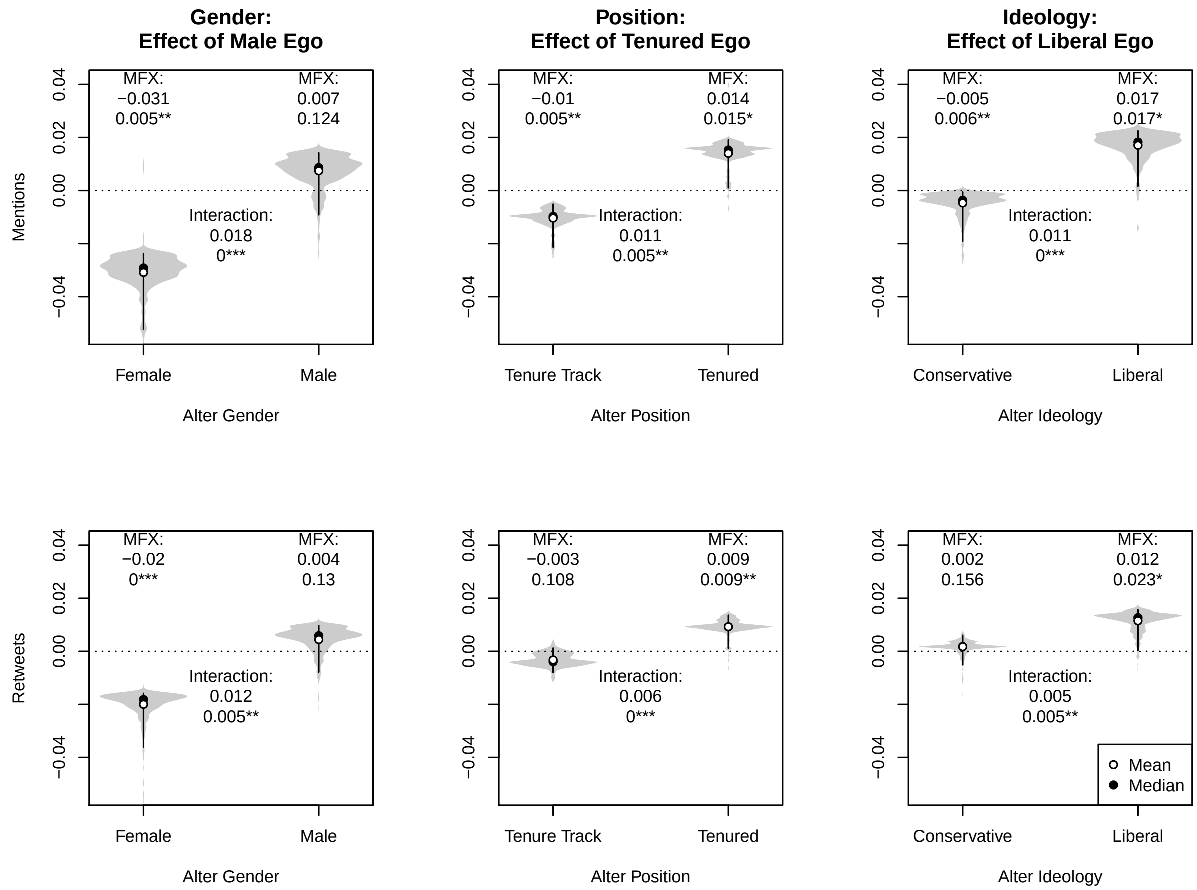

Figure 11: Dyadic Analyses Controlling for Followers. Bootstrapped marginal effects displayed as gray densities with average coefficient and p-value indicated in text. Mean and median bootstrapped estimated indicated by white and black circles, respectively. Bars represent the 95% confidence interval between 2.5% and 97.5%. Mean interaction coefficient and p-value also indicated in text in center of each plot. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

tweets that link to a website in search of URLs that contain the keywords “pdf”, “doi”, “sagepub”, “jstor”, “onlinelibrary”, or “journal(s)*”. Having identified these tweets, we then determine who engaged with these tweets via four actions: re-tweeting, replying, quoting, or favoriting. These measures reveal two important characteristics of political scientists on Twitter. First, we can identify which research is widely shared and how it is disseminated. Second, we can identify which political scientists are most helpful in reaching a broad cross-section of political scientists on Twitter.

We repeat the network analyses summarized above, but redefine a link between two nodes as sharing a URL that links to research. Figure 12 reproduces the centrality analyses using these links, confirming that tenure-track scholars are much more central on #polisci Twitter when it comes to discussing research. We also note that there is some prognostic power for school characteristics, specifically the significant and positive coefficients on graduate enrollment for a scholar's betweenness and Eigenvector centrality in the research network.

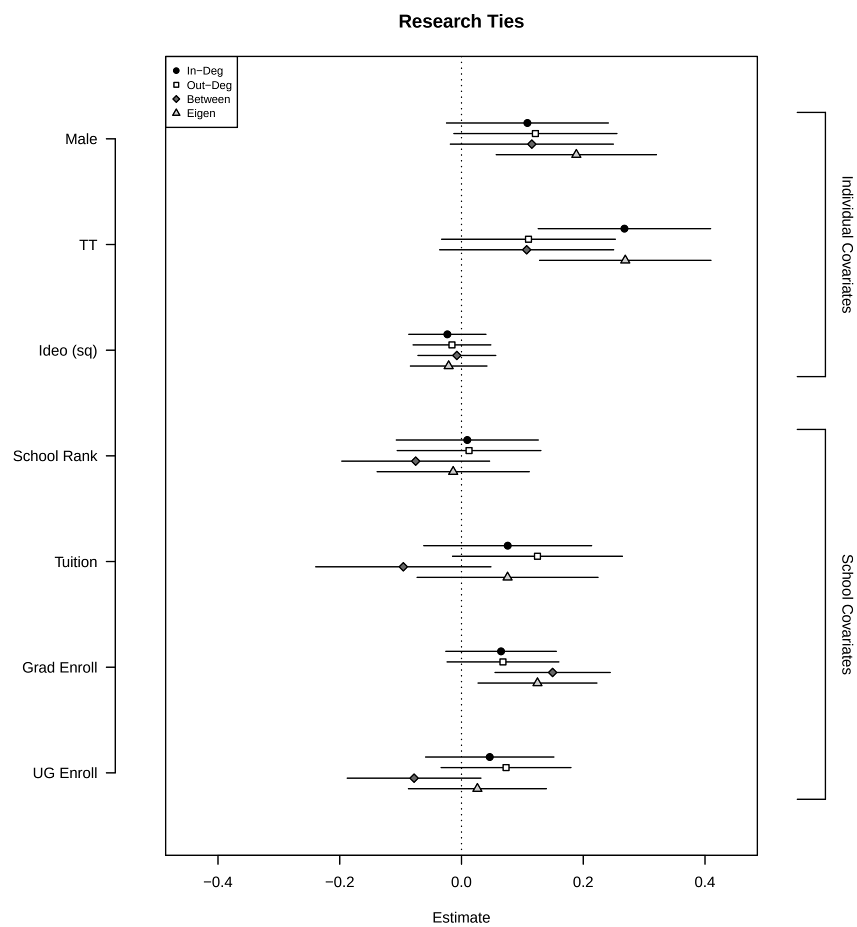

Figure 12: Centrality measures for links defined as research shares. Coefficients (points) and two standard errors (bars) based on multilevel regression of centrality measure on individual-level and school-level covariates (y-axis). Centrality measures given in the legend.

Figure 13 re-runs the dyadic results using research shares as links, finding that, when it comes to sharing research on #polisci Twitter, scholars are generally unbiased. The one exception appears to be among male political scientists who are disproportionately more likely to engage with research tweeted by other men, when compared to female scholars. But while these differences are statistically significant, the coefficient magnitude (capturing the impact on a standard deviation of the outcome variable associated with a movement from zero to one on the dichotomous explanatory variable) is an order of magnitude smaller than those associated with mentions. Put more concretely, gendered biases persist, but they are smaller than the biases associated with overall mentions.

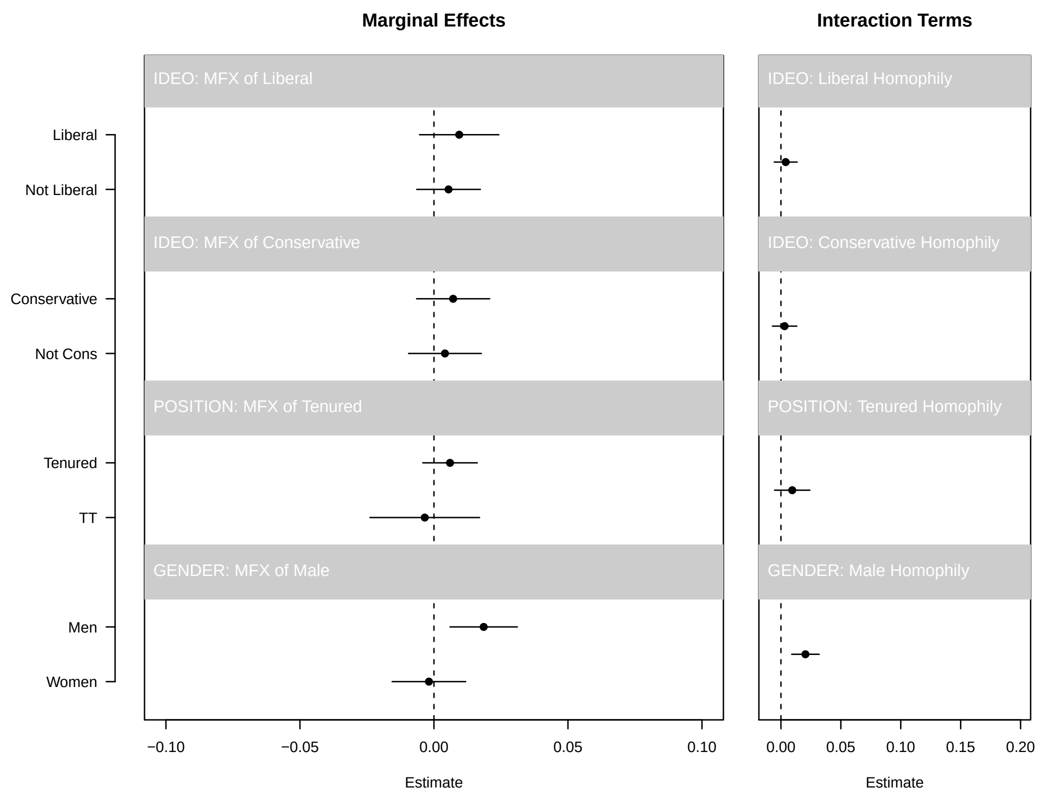

Figure 13: Interaction marginal effects (left panel) and interaction terms (right panel) estimated using dyadic data. Bars indicate two dyad-robust standard errors calculated via multiway decomposition (Aronow, Samii and Assenova, 2015).

5.1 Dissemination, Impact, and Influence

While informative of who engages with whose research on #polisci Twitter, the preceding findings still treat any type of engagement with a tweet linking to research as a binary indicator. But our data allow us to dig deeper into whose research is shared, how widely it is seen, and which scholars in our network are particularly influential in boosting the signal of research.

To operationalize these ideas, we construct four novel measures of influence in research networks. The first two pertain to the spread of a scholar's research and are measured in terms of the number of times a given research URL is shared. The latter two measures identify which users are particularly good at broadcasting research. To fix notation, define each user on #polisci Twitter as $i \in \mathcal{N}$ and each tweet containing original research as t_i.

Other Twitter users $j \neq i$ can engage with t_i in one of four ways.

- First, they can re-tweet t_i: $rt_j^{t_i}$.
- Second, they can reply to t_i: $rp_j^{t_i}$.
- Third, they can quote t_i: $q_j^{t_i}$.
- Fourth, they can favorite (or "like") t_i: $f_j^{t_i}$

All four of these engagements will be broadcast to j's followers and friends in their notifications.[10]

Ideally, we would want to fully trace the way t_i is disseminated throughout the Twitter network, such that j's quote is re-tweeted by k which is replied to by l which is re-tweeted by n and so forth. Unfortunately, the way the Twitter API records data precludes this type of detailed tracing for re-tweets, the most common form of engagement in our data. Specifically, all re-tweets are assigned to the original tweet, regardless of whether j is re-tweeting the original tweet or is instead re-tweeting k's re-tweet. In other words, we can only observe $rt_j^{t_i}$, but not $rt_j^{rt_k^{t_i}}$.

This limitation only applies to re-tweets. We can observe $rt_j^{rp_k^{t_i}}$ and $rt_j^{q_k^{t_i}}$. Furthermore, the same logic doesn't apply to favorites of re-tweets, meaning that $f_j^{rt_k^{t_i}}$ is observable. Nevertheless, the inability to observe how re-tweets spread throughout the network is a non-trivial limitation for our ability to trace how research is disseminated, since 79% of engagements with original research take this form.

With this limitation in mind, we define the following measures of whose research is broadly shared and how it is disseminated. The first measure is simply the ratio of tweets containing original research out of the total tweets by a user. This measure captures how frequently i shares original research. (For now, we are unable to distinguish between i's personal research and others' research).

Our second measure is the average number of re-tweets a user's research tweets receive. We also supplement this measure with the average number of favorites. These measures are not constrained to be re-tweets by other #polisci users.

[10] The likelihood that each of these engagements appears to the engager's follower's is not constant, and depends on the details of Twitter's proprietary algorithm. Re-tweets and quote tweets are by far the most likely to be appear, as expected, but likes and replies sometimes appear as well.

Our third measure focuses on the average number of engagements a user's tweet received from the political science Twitterverse and constitutes a lower bound given the API limitations we describe above. Specifically, consider a tweet by @saadgulzar which shares a working paper and had a total of 28 re-tweets and 49 favorites as of April 2019. This was re-tweeted once by @DrStatePolitics, although we are unable to determine what percentage of the 28 re-tweets this single re-tweet was responsible for. On the low end, it may have contributed only a single re-tweet to this number, but on the high end, it is possible that this re-tweet was responsible for a much larger proportion. While we don't know how many re-tweets @DrStatePolitics's re-tweet was responsible for, we can observe the number of times it was favorited, in this example zero. In addition, @PolPsychProf's tweet was also replied to by @HabermasRulez, who expressed excitement at the prospect of reading the paper. We do know that this reply received zero re-tweets of its own and two favorites, which we count toward the total number of engagements associated with @PolPsychProf's original tweet. Combining these measures, we assign a total number of engagements to this tweet of 4 – one confirmed re-tweet by @DrStatePolitics, one reply by @HabermasRulez, and two favorites of @HabermasRulez's reply.

The preceding measure likely undercounts the penetration of @PolPsychProf's tweet through #polisci Twitter since (1) we don't know how many of the total 28 re-tweets came from re-tweets of @DrStatePolitics's re-tweet and (2) other users may have seen the tweet but not engaged with it. Thus, our fourth measure is the sum of the total followers of each user who engaged with a tweet and captures the total possible audience exposed to the research by our #polisci Twitterverse. Again returning to the running example, @PolPsychProf's tweet would be assigned a value of 1,734 + 734 = 2,468 total followers based on the two political scientists who engaged with his tweet.

For each of these measures, we predict variation along the lines of gender, ideology, and tenure status, using a multilevel model of the same form described above. Specifically, we predict outcome Y_i as a function of individual covariates including gender, ideology, and academic position, as well as institutional covariates including the school's rank, undergraduate tuition, and both undergraduate and graduate enrollment, again controlling for school random effects. The main findings concerning the extent to which political scientists on Twitter share research and have these tweets disseminated are summarized in Table 3. As illustrated, the only consistent finding is that those who use Twitter for sharing research – and those whose research is more widely disseminated – have been on Twitter for a shorter period of time and are more commonly tenure-track. These patterns are consistent with the recurrent theme of younger scholars being more active on Twitter.

Table 3: Research Dissemination

	Shares	**Dissemination of Research**			
	% Research (1)	# RTs (2)	# Favs (3)	Engage (4)	Follows (5)
Male	0.052	−0.090	−0.227	−0.015	0.258
	(0.035)	(0.148)	(0.147)	(0.180)	(0.434)
Tenure Track	0.088^{*}	0.420^{**}	0.533^{***}	0.571^{**}	1.512^{***}
	(0.036)	(0.152)	(0.151)	(0.187)	(0.448)
Moderate	0.057	0.072	−0.028	−0.145	−0.268
	(0.042)	(0.172)	(0.171)	(0.210)	(0.505)
Conservative	0.052	−0.068	−0.068	−0.032	0.200
	(0.042)	(0.180)	(0.179)	(0.221)	(0.530)
Years Online	−0.022	-0.177^{*}	-0.258^{***}	-0.225^{*}	−0.431
	(0.017)	(0.077)	(0.076)	(0.094)	(0.225)
School Rank	−0.004	0.116	0.060	−0.141	−0.271
	(0.028)	(0.114)	(0.109)	(0.151)	(0.349)
R1 Inst.	−0.016	0.027	0.216	0.163	0.518
	(0.067)	(0.281)	(0.263)	(0.383)	(0.876)
State School	−0.104	0.048	0.288	0.024	−0.141
	(0.068)	(0.284)	(0.269)	(0.384)	(0.880)
Grad Enroll	−0.004	0.147	0.160	0.096	0.352
	(0.025)	(0.105)	(0.100)	(0.141)	(0.324)
Observations	1,043	747	747	747	747
Log Likelihood	−849.823	−1,542.188	−1,537.203	−1,691.185	−2,333.524

Notes: Patterns of sharing research on Twitter. First column regresses share of tweets that contain link to research. Ensuing columns regress measures of how popular these tweets are overall (columns 2 and 3) and how much of an impact they make on political science Twitter (columns 4 and 5). All outcome measures are added to 0.01 and logged. * p ≤ .05, ** p ≤ .01, *** p ≤ .001.

6 Conclusion

This paper provides a snapshot of #polisci Twitter as of early 2019. We capture what we believe is the universe of tenure-line academics working at PhD-granting institutions who have a Twitter account. We provide descriptive analyses of this online social network through a variety of lenses. Our motivating interest is to characterize the degree to which attributes of a social network – clustering, homophily, centrality – perpetuate existing inequalities in political science academia along the lines of gender, position, and ideology.

Our findings vary depending on how we define "links" in this network. Focusing on conventional measures such as mentions and re-tweets reveals significant evidence of homophily along the dimensions of gender, ideology, and position. Men are significantly more likely to re-tweet and mention other men, women do the same for other women, and similar patterns manifest among liberals, moderates, and conservatives; and among tenured and tenure-track scholars who use Twitter.

But when we use statuses that contain links to academic research, the story changes. Here we find no systematic differences across ideology or position, suggesting that the dissemination of scholarly research is not truncated by these cleavages. However, there is evidence that men are more likely to engage with research that is shared by male scholars, controlling for other dyadic differences and implementing dyad robust standard errors. Troublingly, there is no evidence of the converse, highlighting an important blockage in the flow of academic research corresponding to a male gender preference.

But we also have reason for optimism. We document significant evidence that female and tenure-track scholars are more likely to be on Twitter than their counterparts. In addition, tenure-track scholars are more likely to use Twitter to share research; are more likely to have these tweets engaged with by other members of the #polisci Twitter community; and are more central in the network overall, regardless of how we define lines between users and how we calculate centrality. Furthermore, female scholars' membership in the most dominant Twitter communities is commensurate to, or greater than, their share of the overall population, suggesting that Twitter is a valuable platform for raising the profile of under-represented groups in political science.

Our findings are based on data that is both incomplete and fluid. In terms of the incompleteness, there are several important nodes in the network that we do not observe. Some of these members of #polisci Twitter, such as @BrendanNyhan and @JohnHolbein1, are central actors who we miss due to their positions at non-PhD granting institutions at the time of data collection. Others, such as @womenalsoknow and @monkeycageblog, are important entities comprised of an assortment of scholars. Furthermore, the contours of this network will have already changed by the time a set of eyes other than the authors' read these words.

Even with these caveats in mind, we present this research as the first of its kind that applies the naval-gazing instincts of academic scholars to a particularly novel platform. Our findings sound both notes of caution and optimism. Caution over the persistence of gender inequalities well-documented elsewhere in political science that persist on #polisci Twitter. Optimism over the attenuation of these inequalities when it comes to arguably the most important aspect of #polisci Twitter – the dissemination of research. We hope that this contribution augments our optimism by highlighting the remaining areas of concern and presents a vision for what a more diverse discipline – and #polisci Twitterverse – could look like.

References

Aronow, Peter M, Cyrus Samii and Valentina A Assenova. 2015. "Cluster–robust variance estimation for dyadic data." *Political Analysis* 23(4):564–577.

Atkeson, Lonna Rae and Andrew J Taylor. 2019. "Partisan Affiliation in Political Science: Insights from Florida and North Carolina." *PS: Political Science & Politics* pp. 1–5.

Barberá, Pablo. 2015. "Birds of the Same Feather Tweet Together. Bayesian Ideal Point Estimation Using Twitter Data." *Political Analysis* 23(1):76–91.

Barnes, Tiffany D and Emily Beaulieu. 2017. "Engaging women: Addressing the gender gap in women's networking and productivity." *PS: Political Science & Politics* 50(2):461–466.

Beaulieu, Emily, Amber E Boydstun, Nadia E Brown, Kim Yi Dionne, Andra Gillespie, Samara Klar, Yanna Krupnikov, Melissa R Michelson, Kathleen Searles and Christina Wolbrecht. 2017. "Women also know stuff: Meta-level mentoring to battle gender bias in political science." *PS: Political Science & Politics* 50(3):779–783.

Bisbee, James, Rajeev Dehejia, Cristian Pop-Eleches and Cyrus Samii. 2017. "Local instruments, global extrapolation: External validity of the labor supply–fertility local average treatment effect." *Journal of Labor Economics* 35(S1):S99–S147.

Breuning, Marijke, Benjamin Isaak Gross, Ayal Feinberg, Melissa Martinez, Ramesh Sharma and John Ishiyama. 2018. "Clearing the Pipeline? Gender and the Review Process at the American Political Science Review." *PS: Political Science & Politics* 51(3):629–634.

Dion, Michelle L, Jane Lawrence Sumner and Sara McLaughlin Mitchell. 2018. "Gendered citation patterns across political science and social science methodology fields." *Political Analysis* 26(3):312–327.

Esarey, Justin and Kristin Bryant. 2018. "Are papers written by women authors cited less frequently?" *Political Analysis* 26(3):331–334.

Eysenbach, Gunther. 2011. "Can tweets predict citations? Metrics of social impact based on Twitter and correlation with traditional metrics of scientific impact." *Journal of medical Internet research* 13(4):e123.

Gray, Phillip W. N.d. "Diagnosis versus Ideological Diversity." *PS: Political Science & Politics*. Forthcoming.

Hindman, Matthew. 2008. *The myth of digital democracy*. Princeton University Press.

Hindman, Matthew. 2018. *The Internet Trap: How the Digital Economy Builds Monopolies and Undermines Democracy*. Princeton University Press.

Jaidka, Kokil, Alvin Zhou and Yphtach Lelkes. 2018. "Brevity is the soul of Twitter: The constraint affordance and political discussion." *Available at SSRN* .

Ke, Qing, Yong-Yeol Ahn and Cassidy R Sugimoto. 2017. "A systematic identification and analysis of scientists on Twitter." *PLoS One* 12(4):e0175368.

Key, Ellen M and Jane Lawrence Sumner. 2018. "You Research Like a Girl: Gendered Research Agendas and Their Implications." *PS: Political Science & Politics* pp. 1–6.

Kreiss, Daniel. 2016. "Seizing the moment: The presidential campaigns' use of Twitter during the 2012 electoral cycle." *New media & society* 18(8):1473–1490.

Marwick, Alice E and Danah Boyd. 2011. "I tweet honestly, I tweet passionately: Twitter users, context collapse, and the imagined audience." *New media & society* 13(1):114–133.

Mohammadi, Ehsan, Mike Thelwall, Mary Kwasny and Kristi L Holmes. 2018. "Academic information on Twitter: A user survey." *PloS one* 13(5):e0197265.

Mourão, Rachel Reis. 2015. "The boys on the timeline: Political journalists' use of Twitter for building interpretive communities." *Journalism* 16(8):1107–1123.

Munger, Kevin. 2017. "Tweetment effects on the tweeted: Experimentally reducing racist harassment." *Political Behavior* 39(3):629–649.

Munger, Kevin. 2018. "Temporal Validity in Online Social Science.".

Ortega, José Luis. 2016. "To be or not to be on Twitter, and its relationship with the tweeting and citation of research papers." *Scientometrics* 109(2):1353–1364.

Peoples, Brandon K, Stephen R Midway, Dana Sackett, Abigail Lynch and Patrick B Cooney. 2016. "Twitter predicts citation rates of ecological research." *PloS one* 11(11):e0166570.

Raghavan, Usha Nandini, Réka Albert and Soundar Kumara. 2007. "Near linear time algorithm to detect community structures in large-scale networks." *Physical review E* 76(3):036106.

Rom, Mark Carl. N.d. "A Liberal Polity: Ideological Homogeneity in Political Science." *PS: Political Science & Politics*. Forthcoming.

Searles, Kathleen and Yanna Krupnikov. 2018. "How Not to Get Ratioed and Other Advice for the Savvy Graduate Mentor." *Political Communication* 35(4):669–673.

Sen, Maya. 2018. "Response to Dion, Sumner, and Mitchell." *Political Analysis* 26(3):335–337.

Shen, Jieli, Regina Y Liu and Min-ge Xie. 2018. "Prediction with confidence—a general framework for predictive inference." *Journal of Statistical Planning and Inference* 195:126–140.

Tufekci, Zeynep. 2014. Big questions for social media big data: Representativeness, validity and other methodological pitfalls. In *Eighth International AAAI Conference on Weblogs and Social Media*.

Usher, Nikki, Jesse Holcomb and Justin Littman. 2018. "Twitter makes it worse: Political journalists, gendered echo chambers, and the amplification of gender bias." *The International Journal of Press/Politics* 23(3):324–344.

Wilson, J Matthew. N.d. "The Nature and Consequences of Ideological Hegemony in American Political Science." *PS: Political Science & Politics*. Forthcoming.