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Student Involvement in a Municipal Election

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An enduring issue in the study of political participation is the extent to which political awareness and engagement are socially or individually motivated. We address these issues in the context of a municipal election which generated a high level of political engagement on the part of college students for whom the election was relevant. An effort was made to interview all these students using an on-line survey, and the students were asked to provide information on their friendship networks. The paper demonstrates that awareness and engagement are not simply a consequence of individually defined interests and awareness, but rather that individuals are informed and engaged based on their locations within structured networks of social interaction.

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An enduring issue in the study of political participation is the extent to which political awareness and engagement are socially or individually motivated. An enormous and sophisticated literature has developed focusing on the individual correlates of political participation, most particularly the participatory resources of the individual (Brady et al. 1995), the individual costs of participation (Downs 1957), and the individual level presence of political interest, political efficacy, and other participatory orientations and values (Verba, Burns, and Schlozman 1997). At the same time, another literature focuses on the socially contingent nature of participation and the role of social mobilization in stimulating engagement, either as a consequence of the larger social contexts within which individuals are imbedded (Huckfeldt 1979), or as a consequence of institutionalized voting procedures and policies (Wolfinger and Rosenstone 1980), or as a consequence of social networks and social contacts (McClurg 2003).

This latter literature on the socially contingent basis of individual engagement has developed more slowly, in large part due to methodological and observational challenges that have impeded its progress. 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 challenges confront studies that are aimed at taking interdependence seriously in the study of political participation. This is not to say that progress has not occurred, but rather that the progress comes at a significant price. Rather than simply adding another battery to a survey, further progress depends on rethinking and reconfiguring the basic template for studies of political participation.

We address these issues within the context of student mobilization and activation. In May of 2010, the city of Williamsburg,Virginia held a municipal election with potentially important consequences for students at the College of William and Mary. At least among the members of the William and Mary student body, the city council election campaign revolved around several previously adopted council measures interpreted by many as being directed at William and Mary students. These included a noise ordinance and a limitation of no more than four unrelated individuals within a single dwelling. In response, student groups made concerted efforts to mobilize student interest and involvement in the election, and one William and Mary student ran as a candidate for the city council. This election provides an opportunity to address several issues regarding the social mobilization of political engagement. In particular, how important are individually versus collectively defined interests in mobilizing student awareness? The data we employ in this paper were collected to take advantage of the opportunity to study the process of political mobilization through the networks of association among the students at William and Mary.

Social Networks and Political Mobilization

Prior to the advent of survey data, empirically based accounts of political participation typically focused on the setting in which participation occurred. Tingsten's (1963) classic account of turnout in Stockholm during the early 1930s 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 higher concentrations of 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.

Some, but certainly not all, of these studies pointed toward the importance of social interaction. Tingsten offered two separate and highly plausible accounts of very different 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 socially contingent 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 contingencies 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 patterns of 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, and 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. 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 are less effective at including considerations related to social interaction effects on participation 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 mother lode of new information 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 creates two problems. Not only does it mean that the measurement of social contingencies lag behind the measurement of individual proclivities, but it also means that progress toward a socially contingent view of political participation must take place within the highly developed context of individual level measurement advances.

Within this setting, the efforts of Edward Laumann become particularly important. Lauman's 1966 Detroit Area Study includes an egocentric network battery as part of a survey of white Detroit males (Laumann 1973). His efforts break new ground, providing a model for the simultaneous incorporation of individual level measures with self-report measures on the social networks of respondents. This innovation leads eventually to a new literature on social and political participation through the inclusion of social network batteries within the General Social

Survey series (Marsden 197xx; Burt 19xx), as well as within a series of both U.S. and international election studies (Huckfeldt and Sprague 1995; Huckfeldt, Ikeda, and Pappi 2005; Huckfeldt, Sprague, and Levine 2000), and beginning in 2000, within the National Election Study (Huckfeldt, Johnson, and Sprague 2004).

Hence McClurg (2003) employs one of these studies to argue that social networks produce strong effects on the likelihood of political participation. Significantly, his argument depends on the synergy between individual characteristics and social contingencies. He contends that networks create opportunities for individuals to surpass individually idiosyncratic resource constraints by obtaining information from other individuals. He is able to move beyond the implicit assumption that individual characteristics determine the structure of social networks, showing that network effects are separate and 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 and factors in affecting participation.

Studies such as McClurg's set a high bar for future contributions to the field. His work, as well as other similar work – in the field (Nickerson 2009), in surveys (Mutz 2006), and in the lab (Levitan and Visser 2009) – 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 is not only socially contingent but individually contingent 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.

In this context, Granovetter's (1985) methodological insight regarding the need for specificity of network effects becomes particularly compelling. Social interaction and social influence must be specified and measured, and they cannot be implicitly assumed on the basis of individual characteristics and properties. Just as important, they cannot be boiled down to internalized norms and attitudes on the part of individuals. Rather, the challenge is to understand political participation and mobilization relative to specific forms of social interaction, and hence the methodological challenges become particularly daunting. 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 in this paper.

Opportunities for Enhancing the Measurement of Egocentric Networks

A primary obstacle to progress along these lines lies in the relatively primitive network measures that are produced through the use of survey based network name generators. The typical network name generator produces up to five names of associates, as well as a battery of questions that the respondent answers regarding each of these individuals. In some instances the members of the network can be interviewed as well, thereby providing self-report validation with respect to the main respondent's perception of the network member's characteristics, beliefs, and values. Moreover, if both the ego and alter are interviewed, it is possible to develop reciprocity measures within the ego-alter dyads. Moreover, some relatively indirect measures of network density for the egocentric network can be obtained, at least in principle, based on the main respondent's perception.

Several problems arise with these procedures. First and most important, they provide limited utility in identifying the larger structure of the networks within which individuals reside. Efforts have been made to study network density and reciprocity (Huckfeldt, et al. 1995), as well as to study the implications of second order contacts (Huckfeldt, Johnson, and Sprague 2002), but these efforts have not fully satisfied the aspiration to combine the highest quality individual level measurement with the highest quality network measures.

The question that arises is whether political mobilization can be studied using advanced network measurement procedures within the context of a survey design that fully addresses the individual correlates of political participation. Great progress has been accomplished with studies that attempt to map the networks of a self-contained population that is more or less completely enumerated. The study that we employ is based on a multi-wave panel study employing on-line surveys of individual students. The target population was all William and Mary students, with a response rate on the first pre-election wave of slightly higher than 50 percent, producing 2,711 responses. The target population for the second pre-election wave included all respondents to the first wave, as well as associates of the first wave respondents who were not interviewed at the first wave. This produced a second wave sample of 1912 respondents, based on a response rate of 65 percent. For the third post-election wave, the target population stayed the same, with a response rate of 65 percent producing a sample of 1910 respondents. Nearly 81 percent of second wave respondents were interviewed at the third, post-election wave.

We restrict our analysis to the first wave of the study, during which respondents were asked to provide "the first and last names of up to five of your closest friends who attend William and Mary." Nearly 1400 respondents provided all 5 names. This means that we have relatively complete information on nearly 30 percent of the target population, and by contemporary standards in survey research, these are entirely respectable response rates. The problem is that we are not aiming to accomplish a normal study with a rectangular matrix of survey respondents. Instead, our goal is to conduct a network survey, and such an effort suffers from compounding rates of non-response. If the non-response rate among individual students is the same as the non-response rate among the students' friends, then only about 10 percent of the data on respondents and their networks will be complete. Moreover, only about 3 percent of the respondents will have three rings of complete information – complete information on the ego, all five of the the ego's alters, and all five of the alters' alters.

While these numbers are daunting, it is important that we place them in context. In a traditional survey setting with an ego-centric 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, Beck and Dalton 1998; Huckfeldt, Johnson, and Sprague 2004). In short, missing data problems are pervasive and compounding in network studies.

The Political Problem

The students at William and Mary are differentially affected by the policies toward code enforcement, and hence their awareness of the problem covaries with their own residential experience at William and Mary. As Table 1A shows, students are more likely to be aware of code enforcement to the extent that they are in a higher academic class and to the extent that they live off campus. And as Table 1B shows, their awareness of the problem and their class standing translate into more negative evaluations of the city council, with no effect due their residential status. The lack of any direct effect for residential location is likely due to the fact that it is mediated by class standing. Not only are advanced students more likely to live off campus – less than 1 percent among freshmen, approximately 15 percent among sophomores, 25 percent among juniors, and 30 percent among seniors – but we will see that they are also more likely to have friends who live off campus.

All the dyads in the data set are considered in Table 2. Part A shows that students who live off campus are more likely to have friends who live off campus, and Part B shows that patterns of association are structured by class standing – a large proportion of a the dyads are located within the same academic class. Finally, Part C shows that class standing is also (and unsurprisingly) associated with the likelihood of having friends who live off campus.

In summary, these data seem to suggest that patterns of association may be as important as an individual's own residential location for generating awareness and mobilizing student sentiment.   And the problem to consider is the relative consequences of individual defined interests versus interests that are socially informed.   Indeed, we are already seeing the hints of the social versus individual level mobilization of interests with respect to the issue in Tables 1 and 2.

Centrality among the Students

Our paper is particularly concerned with the structure of social communication regarding these issues. Recent efforts have proposed different models of influence within communication networks.   One set of expectations is that influence would be widespread – a relatively large number of individuals would be locally defined influentials, where localities are defined in terms of small, immediate, relatively compact networks that surround an individual. Another set of expectations is that a relatively small group of individuals would be hyper-influentials, either because a large number of individuals directly rely on them for information, or because they are connected indirectly to a particularly large proportion of the population (Barabási 2002).

These are particularly important issues for the study of democratic politics. One set of expectations leads to a radically democratic vision in which expertise and political leadership is spread broadly through the population. The other set of expectations leads to the vision of a democratic elite – a small group of individuals who play a particularly outsized role in the deliberations of democratic politics. All respondents to the survey were asked to identify their friends, and on that basis we can identify a centrality measure for the campus as a whole – indegree, or the frequency with which students were named as friends by other students. Moreover, the missing data limitations are less daunting in this instance. Again, nearly half of the students responded to the survey, and other students can be named regardless of whether they responded. More than 1800 respondents identify more than 3,900 friends. Ninety-four percent of the identified friends are nominated by 1 to 4 respondents to the survey, and approximately 1 percent are nominated by 7 or more respondents. In short, and as we might expect, a very small percentage of the respondents are identified at relatively high rates, producing a relatively small handful of the hyperconnected when viewed from the standpoint of the network connecting all the students. At the high end, 1 percent of the identified friends, for a total of 40 individuals, are identified between 11 and 15 times.

We can also identify a locally defined network that is centered on each of the respondents to the survey. Unlike the traditional egocentric network, however, 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 5 friends each. In short, as a first step in this direction, we propose to construct network information for each of the main respondents (egos) that includes as many as 5 of the first ring contacts and 25 second ring contacts.[1]

This provides an opportunity to define centrality both locally and globally. The distribution for global centrality is displayed in Part A of Table 3, where we see that the range of nominations as a friend varies from 1 to 15 for the individuals who have been nominated. In contrast, we can define individuals as being central who are most frequently named as friends within locally defined networks, and Part B shows that 15 percent of respondents are identified as being central in more than one locally defined network.

Finally, Part C of Table 3 shows the relationship between local centrality and global centrality among the main respondents. Not surprisingly, the relationship is strong, but the measures appear to tap different dimensions of centrality among respondents.

The Local Networks

We display two of the locally defined networks as directed graphs. One of the networks (Figure 1a) is characterized by high levels of connectedness and thus redundancy within the network, while the other (Figure 1b) is characterized by low levels of connectedness.

In the high density case, we see that the network is characterized by a large number of bi-directional edges – indicating that both individuals in a dyad reported the other as a discussant – and relatively few individuals only connected to the network by one tie. The first "zone" of the network – the particular individuals that the ego named as discussants – shows an especially high level of interconnectedness. Each of the ego's alters in zone one was named as a discussant by at

[1] We do not include information taken from the interviews of the second zone friends for the simple reason that it would compound our missing data problems. Hence we ientify directed edges toward (but not from) the second zone friends, and we are underestimating network densities accordingly. The dyadic reciprocity rate is .65 for the study.

least one of the other alters in question, and each one of the ego's alters named the ego as well. There is an individual in the second "zone" of the network that was named by three of the ego's alters. This high density pattern of ties leads to a network with only 15 unique individuals, despite the fact that this ego-centric 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 is characterized by a much more obvious clustering of the network by the ego's alters and very few bi-directional edges. Only a handful of individuals in the network were named by more than one other individual in the network. Only two of the ego's alters named the ego as a discussant, and only one alter in the first zone was named by another alter in the first zone (a naming that was not reciprocated). This leads to a total of 27 unique individuals, despite the fact that the network is also complete and has the same number of directed edges (30) as the high-density network.

The quartiles for the count of ties, the number of unique individuals (not including the main respondent), and the number of redundant ties are displayed in Table 4 for main respondents with non-missing data on at least three first order friends. Part A shows that the median number of relationships is 3, with a maximum of 30, and quartile cutoffs of 10, 15, and 20 relationships. Part B shows that the number of unique individuals varies from 3 to 27, with quartile cutoffs of 8, 11, and 14. Finally, if we subtract the number of unique ties from the count of relationships, we arrive at a count of redundant relationships, where the range is from 0 to 24, with quartile cutoffs of 1, 3, and 6. We refer to these as redundant ties because they intensify communication within the locally defined network, but they limit the communication of information from beyond the locally defined network.

The simple regressions between each pairing of the three local networks properties are shown in Parts D, C, and E. Networks with higher counts of unique individuals also tend to include higher levels of redundancy because both are driven by the number of relationships within the network. Hence, in further analyses, we take simultaneous account of the number of unique nodes as well as the total number of identified relationships. At the same time, some individuals end up with more or less of one or the other. Some individuals are located in very densely connected networks with relatively few friends, while other individuals are located in local networks with a high count of individuals but where relatively few name more than one other individual in the network as a friend.

Hence, our examination of density and centrality gives rise to an important question. What are the consequences of network density and individual centrality for the diffusion of awareness among students regarding code enforcement in the city of Williamsburg?

Centrality, Network Density, and the Diffusion of Awareness

The effects of network centrality and density on awareness regarding code enforcement are shown in Table 5. As before, respondents who live off campus are more likely to be aware, as are respondents who are members of more advanced academic classes – seniors as opposed to juniors, juniors as opposed to sophmores, etc. There is no evidence to suggest that locally defined centrality has any effect on awareness, but there is a marginally discernible effect of centrality in the larger network – higher levels of centrality may translate into higher levels of awareness. Finally, we see that locally defined networks with lower density levels (relatively fewer edges, or more unique friends) are related to higher levels of awareness. In short, there is at least some evidence to suggest that individuals with more friends are more likely to be aware of code enforcement, and that individuals in lower density networks are more likely to be aware.

Figure 2 displays how students' exposure to the noise ordinance permeates through the network. The shading of the node indicates the student's self-reported degree of exposure to the noise ordinance. At one extreme, black nodes are those students who have never been to a party where the police issued a citation for violating the noise ordinance, do not know anyone who has been cited, and have never heard of anyone being cited. At the other extreme, bright red nodes are students who have been to such a party and personally know others who have been cited. The figure demonstrates that awareness of exposure to the ordinance is social, but social awareness diminishes quickly across ties. Students recognize when their friends have been exposed, but are less likely to recognize the exposure of friends of friends. These effects are most obvious looking at clusters on the periphery of the network. Cluster A, for example, features a student who has been at a party where the police issued a citation for the noise violation. Her immediate friend has not been to such a party, but recognizes that he knows personally someone who has. Yet, his friend cannot recall having heard of anyone who has. Thus, social experiences may require reinforcement to spread across the network.

A related implication of Figure 2 is that the dense and relatively homogenous networks depicted in Figure 1A may serve to insulate members from recognition of the experiences of others, while the more diffuse networks (e.g., Figure 1B) encourage the transmission of experience. Clusters B and C demonstrate this point. Cluster B is a group who have not been to a party featuring a citation and are unaware of others who have, despite the fact that one member is in a reciprocal relationship with someone who has been to such a party. Thus, the perceptions of the network may insulate members from recognition of discordant experiences. The more central students in the middle of the figure (Cluster C), on the other hand, are quite aware of their compatriot's exposure to the ordinance, even though many have not been to a party featuring a citation themselves. Thus, networks with many bridges and relatively few redundant ties sustain the transmission of colleagues' exposure to the ordinance (Burt 1987).

Implications for the Communication of Awareness

Figure 2 suggests a model of social influence in which any given student's awareness of exposure to the ordinance depends on the experiences of his or her network. Moreover, the experience of the locally defined network conditions the influence of individual friends' experiences. This process resembles an autoregressive model of influence where the influence of individual bits of information is weighted by their deviation from the whole of accumulated information (Huckfeldt, Johnson, and Sprague 2004; McPhee 1963).

Table 6 tests this model empirically, using a series of logistic regressions, with the dyad as the unit of analysis. The response variable is whether the ego recognizes that he or she knows someone personally who police have cited for violating the noise ordinance. Part A considers only the influence of the experience of the alter and the other friends identified by the ego, while Part B incorporates the experience friends of friends (the "Zone 2" network). Model 1 of part A demonstrates that the experience of the ego's immediate friends can transmit awareness to the ego. The model suggests that the ego will be 1.6 times more likely to be aware of their friends' exposure to the noise ordinance if the alter has been directly exposed. Interestingly, if the alter simply knows someone who has been exposed without being exposed directly, the ego is also about 1.6 times more likely to be aware. Importantly, these effects are independent of the ego's self-exposure to the ordinance *and* the exposure of the ego's other friends.[2] Thus, individual alters are not acting as a proxy for the experience of the network more generally. The zone 1

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[2] The model controls for the zone 1 network by including the mean response of all friends, *excluding the alter in the dyad*. Thus the variables range from zero, indicating that no other friends in the network have been exposed, to one, indicating all other friends have been exposed.

network has its own independent effect as well, which exceeds the impact of the alter. Moreover, the network acts indirectly to condition the influence of any single alter.

Model 2 of part A interacts the alter's experience with the alter's deviation from the mean of the network.[3] The negative coefficients (each more than three times the size of its standard errors) suggest that the influence of the alter diminishes as it diverges from the experience of the micro-network. Thus, individual social experiences need reinforcement to permeate through the network. Students who know only a single student impacted by the ordinance are unlikely to be moved that friend's experience, but as more friends are impacted, the influence of each of these experiences increases.

One fear from the analysis in part A is that the observed effects are not effects of the micro-context, but are instead proxies for the greater social context. Model 1 of part B tests this possibility by including the experience of friends of friends (the zone 2 network).[4] The effects of the alter and the zone 1 network remain in model 1 of part B. The direct experience of the zone 2 network also has an independent effect on the ego's awareness, but the experience of the zone 2 network's friends has no significant influence. The results suggest that students' experiences permeate two steps across the network. If one student is at a party that violates the ordinance, the students friends are more likely to be aware of this experience and the friends of the friends are also more likely to be aware. Yet, if this student only knows someone who has been cited, their friends will be more likely to be aware, but this knowledge will have no impact on the friends of friends.

Model 2 of part B pools the zone 1 and zone 2 networks to determine if the broader locally defined network conditions the influence of individual alters. We again see general support for

[3] The network means themselves cannot be included in this model due to collinearity.
[4] In measuring the zone 2 network means, we exclude the ego as well as any zone 1 members.

the autoregressive model, with negative coefficients on each of the interactions between the alter's experience and the network mean.

The implications of the Table 6 models are best seen by using the logit models to generate predicted probabilities across relevant variation in explanatory conditions. Table 7 uses this procedure to address the second model in Part A of the Table 6. As this table shows, the effect of a dyadic friendship is contingent on the distribution in the remainder of the friendship network. A friend's effect is magnified when this friend's message to the respondent is reinforced by the other members of the network. The friend's effect is diminished when the message is contrary to other messages being received by the respondent. The fact that dyadic flows of information and influence are contingent on the larger network is an important result, and we will return to it again in the conclusion.

Conclusion

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 imbedded, ***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 contingencies in politics. The importance of 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 in integrating micro and macro points of view.

At the same time, this paper makes an implicit case for a continuing dedication to methodological individualism in network studies of political behavior. While individual level studies need to address interdependence and social contingencies, 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 the analysis of Table 7. 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 imbedded. Not only is individual behavior autoregressive with respect to the behavior of other individuals, but the influence of one individual on another depends on all the other individuals within these individual's networks. Hence this analysis adds more evidence in support of the view that network portrayals of individual behavior are, by implication, non-linear with a vengeance.

References

Barabási, Albert-László. 2002. Linked: How Everything Is Connected to Everything Else and What it Means for Business, Science, and Everyday Life. New York: Penguin.

Bernard F. Berelson, Paul F. Lazarsfeld, and William N. McPhee. 1954. Voting. Chicago: University of Chicago Press.

Henry E. Brady, Sidney Verba and Kay Lehman Schlozman. 1995. "Beyond SES: A Resource Model of Political Participation," The American Political Science Review 89: 271-294.

Burt, Ronald S. 1995. *Structural Holes: The Social Structure of Competition*. Harvard University Press.

Anthony Downs. 1957. An Economic Theory of Democracy. New York: Harper.

Ronald S. Burt. 1986. "A Note on Sociometric Order in the General Social Survey Network Data," Social Networks 8: 149-174.

Mark Granovetter. 1973. "The Strength of Weak Ties," American Journal of Sociology 78: 1360-1380.

Mark Granovetter. 1985. "Economic Action and Social Structure: The Problem of Embeddedness," American Journal of Sociology 91: 481-510.

Robert Huckfeldt. 1979. "Political Participation and the Neighborhood Social Context," American Journal of Political Science 23: 579-592

Robert Huckfeldt. 1983. "Social Contexts, Social Networks, and Urban Neighborhoods: Environmental Constraints on Friendship Choice," American Journal of Sociology 89: 651-669.

Robert Huckfeldt and John Sprague. 1995. Citizens, Politics, and Social Communication. New York: Cambridge University Press.

Robert Huckfeldt, Paul A. Beck, Russell J. Dalton, Jeffrey Levine, and William Morgan. 1998. "Ambiguity, Distorted Messages, and Nested Environmental Effects on Political Communication," Journal of Politics 60: 996-1030.

Robert Huckfeldt, John Sprague, and Jeffrey Levine. 2000. The Dynamics of Collective Deliberation in the 1996 Election: Campaign Effects on Accessibility, Certainty, and Accuracy, American Political Science Review 94: 641-651.

Robert Huckfeldt, Paul E. Johnson, and John Sprague. 2004. Political Disagreement: The Survival of Diverse Opinions within Communication Networks. New York: Cambridge University Press.

Robert Huckfeldt, Ken'ichi Ikeda, and Franz Pappi. 2005. "Patterns of Disagreement in Democratic Politics: Comparing Germany, Japan, and the United States," American Journal of Political Science 49: 497-514.

V.O. Key, Jr. with Alexander Heard. 1949. Southern Politics. New York: Knopf.

Edward O. Laumann. 1973. Bonds of Pluralism. New York: Wiley.

Kenneth P. Langton and Ronald Rapoport. 1975. "Social Structure, Social Context, and Partisan Mobilization: Urban Workers in Chile," Comparative Political Studies 8: 318-344.

Paul F. Lazarsfeld, Bernard F. Berelson, and Hazel Gaudet. 1948. The People's Choice. New York: Columbia University Press.

Lindsey C. Levitan and Penny S. Visser. 2008. The impact of the social context on resistance to persuasion: Effortful versus effortless responses to counter-attitudinal information. Journal of Experimental Social Psychology, 44(3), 640-649.

Donald R. Matthews and James W. Prothro. 1963. "Social and Economic Factors and Negro Voter Registration in the South," American Political Science Review 57: 24-44.

Peter V. Marsden. 1987. "Core Discussion Networks of Americans," American Sociological Review 52: 122-131.

Scott D. McClurg. 2003. "Social Networks and Political Participation: The Role of Social Interaction in Explaining Political Participation," Political Research Quarterly 56: 448-465.

McPhee, William N. with Robert B. Smith and Jack Ferguson. 1963. *A Theory of Informal Social Influence. In William N. McPhee, Formal Theories of Mass Behavior*. New York: Free Press. 1963.

Diana C. Mutz. 2006. Hearing the Other Side: Deliberative versus Participatory Democracy. New York: Cambridge University Press.

David Nickerson. 2008. Is Voting Contagious? Evidence from Two Field Experiments," American Political Science Review 102: 49-57.

Herbert Tingsten. 1963. Political Behavior: Studies in Election Statistics. Translated by V. Hammarling. Totowa, N.J.: Bedminster. Originally published in 1937.

Sidney Verba, Nancy Burns, and Kay Lehman Schlozman. 1997. "Knowing and Caring about Politics: Gender and Political Engagement," Journal of Politics 59: 1051-1072.

Raymond E. Wolfinger and Steven J. Rosenstone. 1980. Who Votes? New Haven: Yale.

Table 1. Individual correlates of awareness regarding code enforcement and evaluations of the Williamsburg city council.

A. Awareness of code enforcement by academic year in school and residence.

	Coefficient	s.e.	t-value	
academic year	-.43	.03	14.80	N=2470 respondents
off campus	-.45	.08	5.72	R^2=.12
constant	3.87	.08	50.90	s.e. of estimate=1.52

B. Evaluation of city council by awareness of code enforcement, year in school, and residence.

	Coefficient	s.e.	t-value	
awareness	-.23	.02	-13.04	N=2203 respondents
academic year	.12	.03	4.39	R^2= .11
off campus	.03	.07	0.37	s.e. of estimate= 1.26
constant	4.87	.10	50.57	

Awareness=number of affirmative answers to the following questions: Been at party where someone was cited for noise? Know anyone who has been cited for noise? Heard of anyone who has been cited for noise? You or anyone you know been cited for violating the three or four person rule for unrelated individuals in dwelling? Heard of anyone who has been cited? Range is 0-5.

Academic year: 1=freshman, 2=sophomore, 3=junior, 4=senior.

Off campus: 1 if the main respondent lives off campus, 0 otherwise

City council evaluation: range from xx (negative) to xx (positive)

Table 2. Characteristics of main respondents and friends.

A. Off campus versus on campus.

Friend	Main respondent: On-campus	Main respondent: Off-campus	Total
On-campus	85.19	48.59	77.77
Off-campus	14.81	51.41	22.23
N=	3,356	854	4,210 dyads (1406 main respondents)

B. Year in school.

Friend's Year	Main respondent's year: freshman	sophomore	junior	senior	Total
Freshman	86.61	4.76	1.37	1.71	21.93
Sophomore	8.43	75.70	11.92	6.11	27.07
Junior	2.77	13.51	69.62	17.47	26.11
Senior	2.19	6.03	17.09	74.71	24.89
Total	866	1,029	948	933	3,776 dyads (1334 main respondents)

C. Residence of friend by class of main respondent.

Friend's residence	Main respondent class: freshman	sophomore	junior	senior	Total
on campus	93.56	81.03	72.43	66.53	78.01
off campus	6.44	18.97	27.57	33.47	21.99
Total	901	1,086	1,030	1,007	4,024 (1343 main respondents)

Table 3. Centrality within the student body, centrality within local networks, and the relationship between the two.

A. Centrality within the student body. Total number of mentions per respondent.

indegree	percent	cumulative
1	20.6	20.6
2	25.2	45.8
3	22.8	68.7
4	16.7	85.4
5	7.6	93.0
6	4.4	97.4
7	1.5	98.9
8	0.4	99.2
9	0.4	99.6
11	0.1	99.8
14	0.1	99.9
15	0.1	100.0
N=	801	

B. Centrality within locally defined networks: the number of locally defined networks in which the respondent is named most frequently.

number	percent	cumulative
1	84.39	84.4
2	11.74	96.1
3	2.87	99.0
4	0.62	99.6
5	0.25	99.9
6	0.12	100.0
N=	801	

C. Centrality within locally defined networks by centrality within the student body.

	coefficient	s.e.	t-value
Slope	.14	.01	13.25
Constant	.79	.04	21.94

N= 801
R^2= .18
s.e. of estimate = .51

Table 4. Quartiles for total count as well as redundant ties and unique nodes within locally defined networks, and the relationship between the two. For respondents with nonmissing data on at least 3 first order friends.

A. Count – number of relationships (edges)
- Minimum=3
- First quartile=10
- Second quartile=15
- Third quartile=20
- Maximum=30

C. Unique individuals
- Minimum=3
- First quartile=8
- Second quartile=11
- Third quartile=14
- Maximum=26

B. Redundant ties
- Minimum=0
- First quartile=1
- Second quartile=3
- Third quartile=6
- Maximum=27

D. Redundancy by uniqueness.

	coefficient	Std. Err.	t-value	N	R^2	s.e. of est.
slope	.12	.03	4.12	862	.02	3.59
constant	2.65	.34	7.68			

E. Redundancy by count.

	coefficient	Std. Err.	t-value	N	R^2	s.e. of est.
slope	.42	.01	28.73	862	.49	2.59
constant	-2.51	.24	10.36			

F. Uniqueness by count.

	coefficient	Std. Err.	t-value	N	R^2	s.e. of est.
slope	.58	.01	39.76	862	.65	2.59
constant	2.51	.14	10.36			

Table 5. Awareness by density and centrality.

A. Awareness by number of unique friends and number of identified friends within respondent's local network, for all respondents and for those who live on campus.

	All main respondents			On-campus respondents		
	coefficient	s.e.	t-value	coefficient	s.e.	t-value
Unique friends	.04	.02	1.94	.04	.02	2.17
Identified friends	-.03	.02	1.91	-.03	.02	2.10
Respondent lives off campus	.79	.16	4.83			
Academic class	.45	.06	7.96	.46	.06	7.84
Constant	1.18	.25	4.74	1.17	.26	4.54
N=		529			444	
R^2=		.20			.14	
s.e. of estimate=		1.32			1.31	

B. Awareness by density of local network and centrality of main respondent.

	coefficient	s.e.	t-value
Respondent lives off campus	.80	.16	4.87
Academic class	.44	.06	7.79
In-degree (entire network)	.07	.04	1.69
Unique friends (local net)	.05	.02	2.39
Centrality in local networks	.02	.10	0.17
Number of relationships (local net)	-.05	.02	-2.62
_cons	1.10	.27	4.11
N=		529	
R^2=		.21	
s.e. of estimate=		.13	

Table 6. Autoregressive influence in social awareness of noise ordinance enforcement. Logistic regressions with errors clustered on ego. Outcome variable: Ego awareness that someone he/she knows was cited by police for violating noise ordinance.

A. Zone 1 network: discussants named by ego.

	MODEL 1		MODEL 2	
	coefficient	SE	coefficient	SE
Intercept	-2.0	0.13	-2.0	0.14
E Attend	2.3	0.19	2.3	0.19
A Attend	0.5	0.11	1.1	0.40
A Knows	0.5	0.10	1.6	0.33
Z1 Attend mean	0.8	0.24		
Z1 Knows mean	1.0	0.22		
A Attend deviation from Z1 Attend mean			1.0	0.28
A Knows deviation from Z1 Knows mean			0.9	0.26
A Attend X deviation from Z1 Attend mean			-1.5	0.50
A Knows X deviation from Z1 Knows mean			-2.1	0.44
N =	3551 (1185 clusters)			
Log pseudolikelihood =	-1672.9		-1671.6	

B. Zones 1 and 2 network: discussants named by ego and their discussants.

	MODEL 1		MODEL 2	
	coefficient	SE	coefficient	SE
Intercept	-2.4	0.20	-2.4	0.22
E Attend	2.7	0.28	2.7	0.28
A Attend	0.3	0.17	2.5	0.68
A Knows	0.6	0.15	1.3	0.57
Z1 Attend mean	0.6	0.37		
Z1 Knows mean	1.2	0.32		
Z2 Attend mean	1.9	0.40		
Z2 Knows mean	-0.5	0.39		
A Attend deviation from Z1Z2 Attend mean			2.7	0.59
A Knows deviation from Z1Z2 Knows mean			0.8	0.51
A Attend X deviation from Z1Z2 Attend mean			-4.7	1.03
A Knows X deviation from Z1Z2 Knows mean			-1.5	0.91
N =	2036 (646 clusters)			
Log pseudolikelihood =	-886.0		-900.4	

E = ego
A = alter
Z1 = Zone 1 network (discussants named by Ego)
Z2= Zone 2 network (discussants named by Ego's Zone 1 network)
Z1Z2= Zone 1 and Zone 2 networks combined

Attend = attended party where police issued citation for violating noise ordinance
Knows = personally knows someone who was cited by police for violating noise ordinance

Table 7. Predicted probability that ego reports being aware that someone he/she knows was cited by police for violating noise ordinance.[a]

Proportion of Zone 1 Friends knowing someone who had been cited[b]	Friend in dyad does ***not*** know someone cited (A knows = 0)	Friend in dyad ***does*** know someone cited (A knows = 1)	Effect of friend in dyad (Δ)
0	.27	.35	.08
.25	.32	.43	.11
.50	.37	.50	.13
.75	.42	.57	.15
1.0	.48	.65	.17

a. Based on estimates from Model 2 in Table 6A. ***E Attend*** is held constant at 0. ***A Attend*** is held constant at 0. ***Z1 Attend Mean*** is held constant at 0.

b. Calculation of proportion omits the friend in the dyad.Figure 1a. High Density Network

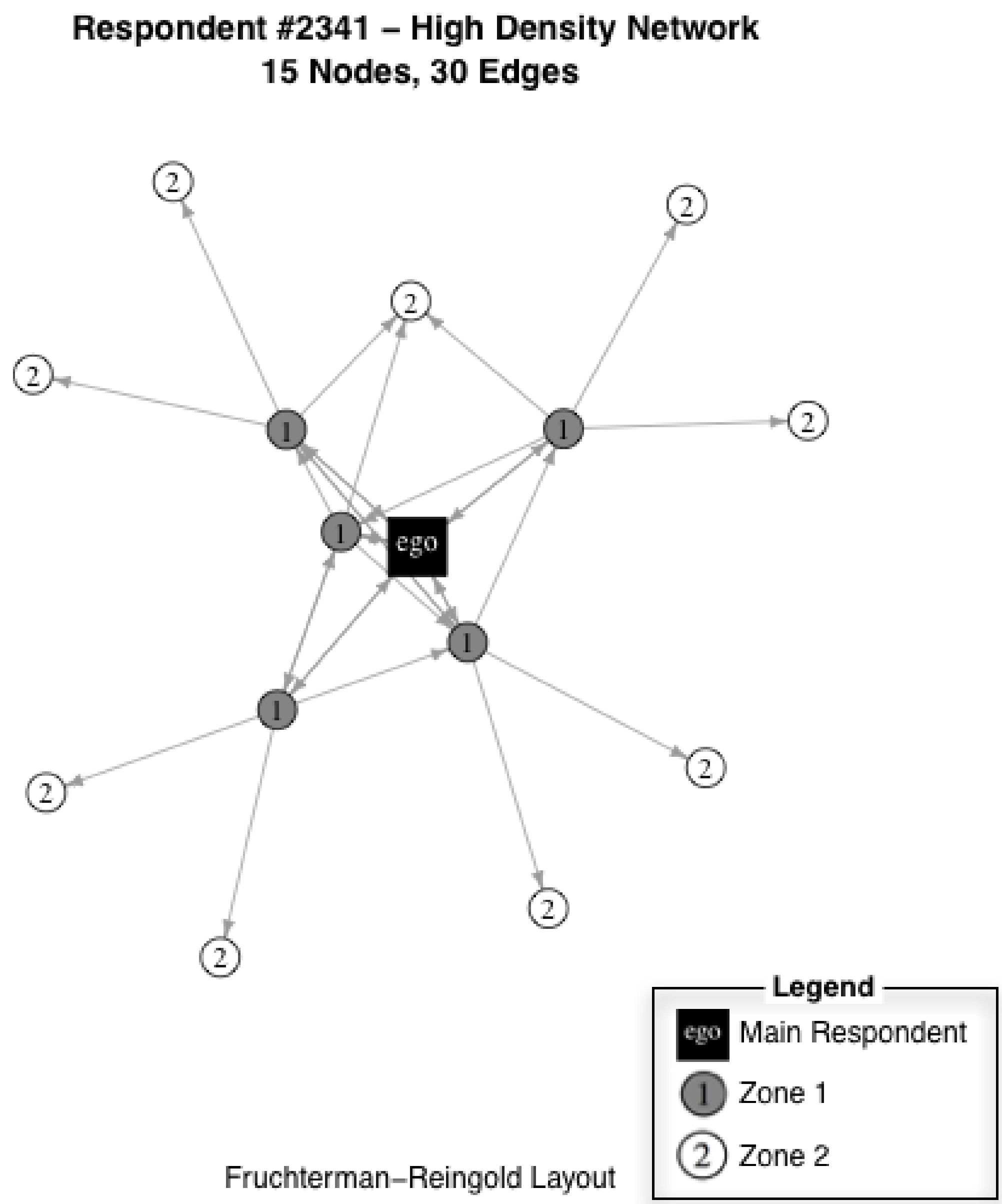


Figure 1b. Low Density Network.

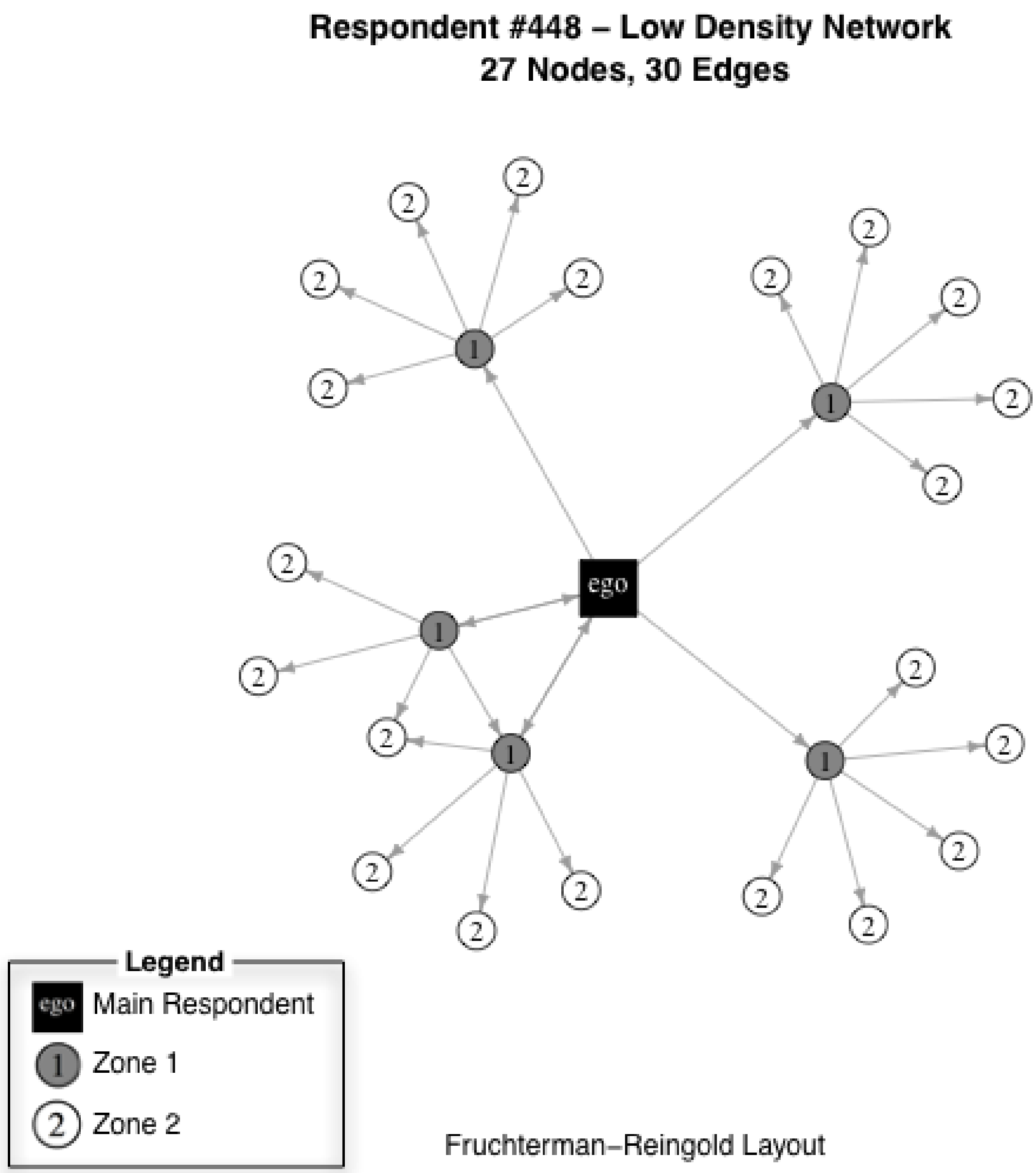
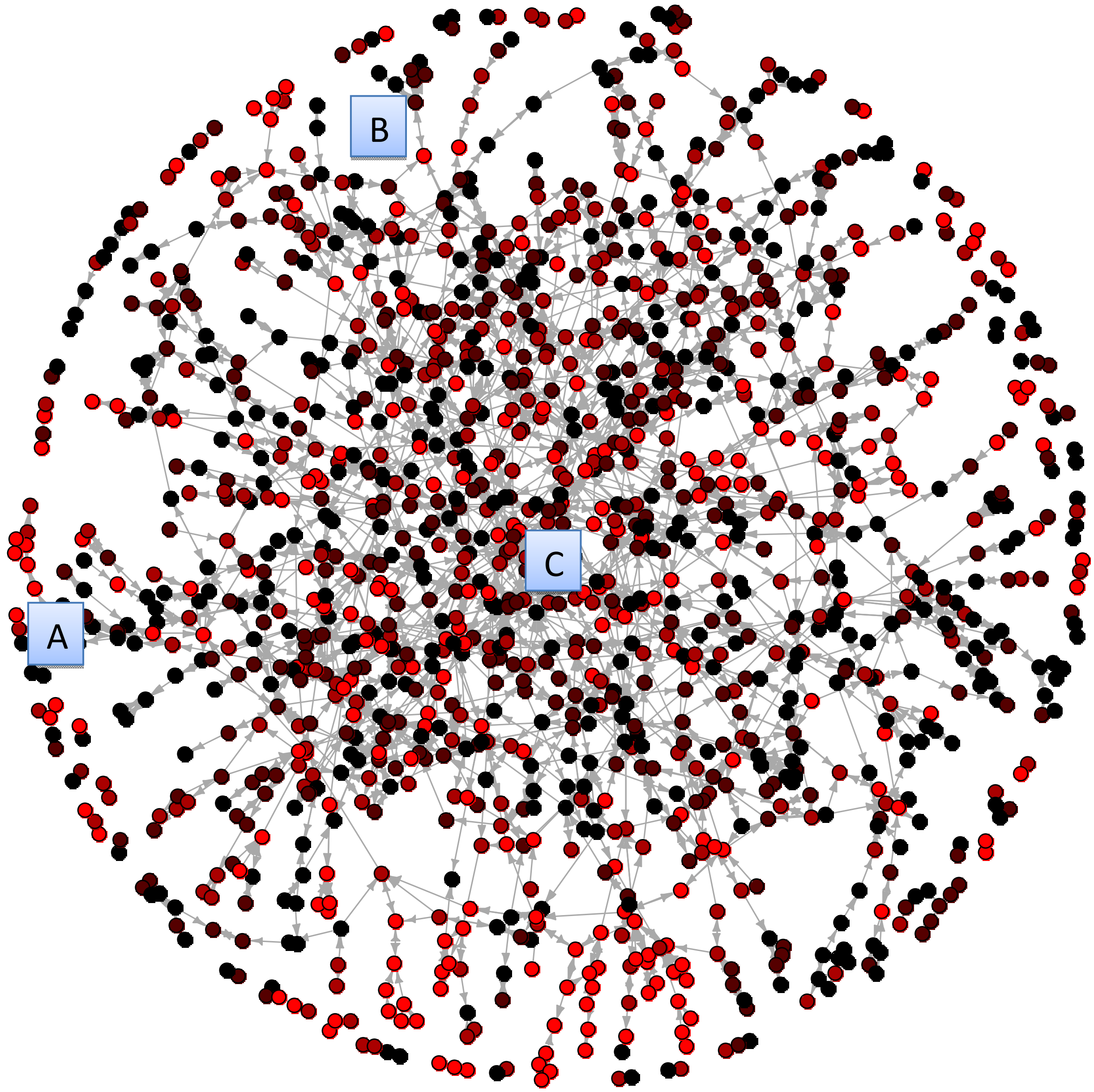

Respondent #448 – Low Density Network
27 Nodes, 30 Edges
ego
Legend
ego Main Respondent
1 Zone 1
2 Zone 2
Fruchterman–Reingold Layout

Figure 2. Diffusion of awareness of exposure to noise ordinance.



NOTE: Color shows self-reported awareness of exposure to noise ordinance. Bright red nodes are those students who are maximally aware (i.e., have been to a party that was cited by police for violation and personally know others who have been cited) and black nodes are those students who are minimally aware (i.e., have never been to a party that was cited by police for violation and have not heard of others who were cited).