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Political Network Size and Its Antecedents and Consequences

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Recent evidence supports the important political role that political network size and distribution plays at both the individual and system levels. However, we argue that the evidence is likely stronger than the current literature suggests due to network size measurement limitations in the extant literature. The most common approach to measuring political network size in sample surveys—the "name generator" approach—normally constrains network size measurement to three to six individuals. Because of this constraint, research often undercounts individual network size and also leads to a misrepresentation of the distribution of the underlying variable. Using multiple data sets and alternative measurement approaches, we reveal that political network hubs—individuals with inordinately large network sizes not captured by name generators—exist and can be identified with a simple summary network measure. We also demonstrate that the summary network size measure reveals the expected differences in communicative, personality, and political variables across network size better than name generator measures. This suggests that not only has prior research failed to identify network hubs, but it has likely underestimated the influence of political network size at the individual level.

Keywords network hubs, network size, political discussion, political knowledge, political participation, name generator

The number of people with whom an individual discusses politics on a regular basis—network size—is an important variable that has implications for many political outcomes. Some of these effects reside at the micro level and suggest the political implications of network size for that specific individual. But network size, and specifically the distribution of network size, also has system- or macro-level implications for the nature of information flow and influence that are important beyond the implications of network size for any single individual.

Having a large political network is a structural resource at the individual level because it facilitates political conversation and exposure to diverse individuals and information.

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First, political network size is a key correlate of the frequency of political conversation. The larger one's network of available political discussion partners, the more likely political discussion is to take place, and the more frequent it is likely to be. A number of studies have demonstrated a strong link between network size and discussion frequency (Eveland & Hively, 2009; McLeod et al., 1999) and between discussion frequency and important political outcomes such as knowledge and participation (Eveland & Hively, 2009; Kwak, Williams, Wang, & Lee, 2005).

Second, larger political networks are likely to contain a more diverse set of individuals than smaller networks. That is, small networks are likely composed primarily of strong ties that are highly trusted but carry primarily redundant information. Large networks are likely composed of a mix of strong and weak ties. The value of weak ties is that they provide access to different perspectives and unique information relative to strong ties. Recent evidence suggests that larger networks are more likely to have weak ties than smaller networks (Gil de Zúñiga & Valenzuela, 2011). And network size (Eveland & Hively, 2009; Jang, 2009; Lake & Huckfeldt, 1998; Mutz, 2002a, 2002b; Pattie & Johnston, 2009; Rojas, 2008), exposure to weak ties (Gil de Zúñiga & Valenzuela, 2011), and having a diverse network (Son & Lin, 2008) have been linked to variables such as political knowledge, tolerance, and/or civic or political participation.

The effect of network size goes beyond its impact on particular individuals. From a system perspective, the distribution of network size has substantial implications for information and influence diffusion. In particular, diffusion of simple content such as information is promoted by a network structure in which most individuals have a small network size composed of strong ties and a few individuals—network hubs—have extremely large network sizes. These rare hubs serve to link otherwise disconnected subsets of the larger system and allow for the thorough diffusion of information through the system. The implication of hubs is the role they play in information and influence diffusion through the larger political system as a whole by their mere presence (e.g., Franks, Noble, Kaufman, & Stagl, 2008; Siegel, 2009).

The goal of the present study is to (a) demonstrate the limitations of constrained name generators as measures of network size and report findings on the distribution of unconstrained political network size to provide empirical parameters for those conducting simulations of network effects on political diffusion (e.g., Centola & Macy, 2007; Fowler, 2005; Siegel, 2009), (b) provide evidence that those with larger political network sizes are different at the individual level from those with smaller networks, and (c) demonstrate the implications of variations in network size measurement approaches in assessing network effects. We employ numerous data sets gathered in a variety of contexts and with complementary methods in order to meet our goals.[1]

Network Size and Distribution

The average size and distribution of various kinds of networks has become a prominent topic of academic research during the past decade. Barabási (2003), for instance, has succinctly summarized evidence that many networks follow a power law distribution, including academic citations, co-appearances in Hollywood movies, the link structure of the World Wide Web, sexual partner networks, and even chemical reactions in cellular structures. A power law distribution implies a large number of units sharing a very low score (i.e., small network size), but with a long tail of the distribution with a few instances of very high scores (i.e., large network size). Those instances in the tail are the hubs. "Power laws mathematically formulate the fact that in most real networks the majority of nodes have only a few links and that these numerous tiny nodes coexist with a few big hubs, nodes with an anomalously high number of links" (Barabási, 2003, p. 70).[2] Following Barabási, Hindman (2009) convincingly demonstrated that political sites on the Internet also form a network structured according to a power law. Although there are innumerable political sites on the Internet, the vast majority experience little traffic and have few if any links leading to them. By contrast, a very small number of political Web sites—those of major news organizations, major presidential candidates and parties, and major blogs—draw the vast majority of traffic.

Although little attention has been paid to hubs in the study of *social* networks, a review of prior evidence suggests that social network size also appears to be heavily skewed, with a few cases having extremely high values, as one would expect in a power law or related distribution.[3] For instance, Fischer's (1982) study of social networks used a modified *multiple* name generator approach (without constraints) and found that the distribution of kin and non-kin social networks revealed peaks relatively low on the size scale, but long tails with some individuals having very large networks. Research based on the "how many people do you know" approach has estimated the average social network to be in the range of 600 individuals (e.g., DiPrete, Gelman, McCormick, Teitler, & Zheng, 2011; McCormick, Salganik, & Zheng, 2010; Zheng, Salganik, & Gelman, 2006). Most importantly for our purposes, in each of these studies as well as others in the literature, the distribution appears to be skewed with a long tail to the right. The evidence suggests that some subpopulations such as clergy, politicians, and labor organizers are likely to have extreme network sizes compared to the norm (Pool & Kochen, 1978; McCarty, Killworth, Bernard, Johnsen, & Shelley, 2001).

Given that these studies do not examine *political discussion* networks, one may ask how useful they are for making inferences about the average size and distribution of political networks. DiPrete and colleagues (2011) found that compared to an acquaintance network, the "trust" network was considerably smaller (median of 550 vs. 17), but the shape of the distributions was very similar with a long tail to the right. This suggests that we can likely anticipate the distribution of subnetworks such as the political discussion network on the basis of the broader social or communication network. Moreover, recent evidence has demonstrated that political conversations tend to take place within our broader social networks. A network analysis by Eveland and Kleinman (2013) reveals a very strong association between the structure of general discussion networks and political discussion networks within voluntary associations. Finally, studies of political discussion in online environments have clearly replicated the finding that the connections between individuals—as demonstrated by their communication patterns—follow a skewed distribution and reveal the presence of communication hubs (e.g., Himelboim, 2011; Himelboim, Gleave, & Smith, 2009).

Therefore, we may expect to find that most individuals discuss politics with just a few other people—spouses, family members, and close friends. But political network size is unlikely to be normally distributed. There are a few in every crowd who discuss politics much more widely than most: political activists who go door-to-door during campaigns lobbying others to vote for their preferred candidate, individuals who are involved in—and possibly organize—political activist groups, or more generally people whose political interest provides the motivation to discuss politics widely and whose life situation gives them the opportunity to do so with many different people.

Most measures of political network size in the political communication literature, including those in the American National Election Study (ANES), the General Social Survey (GSS), and the Comparative National Elections Project, are based on "name generator" approaches. These questions ask respondents to literally name (via free recall) the individuals with whom they have political conversations, and to respond to "name interpreter" questions that ask about the characteristics of those discussion partners, one by one. There are two unfortunate consequences of using name generators as the methodology of choice when attempting to understand political network size. First, using the name generator approach produces a downward bias on estimates of political network size by truncating the distribution. Because of the heavy time demand of name generator questions, for practical purposes this approach normally limits respondents to reporting only three to six political discussion partners (Fowler, Heaney, Nickerson, Padgett, & Sinclair, 2011). The result is an underestimate of political network size for a meaningful number of individuals. And, from a system-level perspective, one particularly small but potentially important subgroup of respondents—the highly connected "hubs" with dozens of political contacts—are unable to be identified at all using this common approach to network size assessment in sample survey data.

Strong and Weak Ties

Traditional constrained name generator approaches produce a network of core ties that tends to be quite intimate, or heavily biased toward family members and close friends (Marsden, 2005). Also, core networks measured by name generators are highly interconnected (Marin, 2004). That is, spouses tend to know friends, and relatives tend to know one another. This tendency for ties to be connected not only to ourselves but to one another reflects the concept of ego-network density. Densely interconnected ego networks are composed of "strong" ties. By contrast, "weak" ties are those who are not tightly interconnected, and they tend to come from formal organizations and work settings. As Granovetter argued nearly 40 years ago, "When sociometric techniques [such as name generators] are used, they tend to discourage the naming of those weakly tied to the respondent by sharply limiting the number of choices allowed. Hence, the proposed importance of weak ties in diffusion is not measured" (1973, p. 1366). More recently, Fowler (2005, p. 287) lamented that "a very small number of people may have substantially more [political network connections than the average]. These "critical nodes" would help to reduce the average path length to realistic levels, but I do not know if they actually exist in political-discussion networks. The [Huckfeldt study] only allows people to name five discussants, and with so few data points it is hard to tell if there is actually a power law in the distribution of [network size]."

As networks grow larger, the average connection with each tie becomes weaker. "Large networks are not simply scaled up versions of smaller networks . . . there are important compositional differences between large and small networks" (Roberts, Dunbar, Pollet, & Kuppens, 2009, p. 143). It follows that the more people we know and interact with, the less likely that everyone else we know knows and interacts with them. Thus, large networks are likely to have more weak ties than small networks (Gil de Zúñiga & Valenzuela, 2011). However, large networks are still likely to include an equivalent number of strong ties—family and friends who know one another—by comparison to small networks (Gil de Zúñiga & Valenzuela, 2011). So, as networks grow, weak ties are added but not necessarily at the expense of maintaining at least a few strong ties.

Barabási (2003) argues that network hubs—those with an abnormally high network size—function to link together numerous smaller, more strongly interconnected subnetworks. This suggests that at least some—and possibly many—of the ties maintained by hubs are weak. This characteristic—with hubs having a mix of strong ties and weak ties—is what makes hubs so important to consider in understanding societal-level information diffusion. As Christakis and Fowler (2009, p. 162) conclude, "It is important to have a mix of strong and weak ties, and hitting the sweet spot is key." Therefore, if our goal is to understand political influence and information sharing at the macro level, excluding network hubs could be detrimental to the accuracy of our interpretations.

In recent years, a number of scholars have supported the importance of a combination of strong and weak ties within networks in order for influence to take place (Burt, 2005; Christakis & Fowler, 2009; Fowler, 2005; Gil de Zúñiga & Valenzuela, 2011; Granovetter, 1973; Putnam, 2000). Within strong ties, information flows easily and quickly. However, because of high levels of homogeneity within strong ties—our strong ties tend to be like us, and like one another—the likelihood of information redundancy within highly interconnected networks is high (Burt, 2005). Thus, a highly interconnected network absent weak ties—regardless of size—would be less likely to encounter new information, and shared information would likely be widely diffused. By contrast, when only weak ties are present the level of trust and frequency of contact are both likely to be low, and thus social influence will be low. Therefore, it is important to have both strong and weak ties present in a network. The weak ties act as bridges across which information flows between otherwise disconnected components of a network. These bridges allow new information, ideas, and behaviors to move throughout the network.

A Measurement Alternative: The Summary Network Size Measure

Critiques of a particular measurement approach are useful when appropriate, but they are most useful when appropriate *and* viable alternatives are available. The alternative of using complex, multiple name generators with no fixed limits is impractical in most cases of sample survey research because these can take inordinately long amounts of time to administer (e.g., Fischer, 1982; McPherson, Smith-Lovin, & Brashears, 2009). The same is true of the "how many people do you know" approach (e.g., McCormick et al., 2010) and the position generator approach (Lin, Fu, & Hsung, 2001), both of which require asking respondents about individuals they know in a variety of categories and/or with a range of rare and common names (and requiring as many as 32 questions!).[4]

However, there is a more efficient alternative: the summary network size measure. This measure simply requires respondents to estimate the number of individuals in their network as a response to a single question. In recent years, this measure has been used by a relatively small number of researchers studying social (Bell, Belli-McQueen, & Haider, 2007; Marsden, 2003) and political (Eveland & Hively, 2009; Gil de Zúñiga & Valenzuela, 2011; Kwak et al., 2005; McLeod et al., 1999; Moy & Gastil, 2006) networks.

The available evidence suggests that problems such as interviewer effects—which are common with name generators—are less problematic with summary network measures (Marsden, 2003). Moreover, summary network measures have been shown to correspond very well to complex name generators without constraints, especially for shorter time frames and for more salient types of interactions (Bell et al., 2007). It is also likely that the significant and troubling relationship between respondent cooperativeness and network size as measured by name generators (e.g., Fischer, 1982; Marsden, 2003; McPherson et al., 2009) would not affect a simple network size summary measure because of its simplicity.

Empirical Assessment

We begin the empirical component of our article by showing that network size is clearly underestimated in studies using the constrained name generators that dominate the political network size literature. In order to do so, we first demonstrate that more general social networks are constrained using such measures. In 1998, the General Social Survey (see Marsden, 2003, pp. 4–5, for methodological details) assessed the size of the "good friend" network of its respondents. Using a single name generator item, the network size was effectively capped at five good friends.[5] The left panel of Figure 1 presents the distribution of network size for this measure. For a random subsample, a similar summary network measure for the number of good friends was assessed. The distribution of this measure is presented in the right panel of Figure 1. Two things are immediately clear. First, the distributions of these two measures of what should be the exact same thing are, in fact, quite different. The distribution of the name generator measure has a negative skew with the longer tail to the left, such that the modal value is five (see Note 5). By extreme contrast, the distribution of the summary network measure is positively skewed, with the long tail to the right and a modal response of two. Second, there is clear "heaping" (Roberts & Brewer, 2001) of the summary measure at values of 10, 20, and many values ending in 0 or 5 from there to the maximum recorded value of 96. This heaping seems to obscure a smooth distribution. Nonetheless, it is also clear that there are "extreme" respondents who report network sizes far in excess of the mean and modal values of either measure. This summary measure provides clear evidence that name generator measures lump hubs together with individuals with much more typical network sizes.

Of course, we acknowledge that a "good friends" network is not the same as a political discussion network. To examine distributions of political discussion networks, we turn to data from seven studies conducted since the turn of the century. The first study is based on complete social network data collected from a probability sample of 25 mid-sized (roughly 10–35 members each) student activity groups at a large midwestern university drawn from a population roster of such groups in the fall of 2008 (see Eveland & Kleinman, 2013).[6] Three of these studies are the final three waves of a four-wave panel study conducted between 1999 and 2001 (see Hoffman & Eveland, 2010). The remaining three studies are (a) a representative telephone survey conducted in a battleground state following the 2004 presidential election (see Eveland & Hively, 2009), (b) an online survey conducted in July 2008 by the company Qualtrics (see Morey, Eveland, & Hutchens, 2012), and (c) a representative online survey conducted in October 2009 by the company YouGovPolimetrix.[7]

Table 1 presents summary information about these studies, including sample size, timing, network size question wording, and descriptive statistics for the network size measure. In each study, the mean political network size varied only slightly from a low of 2.43 in two of the studies to a high of 8.95 in one of the key battleground states immediately after the 2004 general election.[8] However, a consideration of the standard deviations and measures of skewness suggests that mean values are not particularly instructive. In every case the standard deviation was larger than the mean (a finding consistent with several recent published studies, although skewed distributions are rarely noted by the authors), and the measure of skewness was large and statistically significant in all but one case. Median values were always lower than the means, sometimes as much as 40% lower.[9]

Nonetheless, in each study somewhere between 64% and 93% of respondents reported network sizes of six or fewer using the summary network measure. This suggests that the variation in political network size among the majority of individuals is likely to be captured by at least the best capped (at six) name generator measures. However, the last column of Table 1 is particularly instructive. In each study, somewhere between 0% and 7% of respondents report network sizes three and a half times or more larger than six. As we would expect, larger percentages report extreme network sizes during presidential or off-year election campaigns, or in subpopulations like battleground states in which the campaigns are particularly salient.[10] These political network hubs have been all but ignored by prior scholarship, but they are quite apparent in each of our data sets. Figure 2 presents

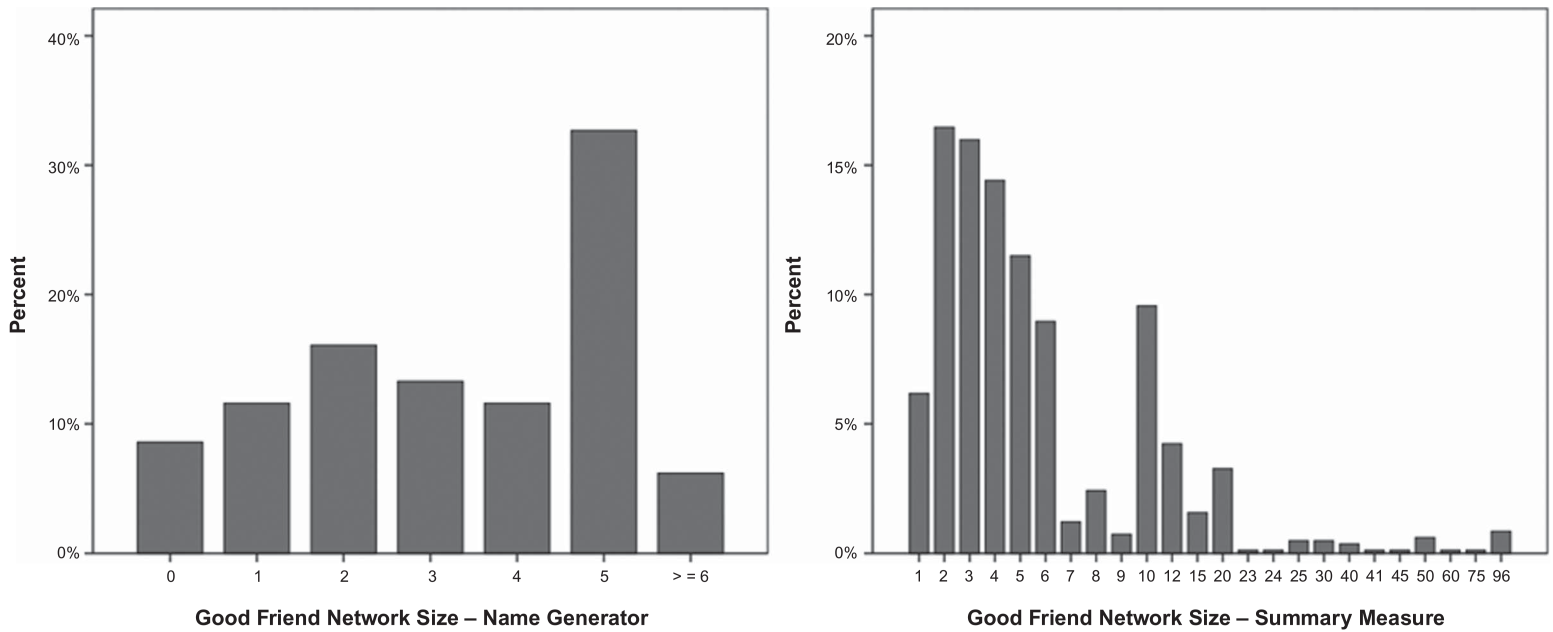

Figure 1. 1998 General Social Survey "good friend" network size comparison by measurement method (name generator distribution is taken from Marsden [2003, Table 1, p. 5]).

Table 1
Descriptive statistics for political network size

	N	M	SD	Median	Skewness	Percent ≤ 6	Percent ≥ 21
Presidential general election							
DDB Nov. 2000	1,149	5.37	7.492	3	5.502*	76.1	2.7 ($n = 31$)
Battleground Nov. 2004	590	8.95	13.367	5	4.339*	63.9	7.3 ($n = 43$)
Activity groups 2008	469	2.43	3.206	1	1.903*	88.3	0 ($n = 0$)
Off-year election							
Polimetrix Oct. 2009	497	5.83	9.202	4	6.080*	80.3	4.0 ($n = 20$)
Post-primary (summer)							
DDB June 2000	1,820	2.43	6.452	0	8.467*	92.6	1.4 ($n = 26$)
Qualtrics July 2008	2,350	4.19	5.615	3	6.957*	85.8	1.3 ($n = 31$)
Non-election (summer)							
DDB June 2001	905	3.63	4.971	3	4.698*	89.2	1.3 ($n = 12$)

Note. DDB question: "Outside your immediate family, how many people do you often talk with about politics or public affairs?" (should be expected to have a lower mean than the 2004 election study due to the exclusion of the immediate family and the reference to the term "often"). *Battleground question*: "How many people did you talk to about politics in an average week?" *Student activity group question*: For each other member of the group, respondents were asked: "Please indicate . . . how often you have talked to _____ about the presidential campaign this quarter (fall 2008)," with response options of not at all, once or twice a month, about once a week, a couple times a week, and almost every day. This measure was dichotomized to contrast not at all (0) against the other response options (1). We then summed the number of 1s to construct the measure of political network size, which was constrained only by the size of the group in which the respondent was a member (13 to mid-30s). *Polimetrix question*: "During a typical week, with how many different people do you usually discuss politics?" *Qualtrics question*: "In a typical week, about how many people do you talk about politics and public affairs with?"

$^{*}p < .05$.

plots of the distributions of the summary political network size questions across the six studies that used them. Figure 3 plots the distribution of network size for the student activity group, which employed a more complete and likely precise sociometric assessment of network size, but on a much smaller network and among a generally less politically active population. These distributions are clearly non-normal, and seem to approximate a power law or log-normal distribution depending on the study. The distribution is perhaps most clear in the student activity group sample in which respondents were asked to mark their discussion partners from a predefined list of fellow group members. This demonstrates what we already suspected—that the summary measure is likely to introduce more "heaping" error into the measure due to respondents estimating rather than enumerating network size as network size increases.

To further illustrate the concept of hubs from a social network perspective, Figure 4 presents a graphical representation of two of the 25 student activity groups from the network study that most closely match the overall network size distribution across groups as shown in Figure 3. Circles represent individuals in the group (or "nodes") and lines represent

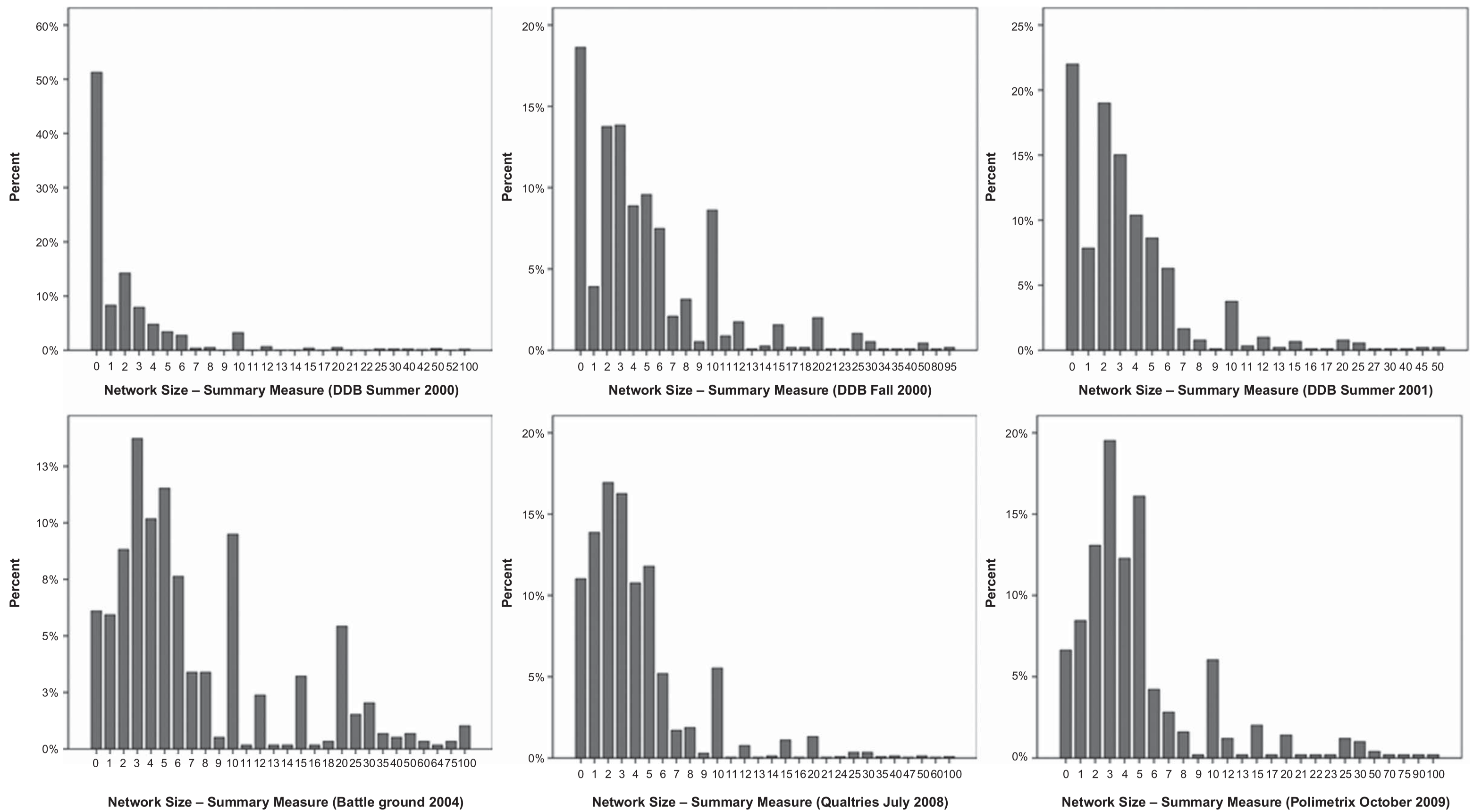

Figure 2. Distribution of political network size measures (A = DDB summer 2000; B = DDB fall 2000; C = DDB summer 2001; D = battleground 2004; E = Qualtrics July 2008; F = Polimetrix October 2009).

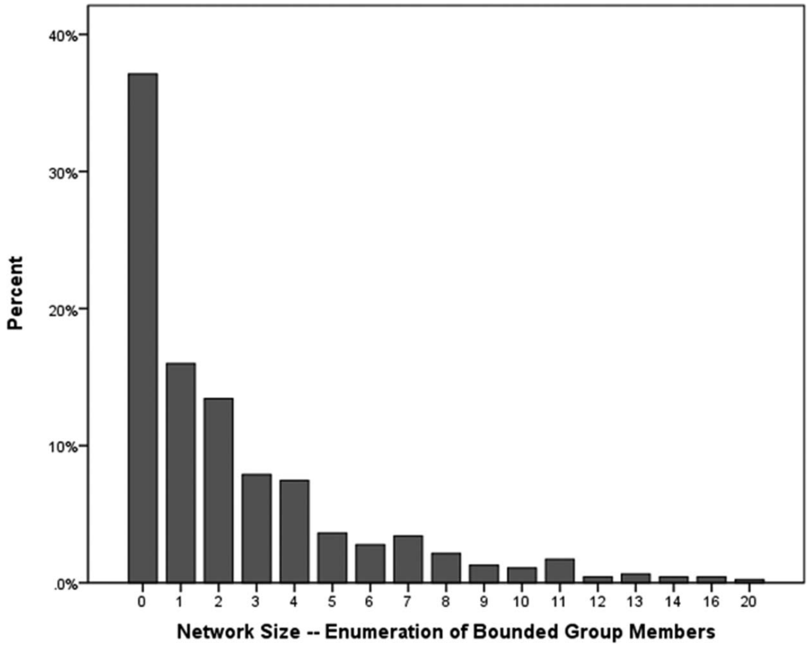

Figure 3. Distribution of political network size based on 1998 student activity group study (maximum possible scores based on group size ranged from 8 to 28).

political discussion ties (i.e., reports of some non-zero frequency of political discussion, or "links"). Arrow heads indicate the direction of the report (i.e., an arrow head pointing into a circle means the person represented by that circle was reported as a discussion partner by the circle at the other end of the arrow), and the size of the circles represents the network size or the number of people an individual reported (i.e., outdegree).[11] Note that most nodes are rather small (indicating zero or just a few ties), but a few are substantially larger (indicating large network sizes).

Next, we offer a direct contrast between the two measurement approaches among the same respondents. In the Qualtrics 2008 study respondents were asked first to name their political discussants using the name generator method by answering the question "Can you think of anyone with whom you discuss government, elections, and politics?" We capped this name generator at three names.[12] Later in the questionnaire we asked these same respondents, "In a typical week, about how many people do you talk about politics and public affairs with?" Note that the name generator does not specify a time frame, whereas the single-item summary measure focuses the respondent on the prior week, which should, if anything, limit responses compared to the name generator. The distribution for both measures is presented in Figure 5. The finding of clearly different distributions based on the measure employed replicates that from the GSS study of good friends in Figure 1. Moreover, more detailed comparisons of responses in the Qualtrics data revealed that those who named no names as part of the name generator reported a range of non-zero values in response to the summary network size measure.[13] Those who provided names for all three options in the name generator (i.e., network size of three) tended to average significantly more than three discussion partners—about five—in response to the summary network measure. But the summary network measure seems to roughly match the findings

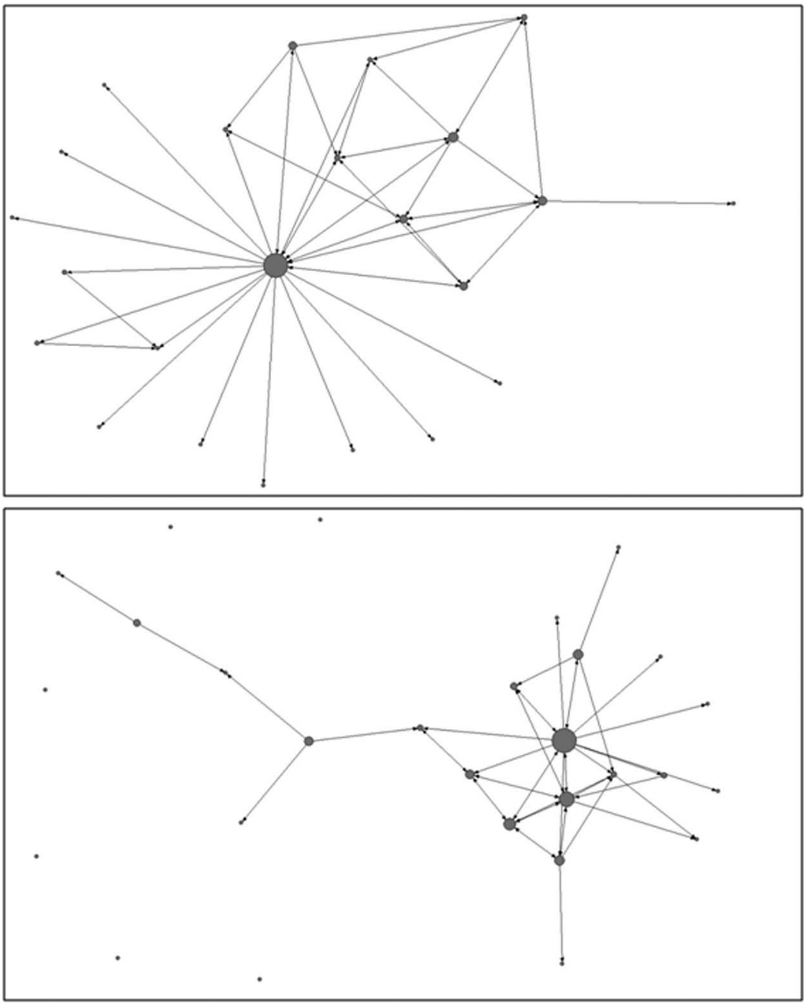

Figure 4. Sociogram for two student activity groups from social network study (individuals represented by circles [size relative to network size] and political discussion ties represented by lines).

of the name generator for network sizes estimated to be two or three. Even here, any error appears to be an underestimate of larger network sizes by the name generator compared to the summary network measure.

Finally, it is useful to demonstrate the reliability of measurement for the summary network measure. Using three-wave panel data from the DDB study gathered in summer 2000, fall 2000, and summer 2001, we are able to assess the (roughly) 6-month test-retest correlation in the logged value of a summary political network size measure.[14] We find that responses correlate moderately to strongly over this long time period that includes the post-primary period at Time 1, the immediate post-election at Time 2, and a non-election period at Time 3. Using data only from respondents who provided responses at all three waves of data collection ($N = 775$), the 6-month correlation between early summer 2000 and fall 2000 was .42. The 6-month correlation between fall 2000 and summer 2001 summary network size measures was stronger at .57. The correlation with 1-year

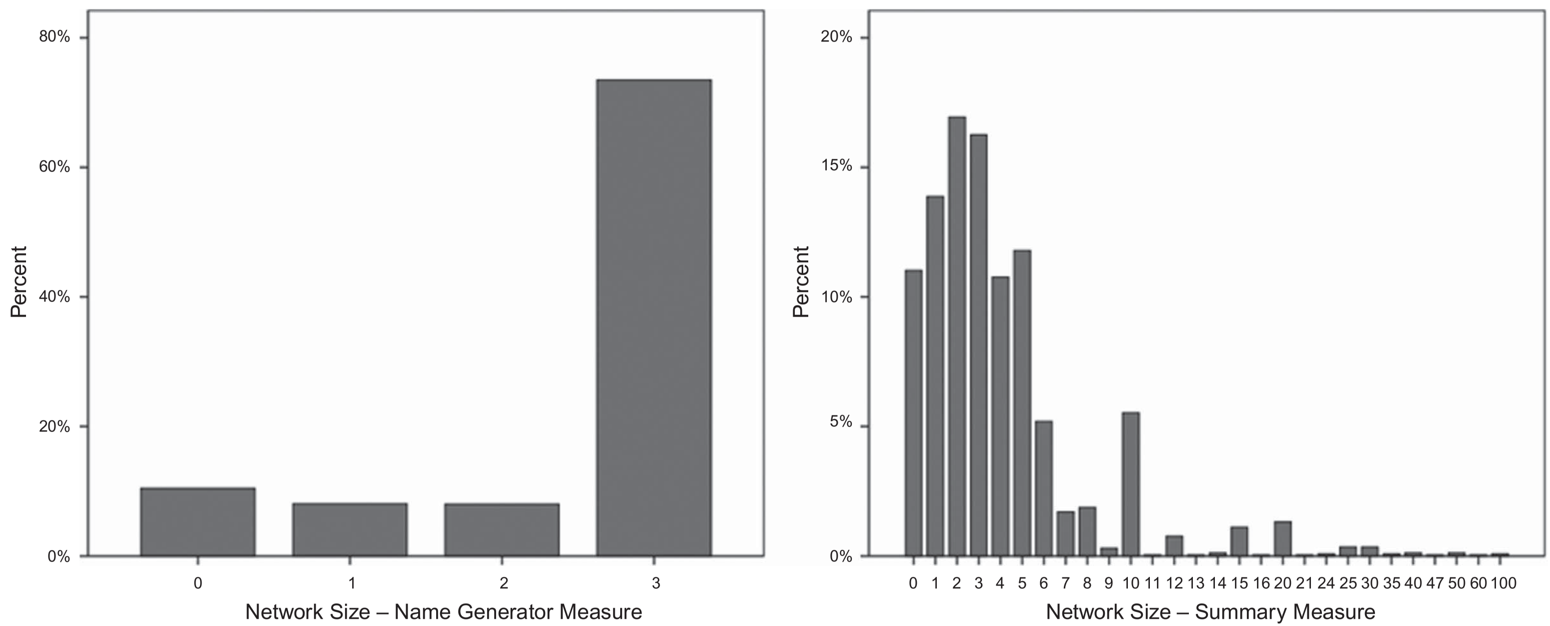

Figure 5. Comparing distributions of name generator and summary measures within the same sample (Qualtrics 2008).

lag was .45. Given the considerable differences in political network sizes because of the alteration of the political context across these three waves of data collection (among those responding at all waves, means vary from 2.12 at Time 1 to 5.46 at Time 2, falling back to 3.55 at Time 3), the strength of political network size correlations over time is impressive.

The Political and Personality Correlates of Political Network Size

Thus far we have offered broad discussions of the possible implications of network size and network hubs for macro-level processes within social systems. But we will present evidence of the individual-level political correlates of political network size across its full range, including the network hubs that often go unmeasured. First we focus on published findings using summary network measures, since studies using name generators fail to capture the true distribution of network size and thus may underestimate the strength of relationships between network size and other variables (see Long 1997, pp. 187–192). Then we will extend this research with evidence from our own data, using alternative methods of analysis given our enhanced understanding of the distribution of political network size.

Prior Research

First, we know that network size is associated with increased levels of exposure to political content. Those with larger political networks are higher in news media use (McLeod et al., 1999; Moy & Gastil, 2006), as well as frequency of engaging in political conversations (Eveland & Hively, 2009; McLeod et al., 1999; Moy & Gastil, 2006), than those with smaller networks. There is evidence that those with larger networks are also likely to be exposed to more political views that conflict with their own (Eveland & Hively, 2009; McLeod et al., 1999). Those with larger political networks tend to be higher in factual political knowledge (Kwak et al., 2005; Rojas, 2008), knowledge structure density (Eveland & Hively, 2009), and awareness of the rationales for opposing viewpoints (Moy & Gastil, 2006). Individuals with larger political networks are also more likely to feel politically efficacious (Moy & Gastil, 2006), engage civically (Gil de Zúñiga & Valenzuela, 2011), and participate in politics (Eveland & Hively, 2009; Kwak et al., 2005).

Empirical Assessment

Unfortunately, this published evidence is based on analyses that do not account for the non-normal distribution of network size. That is, despite the evidence that network size is a highly skewed variable, most scholars have not transformed the variable to make it more appropriate to standard regression models or employed alternative modeling techniques. Moreover, the presence of extreme values—the network hubs—is not discussed. Thus, our understanding of the relationship between the full range of network size and political outcomes remains obscured even in those studies in which data on network size have not been constrained to an arbitrarily low value by the name generator measurement technique.

In order to further assess the correlates of network size using the data available to us, we emphasize the findings from three studies among the seven described above. In each study, we use a summary measure of political network size. We then conduct a series of bivariate regression analyses to determine the association between summary network size and various predictors and outcomes.[15] When summary network size is treated as an outcome, we employ negative binomial regression to account for the non-normal distribution described above. When summary network size is considered a predictor, we employ a log transformation to account for the non-normal distribution and employ a mix of ordinary least squares, negative binomial, and Poisson regression models depending on the nature of the outcome measure.[16] We emphasize measures of variance accounted for given the diversity in measurement scales and analytical approaches, which makes any clear comparison of unstandardized coefficients tenuous. To briefly preview our findings, the results are consistent with prior literature and our expectations, providing support for the use of a summary political network size measure to assess network size generally, and thus to identify network hubs in particular.

Table 2 assesses the impact of political and personality variables on political network size as an outcome variable. Presumably individuals who are interested and highly involved in politics would have larger political discussion networks. Indeed, we find that higher levels of political interest and strength of ideology (or partisanship, depending on the data set) are modestly but significantly associated with having larger political discussion networks. Beyond political measures, the literature would also suggest that network size would be related to personality characteristics (e.g., Clifton, Turkheimer, & Oltmanns, 2009; Mondak, Hibbing, Canache, Seligson, & Anderson, 2010). Our findings indicate that individuals high in dogmatism (see Altemeyer, 2002) and need for cognition (see Cacioppo, Petty, & Kao, 1984) have significantly larger political networks. By contrast, individuals with high levels of fear of social isolation (e.g., Hayes, Matthes, & Eveland, 2013) and high levels of willingness to self-censor (see Hayes, Glynn, & Shanahan, 2005) have smaller political networks.

It may strike some readers that "political network hub" is simply another name for political opinion leader. This is a sensible inference, although the concept of opinion leadership is much broader than mere network size, even if network size may be one component

Table 2
Negative binomial regression results for effects of predictors on political network size

Predictor variables	DDB Nov. 2000	Battleground Nov. 2004	Qualtrics June 2008
Political interest	.208 (.021) .016*	.092 (.016) .008*	.159 (.020) .005*
Strength of ideology	.123 (.031) .003*	.110 (.047) .001*	.027 (.021) .000
Dogmatism	—	—	.223 (.066) .004*
Need for cognition	—	—	.348 (.062) .010*
Fear of social isolation	—	−.169 (.060) .002*	−.085 (.048) .001#
Willingness to self-censor	—	−.206 (.058) .003*	−.484 (.059) .023*
Opinion leadership	.311 (.030) .016*	—	—

Note. Values within cells are unstandardized coefficients and standard errors from bivariate negative binomial regression equations with (raw) network size as the dependent variable. Values in the second row of each cell are measures of variance accounted for (i.e., pseudo-R^2).

#$p < .10$; $^*p < .05$ (two-tailed).

of opinion leadership. We have refrained from making this connection explicit thus far due to the considerable heterogeneity in the conceptualization and measurement of "opinion leadership" across the diverse literatures in which it appears (e.g., Clark & Goldsmith, 2005; Roch, 2005; Siegel, 2009; Weimann, 1994). In short, this definitional debate is one in which we do not wish to engage in the limited space available to us here. However, we can offer some support for the link between network hubs and opinion leadership by the relationship between one self-report measure of opinion leadership (see Shah & Scheufele, 2006) and network size. As we would expect, individuals scoring high on opinion leadership (in general, rather than in regard to a specific topical area) tend to have larger political discussion networks.

Table 3 assesses the impact of (logged) summary political network size on a series of outcome variables. Not surprisingly, there is a very strong and positive relationship between logged network size and the frequency of political discussion. Considerably smaller, but generally still strong, positive relationships exist between network size and exposure to news on television and in newspapers. And individuals with larger political networks are also more likely to be more politically efficacious.

Table 3 also indicates that network size is related to multiple forms of political knowledge, as well as participation. Individuals with larger political discussion networks have more densely integrated knowledge structures. Across all three studies, candidate issue

Table 3
Regression results for effects of (logged) political network size on outcomes

Outcome variables	DDB Nov. 2000	Battleground Nov. 2004	Qualtrics June 2008
Ordinary least squares regression models			
Political discussion freq.	1.169 (.042) .399*	1.635 (.089) .369	1.970 (.042) .490*
TV news exposure	.958 (.080) .112*	.280 (.123) .009*	—
Newspaper exposure	.939 (.085) .096*	.555 (.127) .032*	—
Political efficacy	.230 (.034) .039*	—	.555 (.038) .270*
Knowledge structure density	—	.138 (.037) .023*	—
Negative binomial regression models			
Issue stance knowledge	.167 (.021) .006*	.106 (.027) .003*	.108 (.030) .002*
General political knowledge	—	.108 (.024) .003*	—
Poisson regression models			
Political participation	.401 (.069) .029*	.228 (.070) .013*	.368 (.113) .018*

Note. Values in the first row of each cell are unstandardized coefficients and standard errors from bivariate regression models using logged network size as the predictor. Values in the second row of each cell are measures of variance accounted for (i.e., R^2 or pseudo-R^2).

*$p < .05$ (two-tailed).

stance knowledge and network size also are modestly but significantly related, with larger networks producing more issue stance knowledge. The same relationship holds with a measure of general political knowledge. And our findings from all three studies are consistent with the notion that large discussion networks are associated with higher levels of political participation. Although many of these associations could be attributed to a methodological artifact—individual differences in overreporting of network size and media use, for instance, could produce a spurious correlation—because knowledge is coded for accuracy it is not subject to overreporting and thus provides evidence of correlation despite any possible individual differences in network size overreporting.

Before closing the empirical component of our article, we offer two additional tables that provide evidence supporting our summary network size measurement approach. First, in Table 4 we used the 2004 battleground data—since this study had most of the outcome variables of interest—and constructed two measures of network size as predictor variables. The first measure was the raw summary network measure, ranging from 0 to 100, representing the typical approach to analyzing summary network size measures (e.g., Eveland & Hively, 2009; Kwak et al., 2005; Rojas, 2008; Rojas, Shah, & Friedland, 2011). The second measure repeats our analysis from Table 3 by taking the log of the summary network size measure to account for its highly non-normal distribution (see also Gil de Zúñiga & Valenzuela, 2011). This table reports only variance accounted for in the bivariate models. For every single outcome, the logged measure accounts for numerically higher proportions of variance than the raw measure. In more than half of the cases, the variance accounted for by the logged measure was at least *double* the value generated by the raw measure. These findings demonstrate that prior research has likely underestimated the political importance of network size. Moreover, they suggest that future research should explicitly take into account the (presumably true) non-normal distribution of political discussion network size in models predicting political outcomes in order to avoid inappropriately overlooking the influence of network size due to failure to account for its non-normal distribution.

Table 4
Regression comparisons for logged vs. raw measures of network size (battleground 2004)

Outcome variables	Raw network size	Logged network size
Ordinary least squares regression models		
Political discussion freq.	.144*	.369*
TV news exposure	.008*	.009*
Newspaper exposure	.019*	.032*
Knowledge structure density	.015*	.023*
Negative binomial regression models		
Issue stance knowledge	.001*	.003*
General political knowledge	.001#	.003*
Poisson regression models		
Political participation	.006*	.013*

Note. Values in each cell are measures of variance accounted for (i.e., R^2 or pseudo-R^2).
#$p < .10$; $^*p < .05$ (two-tailed).

Utilizing "censored" measures that do not allow the true distribution of the variable to be observed (as in the name generator approach to tapping network size) can negatively impact the accuracy of relationship estimates. Long (1997) uses simulated data to demonstrate that artificially cutting off the right side of the distribution will lead to overestimates of the intercept and underestimates of the slopes. To demonstrate this impact in our data, in Table 5 we used the Qualtrics 2008 data—which incorporated both summary and name generator measures of network size for all respondents—to compare the implications of using a name generator measure, a raw summary network measure, and a logged summary network measure as predictors. Unfortunately, this study has fewer outcome variables of interest. Nonetheless, the findings clearly indicate that *raw* summary network measures account for less variance in political and communication outcome measures than their name generator counterparts in every test. However, the logged summary network size measure accounts for at least as much variance in outcomes as the name generator measure in every test. And, in the three (of four) cases in which the logged summary measure accounts for a numerically larger amount of variance, the improvement ranges from 1.2 to 2.8 times the variance accounted for by the name generator measure. This is particularly impressive given that the correlation between the logged summary measure and the name generator measure in these data was .52 ($N = 2{,}350$). Table 5 suggests that in addition to being conceptually most valid (by not constraining political network size inappropriately), in general a logged summary measure of political network size is more strongly related to political and communication outcomes than the two most commonly employed alternative measures in the literature.

Summary, Limitations, and Future Directions

"A robust interpretation is one that finds confirmation in many diverse sources, all of which are biased" (Fowler et al., 2011, p. 466). Our findings, across multiple data sets gathered using different sampling methods, in different political contexts, and using both sample and whole network approaches, have demonstrated the limitations of constrained name generator measures of political network size and presented consistent evidence that

Table 5
Regression comparisons for name generator network size (0–3) vs. raw summary network size vs. logged summary network size measures (Qualtrics 2008)

Outcome variables	Name generator network size	Raw summary network size	Logged summary network size
Ordinary least squares regression models			
Political discussion freq.	.173*	.025*	.490*
Political efficacy	.160*	.126*	.270*
Negative binomial regression models			
Issue stance knowledge	.002*	.001*	.002*
Poisson regression models			
Political participation	.015*	.000	.018*

Note. Values in each cell are measures of variance accounted for (i.e., R^2 or pseudo-R^2).
$^*p < .05$ (two-tailed).

alternative measures reveal quite different distributions and inferences about the nature of this concept. We have also provided evidence that those with larger political network sizes are different at the individual level from those whose network sizes are smaller. Finally, we have demonstrated that a logged summary network size measure tends to be reliable and function as a more effective predictor than name generator–derived measures of political network size.

Fowler (2005) concluded that one important parameter in his computer simulation model of voter turnout cascades—the distribution of political network size—may have been poorly estimated. His estimate was derived from a measure of network size based on constrained name generator items. He suggested that "future election surveys with social-network questions should ask people to estimate how many people they have political discussions with so we can get a sense of this distribution to use it to make our large-scale network models more accurate" (Fowler, 2005, p. 287). Since that time, network simulation models have proliferated in political communication and social movement research (e.g., Centola & Macy, 2007; Siegel, 2009). These models are only as good as the parameters they are fed, yet no better estimates of the key variable of political network size have been published to date.

Our findings suggest that name generator methods apparently have underestimated the number of political discussion partners for a meaningful minority of respondents—between 10% and 35%—and have misrepresented the shape of the distribution of this variable. Name generator methods are incapable of identifying network hubs—individuals who have been hypothesized to play a central role in the spread of information and influence at the macro level. Unfortunately, even most studies that have the data to identify these network hubs (i.e., studies using summary network measures) have not addressed their presence or taken the non-normal distribution of this variable into account (e.g., Eveland & Hively, 2009; Kwak et al., 2005; Rojas, 2008; Rojas et al., 2011). Had they done so, the evidence reported in this study suggests that the literature would likely reveal demonstrably stronger empirical relationships between network size and its antecedents and consequences than it currently does. And this more supportive evidence would likely drive more research on the importance of political network size in politics.

We argue that political network size (and by extension network hubs) deserves more theoretical and empirical attention. We justify this claim on the basis of social network theory, which indicates that individuals who are hubs likely have a crucial mix of strong ties and weak ties. This mix makes network hubs the glue that ties the broader political network together. Our findings demonstrate that the typical method used to measure political network size—name generators constrained to single-digit numbers of discussion partners versus unlimited single-item summary measures—matters not only for descriptive statistics but also for the estimation of individual-level relationships between network size and various political, communication, and personality variables. Our findings reveal that compared to the name generator approach, a summary network size measure is more efficient (requiring only a single question), better captures the theoretical (long-tailed) distribution of network size, and (once logged) accounts for more variance in theoretically related communicative and political variables.

Nonetheless, the summary network size measure also has limitations. Most obviously, it is an aggregate measure that fails to capture details about each discussion partner individually. To obtain these details that we still need the name generator approach, or better yet a full sociometric approach (see Eveland & Kleinman, 2013). Since the summary network size measure taps only one thing—network size—in most studies of political networks it should be viewed as a complement to the traditional name generator, not a replacement.

There is also reason to be somewhat skeptical of the precise values reported by some respondents for the summary network measure. Unlike unobtrusive observational measures of network ties in electronic forms of political communication (e.g., Himelboim, 2011), summary network size measures in surveys are reliant on the ability and motivation of respondents to provide accurate responses. Especially as true network size increases beyond a certain point, it is likely that respondents will fail to mentally enumerate their networks and instead rely on a rough estimate, which itself could be either an exaggeration or underestimate. These rough estimates then produce bunching or "heaping" (Roberts & Brewer, 2001) at summary values that end in 5 or 0 (e.g., 20, 25, 30; Bell et al., 2007; McCarty et al., 2001; McPherson et al., 2009). In short, the reliability and validity of responses to summary network size measures is a function of the true value of network size, but probably with decreasing reliability and validity as network size increases. Future scholarship should attempt to find ways to address this measurement reliability issue.

On a final related note, scholars also must address what appear to be a few excessively high values reported by respondents. Are political network size values in the hundreds or even thousands ridiculous exaggerations, or might they be roughly valid even if imprecise? A comparison to the infamous claim of American basketball star Wilt Chamberlain that he slept with 20,000 women in his lifetime may be appropriate here. Although his estimate of the number of sexual partners may not be precise and in fact may be a substantial exaggeration, it is still probably true that Chamberlain was a hub with far more sexual partners than most individuals. Are exceedingly high responses to summary political network size measures much the same?

Despite the acknowledged limitations, the results of summary network size questions have been demonstrated here to have considerable validity and lack the undue focus on strong ties and the constraint on size present in most name generators. But our attempts to understand political network size and political network hubs are not complete. We need to develop consistent measures—using consistent wording regarding the network of interest (politics, public affairs, government?) and the time frame for communication (last week, a typical week, last month, in the past year?). It is toward this future research that we now turn.

Notes

1. In order to conserve space given the large number of data sets we will employ, when possible we will reference published studies for methodological details rather than reiterate in this article. Other study details will be reported in notes at the point the data are addressed.

2. Hubs are empirically identified explicitly apart from the nature of the distribution only if a researcher dichotomizes the distribution into "hubs" and "not hubs." Unfortunately, there has been little work to theoretically define the appropriate cut point that distinguishes these two categories (Vallabhajosyula, Chakravarti, Lutfeali, Ray, & Raval, 2009). Some studies have developed ad hoc cut points such as one eighth of the population (Himelboim, Gleave, & Smith, 2009), whereas others have operationalized hubs by their effect on system connectivity (Vallabhajosyula et al., 2009). Because of the ambiguity of the precise theoretical and empirical definition of a hub, and because often the definition of hub could vary depending on the specifics of the population or distribution, in this article we empirically emphasize the forms of distributions that contain hubs rather than attempting to define a given threshold for being defined a hub in a given data set.

3. There is some debate regarding the exact distribution that best fits *social* network size. For instance, McCormick, Salganik, and Zheng (2010) find a log-normal distribution a better fit than a power law for their data. Jackson (2008, p. 65) argues that while "it is hard to find networks that actually follow a strict power law," it is true that "many social networks exhibit fat tails." Our point

here is not to argue for a specific skewed distribution, but to argue that a normal distribution should *not* be expected, and that the long tail of the distribution should be expected to be to the right.

4. Lin and associates (2001) critique name generators for studies of social capital and argue for the use of a "position generator." "The general technique is to pose one or more questions about the ego's contacts ("names") in certain social contexts or situations which may range from role or content (neighbors, important family or work matters) to closeness (confidences, intimacy, etc.), geographic limits, or for specific periods of time" (p. 62). The related "how many people do you know" approach asks questions about contact with groups with known distributions in society to estimate network size (e.g., McCormick et al., 2010). Although these approaches have advantages over single name generators in terms of breadth of network tapped, they share the limitation of requiring extensive survey questions and thus producing interviewer and cooperation effects much like those we describe later caused by the time demands of name generators. This is not a limitation of the network summary measure due to its brevity. Moreover, position generators and the "how many people do you know" approach are rare in the political communication literature. So, to save space, we do not discuss them in as much detail here as we have the more ubiquitous and established name generator approach.

5. Actually, the name generator in these data is not technically capped, but the name interpreter—the questions asked about named discussants—is capped at five. So, the only information that is available about network sizes greater than five is that the network size was some unspecified value greater than five. See Marsden (2003, Footnote 3) for a discussion.

6. The network size measure is based on dichotomizing each report to did not (0) or did (1) talk about the 2008 presidential election campaign with a given other group member, or "outdegree" in social network terminology (Scott, 1991, p. 72). Results are quite similar when a measure of "indegree" (the number of times a given individual is named by others as a political discussion partner) is used to construct the distribution.

7. This study was based on a nationally representative sample of 500 U.S. adult respondents aged 18 or older. We conducted five independent surveys—one per week for 5 weeks beginning on October 4, 2009—each with a representative national sample of 100 respondents. All surveys began at the end of the given week, and data collection for each took only a matter of a few days. The last survey in the sequence went into the field after November 3, 2009, which was election day. In effect, this is a repeated cross-sectional design with five identical surveys conducted in the course of 1 month. Surveys were conducted online by the company YouGovPolimetrix. YouGovPolimetrix employs a unique "sample matching" methodology (see http://www.polimetrix.com/documents/YGPolimetrixSampleMatching.pdf). Slightly over half (53.4%) of our respondents were female. The majority were White (73.2%), followed by Hispanic (11.2%), Black (10%), and 2% or fewer of other ethnic groups. Nearly 60% of our respondents were married. The mean respondent was 47 years old ($SD = 16$) and had a family income of $50,000–$59,999. Our sample consisted of 34% self-identified Democrats, 28% Republicans, and 31% Independents. These descriptive data match very closely with data from the U.S. Census Bureau's American Community Survey (2006–2008) and the 2008 American National Election Study (a highly respected national face-to-face survey).

8. The exact wording of the questions across these studies varied, as did the time frame to which the question referred. These factors likely contributed to the differences in mean political network size.

9. We should note that across these studies we excluded a total of three respondents for reporting values of network size that we felt must be in error or greatly exaggerated. In the Qualtrics study, one individual reported a political network size of 1,024 (whereas the next highest reports were two individuals reporting network sizes of 100). In the Polimetrix study, one individual reported a network size of 400 and another reported a network size of 1,200 (whereas the next highest report was one individual reporting a network size of 100). These three individuals were excluded from further analyses, although we acknowledge that it is a judgment call to retain or exclude any given case of extremely high network size. For these instances, since two of the three reports were an order of magnitude larger than the highest network sizes otherwise recorded (which ranged from 50–100 across

the studies), and represent about one tenth of 1% of these two studies (and an even smaller proportion of all of the survey respondents), we feel comfortable with these decisions.

10. The exception is the student activity group study, for which network size is measured only with reference to other members of a single group of limited size, and which therefore excludes the vast majority of possible connections, including strong ties such as family members and essentially anyone who is not in college. Moreover, since college students tend to be less politically involved than older adults in general, it is not surprising that the network sizes in this study do not match those of the other six, which are general population studies.

11. Since it is possible that A reports talking politics with B, but B does not report talking politics with A, the size of the circles in this figure does not perfectly match the number of lines attached to that circle. The size of the circles, instead, reflects most closely the concept of self-reported network size as discussed throughout this article.

12. Ideally we would have capped our name generator at six, but as we have noted doing so takes up a large amount of survey time. Readers should keep in mind that most name generator studies are capped at fewer than six names, including but not limited to Mutz's Spencer Foundation survey (capped at three; Mutz, 2002b), the 2000 ANES (capped at four; Nir, 2005), and the Electronic Dialogue project (capped at four; Cappella, Price, & Nir, 2002).

13. This should not be surprising given what we have already described regarding the implications of survey-related variables such as respondent cooperativeness and interviewer effects for name generator estimates of network size. Other studies have looked very closely at the issue of overreporting of zeros in name generator data gathered by the General Social Survey and concluded that in the 2004 GSS there are approximately 208 "excess zeros" out of 356 zeros in the data. This is an astounding 58% of respondents who offered no names for the name generator being estimated as actually being a non-zero value (McPherson, Smith-Lovin, & Brashears, 2009, pp. 674–675).

14. We used a log transformation to account for the non-normal distribution of this variable (see also Gil de Zúñiga & Valenzuela, 2011). We discuss the value of this log transformation in more detail later in the article. The alternative of using a non-parametric correlation (i.e., Spearman's rho) produces almost identical results: $\rho_{T1T2} = .42$, $\rho_{T2T3} = .58$, and $\rho_{T1T3} = .44$.

15. We conduct bivariate analyses because the control variables available to us differ from study to study, and because our emphasis is not on assessing the unique relationship of any given variable with network size, but confirming that network size is correlated with variables in the way we would expect it to be. In effect, a central purpose of these analyses is to establish construct validity for the summary network size measure.

16. We acknowledge that our classification of network size predictors versus outcomes, at least in some cases such as the link between frequency of discussion and network size, is subject to debate. In other cases—for instance, personality traits predicting network size as an outcome—the causal logic is more defensible. In any case, our goal here is not to establish causality but instead merely association.

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