DRAFT

Targeting, Mobilization, and Action: Creating a Caste of Political Participants

Stephen Wendel, 9 February 2009

This paper is under development; frank comments and suggestions are more than welcome.

Introduction

Over multiple election cycles, mobilization by political campaigns can create a core group of individuals who are frequently asked to participate, and frequently respond. While a wealth of research in political science has examined issues such as "who votes?" and "who is asked to vote?" by and large, quantitative analyses have yet to consider the multi-cycle dynamics of mobilization and participation and how they can shape the pool of political participants over time.

I present a simple theoretical framework for the dynamics of political mobilization and participation, which subsumes numerous existing empirical models of political participation. I then employ statistical analyses of the American National Election Studies, along with Monte Carlo simulations, to examine three political acts: voting, making campaign contributions, and volunteering for political parties.

I demonstrate how multi-round mobilization and participation can generate a core of high-participation individuals; the impact from multiple electoral cycles is significantly beyond what would be expected from existing empirical analyses of mobilization or participation. The narrowness of the resulting high-participation group depends on the efficiency and consistency of the targeting process -- both of which are aided by recent technological advancements in individual level (micro)targeting. For campaign contributions and volunteering, this core of mobilized individuals dominates the pool of participants, and serious normative issues of democratic legitimacy and political inequality arise. The results suggest both flaws in existing models of dynamic political behavior and numerous avenues for future research.

Existing Literature

Engaging citizens in politics is a major concern for political scientists (e.g., Lijphart 1997) and political activists (e.g., Guzzetta 2006) alike. For political scientists, two abiding concerns have been low aggregate citizen participation over time, especially in elections[1] (e.g., Macedo et al. 2005), and the impacts of unequal participation on government policy and the vitality of democracy (e.g., Bennett and Resnick 1990; Lijphart 1997). For campaign managers, these concerns are joined by more mundane considerations of mobilizing supporters to win elections or securing the enactment of a policy.

Within American Political Science, numerous well developed lines of research exist on political participation and mobilization, many of which are driven by these fundamental concerns over democracy and inequality. The most prominent research area seeks to answer the question: "who participates?" The vast majority of research has focused on voter turnout (e.g, Downs 1957; Blais 2000; Zukin et al. 2006), with a smaller body of work studying non-electoral participation (e.g., Verba et al. 1995). A thorough review of this literature is outside of the scope of this study (see Niemi and Weisberg 2001), but a few gross generalizations can be made. While each type of political behavior has a different profile, researchers have found that overall those who are most likely to be political active are well educated, wealthy, white (e.g, Verba et

[1] Despite recent increases in turnout in the United States, aggregate turnout lags behind most Western democracies and concerns over unequal participation remain.

al. 1995), politically interested, engaged (e.g., Bartels 2000), asked to participate (e.g., Rosenstone and Hansen 1993), have a sense of duty (e.g., Blais 2000), and wish to be associated with a party and its social group (e.g., Schuessler 2000). In other words, researchers have found evidence that a variety of immutable personal characteristics and malleable attitudinal and behavioral characteristics lead to political engagement.

A second, prominent line of research asks "who is asked to participate?" in activities ranging from voting to street protests. Some researchers have found that those who are asked are simply those who are most likely to answer (i.e., that organizers are strategic, Rosenstone and Hansen 1993); while others have focused on whether individuals have the resources to answer (Verba et al. 1995), or whether they had participated previously (Abramson and Claggett 2001). Researchers have found that at any given moment, organizers consider many of the same personal characteristics that are involved in the individual choice to become politically active -- though perhaps with different weighting. However, Gershtenson (2003) cautions that the profile of who is asked changes over time as parties adapt to changing circumstances.

The short term impact of mobilization on political participation appears empirically robust. Rosenstone and Hansen (1993)'s book provides one of the most strident arguments that political mobilization is a driving force behind participation, stating that: "the level of electoral participation in the United States waxes and wanes in response to political mobilization. People participate in electoral politics in all its forms when they are mobilized to do so. When political mobilization falls, so does the propensity of people to take part" (p. 227). The authors trace changes over time in political activities ranging from writing a letter to elected officials, to attending a local political meeting, to making campaign contributions. Across all of these activities, they found a 6-10% boost in participation among those asked to do so, and a similar impact from dynamic personal characteristics, such as feelings of efficacy. Verba, Schlozman and Brady (1995), providing perhaps the seminal analysis of non-electoral participation, find mixed evidence of the role of institutional recruitment, but stronger support personal recruitment and dynamic personal characteristics, such as civic skills and efficacy. Abramson and Claggett's (2001) and Goldstein and Rideout's (2002) more recent work present methodological advancements, but find substantively the same role for mobilization and efficacy.[2] A growing tide of experimental literature (e.g., Green and Gerber 2004; Nickerson 2008) verifies the impact of certain forms of mobilization on turnout, both on directly targeted individuals and their households.

The long term impact of current participation on the likelihood of future participation has received surprisingly little attention, given its importance for understanding political mobilization. Clearly, a strong correlation exists between current participation and prior participation, even after controlling for socio-economic status and attitudinal factors (Abramson and Claggett 2001). Voting itself can be habit forming (Gerber, Green and Shachar 2003; Green and Shachar 2000), and participation can change internal feelings of efficacy which then affect the likelihood of participating in the future (Finkel 1985), and can affect other household member and social contacts (e.g., Jennings and Niemi 1968). The limited evidence on non-electoral behaviors indicate that participation often spreads through, and is reinforced by an individual's social network, leading to increased participation over time (Verba et al. 1995).

[2] Goldstein and Rideout (2002) strongly critique Rosenstone and Hansen (1993) on some of their more expansive claims about voter turnout in the US, but their findings on the role of mobilization and efficacy are similar. Abramson and Claggett (2001)'s measurement of efficacy is combined with other, less relevant factors; I reran their analyses after disaggregating their variable coding to verify efficacy's independent impact.

While these studies are clearly relevant to the dynamics of mobilization, they employ statistical analyses of a single interaction between organizers and the mobilized. After one such analysis of short-term recruitment effects, Abramson and Claggett (2001) give the warning: “Since past recruitment efforts may have induced past participation the total effect of recruitment, past and present, on current participation may be larger” (p913).

Research into these processes is limited by a scarcity of appropriate data. The empirical foundation of much of the electoral research in the United States, the American National Election Studies (ANES 2008), provides a wealth of cross-sectional data, and a few years of panel studies. Given the long lags between data collections (two years), it is difficult to isolate the effects of multiple rounds of mobilization from other life events. Researchers Verba et al. (1995) and Gerber, Green and Shachar (2003) present two exceptions in their studies of the dynamics of political behavior using a specially targeted survey and field experiments, respectively. Their work however, analyzes up to two cycles of mobilization and participation. Quantitative research into multi-round mobilization and participation is still limited.

This study diverges from existing research on three accounts. First, I consider multiple rounds of mobilization and participation, instead of one-off political campaigns, as is standard. Second, I consider how explicitly modeling the limited resources facing political campaigns shapes the campaigns’ production function (and hence, who is mobilized). Finally, I consider how the accuracy and efficiency of mobilization affects the pool of participations over time. I employ panel data from the American National Election Studies, and base the model of political participation on work by Abramson and Claggett (2001), Rosenstone and Hansen (1993), Goldstein and Rideout (2002) and Verba et al. (1995).

Theoretical Model

Given the considerable body of existing literature, and limitations noted above, I start with a somewhat novel approach. First, I assume that the existing literature is by and large correct, examining various standard, empirical models of single-step political mobilization and participation. I wrap these two components, mobilization and participation, in a single theoretical framework, and show how that framework subsumes much of the existing research. Then, I delve deeper into the issue of mobilization, looking at how different technologies drive patterns of mobilization and participation, drawing upon academic and practitioner literature. Finally, I analyze the implications of this model with a Monte Carlo simulation of multiple cycles of mobilization and participation. I find that repeated cycles can generate a group of political participants, depending on the form of political behavior and the technology of mobilization.

A Simple Cycle of Mobilization and Participation

Political mobilization and participation are messy, complex processes. Each political organizer and each potential participant behave differently, and their interaction depends on each party’s individual characteristics, the means and goal of the mobilization effort, and the overall shifting political context. Happenstance obviously plays a major role, as well. For this analysis, I step back from the details of these processes and present a stylized theoretical model of mobilization; after the outlines are clear, one can return to the gritty details to see how they influence the overall picture. This research centers on a three-stage "cycle of mobilization":

- Step 1: **Organizers select who to ask,** based on their political agenda, the exogenous characteristics of the targeted individuals (race, gender, etc), and endogenous traits of these individuals (experience, level of interest in politics, etc).
- Step 2: **Individuals decide whether or not to act**, based on their own political agenda, the overall political climate, their exogenous characteristics (race, gender, etc), their endogenous traits (experience, etc), whether they were *asked* to participate and by whom.
- Step 3: **The act of participation changes the individual**, providing skills and an increased (or decreased) sense of efficacy. Organizers also change, becoming aware of active individuals.
- Cycle: **Repeat Steps 1-3.**

This cycle is repeated, and individuals' traits evolve over their lifetimes. A simple graphical representation of this cycle is provided in Figure 1.

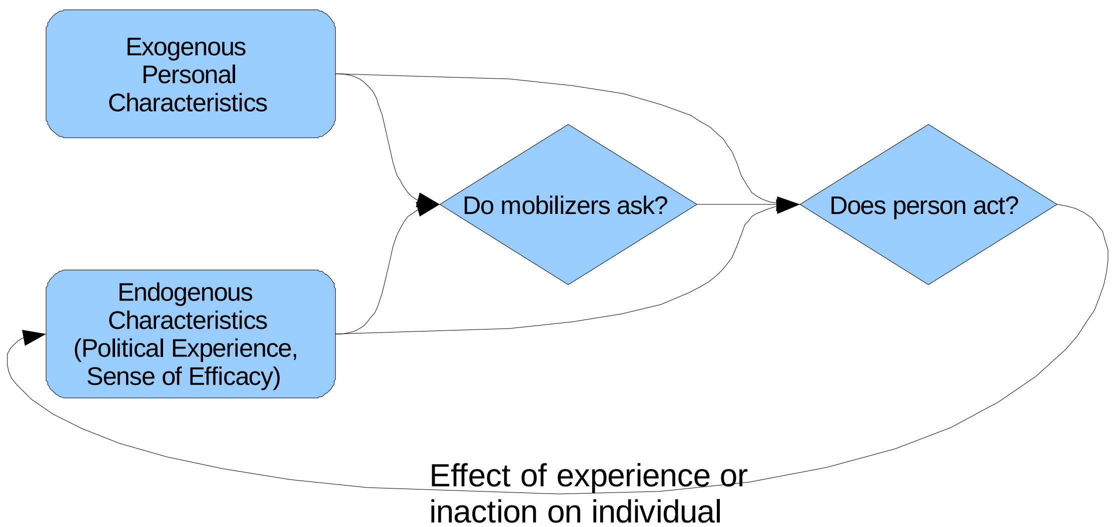

Figure 1: Cycle of Mobilization and Participation

General Mathematical Representation

This theoretical model can be more rigorously represented, and the assumptions made more explicit, by expressing it in mathematical form.   Given a vector of <u>s</u>tatic personal characteristics for individual i, S_i, a vector of mutable <u>h</u>istorical characteristics for that individual i at time t, $H_{i.t}$, and a time-specific political <u>c</u>limate of overall participation and interest in the campaign, C_t, define three functions:

- A <u>m</u>obilization function, $M_{i.t} = m(S_i, H_{i.t}, C_t)$, which determines whether individual i is asked to participate at time t.
    - m is a binary function; either an individual is asked to participate or is not.
    - m is stochastic; personal characteristics are not destiny.

- $\partial m_{i,t} / \partial S_i > 0$, $\partial m_{i,t} / \partial H_{i,t-1} > 0$. Each static and mutable characteristic within the vectors S_i and $H_{i.t}$ is measurable and can be expressed on a numeric scale, where increasing values indicate increased likelihood to be mobilized. I.e, some individuals are more likely to be asked than others, according to their meaningful personal characteristics.
- A participation function, $P_{i.t} = p(S_i, H_{i.t}, M_{i.t,} C_t)$, which determines whether the individual *i* participates at time *t*.
  - p is also a binary, stochastic function, which is monotonically increasing in $S_{i,} H_{i.t,}$ and $C_{t.}$ I.e., Individuals decide whether or not to act, taking solicitations, their personal characteristics, and the overall political climate into account, but their actions are not dictated by these parameters.
- An update function, $H_{i,t+1} = u(Si_, H_{i.t}, M_{i.t}, P_{i.t,} C_t)$ which determines how an individual's endogenous characteristics change given participation (or the lack their of) and the passage of time. Individuals are shaped by their experiences, updating their personal habits (Gerber, Green and Shachar 2003), or feelings of efficacy (Finkel 1985), etc.
  - u is monotonically increasing in $P_{i.t}$, and must allow for a decay of interest and skills over time. Both prior participation, $P_{i.t}$, and the vector of historical characteristics, $H_{i.t}$ (potentially influenced by all previous cycles of participation, $P_{i.1..t}$) shape the update function.

This simple model makes no assumptions about *who* is mobilizing for action – it could be professional organizers, neighbors with burning community concerns, or a demagogue rousing malcontents. These functions will serve as vessels into which one can pour existing models of mobilization, and concoct new ones. In the next section, I start to fill these vessels with empirical substance, examining existing research on American political behavior.

Specifications

Existing Academic Models

Consider two prominent books in the field (Rosenstone and Hansen 1993; Verba, Schlozman and Brady 1995), and two more recent research articles on political participation and mobilization (e.g., Abramson and Claggett 2001; Goldstein and Rideout 2002). Each can be readily expressed within this theoretical framework for mobilization and participation. For example, Goldstein and Rideout (2002)'s model can be written as:

$M_{i,t} =$ logit(B_o + (B_1 Age + B_2 Age^2+ B_3 Gender + B_4 Education + B_5 Black + B_6 South + B_7 Income + B_8 Union + B_9 Partisanship + B_9 HouseCompetitiveness + B_{10} SenateCompetitiveness + B_{11} PresidentialCompetitiveness + B_{12} GubernatorialElection) + (B_{13} * $H_{i,t}$))

$P_{i,t} =$ logit(B_o + (B_1 Age + B_2 Age^2+ B_3 Gender + B_4 Education + B_5 Black + B_6 South + B_7 Income + B_8 Union + B_9 Partisanship + B_{10} Married + B_{11} InterestInPolitics + B_{12} Efficacy + B_{13} HouseCompetitiveness + B_{14} SenateCompetitiveness + B_{15} PresidentialCompetitiveness + B_{16} GubernatorialElection + B_{17} ContestedPrimary + B_{18} PerceptionOfCloseness) + (B_{19} * $H_{i,t}$) + B_{20} $M_{i,t}$

$H_{i,t} =$ $P_{i,t-1}$ (i.e., participated in last election)

This model can be condensed into a clearer cycle of mobilization and participation:

$M_{i,t} = \text{logit}(B_o + B_{sm} S_i + B_{hm} H_{i,t} + B_{cm} C_t)$

$P_{i,t} = \text{logit}(B_o + B_{sp} S_i + B_{hp} H_{i,t} + B_M M_{i,t} + B_{cp} C_t)$

$H_{i,t} = P_{i,t-1}$

Where S_i is the vector of static personal characteristics; $H_{i,t}$ is the vector of mutable historical characteristics; C_t is the vector of characteristics of the contemporary political climate; (B_{sm}, B_{hm},B_{cm}), and (B_{sp}, B_{hp},B_{cp}) are vectors of coefficients for the relative weight of these characteristics in the mobilization and participation process, respectively.

Abramson and Claggett (2001) follow the same format, with small changes in the set of personal characteristics under consideration. Abramson and Claggett (2001) and Goldstein and Rideout (2002) both use a lagged dependent variable to analyze participation, which is a common technique in political science to handle estimation problems with time series cross-sectional data (Beck 2001; Beck and Katz 1995);[3] since mobilization is well documented to be correlated with prior participation, serious estimation bias can occur without this control.[4] Rosenstone and Hansen (1993), and Verba, Schlozman and Brady (1995), use probit and OLS variants, without the lagged dependent variable. All easily fit within the theoretical framework given above; Appendix C provides a more complete specification of each of the models, along with their relevant coefficients.

Adding a Budget Constraint to the Mobilization Function

The models employed by these researchers have a serious deficiency, however. They do not explicitly incorporate a budget constraint, and provide no rationale for *why* an organizer would select one person over another given this constraint. The result is a useful hindsight analysis of mobilization; one that could not, conceivably, be applied in practice.

Instead, organizers must employ a decision rule, implicit or explicit, that guides their choice of who to mobilize given their understanding of how to best secure political gains. In the practitioner literature (e.g., Guzzetta 2006), a range of pragmatic rules are suggested. For political campaigns, a simple rule is to target those individuals who are most likely to *increase* the number of votes in support of the campaign. It can be expressed in terms of the "lift" provided by mobilization. This targeting process will always be inaccurate, however, leading to potentially inefficient mobilization. The resulting specification uses a scoring function:[5]

$$M_{i,t} = \mathrm{TopN}[\, R_{i,t} * (P_{i,t|m=1} - P_{i,t|m=0}) + u_i]$$

Where,

$R_{i,t}$ = the likelihood that the individual *i* would prefer the candidate over her opponent

$P_{i,t|m=1} - P_{i,t|m=0}$ = the *lift* from mobilization, or the change in the probability that the individual will actually turnout to show that support

TopN = an indicator function that is 1 for individuals with the N highest values of the scoring function, and 0 for the rest. N is determined by the campaign's budget.

u_i = stochastic error in calculating each individuals' lift

An alternative targeting rule that has been discussed in the literature, mobilizing a campaign's most likely supporters, is considered under "Sensitivity Analyses", below.

[3] This standard approach is not without controversy (e.g., Wilson and Butler 2004; Beck and Katz 2004; Wawro 2002); among other issues, it assumes a geometric adjustment of y to x (i.e., with an extended impact on y over time; see Beck and Katz 2004). The issue is beyond this scope of this work but deserves further attention.

[4] Abramson and Claggett (2001) demonstrate the bias by re-estimating their equation without a lagged dependent variable; the impact of mobilization on participation, as the change in predicted probability, more than doubles.

[5] For many non-electoral campaigns, such as boycotts and street protests, there is very little chance that any particular person will spontaneously decide to engage in the exact action sought by the organizer. $P_{i,t|m=0} = 0$ and $P_{i,t|m=1}$ is constant for everyone. These campaigns can still be analyzed in this framework, by dropping the "lift" term.

Benchmark Model

The benchmark model builds upon standard multivariate analyses of participation, but includes the "lift" rule to govern mobilization by campaigns. The participation component includes the usual suspects – age, education, income, gender, etc – drawn from the four sets of researchers discussed above. Abramson and Claggett's (2001) research is particularly useful because it analyzes multiple forms of political activity (e.g., voting, campaign contributions and campaign volunteering). Like Abramson and Claggett (2001), I employ the 1992 ANES panel, the most recent panel dataset in which the necessary information is available. Codings of the ANES variables are provided in the Appendix, and are drawn almost exactly from Abramson and Claggett (2001).

The final specification is:

$$M_{i,t} = \text{TopN}[\,(P_{i,t|m=1} - P_{i,t|m=0}) + u_i]$$
$$P_{i,t} = \text{logit}(B_o + (B_1\,\text{Age} + B_2\,\text{Age}^2 + B_3\,\text{Gender} + B_4\,\text{Education} + B_5\,\text{Black} + B_6\,\text{South} + B_7\,\text{Income} + B_8\,\text{Union} + B_9\,\text{Partisanship} + B_{10}\,\text{Efficacy}) + (B_{11}\,H_{i,t}) + (B_{12}\,M_{i,t}) + (B_{13}\,C_t))$$
$$H_{i,t} = P_{i,t-1}$$

Individual researchers would add additional variables of interest to their specification; here I aim at the commonly considered set. For simplicity, I have assumed that campaign organizers have already excluded individuals who are unlikely to prefer their cause, and thus removing the $R_{i,t}$ term from the mobilization function.[6]

Hypotheses for the Dynamic Process

Numerous researchers have estimated the benchmark model's participation function (or similar versions). In so doing, they have only considered one of the ways in which mobilization can impact political behavior. Mobilization can have a direct impact on participation, increasing it during a given year. Authors including Rosenstone and Hansen (1993), Verba et al. (1995), and Green and Gerber (2004) have examined how political mobilization has a significant impact on voter turnout and other political behaviors. This impact is captured by the coefficient B_{12} on present-year mobilization in the participation function.

Mobilization can also have an indirect impact, something that is not adequately captured by the participation function alone; instead, a more thorough analysis of the entire dynamic process is needed. First, mobilization can influence participation by building the habit of participation (Green and Shachar 2000)[7] – and thus having a lasting, indirect impact on participation in future years. For example, consider an individual who otherwise would not vote. For whatever reason, that person is contacted by one of the political parties, and strongly encouraged to vote. Assuming that person successfully turns out to vote, s/he will have begun an internal habit of voting (due to increased comfort with the process, an increased sense of

[6] This assumption is valuable because it allows the analysis to use all of the individuals in voter surveys such as the ANES. It would be invalid if the predictive power of personal characteristics such as income, education and age substantially differed between liberals and conservatives. This assumption should be tested in the future to weigh the increased sample size against potential bias.

[7] Or, increasing an individual's sense of efficacy (Finkel 1985). For simplicity, I only consider the habit of participation here.

efficacy, etc.), and will be more likely to continue to vote in the future – a process triggered by the original act of mobilization. Similarly, mobilization can influence future participation by making individuals more likely to be *mobilized* in the future: by making them more likely to participate in the current year, they are more likely to be targeted for future mobilization, more likely to participate in the future, etc. Whereas mobilization can directly add new individuals to the voter pool, the indirect impacts work by retaining existing voters (Traugott 2004).

I speculate that by incorporating these two indirect impacts in the dynamic model, the total impact of mobilization will substantially increase. Moreover, by including a budget constraint, efficient mobilization will narrowly target certain individuals over time. Specifically, these hypotheses about mobilization and participation are suggested by the above discussion:

> **Hypothesis 1:** The impact of mobilization on participation has been significantly underestimated.
>
> **Hypothesis 2:** Cycles of mobilization and participation will narrowly target a subset of individuals: a class of participants who, over time, are frequently called upon to act. Inefficiency in the targeting process will lead to broader, more randomized, mobilization.

Simulation Execution

I use a simple Monte Carlo simulation, implemented in the R programming language, (R Development Core Team 2008; Imai, King, and Lau 2008) to model the cycle of mobilization and participation. The simulation code is structured as follows:[8]

1. Estimate the political participation function using ANES 1990-1992 panel data, for each of the three forms of participation: voting, campaign contributions, campaign volunteering (see Appendix for details).
2. Implement the mobilization function described above, selecting individuals who would show the greatest "lift" from mobilization, subject to random error.
3. Implement the update function, which records whether each individual participated or not in a given cycle.
4. Using the ANES data, execute a loop that repeatedly applies the mobilization function, the prediction model, and the update function to each individual in the dataset, for a given number of cycles.

I sought to simulate an adult lifetime, with roughly 25 opportunities to participate in midterm or presidential election-year mobilizations. Each execution of the model thus created a panel data set with the 1,097 individuals in the ANES data, and 26 time slices starting with the original ANES data and continuing through 25 subsequent biannual elections.[9] Since the model is stochastic, I executed the Monte Carlo simulation 100 times for each form of political participation. The resulting dataset contained 300 simulation runs, each producing a 1097x26 panel.

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[8] The code itself is included in the Appendix.

[9] Births and deaths (entry and exit from the participant pool) were not modeled in this analysis, and should be considered in future research.

Results

The simulations demonstrate that efficient mobilization can increase overall participation and create a set of individuals that are repeatedly called to action. In the case of campaign volunteering and campaign contributions, these individuals dominate the pool of participants, fostering unequal participation.

Indirect impacts of mobilization substantially increase participation

As noted above, mobilization can have direct or indirect impacts on participation. The direct impact is straightforward to conceptualize and calculate: it is provided by the coefficient on current-year mobilization. For each individual, the direct impact of mobilization is the change in the predicted probability given by the single-time period participation function, with and without mobilization, given the individual's other characteristics. To calculate the indirect impact of mobilization, I first executed the simulation model without mobilization, and determined the probability of participation for each individual, $P_{i|m=0}$. I executed the simulation again with mobilization, and found the total impact of mobilization for each individual, $P_{i|m=1} - P_{i|m=0}$. I subtracted the direct impact of mobilization from the total impact of mobilization (direct and indirect), to discover the indirect impact:

- For voting behavior, the average direct impact of mobilization was 9.3%,[10] and the average impact of mobilization, direct and indirect, per individual was 13.3%.[11] The average indirect impact of mobilization thus was 13.3% – 9.3% = 4.0%. The total impact of mobilization, after one takes indirect effects into account, is 43% greater than expected.
- Even larger indirect impacts occur for campaign contributions and campaign volunteering. The average direct impact of mobilization on volunteering is 29.8%, and the total impact is 50.6%. The indirect impact is 50.6%-29.8% = 20.8% – the total impact is 70% greater than expected. For campaign contributions, the total impact of fundraising appeals is more than double their direct impact.

These findings cast doubt on current, single-round, empirical analyzes of mobilization and participation; if nothing else, the role of mobilization has been substantially underestimated. If mobilization were simply a minor factor in overall turnout and political participation, then a 40% to 100% increase in its actual impact would be an interesting footnote, but nothing more. However, the level and effectiveness of mobilization are two of the few factors that systematically vary between election cycles (Rosenstone and Hansen 1993), and thus provide a potential explanation for both the decline in American voter turnout from the 1960s to 1990s and the apparent recent up-swing. While some researchers have cast aside mobilization as an explanation (e.g., Goldstein and Rideout 2002), their results are based on a incomplete model of

[10] This is the lift assuming that individuals had absolutely no prior experience voting. If the analysis is run with the level of individual participation given in the ANES 1992 panel, then the direct impact of mobilization is significantly less (6.8) and thus the indirect impact is significantly greater (6.5%, or 95% larger than expected). I.e., the estimate given in the text is a conservative figure for the actual indirect impact of mobilization.

[11] Averaged across all of the simulations with mobilization, the participation rate was 73.7%, and without mobilization the rate was 70.0% Since mobilization was only applied to 25% of the population, the total impact per person mobilized was (73.4-70)*4.

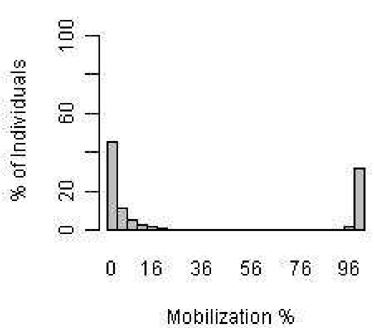
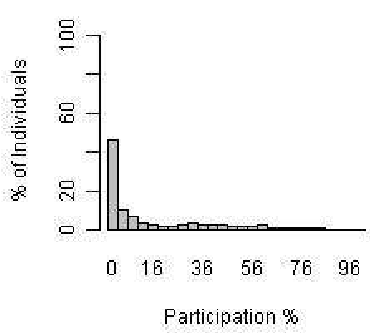
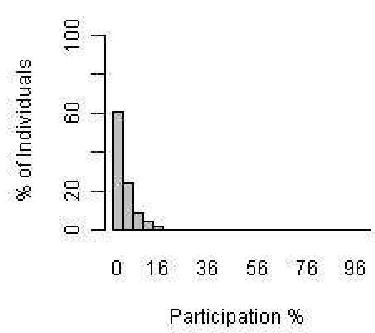
mobilization. The role of mobilization in the rise and decline of turnout over time deserves reconsideration.

Narrow mobilization, and frequently narrow participation

In addition to increasing aggregate levels of participation, mobilization can play a troubling role in fostering unequal participation. Numerous authors have examined the normative and positive consequences of unequal political participation to the health and legitimacy of democracy, particularly for unequal voter turnout (e.g., Macedo et al. 2005). If the political process significantly under-represents particular groups or viewpoints, then political instability and violence among disaffected groups is one of the extreme outcomes. Unfortunately, it appears that the increase in campaign contributors and volunteers due to multiple cycles of mobilization are concentrated in a relatively small, unrepresentative, portion of the population.

As rounds of appeals and campaign contributions proceed through time, a distinct group of individuals appears who are mobilized the majority of the time, and participate at significantly higher rates than the rest of the population. The size of this group is relatively small – but, their impact is considerable. Roughly 33% of individuals in the population are mobilized more than 95% of the time.[12] On average, these individuals account for 89% of all of the instances of donations made to the political parties. In any given cycle, this high-mobilization, high-participation group accounts for between 82% and 94% of all of the individuals making contributions. Table 1 illustrates how this narrow segment of the population is repeatedly asked to make contributions, and how mobilization successfully garners their participation. The first graph shows the distribution of mobilization; the second graph shows the distribution of participation when mobilization occurs; and the third graph provides contrast, indicating how participation would have been distributed if no mobilization had occurred. When repeated appeals for contributions are removed, as shown in column three, the significant disparity between frequent and infrequent participants disappears.

Table 1: Impact of Mobilization on Campaign Contributions

<table>
<tr><th>Frequency with which Individuals are Mobilized</th><th>Participation with Mobilization</th><th>Participation without Mobilization</th></tr>
<tr><td>
</td><td>
</td><td>
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[12] Nearly all of those individuals who are called upon to make a contribution a given cycle are called upon repeatedly. The quantity of money donated, another obvious source of inequality, is not modeled here because of the ANES data used for the analysis. Mobilization is well known to concentrate on major givers, and this dynamic process would be expected to further exacerbate the disparity; this issue should be examined in further research.

For campaign volunteering, roughly 7.6% of the individuals, roughly half of the number of individuals who are mobilized in a given cycle, are mobilized more than 80% the time. These individuals account for 38% of the participation-events. I.e, over the 25-cycle period, when an individual volunteers for a political campaign, 38% of the time that individual is from this coterie of activists. As with campaign contributions, the narrow group is entirely a product of the cycle of mobilization and participation, and does not occur without mobilization. Examining the issue from the other direction, over 60 % of individuals are mobilized less than 10% of the time. This group, a majority of the population, accounts for only 12.5% of the participation-events.

For voting, the impact of multiple rounds of mobilization is rather different. Because voting is a significantly more common activity than volunteering or making campaign contributions, the group of individuals hit by Get Out The Vote efforts are intermixed with those who would have participated regardless, due to their other personal characteristics (income, education, etc). Cycles of mobilization still target a narrow section of the population; for example, 13% of the population is mobilized over 50% of the time. This group does not dominate the pool of participants, however – they are individuals with moderate levels of prior turnout probability who are successfully pushed up into the larger pool of high-probability individuals. The outcome is a slight increase in inequality, since the resulting distribution consists of low probability individuals and an enlarged pool of high-probability individuals, but nowhere near the stark results found for other political behaviors.

One obvious critique of these findings would be that since the impact of mobilization has probably been misestimated in current research models, including the model of participation employed here, any examination of the narrowness of that mobilization process would be unfounded. What would happen if the impact of mobilization had been over-, or under-, estimated by a significant margin, e.g., 50%? To test this scenario, I repeat the entire analysis at varying levels of mobilization-effectiveness. The results are substantively the same. As the impact of mobilization decreases, the gap between high-participation and low-participation individuals decreases, but it still clearly separates the smaller, high-participation group from the rest of the population. As the effectiveness of mobilization increases, the gap widens. The next section considers other variations on the assumptions and parameters used in the benchmark model.

Sensitivity Tests

The effect of inaccurate targeting on mobilization

One could object to the presumption that political mobilizers can effectively target individuals, i.e. that they have sufficient data on the population of potential activists and the methodological tools to target them. To simulate the effect of inaccurate targeting, I reran the campaign contribution simulations with noise injected into the mobilization process. In this version, the organizers are unable to accurately asses the best individuals to target, because of random noise in the "lift" function. A sample of the results, where I injected Gaussian noise with a standard deviation set to 50% of the entire range mobilization scores, is shown in Figures 2 and 3, below. As projected in Hypotheses 2, inefficient mobilization leads to a broader swath of individuals contacted.   Even with such a large amount of noise in the process, however, mobilization (and participation) favor a group of high-participation individuals.

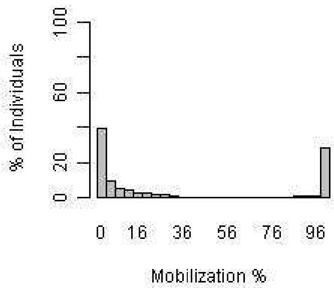

Figure 2: Normal Mobilization for Campaign Contributions

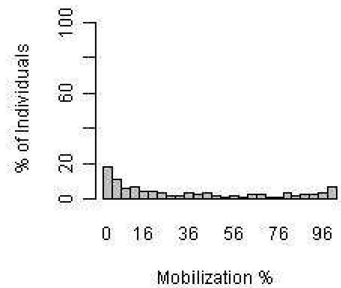

Figure 3: Noisy Mobilization for Campaign Contributions

The assumption of accurate targeting is increasingly valid, at least in high-stakes political campaigns in the United States. The breadth and depth of consumer, demographic and behavioral data that is becoming available about individuals is shocking, if not disturbing. Companies such as Artisotle, Catalist and TargetSmart provide this data, along with comprehensive voter files, to targeting firms for pennies per individual.   While the accuracy of some of the information is questionable, overall there is more than sufficient data to generate a detailed profile on each individual. This flood of data is being harnessed by new behavioral targeting technologies employing machine learning techniques, including micro-targeting. The result is an increasingly accurate targeting process, aimed specifically at individuals with the greatest potential lift from mobilization.[13]   As recently as a decade ago, detailed consumer and demographic data on individuals was simply unavailable; instead, organizers had to rely on census block and precinct level data, and pick “the best neighborhoods” to target.

An alternative mobilization function: likely supporters

Goldstein and Rideout (2002) provide another possible critique of the “efficiency” assumption used in the benchmark model. They argue that historically organizers do not efficiently target high “lift” individuals in their Get Out The Vote campaigns, and actually target those individuals who are already the most likely to cast a vote for the candidate.   This inefficiency is due to fears that the mobilization effort will either energize opponents or, alternatively, fail to turnout the campaign’s strongest supporters.   The resulting mobilization function is:

$$M_{i,t} = \text{TopN}[\, R_{i,t} * P_{i,t|m=1} + u_i]$$

[13] Another arena in which accurate targeting is possible is political protest.   The “data” used for targeting in this case is fundamentally different. As Verba et al. (1995) note, mobilization around political protest comes overwhelmingly from friends and family. Protest spreads through networks of individuals who know each other. Along these networks, the “organizer” is often acutely aware of the interests and relative likelihood of participating for his or her friends and family. The assumption of accurate targeting does not seem out of place.

Where,

$R_{i,t}$ = the likelihood that the individual *i* would prefer the candidate over her opponent
$P_{i,t|m=1}$ = the probability that the individual will actually turnout to show that support (with a vote).
TopN = an indicator function that is 1 for individuals with the N highest values of the scoring function, and 0 for the rest. N is determined by the campaign's budget.

Unfortunately, Goldstein and Rideout (2002) do not employ this function in their analysis, perhaps because of the challenges it poses for statistical estimation; they instead use the more tractable logit function provided above, which lacks a budget constraint. As with noise injected into the mobilization process, this alternative mobilization function lessens the magnitude of the observed effects, but not the substantive findings of this paper.[14]

Analysis

Stepping back from the detailed simulation results, these findings raise a number of interesting questions about political mobilization and participation. The lock-in effect of multiple cycles of mobilization and participation could have a dramatic effect on other, low-frequency, political activities such as political protest. Participants in these activities are a small subset of society, often interacting within that group during the protest. Moreover, once in the cycle, one would expect activists to bond as a community under shared experiences. A community bond and commonality of experience can be a powerful force leading activists to make the personal sacrifices necessary for collective action. Small coteries of like-minded activists may provide insight into a host of collective models. Lohmann (2000) and Marwell and Oliver (1993), for example, both have detailed theories on how small groups of individuals spark larger political movements.

If this analysis is correct, what would the results auger for grassroots mobilization campaigns? Among other factors, they indicate that it would behoove organizers to consider long run implications of mobilization. Political campaigns seeking to elect a candidate naturally focus on who they can push to vote or make a campaign contribution, given the person's current responsiveness, and rarely consider changing the person's future responsiveness. However, organizers somewhat insulated from the immediate rush of a particular campaign, particularly in unions, religious organizations, and national political parties, could benefit from an understanding of how the delayed, indirect impacts of mobilization can lead to greater support for future campaigns. Creative solutions would be needed to utilize short-term opportunities for mobilization at the individual level while informing long-term strategies for engaging citizens in political activity.

[14] For campaign contributions and volunteership in particular, "likely supporters" are similar to the individuals with the greatest "lift". In part, this result is a direct consequence of the fact that a logit model is employed; in both cases, the number of individuals who would normally participate is low, and high propensity individuals are also high response. Over the multiple rounds of mobilization and participation, some individuals are moved into a lower response pool, leading to a divergence between the two groups.

Conclusion

Political campaigns expend vast resources to mobilize their supporters. Organizers know that some individuals will turn out for their candidate regardless of the campaign's mobilization efforts, while others need encouragement and assistance to show up. In the final days of electoral campaigns, organizers will often focus their Get Out The Vote efforts on those marginal voters for whom a direct appeal will most increase their likelihood of turning out to cast a favorable ballot.

Here, I provide a simple theoretical framework that subsumes a set of prior models on political participation and mobilization. This theoretical framework helps move us from narrow analyses of individual campaigns to a wider view of mobilization and participation over time. I examine the stark implications of a particular dynamic model of mobilization and participation, which draws from well known heuristics in the practitioner community and relevant academic research. Across the disparate political behaviors of voting, campaign volunteering, and political contributions, I find that multiple cycles of participation and mobilization generate a coterie of participants. These participants are repeatedly called to action and repeatedly respond. In the case of campaign contributions and volunteering, the mobilized individuals dominate the pool of participants, raising serious normative questions. Moreover, I argue that this effect will increase because of recent improvements in behavioral targeting, i.e., micro-targeting using detailed individual-level consumer data.

If the above theory is correct, then the implications for collective political action are significant. Numerous interesting avenues for future research can be examined within this framework, including the long-term impact of episodes of heavy mobilization, socialization, neighborhood effects (Gimpel et al. 2004), household effects (Jennings and Niemi 1968), and the crossover of skills from one form of political behavior to others. Given the normative issues raised here, further research should also be considered on the demographic profile of mobilized participants, and strategies to mitigate the potential for inequality while still enjoying the benefits of an engaged citizenry.

Appendix A: Works Cited

Abramson, P. R. and Claggett, W., 2001. Recruitment and Political Participation, *Political Research Quarterly* 54, no. 4: 905.

American National Election Studies, 2008. *The ANES Guide to Public Opinion and Electoral Behavior*, Ann Arbor, MI: University of Michigan, Center for Political Studies. Available at: http://www.electionstudies.org [Accessed March 8, 2008].

Bartels, L. M., 2000. Partisanship and Voting Behavior, 1952-1996. *American Journal of Political Science* 44, no. 1: 35-50.

Beck, Nathaniel, 2001. “Time-Series-Cross-Section Data: What Have We Learned in the Past Few Years?,” *Annual Review of Political Science* 4, no. 1: 271.

Beck, Nathaniel and Katz, Jonathan N, 2004. *Time-Series Cross-Section Issues: Dynamics*, Available at: http://politics.as.nyu.edu/docs/IO/2576/beckkatz.pdf.

Beck, Nathaniel and Katz, Jonathan N., 1995. What to do (and not to do) with Time-Series Cross-Section Data. *The American Political Science Review* 89, no. 3: 634.

Bennett, S.E. & Resnick, D., 1990. The Implications of Nonvoting for Democracy in the United States. *American Journal of Political Science*, 34(3), p.771-802.

Blais, Andre, 2000. *To Vote Or Not To Vote: The Merits and Limits of Rational Choice Theory*, Pittsburgh: University of Pittsburgh Press.

Downs, A., 1957. *An Economic Theory of Democracy*, New York: Harper & Row.

Finkel, S.E., 1985. Reciprocal Effects of Participation and Political Efficacy: A Panel Analysis. , 29(4), p.891-913.

Gimpel, J. G., Dyck, J. J. and Shaw, D. R., 2004. “Registrants, Voters, and Turnout Variability Across Neighborhoods,” *Political Behavior* 26, no. 4: 343-375.

Gerber, A.S., Green, D.P. and Shachar, R., 2003. Voting May Be Habit-Forming: Evidence from a Randomized Field Experiment, 47(3), p.540-550.

Gershtenson, J., 2003. Mobilization Strategies of the Democrats and Republicans, 1956-2000, *Political Research Quarterly* 56, no. 3: 293.

Green, D. P., and Gerber, A. S., 2004. *Get Out the Vote! How to Increase Voter Turnout* Washington DC: Brookings Institution Press.

Green, DP and Shachar, Ron, 2000. Habit Formation and Political Behaviour: Evidence of Consuetude in Voter Turnout, *British Journal of Political Science* 30, no. 04: 561-573.

Goldstein, Kenneth M. and Ridout, Travis N., 2002. “The Politics of Participation: Mobilization and Turnout over Time,” *Political Behavior* 24, no. 1: 3-29.

Guzzetta, S.J., 2006. *The Campaign Manual: A Definitive Study of the Modern Political Campaign Process*, Alexendria, Virginia: Political Publications.

Imai, Kosuke King, Gary and Lau, Oliva, 2008. "logit: Logistic Regression for Dichotomous Dependent Variables" in Kosuke Imai, Gary King, and Olivia Lau, "Zelig: Everyone's Statistical Software," http://gking.harvard.edu/zelig

Jennings, M. K. and Niemi, R. G., 1968. “The Transmission of Political Values from Parent to Child,” *American Political Science Review* 62, no. 1: 169-184.

Lijphart, A., 1997. “Unequal Participation: Democracy's Unresolved Dilemma,” *American Political Science Review* 91, no. 1: 1-14.

Lohmann, S., 2000. “Collective Action Cascades: An Informational Rationale for the Power in Numbers,” *Journal of Economic Surveys* 14, no. 5: 655-684.

Macedo, S. et al., 2005. *Democracy at Risk: How Political Choices Undermine Citizen*

Participation and What We Can Do About It, Washington, DC: Brookings Institution Press.

Marwell, G. and Oliver, P., 1993. *The Critical Mass in Collective Action: A Micro-social Theory* Cambridge University Press.

Niemi, Richard G. and Weisberg, Herbert F., 2001. *Controversies in Voting Behavior*, 4th ed. Washington, DC: CQ Press.

R Development Core Team, 2008. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org.

Rosenstone, S.J. and Hansen, J.M., 1993. *Mobilization, Participation, and Democracy in America.* New York: Macmillan.

Schuessler, A.A., 2000. *A Logic of Expressive Choice*, Princeton and London: Princeton University Press.

Traugott, M. W., 2004 "Why Electoral Reform Has Failed: If You Build It, Will They Come?," *Rethinking the Vote: The Politics and Prospects of American Election Reform*. New York: Oxford.

Verba, S., Schlozman, K.L. and Brady, H., 1995. *Voice and Equality: Civic Voluntarism in American Politics*, Cambridge, MA: Harvard University Press.

Wawro, G., 2002. Estimating Dynamic Panel Data Models in Political Science, *Political Analysis* 10, no. 1: 25-48.

Wilson, S.E. and Daniel M. Butler, 2004. *A Lot More to Do: The Promise and Peril of Panel Data in Political Science*, Available at: http://www.stanford.edu/class/polisci353/2004spring/reading/wilson_butler.pdf.

Zukin, Cliff, Keeter, Scott, Audolina, Molly, Jenkins, Krista and Delli Carpini, Michael X. 2006. *A New Engagement? Political Participation, Civic Life, and the Changing American Citizen.* New York: Oxford University Press.

Appendix B: Simulation Implementation

This section describes the Monte Carlo simulation model used in the body of the paper. The simulation is written in the R programming language, with user-defined parameters to establish the static and mutable historical characteristics of individuals as well as the mobilization, participation, and update functions. An additional parameter sets the number of mobilization cycles to execute. The central algorithm of the program is as follows:

```
dta <- loadNESIndividuals();

participModel <- zelig(formula=form, model="logit", data=.dta);
# For Voting Behavior: participModel <- zelig(formula=form,
model="logit.gee", data=.dta);

for (i in 1:numUpdates)
{
	# Update Time Counter
	dta$curTime <- i

	# Update History: with a simple shift
	dta[,historyVar] <- dta[,participVar]

	# Mobilize
	# ... Calculate the expected lift from mobilization
	dta[,"mobScore"] <- changeInPredictedProbFromMob(dta)

	# .. Add Error
	if (mobError > 0)
	{
		dta[,"mobScore"] <- dta[,"mobScore"] + rnorm(n=numIndividuals,
		mean=0, sd= mobError*sd(dta[,"mobScore"]))
	}

	# .. Take the top N individuals
	dta[,mobVar] <- as.numeric(dta[,"mobScore"] >
quantile(dta[,"mobScore"],c(1-.Object@mobilizationBudget)))

	# Participate
	# ...Get the predicted probabilities
	dta[,participProbVar] <- predictedParticipProb(dta)

	# ...decide whether person should participate, based on score
	dta[,participVar] <- as.numeric(runif(numIndividuals) <
dta[,participProbVar])

	# Record the results
	individualHistory <- rbind(individualHistory, dta[,varsToRecord])
}
```

Appendix C: Detailed Analysis of Academic Models of Participation and Mobilization

This appendix illustrates how the research of Abramson and Claggett (2002) and Rosenstone and Hansen (1993) can be expressed within the dynamic framework of participation and mobilization. The case of Goldstein and Rideout (2002) is covered in the body of the text. Coefficients from each author are summarized on the next page.

Abramson and Claggett (2001) use the following equations to estimate the determinants of mobilization and participation:

$M_{i,t} =$ logit(B_o + (B_1 Age + B_2 Gender + B_3 Education + B_4 Black + B_5 South + B_6 Income + B_7 Union + B_8 Partisanship + B_9 PresidentialCompetitiveness + B_{10} GubernatorialElection + B_{11} SenateElection + B_{11} ElectoralVotes + B_{12} Employment Status + B_{13} Log(YearsInCommunity) + B_{14} Homeowner + B_{15} ReligiousAttendance + B_{16} IdeologicalExtremity + B_{17} GroupMember) + (B_{18} * $H_{i,t}$))

$P_{i,t} =$ logit(B_o + (B_1 Age + B_2 Gender + B_3 Education + B_4 Black + B_5 South + B_6 Income + B_7 Union + B_8 Partisanship + B_9 PresidentialCompetitiveness + B_{10} GubernatorialElection + B_{11} SenateElection + B_{11} ElectoralVotes + B_{12} Employment Status + B_{13} Log(YearsInCommunity) + B_{14} Homeowner + B_{15} ReligiousAttendance + B_{16} IdeologicalExtremity + B_{17} GroupMember + B_{18} InterestInPoliticsAndEfficacy + B_{19}CandidateAffect)
+ (B_4 * $H_{i,t}$) + (B_5 $M_{i,t}$))

$H_{i,t} = P_{i,t-1}$

As shown for Goldstein and Rideout (2002) this model can be condensed into a clearer cycle of mobilization and participation:

$$M_{i,t} = \text{logit}(B_o + B_{sm} S_i + B_{hm} H_{i,t} + B_{cm} C_t)$$
$$P_{i,t} = \text{logit}(B_o + B_{sp} S_i + B_{hp} H_{i,t} + B_M M_{i,t} + B_{cp} C_t)$$
$$H_{i,t} = P_{i,t-1}$$

Where S_i is the vector of static personal characteristics; $H_{i,t}$ is the vector of mutable historical characteristics; C_t is the vector of characteristics of the contemporary political climate; (B_{sm}, B_{hm}, B_{cm}), and (B_{sp}, B_{hp}, B_{cp}) are vectors of coefficients for the relative weight of these characteristics in the mobilization and participation process, respectively. Rosenstone and Hansen (1993) do not account for prior participation, leading to the following simplified model:

$$M_{i,t} = \text{probit}(B_o + (B_1 \text{ gender} + B_2 \text{ race} + B_3 \text{ income} + \ldots))$$
$$P_{i,t} = \text{probit}(B_o + (B_1 \text{ gender} + B_2 \text{ race} + B_3 \text{ income} + \ldots) + B_5 M_{i,t}$$

Table A.1, below summarizes the results of these documents in terms of three parameters of interest: the impact of mobilization on participation, the impact of prior participation on current participation, and the impact of prior participation on mobilization. In each instance where data is available, changes in predicted probabilities are given, calculated using average values for all other variables.

Table A.1: Change in Predicted Probabilities

Behavior	Impact of…	Abramson and Claggett	Goldstein and Rideout	Rosenstone and Hansen
Vote Turnout, Presidential Election Year	Mobilization on Participation	4.3%***	8%*	7.80%
	Prior Participation on Current Participation	27.00%	NA**	NA
	Prior Participation on Mobilization	7.90%	NA**	NA
Street Protest	Mobilization on Participation	NA	NA	NA
	Prior Participation on Current Participation	NA	NA	NA
	Prior Participation on Mobilization	NA	NA	NA
Campaign Work	Mobilization on Participation	12.80%	NA	4.80%
	Prior Participation on Current Participation	11.00%	NA	NA
	Prior Participation on Mobilization	26.00%	NA	NA
Contributions	Mobilization on Participation	6.30%	NA	6.60%
	Prior Participation on Current Participation	16.40%	NA	NA
	Prior Participation on Mobilization	36.00%	NA	NA

Appendix D: Operationalization of Variables *[Incomplete]*

This study used ANES 1990-1992 Panel Data, and a participation model based on Abramson and Claggett's (2002) analysis of the same. For consistency, whenever possible the same codings were used here as in Abramson and Claggett (2002). In some cases, insufficient information was provided in their text and has been expanded upon here.

Codings Applied Directly from Abramson and Claggett:

Education: 8 years of education or less were coded 0, 9-12 years of education but no diploma was coded .2, a high school diploma or equivalent was coded .4, some post-secondary education but no four year college degree was coded .6, a college degree or more, but no advanced degree was coded .8, and an advanced degree was coded 1.

Family Income: Family income was set at the midpoint value, in thousands of dollars, of the family income category that the respondent reported. Respondents who fell into the highest income category were assigned the value of 112.5. For respondents who refused to report their income and for those who the interviewer believed did not report their income correctly we used the midpoint value, in thousands of dollars, of the income category that the interviewer thought best described the respondent's family income.

Employment Status: Respondents who reported working 20 or more hours per week were coded 1 and all others were coded 0.

Age: Actual age in years.

Years in the community, logged: This variable is the natural log of the number of years that the respondent reported living in the community. Length of time in the community was set at .25, .75 and 1.5 for respondents who reported that they had lived less than 6 months, 6-12 months, and 13-23 months in the community respectively. Length of time in the community for respondents who reported that they had lived in the community all their life was set at their age.

South: Coded 1 if the respondent lived in Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North or South Carolina, Tennessee, Texas or Virginia and 0 otherwise.

Sex: Female was coded 1 and male 0.

Race: Blacks were coded 1 and all others 0.

Religious attendance: Those who reported that they attended church or synagogue more than once a week, once a week, almost every week, once or twice a month, a few times a year and never were coded 1, .8, .6, .4, .2 and 0 respectively Those who reported that they never attend religious service except for weddings, baptisms or funerals were also coded 0.

Ideological extremity: Respondents who placed themselves at the extreme liberal or conservative ends of the 7 point ideology scale were coded 3, those who placed themselves at the liberal or conservative position of the scale were coded 2, those who chose the slightly liberal or conservative positions were coded 1 and those who placed themselves at the middle position or who claimed that they hadn't thought about their position were coded 0.

Group member: Respondents who reported that they belonged to any organization or took part in any activities that represented the interests and viewpoint of the group that they felt particularly close to were coded 1, otherwise they were coded 0.

Union Family: Respondents who reported that they or some member of their household belonged to a union were coded 1 and all others were coded 0.

Strength of Party Identification: Pure independents and apoliticals were coded 0, leaning independents .33, weak partisans .67, and strong partisans 1.

Concurrent gubernatorial election: This variable was coded 1 if the respondent lived in a state in which a gubernatorial election was held in 1992 and 0 otherwise.

Concurrent senatorial election: This variable was coded 1 if the respondent lived in a state in which a senatorial election was held in 1992 and 0 otherwise.

Electoral vote: The number of electoral votes of the state in which each respondent was coded.

State Close: The absolute value of the difference between Clinton and Bush's percentage of the total presidential vote in the respondent's state subtracted from 100.

Additional Codings: *[Incomplete]*

Political engagement: Was derived from a principal component analysis of five variables: attention to the campaign, whether the respondent follows what is going on in government and public affairs, internal (politics too complicated) and external (additive index based on people like me don't have any say and public officials don't care what people like me think) political efficacy, and political knowledge. The latter variable was an additive index of interviewer's pre-election assessment of the respondent's political knowledge (coded into the 0-1 interval) and whether the respondent knew that the Republican party was the most conservative party, which party controlled a majority of seats in the House and Senate prior to the election, what job or office Dan Quayle, William Rehnquist, Boris Yeltsin, and Tom Foley held, and which branch of government was responsible for deciding if a law was constitutional and which nominated Federal judges.

Presidential candidate affect: Was derived from a principal component analysis of four variables: whether the respondent cared about who would win the presidential election, whether the respondent's pre-election presidential preference was strong or not, the maximum pre-election feeling thermometer rating that the respondent gave for Bush, Clinton or Perot, and the difference between the respondent's highest and lowest rated presidential candidate on the pre-election feeling thermometers.

Appendix E: Estimation of Participation Models *[Incompete]*

The benchmark model's participation function is difficult to estimate empirically, for two reasons. First, it is part of a non-linear, non-stationary dynamic process, which violates the assumptions of many standard estimation procedures (Hendry 1995). Second, a minimum of three periods of participation data are needed to conduct a valid estimation,[15] and appropriate panel data are extremely scarce.

I seek to analyze three political behaviors: voting, campaign contributions, and campaign volunteership. To estimate voting behavior, I employ the ANES 1992 panel, which has complete panel data for 1990 and 1992, and validated voting information for 1988, creating two panel periods each with a lagged dependent variable. I use a Generalized Estimating Equation (GEE) logit approach (Zeger and Liang 1986), which allows for the estimation of non-linear models on longitudinal data. For campaign contributions and campaign volunteership, no appropriate three-year panel data appears to exist. I fall back on the two-period logit model used in Abramson and Claggett (2001), and consider the limitations of that data further on.

Besides the use of a GEE logit for voting behavior, estimating the participation equation for each of the three behaviors is not innovative, and both the functional form and results closely follow Abramson and Claggett (2001). As noted in the text, the statistical model can capture the direct impact of mobilization on participation; it does not, however, capture its indirect impacts. The indirect impacts will show up partially in biased coefficient estimates; since they increase participation through the intermediary of prior participation, one would expect that the prior participation coefficient will be incorrectly high; that expected bias does not detract from the main findings in the paper, if anything, we would expect a greater relative role for mobilization if the bias is removed. Second, indirect impacts will likely show in serially correlated standard errors, beyond the AR1 process included in the model.

Two alternatives would appear promising to handle the indirect effects. If sufficiently detailed multi-year data were available, a researcher might employ an instrumental variables approach to capture these indirect effects. Similarly, if extensive longitudinal data were available on youths entering the voting pool, direct and (time-delayed) indirect effects could be isolated. Since such data is not available, the paper employs a set of simulations to better understand the direct and indirect impact of mobilization separately.

Voter Turnout Model, GEE Logit:

After dropping insignificant terms, the resulting model for voter turnout was:

[15] Researchers such as Abramson and Claggett (2001) estimated a logit model of participation for a single year (1992), pulling in an additional year of data (1990) for the lagged dependent variable. However, since acts of political participation such as voting have well-known cycles (higher participation in presidential years, lower in midterm elections), the lagged dependent variable will incorrectly capture both prior participation due to individual factors and the cyclic overall level of participation in that year. An additional time-specific control is needed to remove this effect, and thus three years of data are needed to uniquely identify the (immutable) independent variables, lagged dependent variable, and fixed temporal effect.

```
Coefficients:
                                   Estimate Naive S.E.  Naive z Robust S.E. Robust z
(Intercept)                       -0.264316   0.415989  -0.6354    0.434823  -0.6079
Lag_Turnout                        1.039014   0.167600   6.1994    0.172313   6.0298
Vote.recruitment                   0.424844   0.181093   2.3460    0.193348   2.1973
Age                                0.028205   0.005372   5.2504    0.005494   5.1343
Education                          1.481872   0.367677   4.0304    0.385836   3.8407
Family.income                      0.005066   0.003513   1.4419    0.003962   1.2785
Strength.of.party.identification  0.555208   0.235579   2.3568    0.244003   2.2754
Internal.efficacy                 -0.703282   0.252583  -2.7844    0.249912  -2.8141
Time.1TRUE                        -1.788598   0.178246 -10.0344    0.175569 -10.1874

Estimated Scale Parameter:  0.9235
Number of Iterations:  1
```

Political Volunteership Model, Logit with lagged dependent variable (all variables)

Coefficients:	Estimate	Std. Error	z value	Pr(>|z|)	Sig.
(Intercept)	-4.7500	1.1800	-4.02	0.0001	***
Age	0.0280	0.0475	0.59	0.5560	
Age2	-0.0002	0.0005	-0.48	0.6320	
Sex	-0.4440	0.2440	-1.82	0.0680	.
Education	1.2000	0.5250	2.28	0.0230	*
Race	0.2480	0.3610	0.69	0.4920	
South	0.4600	0.2770	1.66	0.0970	.
Family.income	0.0001	0.0052	0.01	0.9910	
Union.member	-0.0523	0.3200	-0.16	0.8700	
Strength.of.party.identification	0.8120	0.3850	2.11	0.0350	*
Internal.efficacy	-0.2580	0.3680	-0.7	0.4840	
Campaign.recruitment	1.9900	0.2500	7.98	0.0000	***
Campaign.work.1990	1.4300	0.3140	4.55	0.0000	***

Political Contributions Model (all variables)

Coefficients:	Estimate	Std. Error	z value	Pr(>|z|)	Sig.
(Intercept)	-4.6300	1.3000	-3.57	0.0004	***
Age	0.0083	0.0527	0.16	0.8755	
Age2	0.0000	0.0005	-0.05	0.9600	
Sex	0.1880	0.2640	0.71	0.4758	
Education	0.9530	0.5640	1.69	0.0911	.
Race	-0.7960	0.5680	-1.4	0.1611	
South	0.3700	0.3140	1.18	0.2388	
Family.income	0.0020	0.0054	0.36	0.7159	
Union.member	-0.6650	0.3760	-1.77	0.0774	.
Strength.of.party.identification	0.7610	0.3950	1.92	0.0543	.
Internal.efficacy	-1.1600	0.3870	-2.98	0.0028	**
Monetary.recruitment	2.1300	0.3390	6.28	0.0000	***
Monetary.contribution.1990	2.0300	0.2840	7.14	0.0000	***