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From Respondents to Networks: Bridging Between Individuals, Discussants, and the Network in the Study of Political Discussion

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Abstract Much of our understanding of social influence in individual political behavior stems from representative surveys asking respondents to identify characteristics of a small number of people they talk to most frequently. By focusing only on these few close contacts, we have implicitly assumed that less-intimate associates and features of network structure hold little influence over others' attitudes and behavior. We test these assumptions with a survey that attempted to interview all students at a small university during a highly-salient municipal election. By focusing on a small, well-defined community, we are able to explore the relationship

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between individuals, their close associates, and also less-immediate associates. We are also able to explore features of network structure unobtainable in representative samples. We demonstrate that these less-immediate associates and network features have the potential to exert important influence that conventional survey approaches would miss.

Keywords Political discussion · Social networks · Egocentric networks · Name-generator survey batteries · Attitudes · Political behavior

Introduction

An enduring issue in the study of political behavior is the extent to which political attitudes and behaviors are individually or socially motivated. An enormous and sophisticated literature has developed focusing on the *individual* correlates of political attitudes and behavior, most particularly socioeconomic indicators (Jan and Nagler 2013), value orientations and psychological predispositions (Hurwitz and Peffley 1987; Zaller 1992), and partisan attachment (Campbell et al. 1960). At the same time, another literature focuses on *social* influence over individual political attitudes and engagement, either as a consequence of the larger social contexts within which individuals are embedded (Huckfeldt 1979), as a consequence of institutionalized voting procedures and policies (Leighley and Nagler 1992; Wolfinger and Rosenstone 1980), or as a consequence of social networks and social contacts (McClurg 2003, 2006; Sinclair 2012).

The literature on social influence in political behavior has developed slowly due largely to methodological challenges rather than theoretical objections or inattention. While 70 years' worth of well understood, off-the-shelf survey procedures provide a robust platform for studying the individual correlates of political engagement, significant observational limitations confront studies aiming to take political interdependence seriously. By and large, scholars have made progress in this vein by focusing on the influence of individuals' closest social relations. An untested assumption underpinning this approach is that less-immediate associates exert little influence. By focusing on close relations, previous work has also assumed a limited role for the social network *structure*—the particular patterns of relationships (and absence of relationships) between sets of individuals. Rather than simply adding another battery to a survey, testing these assumptions depends on rethinking and reconfiguring the basic template for studies of political participation. We designed an original survey with these goals in mind.

The survey focuses on the May 2010 municipal election in Williamsburg, Virginia. Our survey targeted all of the roughly 6000 undergraduates at the College of William & Mary and asked respondents to state the full names of their five

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closest friends at the school. By focusing on this small, closed community, we can explore the role of these immediate friends *as well as* second-order contacts—associates identified by their friends. Though survey non-response prevents us from studying the whole network at the university, we can study the structure of relationships within respondents' locally-defined networks. We show that otherwise similar individuals are more or less aware of political issues, depending on the structure of the network. Individuals who are connected to more diverse networks are more aware of local issues. At the same time, the network structure also conditions the potential influence of individual friends, magnifying some voices while muting others. And while we show that immediate friends have the strongest relationship with individual attitudes, incorporating less immediate associates adds further explanatory power to our models. Lastly, we examine the behavioral implications of these social processes. Students who are more aware of local issues are more likely to vote as are those who are more central in the network and have more participatory friend groups. Together, these results suggest that models of political attitudes and behavior will be ill-specified if they focus only on immediate relationships and ignore the broader network.

Social Influence in Individual Political Behavior

The earliest empirical scholars of political behavior highlighted the importance of social influence, but following the rise of nationally-representative surveys, political behavior scholars placed social influence on the backburner. These scholars instead focused their theories on individuals' demographics, perceptions, and other personal characteristics readily measured on survey batteries. With surveys now the dominant mode of study, political behavior scholars seeking to understand social influence have developed batteries measuring the handful of people that respondents' talk to about important matters. Just as surveys have become the dominant mode of study for political behavior, these batteries have become the dominant mode to study social influence. Most theories of social influence have focused on these few close associates. In this section, we trace the development of this literature.

Prior to the advent of survey data, empirical studies of political participation typically focused on the setting in which participation occurred. Tingsten's (1963) classic account of turnout in early 1930s Stockholm used aggregate data to demonstrate the importance of residential location—working class individuals were more likely to vote if they lived in working class precincts. Key (1949) showed that southern whites were more likely to be racially antagonistic and politically mobilized if they lived in counties with more black residents. Matthews and Prothro (1963) correspondingly demonstrated the demobilizing consequences for black citizens—they were less likely to gain admission to voter registration lists if they lived in black majority counties where racially antagonistic whites held the reigns of control with a tenacious grip.

Many of these studies pointed toward the importance of social interaction. Tingsten proposed two distinct and highly plausible social interaction mechanisms (also see Langton and Rapoport 1975). First, workers living in working class precincts may have been more likely to interact with other workers, to recognize their working class interests, and hence to become socially mobilized. Alternatively, party organizations that focus on the mobilization of working class groups may seek economies of scale by targeting their efforts on areas with high concentrations of working-class individuals. In either event, the social nature of political mobilization becomes clear, but the potential mechanisms and their implications are vastly different. The problem was, and indeed continues to be, that students of politics and social mobilization lack the data resources to address these questions.

Surveys and survey research are not the enemies of studying social influence on individual behavior. Indeed, the earliest survey-based studies of elections and political engagement were community-based studies highly sensitive to the presence or absence of social mobilization effects. In the words of Lazarsfeld et al. (1948), politics was best seen as a "social experience." Both the Elmira and Erie County studies of the 1940 and 1948 presidential elections pointed toward political engagement produced through patterns of social interaction (see Berelson et al. 1954: chapters 6–7). The problem was, however, that the relatively crude measurement of social interaction placed severe limits on the ability to specify the nature of the social interaction mechanisms. Based on an often implicit assumption of social homogeneity within patterns of social interaction, the authors assume that middle-class individuals interact with other middle-class individuals, Catholics interact with other Catholics, and so on. Hence, social interaction tends to be measured implicitly, on the basis of direct measures of individual characteristics. The authors also assume that social interaction patterns are affected by the composition of the community's larger population, giving rise to a "breakage effect" (Berelson et al. 1954) that provides an advantage to majority sentiment within the community (see McClurg 2006). Here again, however, social interaction tends to be measured implicitly through an undocumented (but typically correct) assumption that living among members of a particular group leads to interaction with members of that group (Huckfeldt 1983).

Later survey studies were less effective at including considerations related to social influence for two reasons. First, most studies are nationally based, and hence it becomes difficult to identify local climates of opinion. Second, the introduction of the survey gives rise to a massive amount of new knowledge and new individual-level measurement innovations leading to important advances in the measurement of individuals' interests, resources, values, and abilities. Indeed, rapid progress in identifying the individual sources of political engagement is simply not matched by the development of new measurement devices for patterns of social interaction, and this asymmetry creates two problems. Not only does it mean that the measurement of social influences lag behind the measurement of individual proclivities, but also that progress toward understanding social influence in political behavior must take place within the highly-developed context of individual-level measurement advances.

Within this setting, the efforts of Laumann (1973) become particularly important. Laumann's 1966 Detroit Area Study includes a network battery as part of a survey of white Detroit males. Rather than map the entire social network, his survey asks respondents to identify and describe only their three closest friends. This approach is often referred to as *egocentric* network analysis because it focuses on the parts of the network centered around the main respondents and their associates—egos and their alters in network terminology. His efforts broke new ground, providing a model for measuring both individual attributes and the social networks of respondents. This innovation led eventually to a new literature on social and political participation through the inclusion of social network batteries within the General Social Survey series (Marsden 1987; Burt 1986), as well as within a series of both U.S. and international election studies (Huckfeldt and Sprague 1995; Huckfeldt et al. 2005), and beginning in 2000, within the National Election Study (Huckfeldt et al. 2004).

Hence McClurg (2003) employs one of these studies to argue that social networks produce strong effects on the likelihood of political participation. His argument depends on the interaction between individual characteristics and social forces. He contends that networks create opportunities for individuals to surpass individually-idiosyncratic resource constraints by obtaining information from other individuals. He moves beyond the implicit assumption that individual characteristics determine the structure of social networks, showing that network effects are distinct from the effects of social group memberships, as well as the manner in which they enhance the effect of individual education on the probability of participation. In short, he shows that social interaction not only plays a crucial role in affecting levels of participation, but also in defining and identifying the role of individual characteristics in affecting participation.

Continuing in this tradition, recent studies set a high bar for future contributions to the literature. Work in the field (Nickerson 2008; Sinclair et al. 2012), in surveys (Klofstad et al. 2013; Ryan 2010), and in the lab (Levitan and Visser 2009; Ryan 2011) show that we are now in a situation where sophisticated measurement is required *both* at the level of individuals *and* at the level of social networks. Participation depends not only on social networks, but individual characteristics as well, and a great deal of the explanatory progress with respect to political participation occurs at the intersection between individual characteristics and network properties.

The emerging conclusion from this work is that social interaction and social influence must be specified and measured; they cannot be implicitly assumed on the basis of individual characteristics and properties; and they cannot be boiled down to internalized norms and attitudes on the part of individuals. In this context, Granovetter's (1985) methodological insight regarding the need for specificity of network effects becomes particularly compelling. To understand political participation and mobilization relative to specific forms of social interaction, we must confront several daunting methodological challenges. Not only do we need high-quality data on individuals, but also high-quality data on their patterns of interaction. In short, the study of political participation has become an enterprise that builds on methodological individualism within the context of highly-interdependent individuals. One challenge is to ratchet up the quality of network data within survey applications, and that is the issue that we address below.

Opportunities for Enhancing the Measurement of Egocentric Networks

A primary obstacle to progress along these lines rests in the relatively primitive network measures that are produced through network name generators obtained from representative samples. The typical name generator produces around five names of a respondent's close associates, along with the respondent's answers to a battery of questions regarding each associate. In some instances, these associates can be interviewed as well, thereby providing validation to the main respondent's perception of the associate's characteristics, beliefs, and values (Huckfeldt et al. 2004: chapter 4). With both the focal respondent (the ego) and her associates' (the alters) perceptions of their own egocentric networks, second-order contacts can be studied (Huckfeldt et al. 2002) as well as relatively indirect measures of network structures including density and reciprocity (Huckfeldt and Sprague 1995).

These previous efforts provide only preliminary evidence because the name generator approach encounters several limitations when used on samples of relatively large populations. First, focusing only on a few of a respondent's closest relationships will systematically undercount the number of people the respondent interacts with (Eveland et al. 2013), ignoring the attributes of other potentially influential associates. Studying second-order associates addresses this problem, but in cities of even modest size, survey respondents in a representative sample rarely know one another, precluding this opportunity. Second, with respondents rarely interacting with each other, these procedures reveal little about the larger structure of the networks within which individuals reside. Third, people's self-reported perceptions of their network structure may differ from reality (see e.g., O'Connor and Gladstone 2015; Simpson et al. 2011). If second-order contacts and network structures affect individual political attitudes and behaviors, these limitations constitute notable problems in the study of social influence.

A Theory of Influence Beyond Immediate Contacts

Focusing only on individuals' closest relationships, previous work on individual political behavior has left unexplored the role of other, less immediate associates. This omission seems problematic because these more casual associates comprise the vast majority of our social networks and comprise a large proportion of our conversations. Individuals commonly maintain friendly relationships with somewhere between 70 (e.g., Roberts et al. 2009) and 150 people (e.g., Hill and Dunbar 2003). Consequently, there are many opportunities for social influence to occur beyond the reach of the closest five associates. Even if people try to avoid political discussion with all but their closest relationships, some political conversations are bound to arise. Political opinions and information are frequently interjected into previously apolitical conversations (Walsh 2004), perhaps because political zealots cannot help but bring up politics (Huckfeldt and Mendez 2008). Therefore, even if our close relations have the most influence individually, we expect less immediate associates to matter as well. Indeed, across a range of topics outside of politics including obesity and smoking cessation, individuals seem to follow the lead of not only their friends, but also their friends of friends (e.g., Christakis and Fowler 2008; VanderWeele 2011). We expect a similar pattern for political attitudes and behaviors:

Second-Order-Friends Hypothesis Individual political attitudes and behaviors should covary with the political attitudes and behaviors of not only close friends, but less immediate associates as well.

The literature's focus on close associates has also impeded our understanding of influence arising from network structure. While many features of network structure may be consequential, a salient debate focuses on the extent to which an individual's associates interact with each other. This debate hinges on the idea that frequent interaction between associates produces more redundancy in the network. When access to new information is most useful, redundancy can inhibit the diffusion of information or behaviors through the network (e.g., Granovetter 1973; Watts and Strogatz 1998). Sometimes simply receiving new information is not enough to change attitudes or behaviors (Nyhan and Reifler 2010), but instead repeated exposure to information is necessary (Redlawsk et al. 2010). In these cases where reinforcement is required to produce social influence, redundancy encourages diffusion (Centola 2010; Centola and Macy 2007). Rather than take sides in this debate, we argue instead that redundancy can both inhibit and facilitate diffusion. These asymmetric relationships emerge through qualitatively different measures of redundancy.

When few associates know each other, each associate draws from a unique portion of the broader network and may thus provide a great deal of unique information. In this context, redundancy only proxies for the relevant causal mechanism: access to new information. Thus, we expect political information to spread most readily to individuals with greater numbers of unique connections and those more centrally located in the network:

Centrality Hypothesis A Respondents with more unique connections in the network should be more aware of local political issues.

Centrality Hypothesis B Respondents with more central locations in the network should be more aware of local political issues.

While access to unique information may be necessary for individual awareness, political information may require repeated exposure to stick. For example, Huckfeldt et al. (2004) show the influence of any single close associate decreases as the associate's political views differ from those of other immediate associates. In this context, redundancy itself is the causal mechanism, amplifying reinforcing messages while drowning out discordant ones. We therefore expect the influence of any single friend will depend on the structure of relations in the individual's broader network. As the number of ties between an individual's friends increases, the network should provide more reinforcement, magnifying the influence of any single friend. At the same time, in large networks, any single friend's voice may be drowned out by the many other voices it competes with. Hence an associate's influence should decrease as the number of other associates grows. Social influence between friends, then, is magnified by dense interpersonal networks with fewer individuals who are more tightly tied together. These expectations lead to two dyadic hypotheses:

Reinforcement Hypothesis In dyadic analysis, the covariation between a respondent's awareness of political issues and that of her friend should increase with increases in the density of the respondent's egocentric network.

One-Among-Many Hypothesis In dyadic analysis, the covariation between a respondent's awareness of political issues and that of her friend should decrease with increases in the number of the respondents' other associates.

In summary, our theory suggests that studies focusing only on individuals' five closest friends will miss important sources of influence arising from more casual contacts and network structure. These expectations are too broad for any single study to address in full. We thus turn to an initial test, with new data providing a means to measure not only immediate friends, but second-order associates as well. The data likewise provide measures of key aspects of network structure relating to the redundancy in individuals' networks.

Data

Our study relies on an original survey sent via email to all William & Mary students, fielded in the first week of February 2010, prior to the May 2010 Williamsburg municipal election.[1] Students were invited via an email from Rapoport's university email address to complete the online survey and those who did not respond were sent two reminders. Students received no compensation for participating. As we argue above, relying on a small, enumerated target population allows us to explore social contexts in greater detail than a nationally representative sample could afford. Indeed, great progress has been accomplished by studies that attempt to map the networks of such self-contained populations (e.g., Eveland and Kleinman 2011; Lazer et al. 2010; Song and Eveland 2015).

In the survey, respondents were asked to provide "the first and last names of up to five of your closest friends who attend William & Mary." About 1800 respondents identified at least one friend and 1400 identified the maximum of five.[2] Among those responding to the name generator, individuals averaged 4.6 friends, providing almost 8400 names, of whom just over 3900 are unique. Combining respondents and their named friends, the survey thus generated a network which includes 4293 of the 5836 students at William & Mary (74% of the student body).

[1] The study was approved by the College of William & Mary IRB on Human Subjects, PHSC-2010-03-04-6495-rbrapo.

[2] In total, 1833 of the 5836 undergraduates provided at least one friend's full name in the name generator, yielding an AAPOR non-probability internet panel participation rate of 31% (The American Association for Public Opinion Research 2015, 40).

Despite possessing network data on a large portion of the university, we cannot measure non-respondents' attitudes or friendships. Lacking data on many existing relationships in the network, we cannot accurately describe the whole-network structure. Measures summarizing whole-network structure become increasingly biased as response rates decrease (Costenbader and Valente 2003). Rather than explore the entire network, we rely instead on egocentric analysis, where the problems of non-response are less daunting. Because respondents enumerate their first-order egocentric network data in their own survey response, this approach mitigates the missing data problems induced by non-response in the rest of the network.

While the problem of non-response is real, it is important that we place it in context. In a traditional survey setting with an egocentric name generator, we are once again confronted with comparable non-response to the survey as a whole. Among respondents, between 10 and 20 percent typically do not provide any discussants in response to the name generator. And less than half typically provide 4 or more discussants. Finally, of those who do provide discussant information, our own experience is that only about 50 percent provide information that can be used to identify and interview the members of the network for a snowball survey (Huckfeldt and Sprague 1995; Huckfeldt et al. 2004). In short, missing data problems are pervasive and compounding in network studies. By these standards, our response rates are more than adequate.

Our sample differed from the full student body in several ways (see Table A1 in Online Appendix A for details). Perhaps most importantly, 13% of all students voted in the 2010 municipal election compared with 22% of name generator respondents. Our survey is not unique in this regard; most political surveys overrepresent voters, including large national surveys such as the American National Election Study (Burden 2000; Groves et al. 2004; Selb and Munzert 2013). Nonetheless, readers should keep in mind that our results generalize best to relatively engaged populations. For further details on the composition of our sample, see Table A2 of Online Appendix A, which provides summary statistics for all variables we use in our analyses.

Some respondents are likely to have more than five close friends (Eveland et al. 2013). It may be tempting to allow the name generator battery to identify these additional individuals, but these batteries impose large time constraints that might further encourage nonresponse. And, in practice, people rarely identify more than five names when given the option (Marsden 2003). We therefore instead leverage the small size of our target population to study these additional relationships. In this small community, where many respondents are likely to know one another, we can examine whether individual attitudes and behavior covary with those of not only their five nominated friends, but also individuals nominated by those five friends, expanding the potential network size to include as many as 30 associates.

With this design, our analysis rests on the assumption that students associate with their friends' friends. Indeed, by one estimate, 79% of one's close friends know each other (Louch 2000, p. 53). And the likelihood that any two of your friends know each other increases with the frequency and intimacy of your relationship with each one (Louch 2000, p. 57). Thus, by focusing on students' closest friends, we can be confident that they know many of their friends' closest friends too.

This design overcomes many limitations of past network studies, but like past studies, it is also limited in its ability to conclusively demonstrate cause and effect. Readers must be aware that the relationships we explore between individuals and their networks may arise due to the social influence posited by our theory; or instead due to patterns of homophily, in which individuals associate with similar others; or shared environmental influences (Fowler et al. 2011). With these problems in mind, we apply sensitivity analyses to our core results, providing a means to address concerns of bias emerging from unobserved factors. We also provide several complimentary robustness checks to address these confounds.

The Political Problem

The May 2010 Williamsburg municipal election held particularly important consequences for college students. For our purposes, the most relevant issue was a strict noise ordinance, which prohibited any noise after 11 PM that exceeds sixty-five decibels—roughly the noise level of a casual conversation—and audible more than ten feet from the noisemaker. Initial violations constitute a misdemeanor offense punishable by a $300 fine, with subsequent violations ratcheting up to possible penalties of a $2500 fine and a maximum twelve-month prison sentence. Most students attend off-campus parties at least occasionally and anyone doing so was subject to punishment under the ordinance. In response, student groups worked to mobilize student awareness of the issue and participation in the election. This social environment provides an opportunity to evaluate our hypotheses using both an attitudinal and a behavioral outcome variable. The attitudinal outcome measures awareness of the noise ordinance. The behavioral outcome measures turnout in the 2010 municipal election. To avoid the problems introduced by self-reported turnout (see Ansolabehere and Hersh 2012), we rely on validated voting records from the city.[3] Before we turn to these outcomes, we first introduce the relevant measures of network structure.

Summarizing Students' Networks

These data allow us to identify a series of locally-defined networks that are centered on each of the survey respondents. Unlike the traditional egocentric network, this network depends on the survey responses of not only the ego, but also each of the five potential alters, who in turn identify as many as five friends each. In short, as a first step toward moving beyond just the five closest relations, we construct

[3] We rely on a database produced by the Williamsburg Voter Registrar including all registered voters, their date of registration, date of birth, address, and voting history. We used first and last names to find all potential matches between individuals in our student sample and those registered to vote. In each case, we used both the date of birth as well as the address to help confirm that a matched name corresponded to a student. According to Ansolabehere and Hersh (2010) summary measure, Virginia maintains some of the highest-quality registration records in the US.

respondents' two-step neighborhoods—a series of egocentric networks which include information for each of the main respondents (egos), their five named friends (Zone 1 alters), and up to 25 second-order friends identified by Zone 1 friends (Zone 2 alters). See Online Appendix B for details about creating these networks. Zone 2 associates are likely to represent people who interact directly with the main respondent, but less frequently or in less personal contexts than Zone 1 friends. Thus, we expect the relationship between individuals and their Zone 2 associates to persist after controlling for the influence of Zone 1 friends. In contrast, if Zone 2 associates do not interact directly with the main respondent, then any influence of the second Zone must be mediated by Zone 1 friends. In that case, after controlling for the Zone 1 friends (and any preexisting similarities between the main respondent and Zone 2 associates) we would expect no further relationship between the main respondent and Zone 2 alters.

With this approach, we can define network centrality both globally and locally. Global centrality can be measured by *indegree*—the number of people who identified a student as a friend.[4] The missing data limitations are less daunting in this instance. Students can be named as friends regardless of whether they responded. We can define local centrality by identifying the most frequently named student or students in each respondent's two-step neighborhood. These two measures are related, but tap different dimensions of centrality (Spearman's $p = 0.55$; see Figure A1 in Online Appendix A for more descriptive statistics). We believe these measures—which typical surveys cannot provide—can improve our understanding of attitude formation and behavior by operationalizing individuals' access to new information. Political information should diffuse most readily to more central individuals. Before we address this expectation, we must also take into account the amount of reinforcement within individuals' networks.

The Local Networks

As we argue above, network structure varies in terms of its ability to supply new information and its ability to reinforce existing information. In a well-connected friendship group, all individuals know one another, providing a great deal of reinforcing or perhaps redundant information, but little new information. In a less connected group, several individuals may not interact directly and each may thus provide more new information, but fewer opportunities for reinforcement. We can capture this variation by considering the density of respondents' two-step

[4] Indegree provides a better measure of global centrality than either of its variants: outdegree and total degree. In this case, outdegree is equal to the number of people an individual names as friends. Outdegree is thus limited only to survey respondents and provides little variation (as described above, 78% of students responding to the name generator identified the maximum five friends). Total degree is also problematic because it equals the sum of indegree and outdegree. For non-respondents, this sum is always the same as indegree, but for respondents, it is an average of 4.6 units greater than their indegree. Thus, total degree conflates popularity and survey participation.

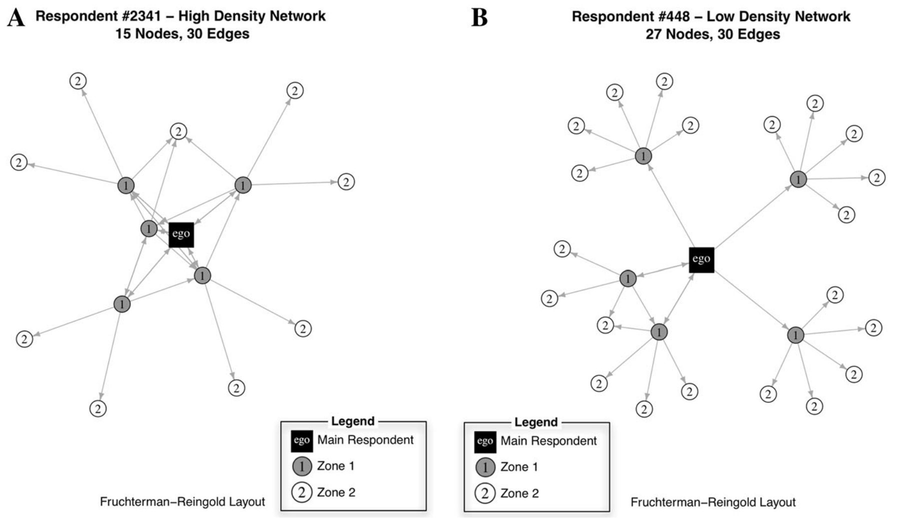

Fig. 1 **a** High density network. **b** Low density network

neighborhoods.[5] Figure 1 demonstrates this point, displaying two of these locally-defined networks as graphs in which individuals are represented as nodes and friendship nominations are represented as directed edges. One of the networks (Fig. 1a) is characterized by high levels of density and thus reinforcement within the network, while the other (Fig. 1b) is characterized by low levels of density.

The high-density network features a large number of bidirectional edges—indicating that both individuals in a dyad reported the other as a friend—and relatively few individuals connected to the network by only one tie. Zone 1, the five individuals ego named as friends, shows an especially high level of reciprocity. Each of the ego's alters in Zone 1 was named as a friend by at least one of the other Zone 1 alters, and each Zone 1 alter named the ego as well. There is also an individual in Zone 2 that was named by three Zone 1 alters. This high-density pattern of ties leads to a network with only 15 unique individuals, despite the fact that this egocentric network is "complete"—we have five alters for the ego, and each of the ego's alters provided a full five alters for themselves as well, leaving us with a total of 30 directed edges.

By contrast, the low-density case features few bidirectional edges and a more obvious separation between the ego's alters. Only a handful of individuals in the network were named by more than one other individual. Only two of the ego's alters named the ego as a friend, and only one Zone 1 alter was named by another Zone 1 alter (the naming was not reciprocated). This pattern leads to a total of 27 unique individuals, even though the network is also complete and has the same number of directed edges (30) as the high-density network.

[5] Alternatively, the local clustering coefficient would provide a measure of the uniqueness or redundancy of friends. We rely instead on the two-step neighborhood density because it captures uniqueness or redundancy of not only friends (Zone 1), but also second-order friends (Zone 2).

These neighborhoods were chosen to highlight the variation in these measures, but they are not anomalous. The median neighborhood in the data has 17 edges, the sparsest has only one, while the densest has 53. The number of unique individuals within these neighborhoods varies from a minimum of 2 to a maximum of 27, with a median of 11. Thus, even with the problem of non-response, these two-step neighborhoods tend to include more than just the five closest friends. Networks with higher counts of unique individuals also tend to include more edges. But some individuals are located in dense networks with relatively few friends, while others are located in local networks with many individuals but where relatively few name more than one other individual in the network as a friend. Hence, in further analyses, we take simultaneous account of the number of unique nodes and the total number of identified edges.

Awareness Results

How do these structures help us understand individuals' awareness of local political issues? The most central issue for students in this election was the noise ordinance. To measure students' awareness, we use an item on the survey gauging their familiarity with the noise ordinance, asking "How familiar are you with the current noise ordinance that applies to residential areas in the City of Williamsburg?". The four response options range from "Not aware of this ordinance" to "Very familiar". Table 1 uses this item as an outcome variable in ordered logistic regressions designed to identify the individual and social covariates that predict awareness of this local issue.[6] As explanatory variables, we include the network structure variables introduced above. Our theory predicts greater awareness of local issues for people with more unique associates (Centrality Hypothesis A) and more central network positions (Centrality Hypothesis B). Thus we expect positive coefficients for the number of unique nodes in an individual's network, her indegree, and local centrality. Before exploring these social relationships we first estimate a model that includes only individual attributes as predictors.

Not surprisingly, Table 1, Model 1 shows that students who have attended a party cited by police for violating the noise ordinance are better aware of this ordinance.[7] Likewise, awareness increases with academic year—we suspect this relationship arose due to increased experience with local policies. These results based only on individual characteristics provide a baseline to which we can compare how well social factors predict this awareness.

Table 1, Model 2 introduces the network measures as covariates. All else equal, the model suggests that individuals tend to be more aware as their networks provide greater access to information via the number of unique individuals (nodes). Though this relationship is consistent with Centrality Hypothesis A, it is not statistically

[6] All tables in this manuscript were originally typeset using the texreg package in R (Leifeld 2013).

[7] This indicator variable is constructed from an item asking, "Have you ever attended an off-campus party where the police issued a citation to you or someone else at that party for violating the noise ordinance?".

Table 1 The network structure predicts individuals' awareness of local issues

	Model 1	Model 2
Outcome variable is noise-ordinance awareness		
Threshold 1 ($Y \geq 1$)	1.83*	1.36*
	(0.09)	(0.12)
Threshold 2 ($Y \geq 2$)	−0.36*	−0.85*
	(0.07)	(0.11)
Threshold 3 ($Y \geq 3$)	−2.63*	−3.16*
	(0.09)	(0.13)
R attended party cited by police (0 = No; 1 = Yes)	1.24*	1.26*
	(0.10)	(0.10)
R's academic year (0 = Freshman; 1 = Sophomore; 2 = Junior; 3 = Senior)	0.25*	0.24*
	(0.04)	(0.04)
Nodes (Number of people in R's two-step network)	–	0.03
	–	(0.02)
Edges (Number of relationships in R's two-step network)	–	−0.01
	–	(0.01)
Indegree (Number of students naming R as a friend)	–	0.13*
	–	(0.04)
Local centrality (Number of two-step neighborhoods where R is most central)	–	0.03
	–	(0.03)
N	2247	2247
Pseudo R^2	0.11	0.13
L.R.	234.35	284.49

Estimates from ordered logistic regressions. Standard errors in parentheses

* $p < 0.05$ (two-tail)

significant ($p = 0.09$). Likewise, the number of edges has a weak, statistically insignificant relationship with awareness. Both indegree and local centrality produce positive coefficients, but only indegree's coefficient is statistically significant. Moving from a student one standard deviation below to one standard deviation above the mean indegree corresponds with a .12 increase in the student's probability of being somewhat or very familiar with the noise ordinance [95% Confidence Interval (0.05–0.19)].[8] In sum, Table 1 suggests individuals who are more central in the broader network (indegree) are more likely to be aware of code enforcement.

Network Structure Moderates the Role of Friends' Experiences

Aside from the direct relationship explored above, our theory also suggests the network structure should moderate the influence of individual friends' experiences. Any single friend should have less influence as an individual's total number of

[8] This and all other reported predictions and confidence intervals come from simulations from the posterior (Gelman and Hill 2007), setting other covariates to their medians.

friends increases (One-Among-Many Hypothesis). At the same time, the influence of any single friend should increase with the local network density, as measured by the number of edges in a students' two-step neighborhood (Reinforcement Hypothesis). We turn to a dyadic analysis to explore these expectations.

Table 2 examines these hypotheses, using the same outcome measure of student awareness as Table 1. We again use ordered logistic regressions, but this time the unit of analysis is an ego-alter dyad; each observation represents a respondent and one of her named Zone 1 friends. We therefore estimate robust standard errors, clustered on the ego. This dyadic specification allows us to use a friend's experience

Table 2 The network structure conditions the ego-alter relationship

	Model 1	Model 2
Outcome variable is noise-ordinance awareness		
Threshold 1 ($Y \geq 1$)	1.24*	1.17*
	(0.17)	(0.17)
Threshold 2 ($Y \geq 2$)	−0.97*	−1.04*
	(0.16)	(0.16)
Threshold 3 ($Y \geq 3$)	−3.34*	−3.41*
	(0.18)	(0.18)
Ego attended party cited by police (0 = No; 1 = Yes)	1.22*	1.21*
	(0.12)	(0.12)
Ego's academic year (0 = Freshman; 1 = Sophomore; 2 = Junior; 3 = Senior)	0.27*	0.27*
	(0.04)	(0.04)
Alter attended party cited by police (0 = No; 1 = Yes)	0.36*	1.10*
	(0.08)	(0.26)
Nodes (Number of people in the ego's two-step network)	0.04	0.05*
	(0.02)	(0.02)
Edges (Number of relationships in the ego's two-step network)	−0.01	−0.01
	(0.01)	(0.01)
Indegree (Number of students naming the ego as a friend)	0.15*	0.15*
	(0.05)	(0.05)
Local centrality (Number of two-step neighborhoods where the ego is most central)	−0.01	−0.01
	(0.04)	(0.04)
Alter attended party × Nodes	–	−0.11*
	–	(0.04)
Alter attended party × Edges	–	0.03
	–	(0.02)
N	7917	7917
Pseudo R^2	0.14	0.14
L.R.	1106.21	1120.91

Estimates from ordered logistic regressions. Observations are Ego-Alter Dyads. Robust standard errors in parentheses, clustered on the ego

* $p < 0.05$ (two-tail)

with the noise ordinance as an explanatory variable. We measure a friend's experience with a dummy variable equal to one if the alter reported attending a party cited by police for violating the noise ordinance. In the models, we control for the ego's experience with the noise ordinance, guarding against the possibility that the apparent social influence effects are actually due to the ego's own experiences. Model 1 also includes the network structure variables from Table 1. To test our conditional expectations, Model 2 interacts the alter's experience with measures of the number of nodes and edges in the ego's two-step neighborhood.

Model 1 shows that the alter's experience exhibits a positive relationship with the ego's awareness of the ordinance, even after controlling for the ego's own experience with the ordinance. As Model 2 shows, however, this relationship is moderated by the number of nodes in the ego's network—just as the One-Among-Many Hypothesis predicts. Figure 2a shows this conditional relationship, demonstrating how the relationship between an ego and alter decreases in magnitude with increases in the number of nodes in the ego's two-step network. When the ego has only seven nodes in her network, shifting from an alter who has not been to a party

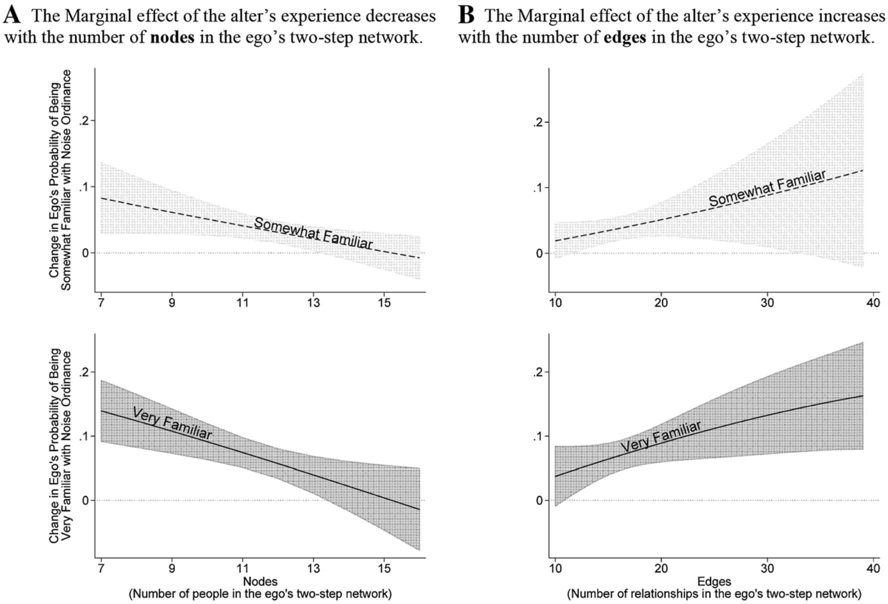

Fig. 2 Marginal effect of the alter's experience. Estimates from Table 2, Model 2. The *lines* plot the marginal effect of whether the alter attended a party cited by police on the probability that the ego is somewhat or very familiar with the noise ordinance. The *shaded regions* indicate 95% confidence intervals. All other covariates are set to their medians for these estimates. When the number of edges is at its median, the number of nodes vary in the data from 7 to 16. We hence constrain **a** to this range. When the number of nodes is at its median, the number of edges vary from 10 to 39 and we constrain **b** to this range. The plot estimates are generated using tools from Long and Freese (2014)

cited by the police to one who has corresponds with a .14 increase in the ego's probability of being somewhat familiar with the noise ordinance and a 0.08 increase in the ego's probability of being very familiar. When the number of nodes exceeds 13, these relationships are no longer statistically significant.

Figure 2b shows how the ego-alter relationship increases in magnitude with the number of edges in the ego's two-step network. Though this interaction is consistent with the Reinforcement Hypothesis, the estimates have too much uncertainty to reject the null. With only ten edges in the network, the alter's experience has no significant relationship with the ego's awareness. At 24 edges, this relationship is moderate in size and statistically significant; a change in the alter's experience corresponds with a 0.11 increase in the ego's probability of being somewhat familiar with the noise ordinance and a 0.07 increase in the ego's probability of being very familiar. At 39 edges, these marginal increases in probability reach 0.16 and 0.13 for being "somewhat" and "very familiar", though the estimate associated with being "very familiar" lacks statistical significance. In sum, these figures suggest students who maintain small, tight-knit friendship networks tend to be most aware of their friends' experiences.

As our theory suggests, individuals with more redundant social networks stand out as particularly sensitive to local issues, but also particularly insulated from them. Table 2 suggests individuals tend to be well attuned to these issues when redundancy equates to having relatively few unique friends, with many overlapping relationships. As Table 1 suggests, however, individuals tend to be less perceptive to these issues when redundancy reduces network centrality, as measured by indegree. Thus paying attention to how we define redundancy—both conceptually and operationally—can pay dividends for the study of political information diffusion.

Second-Order Friends as an Explanatory Variable

Thus far, much like past research, we have considered as covariates only the experiences of a student's five closest friends. We next examine the Second-Order-Friends Hypothesis, exploring what we have missed by ignoring Zone 2 associates. Table 3 presents three regressions with the individual respondent as the unit of analysis, again using an individual's awareness of the noise ordinance as the outcome variable. Model 1 includes only the mean experience of Zone 1 friends. Model 2 introduces as an explanatory variable the experience of Zone 2 friends.[9] Model 3 introduces as controls the network structure covariates studied in the previous tables.

In Table 3, Model 1, the positive coefficient associated with the Zone 1 mean demonstrates that students tend to be more aware of the noise ordinance as more immediate friends encounter experiences with the noise ordinance. This relationship persists in Model 2, where the Zone 2 friends' experiences also exhibit a positive

[9] These means are equal to the number of friends in the zone who state that they have been to a party cited by police for violating the noise ordinance, divided by the number of friends in the zone.

Table 3 Friends' experiences, second-order friends, indegree predict awareness of local issues

	Model 1	Model 2	Model 3
Outcome variable is noise-ordinance awareness			
Threshold 1 ($Y \geq 1$)	1.85*	1.80*	1.16*
	(0.12)	(0.12)	(0.21)
Threshold 2 ($Y \geq 2$)	−0.42*	−0.46*	−1.13*
	(0.09)	(0.10)	(0.20)
Threshold 3 ($Y \geq 3$)	−2.79*	−2.84*	−3.55*
	(0.12)	(0.13)	(0.22)
R attended party cited by police (0 = No; 1 = Yes)	1.02*	0.98*	1.02*
	(0.14)	(0.14)	(0.14)
R's academic year (0 = Freshman; 1 = Sophomore; 2 = Junior; 3 = Senior)	0.27*	0.26*	0.24*
	(0.05)	(0.05)	(0.05)
Zone 1 mean of 'Attended party cited by police'	0.85*	0.72*	0.68*
	(0.18)	(0.19)	(0.19)
Zone 2 mean of 'Attended party cited by police'	–	0.37*	0.42*
	–	(0.19)	(0.19)
Nodes (Number of people in R's two-step network)	–	–	0.03
	–	–	(0.02)
Edges (Number of relationships in R's two-step network)	–	–	−0.00
	–	–	(0.01)
Indegree (Number of students naming R as a friend)	–	–	0.16*
	–	–	(0.05)
Local centrality (Number of two-step neighborhoods where R is most central)	–	–	−0.00
	–	–	(0.04)
N	1403	1403	1403
Pseudo R^2	0.13	0.13	0.15
L.R.	175.55	179.47	212.21

Estimates from ordered logistic regressions. Standard errors in parentheses

* $p < 0.05$ (two-tail)

relationship with the ego's awareness—after controlling for Zone 1 friends' experiences. Thus, including measurement of only Zone 1 friends cannot account fully for the relationships exhibited by these second-order associates.

These relationships remain in Model 3 when controlling for network structure. Using the estimates from Model 3, an individual whose Zone 1 network experience is one standard deviation below the mean has a .51 probability of being somewhat or very familiar with the noise ordinance. This probability increases to 0.61 for individuals whose Zone 1 network's experience is one standard deviation above the mean [First Difference = 0.61 − 0.51 = 0.10; 95% CI (0.04–0.16)]. By comparison, the analogous probabilities are .49 and .56 for individuals one standard deviation below and one standard deviation above the Zone 2 mean [First Difference = 0.07; 95% CI (0.01–0.12)]. These results thus suggest that students' own awareness tends to follow that of their closest friends, but individual awareness also systematically covaries with more distant individuals in the network—as the Second-Order-Friends Hypothesis predicts. Models focusing on only a few close friends would miss this apparent interdependence.

Electoral Participation Results

As a final analysis, we consider the behavioral consequences of these diffusion processes. In Table 4, we regress the validated measure of turnout in the May 2010 municipal election on the measure of noise-ordinance awareness that we used as an outcome measure in Tables 1, 2, and 3. Model 1 of the table includes this measure as well as common individual-level turnout predictors, including validated turnout in the 2009 Virginia gubernatorial election.[10] The model shows a positive coefficient associated with noise-ordinance awareness, suggesting that students who were more aware of the noise ordinance voted at a greater rate. This relationship is not statistically significant, however. Not surprisingly, the single best predictor of participation in 2010 is whether the student participated in the 2009 election. With other variables set to their medians, students abstaining in 2009 had a 0.15 probability of voting in the 2010 election, compared to a 0.65 probability for those who voted in 2009 [First Difference = 0.50; 95% CI (0.43–0.57)].

Table 4, Model 2 introduces as an explanatory variable a measure of Zone 1's mean turnout in the election.[11] This measure produces a large, statistically significant coefficient, but this result presents a simultaneity problem; if main respondents' turnout decisions are influenced by their friends, so too are their friends' decisions influenced by main respondents. We return to this point below. An analysis-of-deviance test suggests that introducing this measure of Zone 1 turnout improves the model fit considerably ($X^2 = 42$; Degrees of Freedom = 1; p value < 0.001). Thus, studies that take interdependence seriously by studying immediate friends can provide additional analytic leverage over the more common atomistic approach.

Table 4, Model 3 introduces the network covariates that can only be captured by moving beyond the first five friends. Both the Zone 1 and Zone 2 coefficients are positive and statistically significant, as is the coefficient associated with respondents' indegree. Setting other variables at their median, a student whose Zone 1 participation was a standard deviation below the mean is predicted to have a .11 probability of voting, compared to a 0.20 probability for students whose Zone 1 participation was a standard deviation above the mean [First Difference = 0.09; 95% CI (0.06–0.13)]. In this case, students embedded in high-participation Zone 1 networks are predicted to vote at almost double the rate as those in low-participation

[10] The other controls are the respondent's interest in national politics ("In general how interested are you in national politics?"), family economic status ("How would you describe your family's economic status?"), and indicators of race and gender.

[11] Zone 1's mean turnout is equal to the number of validated voters in the respondent's Zone 1 network, divided by the total number of friends in Zone 1. An analogous Zone 2 measure is introduced in Table 4, Model 3.

Table 4 Validated turnout as a function of individual attributes and network measures

	Model 1	Model 2	Model 3
Outcome variable is validated turnout in the 2010 municipal election			
Intercept	−1.86*	−2.33*	−3.02*
	(0.38)	(0.40)	(0.46)
R's noise-ordinance awareness (0 = not aware; 1 = not very; 2 = somewhat; 3 = Very)	0.16	0.14	0.08
	(0.09)	(0.09)	(0.10)
R attended party cited by police (0 = No; 1 = Yes)	0.04	0.07	0.15
	(0.17)	(0.17)	(0.18)
R's academic year (0 = freshman; 1 = sophomore; 2 = junior; 3 = senior)	−0.31*	−0.25*	−0.26*
	(0.07)	(0.07)	(0.07)
R's interest in national politics (0 = not at all; 1 = not very; 2 = somewhat; 3 = Very)	0.03	0.03	−0.02
	(0.10)	(0.10)	(0.10)
R validated turnout in the 2009 VA gubernatorial election (0 = No; 1 = Yes)	2.37*	2.30*	2.28*
	(0.17)	(0.18)	(0.18)
R's family economic status	0.08	0.05	0.03
	(0.09)	(0.09)	(0.09)
R is White? (Asian/Latino/other is reference cat.)	0.37	0.37	0.41
	(0.21)	(0.22)	(0.22)
R is Black? (Asian/Latino/other is reference cat.)	−1.52*	−1.35*	−1.28*
	(0.65)	(0.64)	(0.65)
R is female (0 = No; 1 = Yes)	−0.25	−0.20	−0.19
	(0.14)	(0.15)	(0.15)
Zone 1 mean turnout in Williamsburg 2010 election	–	1.96*	1.67*
	–	(0.30)	(0.31)
Zone 2 mean turnout in Williamsburg 2010 election	–	–	1.04*
	–	–	(0.33)
Nodes (Number of people in R's two-step network)	–	–	0.06
	–	–	(0.03)
Edges (Number of relationships in R's two-step network)	–	–	−0.02
	–	–	(0.02)
Indegree (Number of students naming R as a friend)	–	–	0.16*
	–	–	(0.07)
Local centrality (Number of two-step neighborhoods where R is most central)	–	–	−0.05
	–	–	(0.05)
AIC	1343.68	1303.69	1293.40
BIC	1396.37	1361.66	1377.72
Log Likelihood	−661.84	−640.85	−630.70
Deviance	1323.68	1281.69	1261.40
N	1436	1436	1436

Estimates from logistic regressions. Standard errors in parentheses

* $p < 0.05$ (two-tail). Analysis of deviance tests suggest Model 2 provides a significant improvement in fit over Model 1 ($X^2 = 42$; DF = 1; p value < 0.001) and Model 3 provides a significant improvement in fit over Model 2 ($X^2 = 20.3$; DF = 5; p value < 0.001). See Online Appendix D for sensitivity analysis and Online Appendix E for alternative specifications dealing with the simultaneity between the turnout of respondents and their friends

Zone 1 networks. Similarly, setting Zone 2 participation one standard deviation below or above its mean generates predicted probabilities of 0.12 and 0.17 [First Difference = 0.05; 95% CI (0.02–0.10)]—almost a one-third increase in participation rate. Indegree's predictive power is similar in magnitude. Moving from someone one standard deviation below the mean indegree to one standard deviation above the mean changes the predicted probability of voting from 0.12 to 0.18 [First Difference = 0.06; 95% CI (0.01–0.14)]. Thus, even after controlling for the increase in awareness associated with more central individuals, we see further evidence that network structure matters (providing further support for Centrality Hypotheses B).

Not only do these additional network measures exhibit substantively strong relationships, they also improve the model's fit over Model 2 ($X^2 = 20.3$; DF = 5; p value < 0.001). In Online Appendix C, we examine the accuracy of predictions from each model. The analysis suggests that Model 2, which considers just Zone 1 improves predictions over the atomistic approach seen in Model 1. And moving beyond Zone 1 provides modest, but consistent improvement over Model 2. Thus, we stand to gain further traction on individual political behavior when we consider not only immediate friends, but also less immediate associates and network structure.

Are These Relationships Causal?

These results are consistent with social influence, but as discussed above, they may be confounded by latent homophily or shared environments. In Online Appendix D, we therefore subject our results to sensitivity analysis (see VanderWeele 2011) to determine how robust our estimates are to bias created by these or other confounds. The analysis suggests that large levels of bias would be required to explain away the apparent social influence.

In addition to these confounds, the coefficients associated with Zone 1 and Zone 2 may be the product of mutual causality, in which the main respondent's turnout decision both influences, and is influenced by, her friends' turnout decisions. Though the sensitivity analysis allows readers to evaluate how the coefficients would change under different assumptions about this bias, we provide in Online Appendix E two other approaches to address this issue. First, we reestimate the Table 4 models using an instrumental variable approach which purges the influence of the main respondent from the Zone 1 and Zone 2 measures. Second, we apply a spatial regression, which provides a means to account for the interdependence of neighboring observations, where neighbors in our case represent respondents and their friends.

Sensitivity analysis, instrumental variables models, and spatial regressions all lead to sustained support for our theory. Admittedly, each approach requires strong assumptions. Given this challenge, it may be tempting to revert to the discipline's dominant approach, which is to treat individuals' political behavior as disconnected from that of their friends. If social influence exists, however, this atomistic approach requires untenable assumptions too—these assumptions are just less apparent when the theory ignores the interdependence. Thus, given strong theoretical reasons to expect social influence, we believe the best strategy is to be clear about our assumptions, providing as many robustness checks as possible. We leave it to our readers to infer, and future work to explore, what causal processes may be shaping the patterns we have observed.

Conclusion

Our analyses demonstrates that the strength of the relationship between an individual and any one of her friends varies with the attributes of the broader network. Including as an explanatory variable a network average—some political attitude or individual attribute averaged across three to five discussants identified via name-generator—will fail to capture these complicated dynamics. For lack of better measurement, however, even the best recent research on social influence in political attitudes relies on exactly this approach (e.g., Levitan and Visser 2009; Lyons and Sokhey 2014, Sinclair 2012; Sokhey and McClurg 2012). The analyses above suggest this common approach will overestimate the influence of some associates, while overlooking the influence of others. The attributes of individuals and a handful of discussants are not enough to specify the magnitude of this influence. Instead, scholars must also consider the structure of the individual's broader network and the distribution of attributes throughout.

Students of interdependence in politics face formidable obstacles in the analysis of political behavior. Good data are hard to find, and their analysis is often less than straightforward. Moreover, the high quality data on individuals that have become a defining ingredient in political science research places a high bar on social network studies. In order to make significant inroads in political science research, network studies must produce high quality data and analysis on *both* the networks within which individuals are embedded, *as well as* the social and political characteristics of individuals.

Significant advances have been made in the use of name generators, egocentric networks, and snowball surveys, but these studies are limited in their ability to provide the rich measures of networks that are likely to generate continuing progress in establishing the nature of interdependence and social influence in politics. Continuing this progress has never been more important. The key to political analysis is establishing the linkages between macro and micro politics. Unless political analysis can move beyond the micro to address the macro, it will fail to fulfill its mission, and specifying the networks of relations that tie political actors together is a crucial ingredient for integrating micro and macro points of view.

At the same time, this paper makes an implicit case for a continuing dedication to studying the role of the individual in network studies of political behavior. While individual-level studies need to address interdependence and social influence, network studies generate enormous benefits by addressing the crucial role of the individual-level variation within the networks. We have self-consciously focused this paper on improving the measurement quality of the egocentric networks that surround particular individuals.

The payoff to such a commitment comes in our final three tables. It is not simply that individuals depend on other individuals for their awareness of the political world. It is rather that dyadic relations among individuals fundamentally depend on the larger constraints of the network within which these dyads are embedded. Not only is individual behavior autoregressive with respect to the behavior of other individuals, but the influence of one individual on another depends on the other individuals within the network. Hence our analysis adds more evidence in support of the view that network portrayals of individual behavior are, by implication, non-linear with a vengeance.

Compliance with Ethical Standards

Ethical Approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Informed Consent Informed consent was obtained from all individual participants included in the study.

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