Turnout in a Small World

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Abstract
This paper investigates between-voter interactions in a social network model of turnout. It shows that if 1) there is a small probability that voters imitate the behavior of one of their acquaintances, and 2) individuals are closely connected to others in a population (the "small-world" effect), then a single voting decision may affect dozens of other voters in a "turnout cascade." If people tend to be ideologically similar to other people they are connected to, then these turnout cascades will produce net favorable results for their favorite candidate. By changing more than one vote with one's own turnout decision, the turnout incentive is thus substantially larger than previously thought. We analyze conditions that are favorable to turnout cascades and show that the effect is consistent with real social network data from Huckfeldt and Sprague's South Bend and Indianapolis-St. Louis election surveys. We also suggest that turnout cascades may help explain over-reporting of turnout and the ubiquitous belief in a duty to vote.

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How does the turnout decision of a single person affect an election? Decision-theoretic models of voting show that the probability of one vote being "pivotal" in a large electorate is extremely small (Tullock 1967; Riker and Ordeshook 1968; Beck 1974; Ferejohn and Fiorina 1974; Fischer 1999; Fowler and Smirnov 2007). Empirical models use election returns to confirm this finding (Gelman, King, and Boscardin 1998; Mulligan and Hunter 2001). Because the number of individuals in modern electorates is quite large and interactions between individuals are complex and unobserved, these models of turnout assume that voters are *independent* of one another. In other words, a single decision to vote affects no other decisions to vote in the electorate.

Game-theoretic models relax the independence assumption, showing that strategic interaction can play a significant role in the decision to vote (Ledyard 1982, 1984; Palfrey and Rosenthal 1983, 1985). However, turnout in these models is typically quite low because the cost of voting (gathering and processing information, waiting in line at the polls, and so on) induces most people to free ride on the efforts of a handful of voters. In equilibrium, the impact of an extra person voting is to *reduce* the incentive for others to vote.

This contrasts with a growing body of empirical evidence suggesting that a single decision to vote *increases* the likelihood that others will vote. Turnout is highly correlated between friends, family, and co-workers even when controlling for socioeconomic status and selection effects (Lazarsfeld et al 1944; Berelson et al 1954; Campbell et al 1954; Glaser 1959; Huckfeldt and Sprague 1995; Straits 1990; Knack 1992; Kenny 1992, 1993; Mutz and Mondak 1998; Beck et al 2002). This literature illustrates the importance of social interactions for political activity (see Zuckerman in this volume), but unlike the other literatures on voting it does not consider the impact of these interactions on aggregate turnout, election results, or the incentive to vote.

This article bridges the gap between these literatures by exploring the impact of a single decision to vote on a socially connected electorate. If people choose whether or not to vote in part based on the turnout decisions of their friends and acquaintances, then a single person may affect not only her acquaintances, but her acquaintances' acquaintances, her acquaintances' acquaintances' acquaintances, and so on throughout the population. Depending on characteristics of the social network, even a small conditional correlation between acquaintances can cause a chain reaction that leads to large aggregate changes in turnout. I call this chain reaction a *turnout cascade*.

Several features of real world social networks might affect the size of a turnout cascade. In particular, I am interested in the *small world* property. This is the idea that in spite of the large size of most social networks, people can connect themselves to one another through a very small number of intermediaries. Using a small world network, I develop a model of turnout that suggests a single person's decision to vote can affect the turnout decision of several other people. Moreover, this increase in turnout tends to benefit the candidate preferred by the person initiating a turnout cascade because of the high concentration of shared interests between acquaintances in real political discussion networks. Therefore *the incentive to vote is larger than previously thought*. This incentive is increasing in several features of the social network that have elsewhere been shown to yield increases in turnout. For example, it is increasing in the number of interactions with people who vote (Ansolabehere and Snyder 2000; Gerber and Green 1999, 2000a, 2000b; Brown et al 1999; Gray and Caul 2000; Radcliff 2001; and Radcliff and Davis 2000), the clustering of social ties (Cox et al 1998; Monroe 1977), and the concentration of shared interests (Busch and Reinhardt 2000). It might help to explain the "duty to vote" norm expressed by many and it implies a paradox of (not lying about) voting that I explore in the summary.

The model also predicts a feature of individual level turnout that has previously gone unnoticed. People with a mix of "strong" ties to people in their social clique and "weak" ties to people outside their clique (Granovetter 1973) can initiate larger turnout cascades than people with all weak or all strong ties. Thus, they have a greater incentive to vote and to influence others to do the same. Data from Huckfeldt and Sprague's Indianapolis-St. Louis Election Study (ISLES) confirms this effect on both turnout and the likelihood that an individual tries to influence an acquaintance. This finding has important implications for the literature on social capital (e.g. Putnam 2000) because it suggests that increasing the density of social networks helps encourage civic engagement up to a point, but if they are too dense then civic engagement may actually decline.

This article proceeds as follows. I identify several important characteristics of large-scale social networks and describe a model developed by Watts and Strogatz (1998) that features these characteristics. This is used to place voters in a small world model of turnout in which people have a small chance of influencing the voting behavior of their acquaintances. I then measure characteristics of real political discussion networks from Huckfeldt and Sprague's ISLES and the South Bend Election Study (SBES) in order to define features of the model so that I can generate a realistic estimate of the size of turnout cascades. I report the results of the model when it is tuned to look like the network implied by the ISLES and I also study the impact of changes in social network characteristics on turnout. Individual-level data from the model is then used to show that the density of relationships among one's acquaintances has a curvilinear impact on turnout cascades and therefore the incentive to vote. This prediction is confirmed by empirical models of turnout and influence in the ISLES. Finally, I reflect on the importance of turnout cascades for revising traditional models of voting and summarize the results with implications for future research.

Large Scale Social Networks

Watts and Strogatz (1998) identify three main features of real large-scale social networks that should be captured in any attempt to model them. First, these networks tend to be *sparse*, with an average *degree* (the number of ties a person has to other people in the network) that is much smaller than the *size* (the number of people) of the network. Second, social connections are highly *clustered*. That is, people tend to form ties in tightly-nit cliques in which everyone is tied to everyone else. The *clustering coefficient* is a measure of this property, giving the probability that any two individuals to which a person is tied also have a tie between them (in other words, how likely is it that your friend's friend is also your friend?) Third, large-scale social networks tend to exhibit the *small world* phenomenon. In spite of the large number of people in the network, there is a relatively short *average path length* connecting any two people through intermediaries.

Computer databases have recently made it possible to confirm that a wide variety of large-scale social networks are sparse, clustered, and have low average path lengths. For example, Newman (2001a,b,c) and Barabasi et al (2001) show that academic co-authorship networks in a wide variety of disciplines are sparse, clustered, and have low average path lengths. Newman, et al. (2002) also document these properties for company directors of the Fortune 1000 and Hollywood movie actors (see also Watts and Strogatz 1998).

Though networks of academics and actors are suggestive of what a network relevant for turnout would look like, there is no guarantee that they would necessarily exhibit the same features. Fortunately, several studies of *political discussion networks* have been conducted in recent years that might help us to estimate these features. In particular, Huckfeldt and Sprague's Indianapolis-St. Louis Election Study (ISLES) and South Bend Election Study (SBES) ask typical questions about political attitudes and behavior, but they also ask respondents to name people with whom they discuss politics. These "discussants" are then contacted to take the same survey (called a "snowball" survey). Though surveys like these do not provide a fully connected map of everyone in the network and how they are tied to everyone else, statistical information about their relationships and activities can be used to estimate properties of the large-scale political discussion network.

The Watts-Strogatz (WS) Model

Once their features are known, how should these networks be modeled? Until recently, attempts to model large networks involved the formation of *fixed random networks*. These networks randomly connect every person in the network to one or more other people in the network. While random networks can yield the small world property of low average path length with a low average degree, they typically fail to produce realistically high levels of clustering. This might have a critical impact on the flow of interactions within the network since higher clustering affects the total number of paths between any two individuals (see the Appendix). Other attempts to model large networks place individuals on a two-dimensional square grid and connect them to their nearest neighbors on the grid (see Johnson and

Huckfeldt in this volume). This approach eases visual inspection of the model and achieves high levels of clustering, but the average path length between individuals is quite high meaning that these networks do not have the small world property.[1]

Watts and Strogatz (1998) develop an alternative model that combines a highly ordered underlying structure of social ties with random "rewiring" of these ties. Each individual is placed on a lattice in which people are connected to a number of their nearest "neighbors" on the lattice.[2] Then with some probability each of these ties is deleted and reconnected to a randomly chosen individual in the graph. One can think of each of these rewired connections as a "weak tie" (Granovetter 1973) that connects an individual to another group of people outside her core set of acquaintances. As the number of these weak ties increases, the graph becomes less ordered and more like a random graph and both the clustering coefficient and the average path length decline. However, the path length declines much more rapidly than clustering, so for a range of rewiring probabilities this procedure produces small world graphs that are highly clustered. The rate of rewiring can be tuned to match the features of a particular social network—too low and the graph will cease to display the small world property, too high and the level of clustering will be unrealistically low.

A Small World Model of Turnout

Mathematical details of the model and a short analytical description are in the Appendix, but here I want to highlight the main features. To study turnout cascades in the context of a social network, the WS model is used to generate a small world network with a given size, average degree, clustering coefficient, and average path length. Each citizen in the network is then assigned an ideological preference on a one-dimensional left-right scale. This procedure allows us to control the degree of correlation in preferences between neighbors. Next, each of these citizens is assigned an initial turnout behavior and then they are randomly chosen one at a time to interact with one of their neighbors. In each of these interactions, there is a small probability that a citizen will change her turnout behavior to match the behavior of her neighbor. Finally, after a given number of interactions between citizens and their neighbors have taken place there is an election between two candidates.

Turnout in the model is deterministic and endogenous. Once citizens start interacting, cascades begin to form at each point where imitation takes place. Some of these cascades are turnout cascades, but others are abstention cascades since people are equally likely to imitate either kind of behavior. Moreover, these cascades may flow across one another, changing some citizens back and forth between a decision to abstain and a decision to vote. Picking out the net effect of a single cascade amidst all these interactions could be very difficult, but I simplify the procedure with a counterfactual. I allow one citizen to remain unaffected by her neighbors. I then compare the aggregate turnout outcome when she abstains and when she votes, holding all else constant.

The model is based on several assumptions that may be unrealistic but are useful for keeping things simple. For example, unlike other authors in this volume I assume that *all social ties are equal*. There are no elites and no special relationships. This assumption does not seem unreasonable since Huckfeldt and Sprague (1991) show that the likelihood of influence between acquaintances does not depend either on the degree of friendship or judgements of political competency. I also make the assumption that *ties are bilateral* so that influence can run equally in either direction. This is contrary to another finding by Huckfeldt and Sprague (1991). When asked to name other people with whom they discuss politics, many people do not name the people who originally named them as discussants (even between husbands and wives!). However, their survey design may be responsible in this case since discussants were not asked directly if they knew or spoke with the person who named them.

Note also that this analysis is *not strategic*. I set aside this feature for future work because I want to explore the simplest manifestation of the turnout cascade phenomenon and how that might affect the decision to vote. Like other decision-theoretic work on turnout (Downs 1957; Riker and Ordeshook 1968; Ferejohn and Fiorina 1974; Aldrich 1993) I assume that a rational individual is faced with a choice that depends on the choices of all other voters. However, this individual abstracts away from the strategic problem by assuming certain uniform characteristics in the population (such as the propensity to vote) in order to make her decision.

Related to this, I assume that people are *sincere* in their political discussions with one another. This is not an unreasonable assumption—many people say they vote because they do not want to tell their friends and family that they did not (Knack 1992). Implicit in this explanation is the assumption that they also do not want to lie. However, individual level surveys indicate that a significant number of people who do not vote say that they did (Granberg and Holmberg 1991). Strategic lying would probably weaken the effect that political discussions have on actual turnout behavior, but I leave this feature out of the model for now to keep things simple.[3]

Features of Political Discussion Networks

The next step is to use real political discussion network data from the ISLES, SBES, and other sources to help us choose appropriate features for the model. These features include the size of the network, the average degree, the average number of interactions between acquaintances, the clustering coefficient, the average path length, the imitation rate, and the correlation of preferences between acquaintances.

Size of the Network

McDonald and Popkin (2001) note that there are currently about 186 million eligible voters in the United States. However, modeling so many voters is computationally intensive. A model with 1 million voters takes several minutes to generate a single counterfactual and hundreds of thousands of these are needed to do appropriate statistical analysis. Therefore, I limit the number of voters and explore the impact of the size of the electorate on turnout cascades by letting the number of voters vary between 1,000 and 100,000. This means that results for larger networks like the set of voting eligible citizens in the U.S. must be extrapolated which makes stronger assumptions about the model (King 2002).

Average Degree

Sociologists note that most people have about 100 to 1000 significant friendship and family acquaintances (Pool and Kochen 1978; Freeman and Thompson 1989; Bernard et al. 1989). However, the number of political discussants named in the ISLES is much smaller. Of those who name discussants, 618 reported one, 797 reported two, 695 reported three, 469 reported four, and 1065 reported five or more. Unlike earlier studies (e.g. South Bend) that asked people to name a fixed number of political discussants, the ISLES used an open-ended name generator, allowing people to name as many discussants as they wanted to up to 5. Since the sample is truncated the average of 3.15 discussants named is probably too low. It is also possible that people have difficulty recalling all the people with whom they discuss politics, and privacy concerns may limit the number of discussants they are willing to name. To be conservative I will assume an average degree of 4 for the ISLES but I will let this vary up to 20 to explore the impact of network characteristics on turnout.

Average Path Length and the Clustering Coefficient

Very little is known about the true average path length of real political discussion networks. However, independent control over both the average path length and the clustering coefficient in the WS model is not possible since both are determined by the rewiring rate. Thus a rewiring rate is chosen that generates a realistic clustering coefficient. There are two different estimates of the clustering coefficient using the ISLES data because respondents were asked separately if each of their discussants *talked* to each of their other discussants, and if each of their discussants *knew* each of their other discussants. The probability that two of one's discussants know one another is about 0.61 while the probability that they talk to one another is 0.47. These numbers indicate that the rate of clustering in the ISLES is consistent with other social networks, but they raise an interesting question. Which measure is more relevant for a model of imitation? Since discussion is the obvious way in which people might send and receive information about their turnout choice, the lower estimate based on talk is used. However, it is important to bear in mind that more casual relationships can have an effect on political behavior as well. As Huckfeldt (1984, p.414) writes: "the less intimate interactions that I have ignored—discussions over backyard fences, casual encounters while taking walks, or standing in line at the grocery, and so on—may be politically influential even though they do not occur between intimate associates."

Number of Interactions

Many interactions might affect people's decision to vote. For example, people might be affected by merely observing their acquaintances' behavior (Do they vote? Do they participate in community or group activities? Do they have a political sign in their yard?). They might also be affected by political discussions with their acquaintances. Political discussions are used to estimate the frequency of interactions because the information about discussions is better than information about other kinds of interactions. However, it is important to realize that this makes the estimate of the number of interactions conservative.

In the ISLES respondents say they talk with each of their discussants about three times a week on average, but how often are these conversations about politics? 21.3% say "often" and 51.2% say "sometimes" while everyone else says "rarely" or "never." These numbers are also consistent with the Comparative National Elections Study of the 1992 U.S. Election (Huckfeldt et al 1995). It is difficult to translate qualitative responses into actual frequencies, but given the stated frequencies a conservative interpretation is that about a third of these conversations are about politics. This means that people probably have on average about one discussion a week on politics with each of their discussion partners. Another variable to consider is how long a time period is relevant to the turnout decision. Lazarsfeld et al (1944) and Berelson et al (1954) note that political discussions are more frequent during campaigns. In most countries candidate selection happens several months prior to the election, but voter attention is probably increasingly focussed as Election Day approaches. To form a reasonable guess for the relevant time period, note that the average primary in the United States Presidential Election is held about 5 months (or about 20 weeks) prior to the general election. This means that respondents would have around 20 discussions per discussant during the most salient period for their turnout decision. This number might seem low to some and high to others, but since lower numbers are conservative I will let it vary from 1 to 20 when exploring the impact of the number of discussions on turnout.

Imitation Rate

It is well known that turnout is highly correlated between friends, family, and co-workers (Lazarsfeld et al 1944; Berelson et al 1954; Campbell et al 1954; Huckfeldt and Sprague 1995; Mutz and Mondak 1998; Beck et al 2002). For example, Glaser (1959) finds a strong relationship in the turnout decision between spouses. More recently, Straits (1990) confirms Glaser's finding, and Knack (1992, p. 137) notes that many people vote because "my friends and relatives almost always vote and I'd feel uncomfortable telling them I hadn't."[4] The literature on mobilization also shows that asking people to vote is an effective tool for increasing turnout (e.g. Wielhouwer and Lockerbie 1994; Gerber and Green 1999, 2000a, 2000b). Even individuals who are unaffiliated with organized mobilization efforts may attempt to influence the turnout behavior of their peers. 34% of respondents in the ISLES say they tried to convince someone to vote for their preferred candidate, indicating that many people believe there is a chance others will imitate them. These efforts might be aimed at influencing vote choice (see Levine; Johnston and Pattie; Huckfeldt, Johnson, and Sprague; and Jennings and Stoker in this volume), but they also convey messages about whether an election is important or not, and this might affect their decision to turnout.

How much of this correlation in turnout behavior is due to imitation rather than individual incentives and status variables that happen to be correlated between peers? Using social network data from the SBES, Kenny (1992) develops a simultaneous regression model of respondent and discussant turnout, controlling for age, education, income, interest in politics, and strength of party identification. He finds that respondents are 15% more likely to turnout if one of their discussants votes, which is close to what one would estimate if one looked at the simple correlation ($\rho = 0.2$). This effect also extends two steps to one's *discussants' discussants*. In the SBES validated turnout is 75% among respondents whose discussants reported that all *their* discussants voted compared to 61% for those reporting at least one abstention. In the ISLES data perceived turnout among discussant's discussants is 92% for respondents who say they will vote and 78% for those who say they will not.

These numbers may represent the total effect of imitation but they do not give us the *per discussion* imitation rate required by the model. One might think that the imitation rate can be inferred from the number of discussions and the total effect, but this misses the important point that imitation also occurs between a discussant and each of her other discussants. In expectation these other relationships act to moderate the influence of a single turnout decision, so the *per discussion* imitation rate should be higher than a simple probability calculation would imply (see the Appendix). In principle a realistic imitation rate can be selected by changing it until the model correlation matches real correlation in turnout. If respondents base their answers about political discussions on their past month of activity, then an imitation rate of about 5% is needed to generate a turnout correlation with acquaintances ($\rho = 0.23$) and acquaintances' acquaintances ($\rho = 0.13$) consistent with the ISLES data.

Concentration of Shared Interests

A consistent finding in the social voting literature is that people tend to segregate themselves into like-minded groups. As a result, most social ties are between people who share the same interests. When people with ideological or class-based interests are not surrounded by like-minded individuals in their physical neighborhoods and workplaces they tend to withdraw and form relationships outside those environments (Huckfeldt and Sprague 1987, 1988; Noelle-Neumann 1984; Finifter 1974; Gans 1967; Berger 1960). Thus preferences between acquaintances tend to be highly correlated.

The concentration of shared interests does not affect *total* turnout, but it is very important for *net favorable turnout*. If there were no correlation in preferences, then any turnout cascade could be expected to include as many people who disagree as agree. With correlation, however, turnout cascades are more likely to affect like-minded individuals and yield net favorable changes for one's preferred candidate in expectation. This means that in environments with a high concentration of shared interests the incentive to turnout might be magnified by the number of like-minded individuals one can motivate to go to the polls.

The model allows us to fine tune how closely neighbors share interests with one another. Huckfeldt, Johnson, and Sprague in this volume show in a number of ways how concentrated interests are between discussants. The most relevant to the model here is the correlation between self-reported liberals and conservatives, which is about 0.66 in the ISLES. The correlation between Republicans and Democrats is somewhat lower at 0.54. It is worth pointing out here that these estimates are based on interviews with both the respondent and the discussant. Using the respondents' *perception* of how liberal or conservative their discussion partners are causes the concentration of shared interests to be even higher because people tend to overestimate the likelihood that their associates hold their own political preferences (Huckfeldt, Johnson, Sprague, and Craw 2002; Huckfeldt and Sprague 1995; Fabrigar and Krosnick 1995).

Results

Turnout in a Social Network Like the ISLES

Figure 1 shows the distribution of turnout results when a single person chooses to vote in a social network with features very similar to the political discussion network in the ISLES. Notice first that the size of these turnout cascades varies widely. In the left graph total change in turnout varies between 1 and 25, indicating that small differences in local configurations can generate large differences in the size of a particular turnout cascade. The modal change in turnout is 1 but 82% of the time it is greater than one and the average change in turnout is about 4. This means that *a citizen can expect to change the turnout decision of about 3 other people with her own turnout decision.*

Not everyone in a turnout cascade is likely to have the same preferences, though. Some people motivated to vote will choose the left candidate and others will choose the right. How does this affect the aggregate outcome of the election? The right graph in Figure 1 shows the distribution in the "net favorable change" in the vote margin for the candidate preferred by the person making the decision whether or not to turnout. Once again, the outcomes vary widely, with a substantial portion of them falling below 1. The graph shows that about 8% of the time the vote margin for a citizen's preferred candidate actually *decreases* because her favorite candidate's *opponent* gains a greater portion of the votes in the resulting turnout cascade. Another 8% of the time her turnout has a net neutral impact on the vote margin. However, since citizens are embedded in networks of shared preferences, the decision to turnout usually leads to a net gain for one's preferred candidate, and this net gain ranged up to 18 votes in the simulation. Again, the modal change in the vote margin is 1 but 60% of the time it is greater than one and on average the preferred candidate gains 2.4 votes. In other words, *a citizen can expect to increase the vote margin of her favorite candidate by about 2 to 3 votes with her own turnout decision.*

Turnout in a Variety of Social Networks

Figure 1 is based on features estimated with the use of political discussion network survey data, but the true social network might be somewhat different. To characterize how features of the social network and assumptions about citizen interactions affect the expected size of a turnout cascade, I randomly search the feature space near the estimates I derived from the ISLES and run the model hundreds of thousands of times. As in the model based on ISLES, the size of individual turnout cascades varies widely, ranging up to 100 in the 343,300 election counterfactuals simulated. However, the *expected* change in turnout only ranges up to 18 when these counterfactuals are averaged for each unique social network.

Figure 2 shows the results of this exercise. Each data point in the graphs represents the expected size of a turnout cascade for a social network generated by a unique combination of features. It is difficult to conceptualize six dimensions at once so I present six graphs, each showing how turnout changes with respect to each feature of the model. The solid lines on these graphs indicate the mean effect on expected total turnout generated by locally weighted polynomial regression (LOESS—see Cleveland 1979; Cleveland and Devlin 1988). Sufficient statistics for the feature space searched are presented in the Appendix.

Notice first that turnout cascades tend to increase strongly with the number of discussions and the probability of imitation since each discussion is a new opportunity to change someone's mind and start a chain reaction in the population. This finding is consistent with studies that show mobilization efforts increase turnout (Ansolabehere and Snyder 2000; Gerber and Green 1999, 2000a, 2000b), especially when they are carried out by unions and labor parties that have ties to their target audience (Brown et al 1999; Gray and Caul 2000; Radcliff 2001; and Radcliff and Davis 2000).

Clustering and the average degree also have a positive effect on the turnout rate, though the effect is weaker than others previously mentioned. As the number of acquaintances or the probability that one's acquaintances know one another is increased, the number of paths between individuals increases dramatically. This increases the number of ways a single turnout decision can be transmitted to other people in the population, but it also exposes each person in a turnout cascade to a larger number of external influences that might end the cascade. The cross-cutting effects cancel one another to a large degree, but the overall effect on turnout remains positive. These findings are consistent with recent empirical work on social capital and aggregate turnout. In particular, Cox et al (1998) show that social density is related to higher turnout in Japan and Monroe (1977) shows that rural areas in the United States where social network connections are more clustered have much higher turnout than urban areas in spite of lower levels of education and income.

The total number of citizens in a network has only a very small effect on the average size of turnout cascades. I originally believed that the size of turnout cascades would scale strongly with N because of the increased number of people who might be influenced by a cascade. However, the small effect indicates that turnout cascades are primarily *local* phenomena, occurring in a smaller part of the population with short path lengths to an individual.

Finally, notice that the small world phenomenon has a pronounced and nonlinear effect on turnout. As the average path length drops, the size of the turnout cascade rises quickly. In fact, Figure 3 shows that there is a power law relationship between turnout and the average path length. The size of the turnout cascade T is proportional to the inverse of the square root of the average path length L:

$$T \propto L^{-\frac{1}{2}}.$$

This relationship suggests that turnout might be even higher than estimated. For example, in the model based on ISLES the average path length is about 20, but if it is dropped to the "six degrees of separation" reported by Milgram (1967) then expected turnout would be even higher by about 83%. No one knows the true average path length for a typical political discussion network, but this result indicates that it might be very important for how much influence a single individual can expect to have.

How favorable are turnout cascades to the people who initiate them? Each data point in Figure 4 plots the net favorable change versus the total change in turnout for a given network. For all simulations there is a strong relationship between net favorable turnout and total turnout, and nearly all of the variation in this relationship can be explained by preference correlation. To demonstrate this, the expected relationship for three different samples, those with medium ($\rho = 0.5 \pm 0.025$), medium-high ($\rho = 0.8 \pm 0.025$), and high ($\rho = 1.0 \pm 0.025$) concentrations of shared interests are plotted. Intuitively, as preference correlation approaches 1, the net favorable change approaches the total change in turnout because the turnout cascade is affecting many people with the same preferences. As it approaches 0, the net favorable change approaches 0 because the preferences of people affected will be more evenly distributed between left and right.

This implies an important finding. *The high concentration of shared interests in social networks may magnify the incentive to participate.* In a social network where preferences are randomly distributed, the counterfactual impact of a single vote on the outcome of the election will be just that—a single vote. However, if my turnout behavior has a positive impact on the people who surround us and they share my interests, then the counterfactual impact of a single vote on the outcome of the election may be several times a single vote. Therefore, the incentive to vote should be higher when conditions are favorable for turnout cascades and it should be increasing in the concentration of shared interests. This helps to explain the finding by Busch and Reinhardt (2000) that geographic concentration of shared interests increases aggregate level turnout.

The Curvilinear Effect of Local Clustering

Though the small world model of turnout produces effects that are consistent with studies of aggregate turnout, the question remains: do turnout cascades really create individual incentives to vote? To answer this question, individual level data on clustering from the model using the ISLES is regressed on the net favorable change in turnout (see Table A-2). This relationship should be very noisy because it involves individual turnout cascades like those in Figure 1 rather than expected turnout cascades like those in Figures 2 and 4. However, in spite of the noise Figure 5 shows that there is a curvilinear relationship between favorable turnout cascades and the probability one's friends know one another. Moderate levels of clustering yield more favorable turnout cascades than either very low or very high levels.

Why might this be the case? Clustering increases the number of paths available to influence other people in the network. People with acquaintances who do not know one another can only affect their acquaintances *directly*, but when these acquaintances know one another it opens up new paths to influence them *indirectly*. Moreover, this multiplies the number of connections one has to the rest of the social network via these new paths. At the extreme, however, individuals in groups that are very highly clustered may have several paths of influence *within* the group but they will also have *fewer connections to the rest of the social network* because there are constraints on the number of relationships a person can have. In the model this is imposed by the initial choice of the average number of discussants, but one can imagine that in real life people only have time to maintain a finite set of relationships so tightly-knit groups tend to keep to themselves.

The model thus predicts a curvilinear relationship between clustering and turnout, but does this exist for real data? The proportion of each respondent's discussants who know one another in the ISLES is regressed on vote intention (see the Appendix). Figure 4 shows that a statistically significant curvilinear relationship exists—respondents with a mix of friends who do and do not know one another are about 1.5% more likely to vote than people in dispersed or highly clustered groups. To see if this difference in turnout is related to the desire to create favorable turnout cascades, clustering is also regressed on the self-expressed desire to influence others to vote for a certain candidate. Here the curvilinear relationship is even stronger—people with moderately clustered acquaintances are about 8% more likely to try to influence others than those in dispersed or highly clustered groups. Turnout cascades may not exist, but these findings suggest that people may *believe* that they do.

This finding has important implications for the literature on social capital (e.g. Putnam 2000). This literature argues that civic engagement will be higher in societies with more clustered social ties. The model suggests that this is true, but only up to a certain point. When relationships become too clustered, individuals lose touch with the rest of the social network and are less able to influence participation beyond their circle of acquaintances. This reduces their individual incentives to be engaged in civic society and encourage others to do the same. As Kotler-Berkowitz and Gimpel, Lay, and Schuknecht argue in this volume, diversity in one's social connections can increase the incentive to participate by opening up new paths of influence to and from the rest of the network. However, the model also suggests that too much diversity hurts participation because it increases the likelihood that participation will be stimulated among people who do not share the same interests.

Turnout Cascades and Rational Models of Voting

The existence of turnout cascades suggests that previous models of turnout have underestimated the benefit of voting. Decision-theoretic and game-theoretic models assume that the expected value of voting is the benefit one would receive by having one's favorite candidate elected times the probability that one's vote matters to the outcome (Downs 1957; Tullock 1967; Riker and Ordeshook 1968; Beck 1974; Ferejohn and Fiorina 1974; Ledyard 1982, 1984; Palfrey and Rosenthal 1983, 1985). This probability is extremely small because a single vote only matters in two cases: if the election results in an exact tie or a one-vote deficit for one's favorite candidate. There have been several variations of this argument, but they have in common the idea that the probability of being pivotal in large electorates is inversely proportional to the number of people in the model. However, since turnout cascades mean that a single turnout decision can change the margin of victory by more than one vote, they should increase the probability of being pivotal. For example, in a large electorate the probability that a favorable cascade of two votes is pivotal is approximately twice the probability that one vote is pivotal. Three votes approximately triples the probability, and so on. Generalizing, this means that *the expected benefit from being pivotal is proportional to the net favorable change in the margin of victory yielded by a turnout cascade*.

Fowler and Smirnov (2007) develop an alternative "signaling" model of turnout that typically yields much higher expected utility than the pivotal model. If politicians use the margin of victory in the past election to adjust their future platforms, then each vote has a marginal impact on future policies. Therefore, people may have an incentive to signal their preferences by voting even when they would not be pivotal. Fowler and Smirnov show that the signaling benefit from voting is proportional to the change in the margin of victory, so a net favorable change in turnout of two votes would double the benefit, three would triple it, and so on. Thus *the expected benefit from signaling is also proportional to the net favorable change in the margin of victory yielded by a turnout cascade.*

Turnout cascades should have an effect on other kinds of benefits, too. For example, consumption models of voting assume an additional benefit derived from fulfilling one's civic duty to vote (Riker and Ordeshook 1968; Jones and Hudson 2000; Blais and Young 1999; Blais, Young, and Lapp 2000; Rattinger and Kramer 1995). Though it is difficult to quantify how a turnout cascade would affect the duty motivation, I note that many civic duty models emphasize the social aspect of voting and argue that people derive utility from contributing to a public good. This suggests that they might derive additional benefit from voting if they knew they were influencing others to contribute to that good. Thus, *the benefit from fulfilling one's civic duty might also be increasing in the size of turnout cascades*.

Thus, turnout cascades multiply the benefit associated with deciding to vote in a number of models. But can they make a rational model of turnout plausible? If we multiply the pivotal and signaling motivations by the conservative estimate of a 2.4 voter net favorable change in the margin of victory, the cost-benefit threshold at which voting yields positive expected value is no more than 1:5000 for a one million person electorate.[5] In other words, "rational" voting requires that the benefit from being able personally to choose which candidate wins the election must be at least 5000 times larger than whatever costs are incurred by voting, such as learning about the campaign, waiting in line at the polls, and so on. What if we use a less-conservative estimate? Changing the average path length from 20 to 7, the number of acquaintances from 4 to 20, and the probability that acquaintances know one another from 0.4 to 0.6 in a network like the ISLES generates an expected change in turnout of 14 and an expected increase in the margin of victory of 8.4 votes. This changes the cost-benefit threshold to 1:1500, which may still be too low to explain most turnout. Thus, while turnout cascades make rational voting more plausible than previously thought, we are still left with Aldrich's (1993) conclusion that rational voting must be a "low cost-low benefit" activity.

Summary and Discussion

The model of turnout in a large scale network suggests that a single person's decision to vote affects the turnout decision of at least four people on average in a "turnout cascade." Given the high concentration of shared interests between acquaintances in real political discussion networks, this means that a single decision to vote can increase the vote margin for one's preferred candidate by at least two to three votes. Therefore the incentive to vote, whether it is based on affecting the outcome of the election or some other benefit related to turnout, is larger than previously thought.

Turnout cascades and the incentive to vote are increasing in several features of the social network that have been shown to be associated empirically with higher turnout. In particular, they are increasing in the number of interactions with people who vote (Ansolabehere and Snyder 2000; Gerber and Green 1999, 2000a, 2000b; Brown et al 1999; Gray and Caul 2000; Radcliff 2001; and Radcliff and Davis 2000), the clustering of social ties (Cox et al 1998; Monroe 1977), and the concentration of shared interests (Busch and Reinhardt 2000). The model also suggests that there is a power law relationship between turnout cascades and the average distance between any two individuals in the network: as the world gets smaller, the capacity to influence others increases exponentially and so should the incentive to participate.

At the individual level, the model predicts a feature of turnout that has previously gone unnoticed. The relationship between the size of turnout cascades and the number of one's acquaintances who talk to one another is curvilinear. In the language of Granovetter (1973), people with a mix of "weak" and "strong" ties can initiate larger turnout cascades than people with all weak or all strong ties, and they therefore have a greater incentive to vote and to influence others to do the same. Using data from the Indianapolis-St. Louis Election Study, I find exactly this effect on both intention to vote and the likelihood that an individual tries to influence an acquaintance. This suggests a revision to the social capital literature. Civic engagement does not increase monotonically as the density of social relationships increases. When these relationships within a group become too dense, civic engagement actually declines because people are less connected to the rest of society.

The model suggests a possible explanation for why so many people assert that there is a "duty" to vote (Riker and Ordeshook 1968; Jones and Hudson 2000; Blais and Young 1999; Blais, Young, and Lapp 2000; Rattinger and Kramer 1995). Establishing a norm of voting with one's acquaintances is one way to influence them to go to the polls. People who do not assert such a duty miss a chance to influence people who share similar views, and this tends to lead to worse outcomes for their favorite candidates. In large electorates the net impact on the result might be too marginal to create a dynamic that would favor people who assert a duty to vote. However, arguments about the civic duty to vote originated in much smaller political settings like town meetings where changing the participation behavior of a few people might make a big difference (de Tocqueville 1835). In future work I will explore the dynamic of changing electorate size in order to see if a duty to vote emerges as a strategy in small electorates and remains as the size of the electorates increases.

The model also suggests a new *paradox of (not lying about) voting*. I assume that all people in the model are sincere, but we know that some people lie about voting. Suppose we allow some people to be strategic in their discussions. If they believe that their political discussions can cause turnout cascades among sincere voters, they may tell other people that they vote in order to increase the vote margin for their favorite candidates without even going to the polls! In fact, as long as they know they share interests with others around them, they can do this without knowing anything about the coming election since their acquaintances are likely to vote how they would vote if they took the time to learn about the candidates and make a decision. This may help to explain over-reporting of turnout in election surveys, but it raises another question: if people are strategic, why would they ever say that they do not vote?

Finally, future research should investigate turnout cascades in alternative network models that allow for more realistic average path lengths. The literature on preferential attachment and scale-free networks notes that another feature of many real networks is a power-law distribution of the degree (Albert and Barabasi 2002). In other words a very large number of people may have only a few acquaintances (as in the WS model), but a very small number of people may have substantially more. These "critical nodes" would help to reduce the average path length to realistic levels, but I do not know if they actually exist in political discussion networks. The ISLES only allows people to name five discussants, and with so few data points it is hard to tell if there is actually a power law in the distribution of the degree. Future election surveys with social network questions should ask people to estimate how many people they have political discussions with so I can get a sense of this distribution and use it to make my large scale network models more accurate.

Appendix

The Model

I start by placing N citizens on a closed one-dimensional lattice (a circle with N equidistant points on it). Each citizen i is adjacent to citizens $i+1 \pmod N$ and $i-1 \pmod N$. I assign each citizen i an ideal point in one-dimensional issue space $Q_i \in [0,1]$ such that $Q_i = \alpha(i/N) + (1-\alpha)\varepsilon$ where ε is a uniform random variable distributed on $[0,1]$ and $0 < \alpha < 1$ is a feature that can be adjusted to control the correlation between the preferences of adjacent citizens. Notice that when $\alpha = 0$, preferences are randomly distributed on the unit interval, whereas when $\alpha = 1$ the preference of the i^{th} citizen correlates very closely with the adjacent citizen: $Q_i = Q_{i-1} + 1/N$.

Next I construct a pattern of social ties that are *simple* (no more than one tie between two individuals) *undirected* (each tie goes in both directions) and *unweighted* (no tie is given greater importance than any other tie). A tie between citizens i and j is denoted by (i, j) and k is the *degree*, or the total number of ties connecting a particular citizen to other citizens. I assume the graph is *connected*, so $k_i > 0 \forall i$. Each citizen i is connected to the k most adjacent citizens on the lattice $i+1, i+2, \ldots i+k/2 \pmod N$ and $i-1, i-2, \ldots i-k/2 \pmod N$, where k is restricted to be even. A number of "shortcuts" are then introduced by randomly removing each tie (i, j) with probability $0 < \beta < 1$ and replacing it with a tie to a randomly chosen individual $(i, j'), j' \neq i$. Since the graph must remain connected, only citizens with degree $k_i > 1$ are eligible to have a tie rewired.

At time $t = 0$ each citizen i is randomly assigned a turnout behavior such that $V_i = 1$ (vote) with probability p and $V_i = 0$ (abstain) with probability $(1-p)$. In the first round at time $t = 1$ Nk interactions occur one at a time in which a tie (i', j') is chosen at random and with probability q citizen i imitates the turnout behavior of citizen j: $V_i = V_j$. The round is then repeated D times until the end of time $t = D$. This allows each citizen to interact with each of his or her neighbors D times on average. Then in period $t = D+1$ an election is held in which each citizen that has decided to turnout casts a ballot for the left candidate if $Q_i < 0.5$ and the right candidate if $Q_i \geq 0.5$.

Analysis

What is the probability that citizen j is affected by citizen i's decision to turnout? Suppose the simplest case, where there is only one *path* between i and j and they are directly connected by a single tie. A decision to turnout by i *increases* the probability that j turns out by $q(1-p)$, or the imitation rate times the probability that the neighbor was not already going to turn out. Similarly, a decision to abstain *decreases* the probability that j turns out by qp. Changing one's decision from abstention to turnout should thus make j more likely to turnout by $q(1-p)-(-qp)=q$. This is an important result because it suggests that turnout cascades do not depend on initial turnout probabilities in the population.

Citizen i is not the only one with a chance to influence j—she might imitate any of her neighbors with probability q. The order of their interactions is extremely important—if i is the last discussant she does not have to worry about her influence being undone by a later discussant. If she is the second-to-last discussant, however, there is a chance that j imitates i but then later imitates the last neighbor. Thus the probability that i's influence remains must be multiplied by the probability that j does not imitate the last neighbor: $q(1-q)$. If i is third-to-last, the probability would be reduced still further to $q(1-q)^2$, and so on up to $q(1-q)^{k-1}$. Since discussions take place in random order, the total probability that i affects j must then be averaged over each position i might have in the order:

$$\frac{1}{k}\sum_{a=0}^{k-1} q\left(1-q\right)^{a}$$

If i and j have $D>1$ discussions, then the probability of imitation becomes increasingly complex to model analytically. For example, if $D=2$ and $k=2$, then i has two discussions with j, but j also has two discussions with her other neighbor (call her h). These discussions occur in $(Dk)!/\left[D!(D(k-1))!\right]=6$ combinations with equal likelihood: $iihh, ihih, ihhi, hiih, hihi, hhii$. If i gets the last two discussions, she does not face the possibility of having her influence reversed and the probability of imitation is simply the complement of two failures $1-\left(1-q\right)\left(1-q\right)$. However, if i's discussions occur second and fourth in the sequence I must include the possibility that the third discussion with h reverses any imitation that takes place in the second discussion with i: $1-\left(1-q(1-q)\right)\left(1-q\right)$. Following this logic, the total probability of imitation is

$$\frac{1}{6}\sum_{a_1=0}^{2}\sum_{a_2=a_1}^{2} 1-\prod_{b=1}^{2}\left(1-q\left(1-q\right)^{a_b}\right)$$

and I can generalize the probability for all D and k :

$$\frac{D!(D(k-1))!}{(Dk)!}\sum_{a_1=0}^{D(k-1)}\sum_{a_2=a_1}^{D(k-1)}\cdots\sum_{a_D=a_{D-1}}^{D(k-1)}1-\prod_{b=1}^{D}\left(1-q\left(1-q\right)^{a_b}\right).$$

Now suppose that i and j are not directly connected, but they share a single neighbor in common. If so, then the probability of imitation is

$$(1/2)\left(\frac{D!(D(k-1))!}{(Dk)!}\sum_{a_1=0}^{D(k-1)}\sum_{a_2=a_1}^{D(k-1)}\cdots\sum_{a_D=a_{D-1}}^{D(k-1)}1-\prod_{b=1}^{D}\left(1-q\left(1-q\right)^{a_b}\right)\right)^2$$

since there is only a 50-50 chance that i 's neighbor is influenced *prior* to her discussions with j and now *both* the neighbor and j must imitate the neighbor before them on the path. This generalizes to

$$(1/2)^{L_{i\to j}-1}\left(\frac{D!(D(k-1))!}{(Dk)!}\sum_{a_1=0}^{D(k-1)}\sum_{a_2=a_1}^{D(k-1)}\cdots\sum_{a_D=a_{D-1}}^{D(k-1)}1-\prod_{b=1}^{D}\left(1-q\left(1-q\right)^{a_b}\right)\right)^{L_{i\to j}}$$

where L is the *path length*, or the number of ties on the path between i and j.

Relaxing the constraint of a single path between each pair of citizens complicates things considerably. Each path represents another way for i to affect j, so the expected total must also be summed over the total number P of these paths:

$$\sum_{c=1}^{P}(1/2)^{L^c_{i\to j}-1}\left(\frac{D!(D(k-1))!}{(Dk)!}\sum_{a_1=0}^{D(k-1)}\sum_{a_2=a_1}^{D(k-1)}\cdots\sum_{a_D=a_{D-1}}^{D(k-1)}1-\prod_{b=1}^{D}\left(1-q\left(1-q\right)^{a_b}\right)\right)^{L^c_{i\to j}}$$

For even small graphs the number of these paths grows combinatorially with the average degree k of the graph. It also grows quickly as the number of shortcuts between paths grows. To see why, consider the effect of a single extra tie between one's neighbors. Suppose a network with five citizens $\{A,B,C,D,E\}$ and four ties $(A,B),(A,C),(B,D),(C,E)$. A connects to each of the four members of this graph in four unique paths: $(A\to B),(A\to C),(A\to B\to D),(A\to C\to E)$. What happens if there also exists a tie (B,C)? This opens up four new paths: $(A\to B\to C),(A\to C\to B),(A\to C\to B\to D)$, and $(A\to B\to C\to E)$. Thus, as the number of shortcuts increases, so does the possibility that some of the citizens on a path between i and j have more than one path between them. I do not attempt to characterize the exact number of paths for a given small world graph. Instead I use a graph statistic that relates to the number of shortcuts in a graph. This is the *clustering coefficient,* or the probability C that any two of a citizen's neighbors are also neighbors with one another.

Finally, the expected total change in aggregate turnout T when citizen i decides to turnout would then be her own vote plus the sum of these probabilities for all citizens:

$$T = 1 + \sum_{j=1}^{N-1} \sum_{b=1}^{P} (1/2)^{L_{i \to j}^{b} - 1} \left(\frac{D!(D(k-1))!}{(Dk)!} \sum_{a_1=0}^{D(k-1)} \sum_{a_2=a_1}^{D(k-1)} \cdots \sum_{a_D=a_{D-1}}^{D(k-1)} 1 - \prod_{b=1}^{D} \left(1 - q\left(1-q\right)^{a_b}\right) \right)^{L_{i \to j}^{b}}$$

It should be clear by now that the complexity of this problem makes very it difficult to study in closed form. I therefore analyze the model computationally.

To determine the effect of a single turnout decision, I choose features $\{N;k;\alpha;\beta;q;D\}$ to generate a social network and randomly choose a single citizen to be "Ego." When Ego interacts with her neighbors she never imitates their behavior: $q_{Ego} = 0$. I run the model first assuming that Ego abstains $V_{Ego} = 0$. I then run it again with the assumption that Ego votes $V_{Ego} = 1$, holding all features and the realizations of all random variables constant. I compare turnout at time $t = D + 1$ for both cases and then generate expected values by repeating this procedure for a given social network 100 times, assigning a different citizen to be Ego every time. I then change the features that generated the network and start again.

To characterize the general behavior of the model, I draw random features on a uniform distribution over the range of relevant values. Table A-2 shows statistics for the features that were used to generate the results in Figures 2, 3, and 4. This table also summarizes graph statistics. Exact statistics are computationally intensive so I use sampling techniques to estimate them. I measure preference correlation (ρ) by randomly sampling preferences Q_i and Q_j from 10,000 (i, j) ties and finding the Pearson's correlation. I measure the clustering coefficient (C) by randomly sampling 10,000 "connected triples” in which there are ties between (i, j) and (j, h). C is the proportion of these triples for which there also exists a tie (i, h). Finally, I measure average path length (L) by randomly choosing a citizen i and averaging the shortest path between i and j for all j. I repeat this procedure 100 times and average the averages.

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Endnotes

[1] It is worth noting here that the small world property might dramatically affect the results in Johnson and Huckfeldt since information tends to flow more quickly through small world networks.

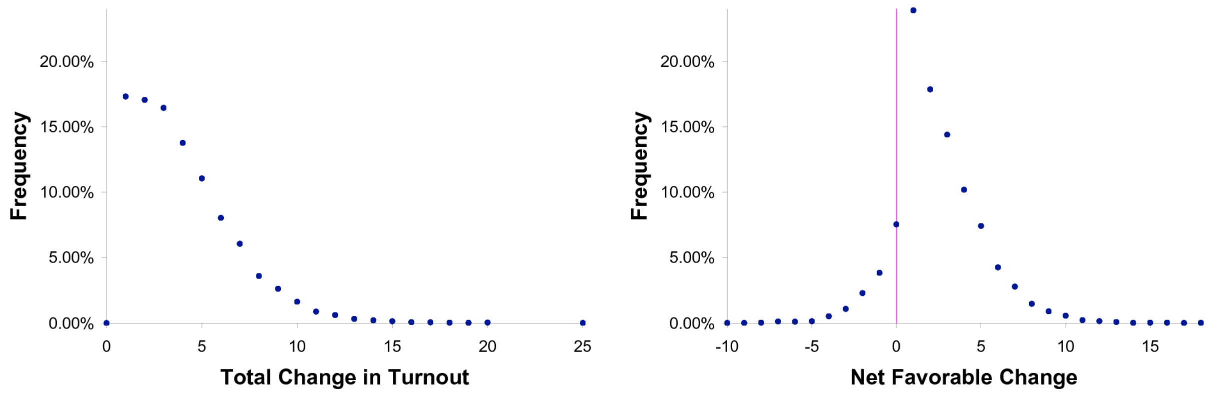
[2] The term "neighbor" is not restricted to someone who is physically proximate. In the context of a social network the term simply means someone with whom a person has a connection.

[3] A wide variety of threshold models do incorporate strategic behavior, especially those used to explain spontaneous collective action like mass protests (e.g. Lohmann 1994; Kuran 1989, 1991, 1995; Birchoux and Johnson 2002). However, they do not attempt to use empirical data to generate predictions for real networks, nor do they consider the impact of changes in the network structures on the flow of information and resulting behaviors.

[4] This quote raises the important point that there may be costs and benefits associated with voting that explain *why* people imitate the behavior of their acquaintances. For example, there may be a benefit from conforming with one's peers or a cost associated with lying to them. In this article I set aside the important question of *why* people imitate one another in order to focus on *how* imitation affects aggregate turnout.

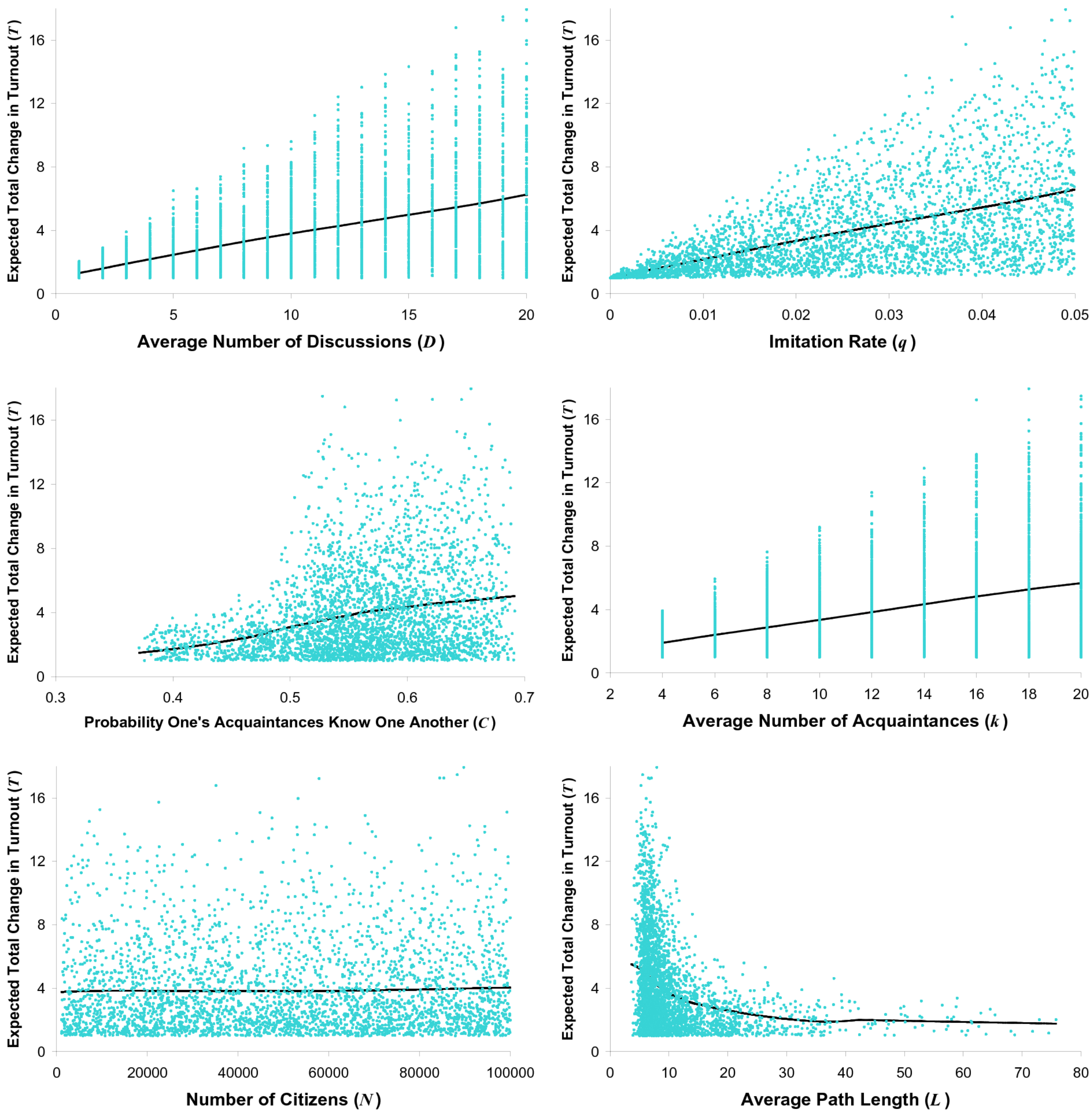
[5] Figure 2 in Fowler and Smirnov (2002) shows that the cost-benefit threshold implied by both the signaling and pivotal motivations ranges up to about 1:13000.

Figure 1. Turnout Cascades in a Social Network Like the ISLES



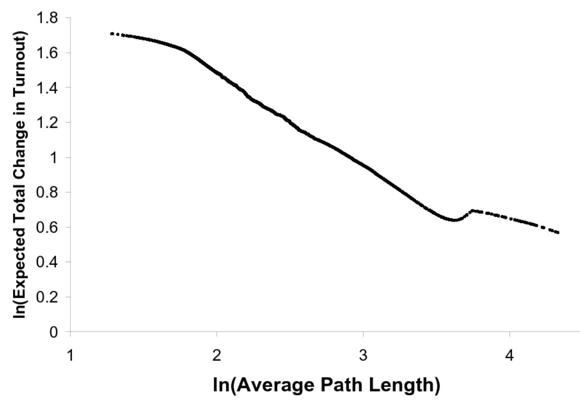
Note: Each data point represents the frequency over 10,000 trials of the change in aggregate turnout from changing a single turnout decision in a social network like the ISLES political discussion network. The simulation is based on a network with 100,000 citizens, 4 neighbors per citizen on average, 20 interactions with each neighbor on average, a 0.4 probability that neighbors know one another, an imitation rate of 0.05, a correlation in preferences of 0.66 and an average path length of about 20.

Figure 2. Determinants of Turnout Cascades



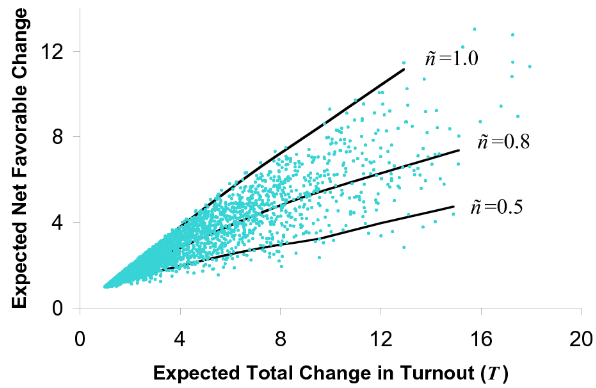
Note: Each data point represents the expected change in aggregate turnout from changing a single turnout decision for each unique social network. Solid lines indicate mean effects on turnout generated by LOESS using a bandwidth of 0.8 (Cleveland 1979; Cleveland and Devlin 1988).

Figure 3. *Power Law Relationship Between Average Path Length and Turnout*



Note: Solid line indicates mean effect on turnout generated by LOESS using a bandwidth of 0.8 (Cleveland 1979; Cleveland and Devlin 1988). A regression of average path length L on the change in turnout T yields: $\ln(T) = 2.20(\pm 0.10) - 0.48(\pm 0.04)\ln(L)$ (95% confidence intervals in parenthesis).

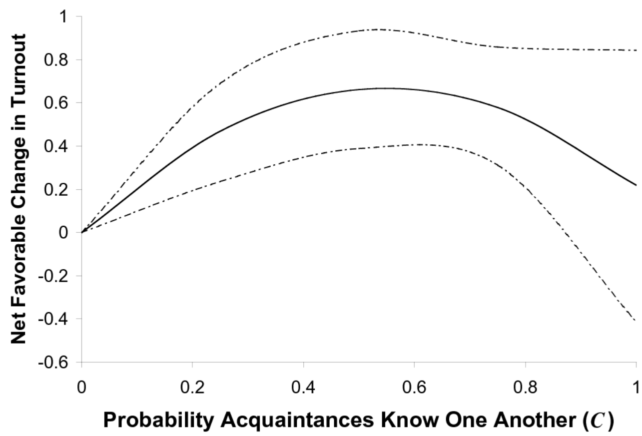
Figure 4. How Concentration of Shared Interests Affects Turnout



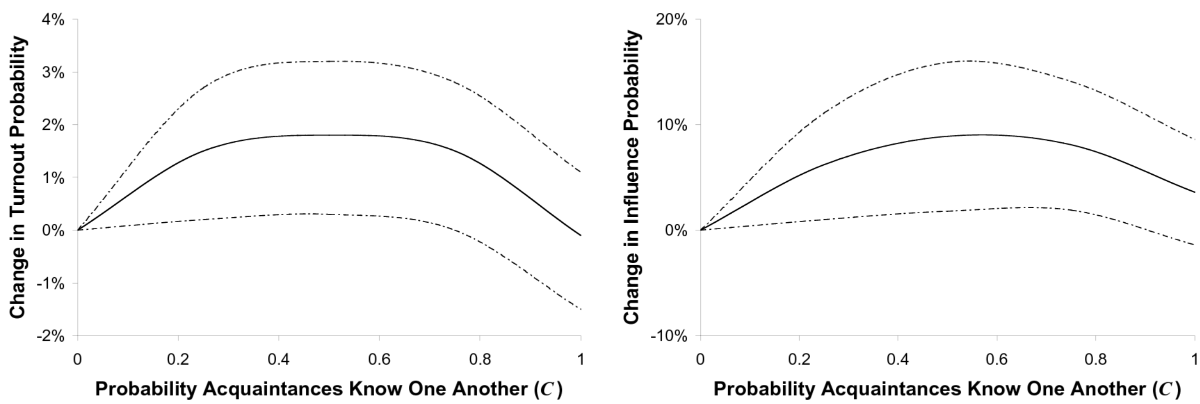
Note: Each data point represents the expected change in aggregate turnout from changing a single turnout decision for each unique social network. Solid lines indicate mean effects on turnout generated by LOESS using a bandwidth of 0.8 (Cleveland 1979; Cleveland and Devlin 1988). In the right graph I show three of these lines, restricting the sample to networks with medium ($\rho = 0.5 \pm 0.025$) medium-high ($\rho = 0.8 \pm 0.025$) and high ($\rho = 1.0 \pm 0.025$) preference correlation.

Figure 5. How Clustering of Relationships Affects Turnout

<u>Predicted:</u>



<u>Actual:</u>



Note: Solid lines are simulated expected values of the first difference changing C from 0 and holding all other variables at their means (King et al 2000). Dashed lines are simulated 95% confidence intervals. Estimates based on models in Table A-2.

Table A-1. Summary Statistics of Social Networks Sampled (Figures 2, 3, & 4)

	Mean	Std. Dev.	Min	Max
Number of Citizens (*N*)	50391	28826	1055	99978
Number of Acquaintances (*k*)	12.11	5.19	4	20
Ave. Discussions per Acquaintance (*D*)	10.52	5.76	1	20
Imitation Rate (*q*)	0.025	0.014	0.000	0.050
Correlation Parameter (α)	0.752	0.144	0.500	0.999
Short-Cuts Parameter (β)	0.055	0.026	0.010	0.100
Average Path Length (*L*)	10.95	8.33	3.60	75.73
Pr. Acquaintances Know One Another (*C*)	0.561	0.067	0.371	0.692
Concentration of Shared Interests (ρ)	0.808	0.143	0.447	0.991
Expected Total Change in Turnout (*T*)	3.86	2.83	1	17.94
Exp. Net Favorable Change in Turnout	2.74	1.68	0.98	13.02

Note: Number of social networks sampled = 3343.

Table A-2. How Clustering of Relationships Affects Turnout (Figure 5)

	Predicted: Net Favorable Change		Actual: Intention to Vote		Actual: Influence	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Probability Acquaintances Know One Another (*C*)	0.207	0.313	-0.018	0.098	0.094	0.080
Probability Acquaintances Know One Another^2 (C^2)	-2.242*	0.879	-1.584*	0.772	-0.727*	0.360
Age			0.016*	0.003	-0.009*	0.002
Education			0.074*	0.017	0.014	0.011
Employed			0.074	0.092	-0.052	0.055
Group Membership			0.359*	0.095	0.311*	0.077
Income			0.027	0.033	0.061*	0.019
Interest in Campaign			0.969*	0.101	0.922*	0.066
Married			0.170*	0.082	-0.035	0.049
Constant	2.395*	0.150	-0.908*	0.342	-0.925*	0.202
N	10000		4352		4352	
Adjusted/Pseudo R^2	0.003		0.15		0.07	

Note: OLS regression for Net Favorable Change Model, probit regression for Turnout and Influence models. *C* is centered at 0.5 before squaring to reduce collinearity. Data for Net Favorable Change model is based on a network with 100,000 citizens, 4 neighbors per citizen on average, 20 interactions with each neighbor on average, a 0.4 probability that neighbors know one another, an imitation rate of 0.05, a correlation in preferences of 0.66 and an average path length of about 20. Missing data for actual models imputed using EMis (King et al 2001). Controls included because they correlate with *C* or C^2 and might be causally prior (King, Keohane, and Verba 1994). *p <.05