ABSTRACT

Title of Document:	THE DYNAMICS OF POLITICAL PARTICIPATION: AN ANALYSIS OF THE DYNAMIC INTERACTION BETWEEN INDIVIDUALS AND THEIR POLITICAL MICRO-ENVIRONMENT
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While political choices are rarely isolated or simultaneous, the vast majority of empirical models in political science assume they are. This dissertation examines the dynamic interactions over time between individuals and their micro-environment, in which a single factor both influences, and is influenced by, the act of voting. These dynamic interactions occur in a surprisingly broad swathe of the current literature on American voting behavior, as implicit but unexamined elements of four major research traditions. When these interactions are present, they establish feedback cycles that pose both theoretical and statistical challenges if not analyzed appropriately. Researchers ignoring these cycles tend to underestimate long term influences on voting behavior, make unrealistic assumptions about changes in voting behavior over time, and produce biased results under certain conditions.

I propose a methodology that can successfully identify and model these interactions: employing simulation models to represent dynamic interactions in an intuitive format, and using optimization techniques to conduct parameter estimation and hypothesis testing against empirical data. To guide the development of these simulation models, I outline a theoretical framework of the major pathways by which dynamic interactions can influence voting behavior.

I then present two applications of this methodology, to study the dynamic impacts on voting of political mobilization, and of social conformity over time. In both cases, the models receive strong statistical support, in benchmark tests against existing econometric models and against empirical data on voting behavior. Both mobilization and social conformity have unstudied indirect impacts that can lead to an additional 1.7% to 4% increase in voter turnout beyond existing models. Targeted use of peer pressure can lead to even more significant increases in turnout – up to a 30% increase among otherwise indecisive voters. In the long term, targeted mobilization can create cadres of repeatedly-mobilized activists, which raises questions about whether political campaigns effectively use their mobilization funds to build their parties in the long term. These two simulation models also provide a foundation for a host of new research questions, ranging from the impact of high-intensity get-out-the-vote drives on future mobilization efforts, to the effects of an aging population on turnout behavior over time.

THE DYNAMICS OF POLITICAL PARTICIPATION:
AN ANALYSIS OF THE DYNAMIC INTERACTION BETWEEN INDIVIDUALS
AND THEIR POLITICAL MICRO-ENVIRONMENT

By

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Chapter 1: Introduction

Overview

In each political decision, from voting to protesting in the streets, an individual's options and incentives are shaped by a long history of prior actions and relationships. The result is a dynamic micro-context of political behavior – in which the residues of prior experiences and of interactions with one's political environment shape current and future decision making. Yet, while political choices are rarely isolated or simultaneous, the vast majority of formal and empirical models in political science assume they are. The notion that past experiences affect current political decisions is nothing new to political science, but political scientists have been hamstrung by a lack of data and methodological tools. As a result, few parsimonious, empirically tested models of the dynamics of political behavior exist.

While no simple solution exists to the data problems and methodological challenges that have confronted other researchers, I offer an approach to study dynamic political behavior that can ease these constraints, in exchange for a moderate increase in methodological complexity. In certain cases, dynamic processes can be better understood using existing data and econometric techniques, carefully applied. For the more challenging cases, a three stage process renders them tractable: using a theoretical framework to help identify and elaborate models of specific dynamic processes, empirically testing the models against existing non-dynamic research, and then extending

the models into novel, testable, hypotheses via simulation modeling. Instead of attempting to develop a unified dynamic model of all political participation, I illustrate how this approach can help us elaborate, contextualize, and empirically test highly specific models of particular dynamic processes. The approach can be applied to dynamics occurring in a broad range of political behaviors without relying on gross generalizations or departing from the rigors of empirical testing.

I examine national voting behavior in the United States, and two particular processes that affect it: the interaction between political mobilizers and individual voters, and the interaction between voters and their social network via social conformity pressures. In each case, the core research question is:

"How do cycles of interaction, with political mobilizers or with one's social network, change voting behavior from what is predicted by existing, single stage models?"

The central hypothesis is that positive feedback loops exist that have significant short and long term effects unless balanced by opposing processes. In the short term, these loops establish mechanisms by which mobilization and social influence *indirectly* increase voter participation, above and beyond their direct impact on turnout. In the long term, however, these loops can lead to increasingly narrow participation as previously active individuals are recruited or nudged to participate more than their peers. In the case of mobilization, the hypothesized feedback mechanism occurs through the mobilizers' desire to target already active individuals; in the case of social networks, the feedback

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mechanism occurs when individuals' increased (or decreased) participation shapes their peers' "descriptive norms", i.e., their understanding of "normal" turnout behavior to which they try to conform. In both cases a web of other interrelated feedback processes exist: increasing, decreasing, and channeling political participation over time. Clear effects of the dynamics of mobilization and of peer pressure can nevertheless be isolated and meaningfully studied, and can inform a broader discussion of the system's dynamics.

The goal of the research is two-fold: to provide new substantive and empirical insights into the impact of mobilization and peer pressure on voting behavior, and to make a methodological contribution by demonstrating how tools developed in computational social science, system dynamics, and econometrics can be usefully applied to study a broader range of dynamic interactions between individuals and their micro-environment.

Why Dynamics Matter

In itself, the observation that political participation is shaped by complex interactions over time, and that existing models of political behavior do not capture all of these interaction, is trivial. After all, useful models are generally simplifications of an irrepressibly complex reality. The more interesting issue for political scientists is whether modeling dynamic interactions can provide sufficient improvement in accuracy and theoretical insight to warrant the effort. There are significant methodological and theoretical reasons for believing that this is the case.

Three main problems can arise with modeling the dynamics of voting behavior –

specifically, when a dynamic interaction is present between the act of voting itself and factors influencing the decision to vote which can change endogenously over time. Unless careful attention is paid to the dynamic interaction, biased results occur when complex interactions are misspecified, estimation of the decision-making process will underestimate the long-term impact of these endogenous factors, and unrealistic assumptions can be made about the secular growth of voting behavior over time.

When the Problem Occurs: Dynamic Interactions

The decision to vote is shaped by a host of personal and environmental factors, ranging from one's early life socialization, to information about the election, to the weather. When one or more of these factors can both influence voting and be influenced by it, i.e., when causality runs in both directions, then empirical analysis is challenging. I am concerned with a particular type of dual-causality, in which there is a clearly defined cycle over time between the individual's decision to vote and a factor that influences the decision to vote – which, for ease of reference, I call "dynamic (voting) interactions". These dynamic interactions are actually quite common, if implicit and unexamined, in contemporary models of voting behavior. In Chapter 2, I analyze major research traditions in voting behavior and draw out these implicit dynamic interactions; to introduce the point here, however, I'll brieflly reference the literature on voter mobilization.

Researchers studying voter mobilization have generally addressed two distinct questions – the impact mobilization has on voting, and who is targeted for mobilization. On the first question, Rosenstone and Hansen (1993)'s book provides one of the most

strident arguments that political mobilization drives voter participation. Abramson and

Claggett's (2001) and Goldstein and Ridout's (2002) more recent works on voting

behavior present methodological advancements, but find substantively the same role for

mobilization.[1] A growing tide of experimental literature (e.g., Green and Gerber 2004;

Nickerson 2008) also verifies the impact of certain forms of mobilization on turnout, both

on directly targeted individuals and their households. On the second question,

researchers have found that at any given moment, mobilizers consider many of the same

factors that determine whether an individual participates at all – including education,

race, prior participation (e.g., Rosenstone and Hansen 1993). Brady, Schlozman and

Verba (1999) develop this concept as "rational prospecting".

Most importantly for this discussion, two separate lines of analysis have shown

that campaign mobilization affects voting behavior, and that campaigners take into

account the prior participation of individuals when they select whom to mobilize.

Bringing these two sets of analyses together, a dynamic interaction results. Figure 1,

below, illustrates the nucleus of this interaction over two election cycles.
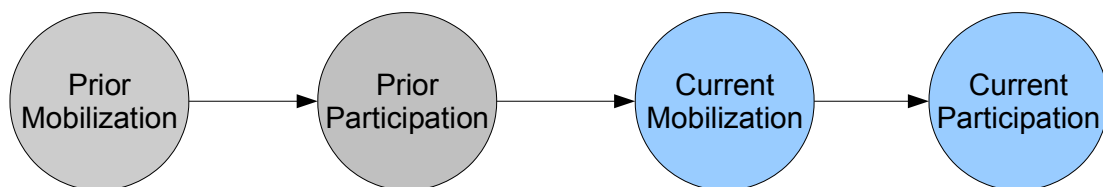
Figure 1: A simple, two election model of the role of mobilization on participation

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[1] Goldstein and Ridout (2002) 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.
Chapters 2 and 4 analyze the voter mobilization literature in detail.

Issue 1: Estimating Long Term Impacts on Voting Behavior

The central problem of understanding dynamic interactions is a problem of interpretation and theory; the statistical estimation of a dynamic interaction such as voter mobilization can provide an answer that is mathemetically correct, but does not incorporate all of the factors that are theoretically relevant. Specifically, reserchers generally estimate the marginal impact of mobilization on voting behavior as the marginal change in the probability of voting due to a unit change in mobilization in the same year. However, from the perspective of a political party investing in mobilizing voters, the relevant impact is broader – the party will influence both the current election and future elections with its current-year investment. That indirect, subsequent-election, impact is often missing from the interpretation of current models.

This indirect impact can be seen by considering the effect of prior mobilization on current participation, and a simple manipulation of standard equations used to estimate voting behavior and mobilization. The first step is to take a stylized analysis of voting and mobilization, and structure it to highlight the dynamic interaction.[2] Without loss of generality, one can model voting behavior as a function of mobilization, prior voting history, plus "everything else". Prior voting history is especially important. Numerous authors have included prior voting history as a control for other factors influencing current mobilization, often for practical reasons of serial autocorrelation, and with theoretical underpinnings such as habit formation (Gerber, Green and Shachar 2003) and self-efficacy (Finkel 1985).

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[2] A more detailed analysis, using a range of examples from the current literature on voting is conducted in Chapter 2. At this stage, merely the core algebra is needed, without discussing the nuances of each model.

The stylized model of voting can be written as:

$$P_t = f(\alpha_0 + \alpha_1 M_t + \alpha_2 X_t + \alpha_3 P_{t-1})$$

Where P_t is participation at time t, M_t is mobilization at time t, P_{t-1} is participation at time t-1, and X_t covers all other factors of interest that influence participation such as income, education, and the competitiveness of the election. Similarly, mobilization can be depicted as a function of prior participation, plus everything else:

$$M_t = g(\beta_0 + \beta_1 P_{t-1} + \beta_2 Y_t)$$

Where Y_t covers all other factors of interest that influence mobilization, such as party affiliation, income, gender and electoral district.[3]

For simplicity of presentation, assume that the mobilization and participation functions are both linear. The voter participation function can then be re-written as:

$$P_t = \alpha_0 + \alpha_1[\beta_0 + \beta_1 P_{t-1} + \beta_2 Y_t] + \alpha_2 X_t + \alpha_3 P_{t-1}$$

Figure 2, on the next page, illustrates these parameters.

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[3] Note – I do not include a lagged dependent variable for mobilization, for two reasons. First, this stylized model is drawn from existing research on mobilization – other researchers do not appear to use a LDV for mobilization in their work – and I will make an argument about the structure of current models based on this relationship. Second, I assume that campaigns re-evaluate how to contact each year, rather than re-use the same outdated list of targeted voters. This is both theoretically reasonable, and avoids problems of auto-correlated independent variables that Achen (2000) highlights, in the participation function above.

X_{t-1}: Other Participation Factors

Y_t: Other Mobilization Factors

X_t: Other Participation Factors

α_2

β_2

α_2

M_{t-1}: Prior Mobilization

α_1

P_{t-1}: Prior Participation

β_1

M_t: Mobilization

α_1

P_t: Current Participation

α_3
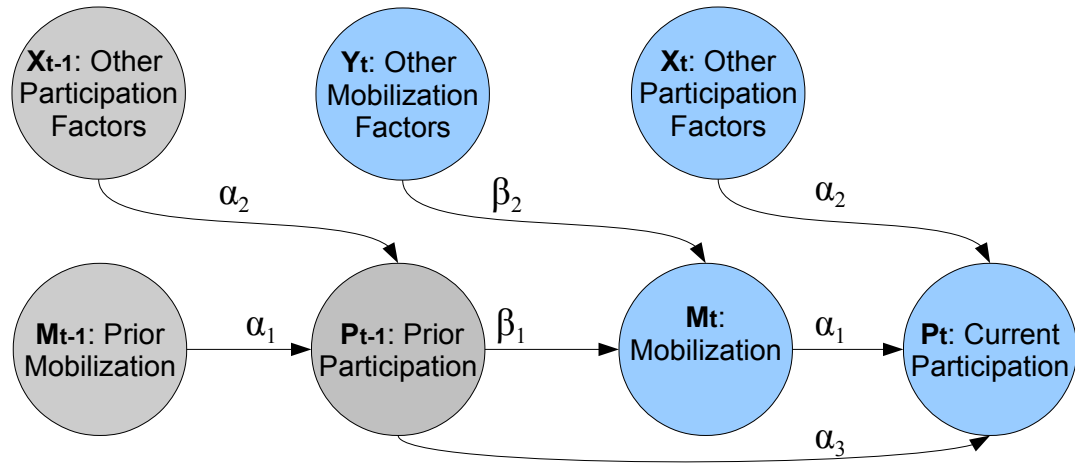
Figure 2: A two-election model of mobilization and participation, with exogenous factors

The direct impact of current mobilization on current participation is given by $\alpha_1 M_t$. Since $\alpha_1 \beta_1 P_{t-1}$ and $\alpha_3 P_{t-1}$ are perfectly collinear, M_t and P_{t-1} are partially collinear, and the estimation process will be inefficient with inappropriately high standard errors. However, this does not introduce bias (barring other statistical problems such as omitted, correlated variables), and statistical estimation would lead to an accurate assessment of α_1, the marginal impact of mobilization on voting behavior.

The indirect impact of *prior* mobilization on current participation can be seen by breaking P_{t-1} into its component parts. The voter participation function can then be re-written as:

$$P_t = \alpha_0 + \alpha_1[\beta_0 + \beta_1[\alpha_0 + \alpha_1 M_{t-1} + \alpha_2 X_{t-1} + \alpha_3 P_{t-2}] + \beta_2 Y_t] + \alpha_2 X_t + \alpha_3[\alpha_0 + \alpha_1 M_{t-1} + \alpha_2 X_{t-1} + \alpha_3 P_{t-2}]$$

In which, prior-year mobilization M_{t-1}, influences current participation, P_t, via two routes. First, prior mobilization affects prior participation, which affects current participation. As noted above, the role of prior-year participation can be considered in

terms of implicit habit formation or improved feelings of self-efficacy. In this case, mobilization improves the chances of voting, which builds an internal voting habit (or self-efficacy) that carries over into the next election.

Second, prior-year mobilization affects current participation by changing the decision criteria of the political parties themselves. Mobilization improves the chance of voting, which is recorded in the voter files that political parties use to target individuals for future mobilization. The consequences of this feedback process are significant, both theoretically and mathematically, and are discussed below; for now however, this process serves as another route by which prior-year mobilization influences current-year voting behavior.

In the simple linear model, these two indirect impacts can be expressed as:[4]

$\alpha_1[\beta_1[\alpha_1 M_{t-1}]]$, the indirect impact of prior mobilization on participation via current

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[4] Taking the model further into subsequent years, we can expect that this effect rapidly decays over time, as is often the case with first-order serial auto-correlation models. Given the core participation and mobilization functions (lagged):

$P_{t-2} = \alpha_0 + \alpha_1 M_{t-2} + \alpha_2 X_{t-2} + \alpha_3 P_{t-3}$

$M_{t-1} = \beta_0 + \beta_1 Y_{t-1} + \beta_2 P_{t-2}$

Then,

$M_{t-1} = \beta_0 + \beta_1 Y_{t-1} + \beta_2[\alpha_0 + \alpha_1 M_{t-2} + \alpha_2 X_{t-2} + \alpha_3 P_{t-3}]$

$P_t = \alpha_0 + \alpha_1[\beta_0 + \beta_1 Y_t + \beta_2[\alpha_0 + \alpha_1[\beta_0 + \beta_1 Y_{t-1} + \beta_2 P_{t-2}] + \alpha_2 X_{t-1} + \alpha_3 P_{t-2}]] + \alpha_2 X_t + \alpha_3[\alpha_0 + \alpha_1[\beta_0 + \beta_1 Y_{t-1} + \beta_2 P_{t-2}] + \alpha_2 X_{t-1} + \alpha_3 P_{t-2}]$

$P_t = \alpha_0 + \alpha_1[\beta_0 + \beta_1 Y_t + \beta_2[\alpha_0 + \alpha_1[\beta_0 + \beta_1 Y_{t-1} + \beta_2[\alpha_0 + \alpha_1 M_{t-2} + \alpha_2 X_{t-2} + \alpha_3 P_{t-3}]]] + \alpha_2 X_{t-1} + \alpha_3[\alpha_0 + \alpha_1 M_{t-2} + \alpha_2 X_{t-2} + \alpha_3 P_{t-3}]]] + \alpha_2 X_t + \alpha_3[\alpha_0 + \alpha_1[\beta_0 + \beta_1 Y_{t-1} + \beta_2[\alpha_0 + \alpha_1 M_{t-2} + \alpha_2 X_{t-2} + \alpha_3 P_{t-3}]] + \alpha_2 X_{t-1} + \alpha_3[\alpha_0 + \alpha_1 M_{t-2} + \alpha_2 X_{t-2} + \alpha_3 P_{t-3}]]$

$P_t = \alpha_0 + \alpha_1\beta_0 + \alpha_1\beta_1 Y_t + \alpha_1\beta_2\alpha_0 + \alpha_1\beta_2\alpha_1\beta_0 + \alpha_1\beta_2\alpha_1\beta_1 Y_{t-1} + \alpha_1\beta_2\alpha_1\beta_2\alpha_0 + \alpha_1\beta_2\alpha_1\beta_2\alpha_1 M_{t-2} + \alpha_1\beta_2\alpha_1\beta_2\alpha_2 X_{t-2} + \alpha_1\beta_2\alpha_1\beta_2\alpha_3 P_{t-3} + \alpha_1\beta_2\alpha_2 X_{t-1} + \alpha_1\beta_2\alpha_3\alpha_0 + \alpha_1\beta_2\alpha_3\alpha_1 M_{t-2} + \alpha_1\beta_2\alpha_3\alpha_2 X_{t-2} + \alpha_1\beta_2\alpha_3\alpha_3 P_{t-3} + \alpha_2 X_t + \alpha_3\alpha_0 + \alpha_3\alpha_1\beta_0 + \alpha_3\alpha_1\beta_1 Y_{t-1} + \alpha_3\alpha_1\beta_2\alpha_0 + \alpha_3\alpha_1\beta_2\alpha_1 M_{t-2} + \alpha_3\alpha_1\beta_2\alpha_2 X_{t-2} + \alpha_3\alpha_1\beta_2\alpha_3 P_{t-3} + \alpha_3\alpha_2 X_{t-1} + \alpha_3\alpha_3\alpha_0 + \alpha_3\alpha_3\alpha_1 M_{t-2} + \alpha_3\alpha_3\alpha_2 X_{t-2} + \alpha_3\alpha_3\alpha_3 P_{t-3}$

And the impacts of M_{t-2} on P_t are: $M_{t-2}(\alpha_1^3\beta_2^2 + \alpha_1^2 \alpha_3\beta_2 + \alpha_1^2\alpha_3\beta_2 + \alpha_1\alpha_3^2)$. Since voting and mobilization are binary, and the maximum value of each is 1 (putting aside the fact that we are using a linear model for simplicity of presentation), then we would expect the estimated coefficients for voting and mobilization, $\alpha_{1...3}$ and $\beta_{1...3}$ to be less than one. Each multiplication of those coefficients, such as $\alpha_1^3\beta_2^2$, would rapidly approach zero, and indicate no effect on future voting behavior. In other words, for practical purposes this type of indirect effect of mobilization is likely to be irrelevant beyond the next election, if a model with a single period lag is employed. This analysis is based on the general behavior of serially auto-correlated

mobilization, and $\alpha_3[\alpha_1 M_{t-1}]$, the indirect impact of prior mobilization on participation via prior participation.

Other authors have discussed the implications of serially correlated models on future time periods (e.g., Beck and Katz 2004); the mathematics is nothing new. However, this general statistical lesson does not appear to be considered in the specific context of dynamic voter interactions, leading to only a partial picture of the relevant influence of mobilization on voter behavior. From the perspective of a political party, the importance of mobilization may be more than its marginal impact on participation, α_1. As an investment, it affects subsequent years of voter behavior as well. More subtly, it affects the political party's own process of *mobilization* in the future, which I analyze in detail later. These indirect impacts are present in current models of mobilization, but unless attention is paid to them, they are neither analyzed nor interpreted correctly. This relationship is not limited to the specific case of mobilization and voting, however; in Chapter 2, I discuss how these indirect impacts are quite common in voting behavior research, including in models of political information, resource mobilization, and social networks, and in Chapter 5 I develop a detailed model of dynamic interactions via social networks.

Assuming that other statistical problems are not present, then these indirect impacts do not require any additional data to estimate – if one can estimate the impact of current mobilization and prior participation on current participation, and the impact of prior participation on current mobilization, then these indirect impacts "come along for

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models of voting behavior; a more detailed examination of the potential problems in these models is included below.

the ride", as it were. If one can correctly estimate direct impacts, one can estimate indirect impacts.

Unfortunately, there appear to be a set of cases in which the statistical assumptions underlying the core models, of mobilization behavior and voter turnout, are violated when dynamic interactions are present, and estimating the direct impacts are problematic.

Issue 2: Unrealistic Assumptions and Feedback Loops

When researchers study two components of a dynamic interaction in isolation, such as mobilization and voting behavior, the result is often that a feedback loop is (unintentionally) ignored between the two variables, which leads to wildly unrealistic predictions. In order to align the model with empirical reality, more nuanced assumptions are often required. In Chapter 3, I describe feedback processes in general, and how they can occur across a broad swathe of the voting literature; for now, let us focus on the specific example of mobilization and voting.

Recalling the stylized model above:

$$P_t = f(\alpha_0 + \alpha_1 M_t + \alpha_2 X_t + \alpha_3 P_{t-1})$$

$$M_t = g(\beta_0 + \beta_1 Y_t + \beta_2 P_{t-1})$$

Two problems arise. First, when dynamic interactions are present, the functional form used in most voting models is not appropriate for processes that occur over more than two time periods. Consider what can happen to this stylized model over multiple elections when instead of thinking about individuals in a population, where P and M are

binary, consider P and M as percentages of the overall population, i.e., P and M are continuous variables over [0,1] representing the percent of people who are voting and mobilized, respectively. To make the analysis clearer, also assume that mobilization and voting behavior are linear functions. Put aside for the moment the substantive meaning of each term, which I will discuss shortly, and trace the mathematical implications of these functions:

Table 1: A Simple Process

$$P_t = \alpha_0 + \alpha_1 M_t + \alpha_2 X_t + \alpha_3 P_{t-1}$$

$$M_t = \beta_0 + \beta_1 Y_t + \beta_2 P_{t-1}$$

As an example, in period 1, assume that P_o and M_o are 0.5. Assume further that all coefficients 0.3, X and Y are constant at 1. Table 1 traces P and M over time. In the absence of any other factors, these equations and parameters would predict that P (participation) and M (mobilization)

Time	P	M
0	0.50	0.50
1	0.78	0.63
2	0.87	0.70
3	0.90	0.72
4	0.91	0.72
5	0.91	0.73
6	0.91	0.73
7	0.91	0.73
8	0.91	0.73
9	0.91	0.73
10	0.91	0.73

increase over time to include the majority of the population. Clearly this is unrealistic.

The reason this unrealistic result occurs is that the stylized model of participation and mobilization, a generalization of the existing literature on mobilization (e.g., Abramson and Claggett 2001), is similar to the well-known first-order autoregressive process, AR(1).[5]   The AR(1) process, and related processes without such well-mapped mathematical interpretations (including processes that are closer to the logit models and

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[5] The stylized model differs from an AR(1) process on two accounts: in an AR(1) process f() and g() would be linear, whereas in contemporary political science models they are often some derivative of a logit function, and P and M are binary, whereas AR(1) processes are continuous. The table presented on the right is a case where the stylized model is constrained so that it lines up exactly with an AR(1) process. The implications of these two changes – linear vs. logit functional forms and binary vs. continuous variables, is discussed below.

other functional forms used in political science), have long been studied in the System Dynamics literature as feedback loops.

In Chapter 3, I provide a System Dynamics interpretation of this stylized model, and examine the behavior of the original functional form (with a logit, rather than linear, functional form, and a binary dependent variable). In brief however, with AR(1) and similar processes, we would expect a system with this type of feedback loop either to grow rapidly, fall rapidly, or asymptotically approach a steady-state value.[6] This behavior arises simply because of the selected functional form employed in most political science analyses of these dynamic interactions, and is unrelated to any substantive meaning we may want to apply to the variables.

The obvious solution to this problem is to argue that the true process(es) underlying voting behavior use a different functional form, such as one in which there are limits placed on the feedback present in dynamic interactions. In the case of mobilization, there are good theoretical reasons to place limits on that growth, and the substantive implications of a simple feedback loop are untenable. Rosenstone and Hansen's mobilization model (1993), for example, explains mobilization as a function of the characteristics of individual voters. In that model, if the population were suddenly to become more attractive to mobilizers, then mobilization would shoot up and campaigns would contact significantly more people. That is unrealistic. Instead, mobilizers have a limited budget to spend on mobilization and pick "the best" voters according to some

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[6] In this case, these two equations simplify down to $P_t = (\alpha_0 + \alpha_1\beta_0 + \alpha_1\beta_1 Y_t + \alpha_2 X_t) + P_{t-1}(\alpha_3 + \alpha_1\beta_2)$. Assuming that X_t and Y_t are constant (as in the demonstration above), and $|\alpha_3 + \alpha_1\beta_2| < 1$, then the system will approach its steady state of $(\alpha_0 + \alpha_1\beta_0 + \alpha_1\beta_1 Y_t + \alpha_2 X_t) / (1 - (\alpha_3 + \alpha_1\beta_2))$. When $|\alpha_3 + \alpha_1\beta_2| > 1$ the system will rise (or fall) to (negative) infinity.

criteria. The same logic can apply for other dynamic interactions, such as between voters and the amount of political information they have. While politicians dump a seemingly infinite amount of money into TV ads and mailings, there is an upper limit on how much political information and stimulation the public can receive to prompt them to vote. Resource constraints such as these provide a theoretically meaningful, and mathematically effective, means to limit positive feedback loops, and are analyzed in further detail in Chapter 3.

While various methods exist to handle feedback loops and model a more realistic and theoretically grounded understanding of dynamic interactions, they come at a cost – complexity. It is difficult, for example, to estimate a time-varying upper limit on the number of people mobilized (the dependent variable) with a standard logit model. Moreover, this complexity can break the standard assumptions of stationarity that underlie time-series models used by political scientists. This is one example of the statistical challenges that face modelers of dynamic interactions.

Issue 3: Statistical Challenges in Modeling Dynamic Interactions

The previous two sections assumed that we knew and could reliably measure the key determinants of voting and mobilization that were either theoretically important to the model or needed to be controlled for and the functional relationship between all of the variables. If that were not the case, then dynamic interactions would violate standard econometric assumptions used in modeling voting behavior. Attempting to model them without the appropriate temporal component delivers misleading models and inaccurate results.

In general, if temporal dynamics are misspecified in statistical models, the results will be biased coefficient estimates, often by a large factor (de Boef and Keele 2008). While econometric techniques exist to handle a wide range of autoregressive processes (Hendry 1995), one challenge is that researchers must have some prior knowledge of the process's structure, and its temporal scale (Shellman 2004) to estimate them correctly. Moreover, these techniques assume stationarity, i.e. that the joint probability distribution of the data generating process does not change over time or space.[7] Non-stationary processes would be misestimated. Compounding these statistical problems are widespread problems in gathering appropriate panel data, ranging from data on individual voting behavior to other political behaviors such as social protest.

In the specific context of research on voting in American political science, these challenges are commonplace. The determinants of voting behavior are often modeled with static and cross-sectional data – demographic characteristics, characteristics of the election under study, etc. The paramount data source used by American political scientists, the ANES, has limited time series information on voting. Even less data is available on voting and mobilization over time, or on social influence and voting over time.[8] As noted above, where time-series cross-sectional data is used, often modelers include a lagged dependent variable, or autoregressive error term, to account for historical (but stationary) effects (Beck and Katz 2004). These models contain excellent insights into political behavior, and provide accurate results if the underlying processes

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[7] And the process is not readily convertible into a stationary process via detrending, time-specific fixed effects, etc.

[8] Many researchers fall back on the Verba et al.'s (1995) cross sectional mobilization data, or Huckfeldt and Sprague's snowball studies in South Bend, Indiana and St. Louis, Missouri (1995, 2000).

have no enduring impact beyond single-stage lags or very specific processes of decay. They also lead one to wonder what would happen if more complex dynamic interactions were possible, beyond second-order autocorrelation and into non-stationary processes. Chong's (1991) model of collective action provides one intriguing example, where difference equations are used to explicitly trace the time path of a system. Other innovative examples include Box-Steffensmeier and Lin (1996), Marwell and Oliver (1993), and Lohmann (1994; 2000), largely outside of the domain of voting behavior.

Estimation methods are available that can handle these nuanced models, while still providing accurate estimations and predictions. Fully developing this method, and demonstrating its applicability to a wide range of voting models in political science, constitutes a significant portion of the chapters ahead.

Chapter Outline

The subsequent chapters are structured as follows: In Chapter 2, I briefly review the study of voting behavior in political science, and demonstrate how dynamic processes are quite common – either implicitly or explicitly. I discuss how the long-run dynamic interactions that are likely to occur in each model raise serious methodological and substantive concerns for a set of existing econometric results.

In Chapter 3, I present a general theoretical model that facilitates the identification and study of dynamic political interactions. In the elaboration of the model, I show how major theoretical traditions in the study of political behavior can be reanalyzed to focus on their dynamic interactions. I then build upon the theoretical

model to outline a three-stage process of identifying, estimating, and testing dynamic models of political behavior.

Next, in Chapter 4, I develop theoretical and econometric model of the dynamics of mobilization, drawing upon and extending the existing literature. I test the model against a panel dataset on voting and mobilization, the 1990-2 ANES panel, and then provide novel predictions about the formation of cadres of mobilized activists over time.

In Chapter 5, I repeat the process of theoretical specification and testing with a new target: the influence of multiple cycles of peer pressure on voting behavior. As with mobilization, I present a detailed theoretical and econometric model, which incorporates the direct and indirect effects of peer pressure. I test them on two datasets collected by Huckfeldt and Sprague (1995, 2000).

Finally, in Chapter 6, I review the research presented and discuss the implications of the work on our understanding of dynamic political behavior. I conclude by discussing a range of new avenues for research, including the use of a computer simulation as a platform for developing and testing novel models of dynamic political behavior, allowing researchers to explicitly study the political micro-context of individual decision making.

Chapter 2: Theoretical Background

Introduction: A Dynamic Blind Spot

The goal of this chapter is twofold: to demonstrate that dynamic interactions are an implicit, but surprisingly common, part of many models of voting behavior, and to discuss in detail why these dynamic interactions are important.

To illustrate the first point, I examine the central premises of four different research traditions in the voting behavior literature, and identify dynamic interactions that shape the underlying behavior. In most cases, the dynamic interactions are not directly considered by researchers. Instead, voting behavior is usually modeled in political science research with immediate, temporally isolated impacts on voting. For example, mobilization has been shown to affect turnout in the current election, but has not been studied in terms of future elections; social pressure has been shown to affect current turnout, but not (yet) future behavior.

The current focus on contemporaneous factors fits the tools and data available to political scientists: the ready availability of cross-sectional, nationally representative surveys of voter participation from the ANES, and the lack of rich alternative datasets. This has facilitated a strong focus on individual determinants of political participation, eschewing historical and contextual influences. Moreover, most econometric techniques used in political science are designed for static data, or for time series cross-sectional data with short time periods and strong assumptions about the specific types of temporal

influence over those periods. The resulting models feature the isolated individual buffeted by turnout influences at the moment of the voting decision; time is collapsed into a set of unrelated snapshots, each of which is explained by its contemporaneous factors.

The field is not devoid of empirical analysis of political behavior over time, of course. The most common technique researchers employ is to control for potentially confounding historical influences by adding time-lagged variables to otherwise static models. This approach provides a clearer snapshot at each point in time, but fails to connect those snapshots with a temporal story. It treats history and temporal interaction as a nuisance to be removed from the model, and not a core part of the model itself. In contrast, a budding literature has explicitly sought to examine one form of dynamic change in individual level voting – via the formation of habits (e.g., Green and Shachar 2000, Aldrich et al. 2008). This literature is very promising, and shows how a direct focus on dynamic interactions, instead of treating them as a problem to be controlled, can provide new insights; however, the approach is still new and faces a number of logical and methodological problems that will be discussed below.

With each of these four research traditions, I take a novel approach – I focus on the temporal interaction itself, and momentarily put aside the contemporaneous explanatory variables that are usually studied. I then generate a stylized model for each research tradition, in which the temporal component is brought to the fore. From this new perspective, I argue that one can gain insight into the dynamic interactions at work in each research tradition, as well as better understanding, and more accurately estimating, the influence of non-dynamic contemporaneous factors.

To illustrate the second point, that dynamic interactions are worth the effort to examine, I build on the initial summary given in Chapter 1 that introduced three major statistical challenges. A priori, relying on a-temporal models, tools, and data should not necessarily be a problem – by removing confounding influences researchers might be developing clearer, more parsimonious but still accurate models of political behavior. In practice, however, this particular simplification poses serious challenges. In the sections below, I describe in detail why these tools and assumptions are inappropriate for dynamic political behaviors such as voting, and how their use leads unwittingly to theoretically circumscribed models and biased estimation, even of their non-dynamic variables.

Temporal Dynamics within the Existing Voting Behavior Literature

As one author puts it: "Almost every possible explanation [of voting behavior] seems to have been explored: ranging from the more conventional rational choice, sociological, and psychological explanations, to more exotic explanations like rainfall or genetic variation (van Ham and Smets 2010, p1)." Excellent summaries of this literature exist, including Niemi et al. (2010); instead of rehashing the overall literature, in this section I will examine the existing literature and demonstrate how it can be reexamined from the perspective of dynamic interactions.

The major research traditions in voting behavior, the Michigan "social-psychological model" (Campbell et al. 1960), the Columbia School (Berelson et al. 1954; Huckfeldt and Sprague 1995), and Rational Choice (Downs 1957; Fiorina 1981), each identify key factors that influence the individual decision to vote: early-life socialization,

ongoing social pressure, and economic costs and benefits. Additional, less prominent traditions such as Expressive Choice (Schuessler 2000), Resource Mobilization (McCarthy and Zald 2001), Civic Volunteerism (Verba et al. 1995), Institutional Mobilization (Rosenstone and Hansen 1993), and habit formation (Gerber et al. 2003), further enrich the debate with other factors that drive turnout, including personal expression, civic skills, and an internal sense of political efficacy.

In each tradition, a simple question can be used to identify underlying dynamic interactions between the individual and his or her micro-environment: why would factors that influence turnout change over time? I argue that in these models, a key determinant of turnout is, in turn, partially affected by the act of turnout itself.[9] There is a cycle of interaction, in which the individual responds to his or her decision-making environment, and the decision-making environment updates based on the individual's experiences, which in turns affects future pressures on the individual and so forth.

These dynamic interactions often lurk beneath the surface of existing research, surfacing in the authors' notes for future research, and in anecdotal discussions of other confounding factors. Because of challenges in data collection, theoretical elaboration, and econometric tools, the interactions are rarely brought to light during the model building and empirical testing phases of research. I seek to haul them out for review. I show that despite their diverse theoretical origins, there are striking similarities among these processes. The dynamic interaction between the voter-as-decision-maker and the

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[9] That is, a theoretically interesting determinant of turnout is part of a dynamic interaction. I do not mean to state the obvious: that current participation is strongly correlated with prior participation. Rather, a meaningful factor such as peer pressure or personal political engagement changes over time. This factor can help explain *why* current participation is strongly correlated with prior participation.

micro-context of that decision can be identified and studied for its effects. This analysis can provide insight both into political behavior generally and into their specific host models.

In the four subsequent sections of this chapter, I examine four different research traditions from the voting behavior literature. I first review their core theoretical arguments. Then, I discuss dynamic elements of the models, that the authors either explicitly analyze or that one can readily envision in the process being studied. Finally, I present stylized econometric versions of the core theoretical arguments, in which the dynamic elements are highlighted.

Rational Choice and Voting Behavior

Core Theoretical Argument

Rational choice models of voting behavior are quite diverse, and range from attempts to explain overall voter turnout ("strong rational choice") to less ambitious work to explain marginal changes in turnout ("weak rational choice"). At the core of both approaches is the belief that policy outcomes are of paramount importance to the voter, and that economic costs and benefits shape that choice. In the former category, Downs (1957) first popularized the central problem of rational turnout – assuming that an individual cares only about the political outcome of an election, would the costs outweigh the benefits? Costs include such factors as the time required to vote, and the effort to learn about the candidates and their policy positions in order to decide how to vote. Benefits entail the *expected value* of voting, in terms of the difference in policy positions between the candidates, the utility of those policy positions to the individual, and the

probability that the individual's act of voting would be decisive over the outcome. Unfortunately, the probability that the individual could influence the election is so minuscule as to forestall any participation at all (Tullock 1967; Brennan and Buchanan 1984). The costs of participation, no matter how small, would arguably outweigh the benefits in a "strong" rational choice model.

While individuals could rely on heuristics and daily experience (Popkin 1991) to decrease costs, Downs and others turned to non-economic considerations, such as the desire to maintain democracy or to fulfill a civic duty, to explain participation (Downs 1957[10]; Blais 2000). This move prompted critiques of non-falsifiability (Green and Shapiro 1996) and led other scholars to give up the search for a comprehensive model of turnout, and instead examine marginal changes in turnout due to marginal changes in costs and benefits (Aldrich 1993). This less demanding rational choice approach has had greater empirical success (Teixeira 1992, Rosenstone and Hansen 1993), in examining the impact of weekend voting, registration procedures, and decreased information and turnout costs via mobilization.

Recent work from a rational choice perspective has sought to magnify the voter's benefit from voting by examining the indirect effects of participation on others. While the probability that a single individual will determine an election is negligible, the individual may see their action (or discussion of the action) as having an influence on other voters. The total benefit that a potential voter perceives for voting is thus much larger, and more likely to overcome the costs of action. Authors such as Fowler and Kam (2007) show

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[10] Downs also discussed the importance of party loyalty, but did not specifically feature it is a determinant of turnout.

how incorporating group-oriented and altruistic preferences into a rational choice voting model can boost predicted participation in this way.

Dynamic Interactions

In both "strong" and "weak" rational choice models, dynamic interactions can be found in the calculation of costs and benefits as individuals become more experienced with voting. For example, the costs of participation, particularly information costs, are likely to decrease with experience: the act of voting teaches the person where to go to vote, where to park, how to get time off from work, etc. Prior experience also increases information about the benefits of voting: before each election, active voters are targeted for pamphlets, calls, and even in-person visits by volunteers to inform (and persuade) about the election. In each case, the individual's currently available information is shaped by prior participation, and itself shapes future participation.

While alternative mechanisms could be considered, it seems unlikely that lower information costs would *discourage* future participation in a systematic manner (except in exceptional circumstances of widespread disillusionment, etc.). Instead, a simple positive feedback cycle can be identified – in which prior participation is likely to increase future participation, from a rational choice perspective. This impact is likely to be nonlinear, as the value a voter places on new information may to be subject to diminishing marginal returns, and be contingent on personal events (such as moving homes or redistricting).

Sample Econometric Model, Incorporating Dynamic Interactions

A wide diversity of rational choice models exists, and it would do the field a disservice to attempt to extract a "summary model" from this diversity. For my purposes, I will highlight one well developed model, the Civic Volunteerism Model of Verba, Schlozman and Brady (1995, 2000) that employs a "weak" rational choice approach: it uses a non-rational choice framework to explain base levels of turnout, but uses rational calculations to explain marginal changes. In their model, the authors focus on three factors that determine political participation: motivations (benefits), resources and political engagement[11] (costs and constraints) and mobilization (presented as a mix of benefits and costs).

When the authors analyzed the empirical performance of these concepts (Verba et al. 1995, 2000), they found that narrow definitions of benefits as personal economic value fail to find strong empirical support. However, broader a definition of benefits that included social and civic benefits was supported. These findings are in line with work on civic duty and voting (Blais 2000), as well as the role of altruism in voting (Fowler and Kam 2007, Rotemberg 2009). I will focus on two factors that found support in their model: personal resources and political engagement.

The authors found strong support across a range of political behaviors, including voting,[12] that increasing resources and political engagement increases participation on the

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[11] The basic version of the model focuses on resources (time, money, skill), but their full analysis in Verba et al (1995) devotes considerable time to the interaction between resources and engagement (information, efficacy, interest, partisanship), which are of more interest here in a discussion of rational choice models.

[12] The relative importance of various factors varied considerably across the three forms of behavior studied. Voting was driven by income, political interest, political information, the sense of political efficacy, and partisanship (see Verba et al 1995 pg 358).

margin. They note that some resources are set by inflexible socio-economic characteristics (e.g., education, income), but others are built up through the act of participation itself (e.g., political information, self-confidence, and a sense of efficacy). In fact, they warn about the difficulties in estimating the impact of factors such as political information because of "ambiguity of causal direction". They anecdotally describe a potentially confounding dynamic cycle of interaction over time, but do not analyze that cycle in their empirical work. Their model provides an excellent platform from which to analyze those underexplored dynamics of participation, and to show the dangers in failing to do so.

Verba et al. (1995) employ a linear, additive relationship between voting and its determinants (demographic and contextual factors). Whereas other non-linear or non-additive relationships could be considered, and are considered by subsequent researchers, their model fits the common use of OLS regression at the time. They formalized their theoretical model as follows (Verba et al. 1995, p358):

$$
\begin{aligned}
\text{Probability of Voting (Pr\_Vote)} =\ & B_o + B_1\,\text{Education} + B_2\,\text{Vocabulary} + B_3\,\text{Income} \\
& + B_4\,\text{Job\_Level} + B_5\,\text{Voluntary\_Organization\_Affiliation} + B_6\,\text{Religious\_Attendance} \\
& + B_7\,\text{Civic\_Skills} + B_8\,\text{Political\_Interest} + B_9\,\text{Political\_Information} + B_{10}\,\text{Efficacy} \\
& + B_{11}\,\text{Partisanship} + B_{12}\,\text{Eligiblity\_To\_Vote}
\end{aligned}
$$

In their comments in the text, they sketched out additional functions that determine political interest, information, and efficacy over time. Each of these is, in part, determined by prior voting behavior.

For the moment, I will leave them in a greatly simplified form:

$$Political\_Interest_{i,t} = f(Vote_{i,1..t-1}, Political\_Interest_{i,t-1}, ?)$$

$$Political\_Information_{i,t} = f(Vote_{i,1..t-1}, Political\_Information_{i,t-1}, ?)$$

$$Political\_Efficacy_{i,t} = f(Vote_{i,1..t-1}, Political\_Efficacy_{i,t-1}, ?)$$

Combining these two sets of functions, we have a dynamic interaction: the act of voting is both determined by, and helps determine, levels of political interest, information, and efficacy.[13]

In highlighting these dynamic interactions, I do not mean to critique the groundbreaking work of Verba et al. (1995) or other rational choice scholars. Instead, as I mentioned at the start of this chapter, my first goal is to show how such dynamic interactions are common throughout the literature on voting behavior. For good reasons of econometric limitations, data availability, and theoretical parsimony, these dynamic interactions are rarely analyzed in the literature. Later on, I will argue that in many cases these interactions provide valuable insight, and that there are new techniques to overcome econometric and data challenges, while retaining parsimonious models. Before pursuing that argument however, I will return to the task at hand: identifying these dynamic interactions in the existing literature.

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[13] While the Civic Volunteerism model uses a decision theoretic framework, and aligns well with the econometric analysis conducted later in this dissertation, there is no reason to assume that a game theoretic model that employed imperfect information and learning could not alternatively be used to study this dynamic interaction.

Social Interaction: Columbia School and Beyond

Core Theoretical Argument

Intuitively, social relationships play an important role in political behavior, from shaping political opinions to spurring participation. Since the 1950s, the preponderance of political science research has examined the isolated individual, and how personal characteristics shape political behavior. Nevertheless, political scientists are rediscovering the social logic of politics, with a host of interdisciplinary research centers, publications, and conferences examining the topic, building on the initial work of Berelson et al. (1954), or the "Columbia School" of sociologists.[14] Berelson and his colleagues examined the social influence arising from major societal cleavages: religious, ethnic, and class-based. They posited that individuals often interacted with others of the same group and followed the cues of political leaders of the same group, and voted accordingly. Individuals who were cross-pressured would show instability in their political preferences, and, as expounded upon by later authors, may be less likely to participate in order to avoid social conflict (e.g. Mutz 2002).

Since the early work by Berelson et al. (1954), researchers have focused on two characterizations of the social environment: the intentional political discussion an individual has within their social network, and the day-to-day often unintentional interactions an individual has with people and expressions of their political beliefs (via lawn signs, bumper stickers, etc.). The latter, more established, approach can be found in the work of Huckfeldt and Sprague (1995), who found empirical evidence that casual

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[14] While started in sociology, this approach has also been taken up by American political scientists and hence is discussed in this section.

political observations shape the decision to participate – as more neighbors participate, so do you. Cho and Rudolph (2008) provide a more recent analysis, in which casual observations shape participation, via a spatial autocorrelation model of diffusion. Campbell (2006) argues that individuals absorb norms of civic and political participation, largely based on whether consensus (within a homogeneous population) or conflict (within a heterogeneous population) prevails in their environment. Participation, when it occurs, can also be strongly clustered, as Cho (2003) shows for political contributions by ethnic minorities. Other scholars have examined the role of regional political heterogeneity, including Alesina and La Ferrara (2000), who posit that individuals prefer interacting with others who are similar, and tend to withdraw from community interaction (and political participation) when confronted with diversity. Similarly, Mutz (2002) argues that a conflicted social environment leads to lower participation via political ambivalence and conflicting social accountability pressures.[15] Putnam's work on social capital (1995a; 1995b; 2000) also argues for a strong influence of everyday interactions via formal organizations.

Research on the influence of personal social networks on voting has blossomed more recently, as new technologies from sociology and computational social science have crossed over into political science. For example, a series of formal models of social networks have provided significant insight into the particular conditions under which social networks influence individual political participation. Siegel (2009) analyzes the formal characteristics of plausible social networks, looking at how an individual's

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[15] Kotler-Berkowitz (2005) finds the opposite, using a model of information and opportunities for participation: diversity in social contacts increases turnout.

network responds to changes in the number of interconnections. He demonstrates how the structure of the network influences the manner in which social interactions shape participation; without specific knowledge of the network structure, the causal impact of a general "social network" cannot be forecasted. Fowler's (2005) research using social network data from Huckfeldt and Sprague's field studies (1995, 2000) similarly finds that network characteristics have a non-linear, contingent impact on political participation. McClurg (2003) counters Putnam's findings on social capital with evidence that informal, politically oriented, discussion has a major impact on participation instead of generic involvement in formal organizations. These formal models and observational studies of social network data are also supported by innovative field experiments, such as Nickerson (2008), in which household members influence each other's votes directly.

Three challenges arise with the social influences literature, however. First, while researchers in the field agree that social influences exist, they disagree on which particular forms of influence are active and find conflicting evidence as to their importance. This disagreement is most clearly seen in the literature on the political heterogeneity of an individuals' social context; as noted above, authors have found that heterogeneity increases, decreases, or fails to influence political participation. A second problem arises in the causal value of social influence explanations. Social influence is necessarily an incomplete explanation – members of one's social network (or community) had to have garnered their own political views somewhere. This problem is similar to that noted by Lichbach (1995) in his discussion of community-oriented solutions to the collective action problem: norms have to come from somewhere. A third, and related problem, lies in the dynamic process by which social norms are formed and

updated. Empirical models of social influence do not appear to have explicitly captured the fact that social interactions are both determinants of political participation, and themselves determined by it.[16] As is the case with rational choice models of voting, no researchers appear to have conducted empirical analyses of the multi-cycle influence that social interactions have on political participation.

Dynamic Interactions

If one accepts the core argument from both research traditions that social influence is a causal factor determining turnout, then each could be readily extended to show feedback cycles over time. The social network tradition (e.g., Fowler 2005), establishes one simple feedback loop: person A converses with person B, potentially influencing person B's turnout (and preference) according to an imitation probability.[17] B then converses with C, potentially influencing C's turnout, C then converses with A, potentially influencing A's turnout, etc. While rarely discussed in the literature directly, the logic of these models implies reversibility – C can converse with A, affecting turnout in the future, and setting up a feedback loop. I will analyze the theoretical and empirical implications of this particular cycle at length in Chapter 5.

The literature on social influence also demonstrates a positive feedback cycle caused by peer-group selection: individuals tend to self-segregate, withdrawing from contentious relationships where possible (e.g. Huckfeldt and Sprague 1987). This also

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[16] Fowler (2005) provides key insights into such a model, by examining the knock-on effects of political participation through a population. However, he does not examine the ramifications of multiple cycles of participation over time.

[17] Fowler estimates the imitation rate that fits Huckfeldt and Sprague's South Bend Election Studies at 5%.

creates a feedback cycle: individuals who participate (or not) will tend to discuss politics with likeminded individuals in the future; those likeminded individuals reinforce expectations (or not) to vote, which increases participation, etc., and the future incentive to seek out likeminded individuals. It may also lead, subtly, to changes in overall social linkages, as people become better friends of those with whom they interact politically.[18]

Similarly, work on *impersonal* social influence also implies the same type of positive feedback cycle. Huckfeldt and Sprague's early work (1995) and more recent work with explicitly spatial models (Cho 2008) show that localized participation encourages more participation. Assuming that individuals who are motivated to participate in one election are more likely to express their intentions in the future through lawn signs or public conversation, and that individuals are relatively unlikely to move to opposing neighborhoods in the interim between elections, then local impersonal interactions shape future, as well as current, participation by changing the political expressions of the entire neighborhood. The expected outcome would be what Cho and others have observed: concentrated pockets of participation, and of non-participation.

This positive feedback cycle can be logically separated from the disagreements within the social influence literature, for example on the role of heterogeneity. As noted above, in the literature on political discussion, there is disagreement on the effects of heterogeneity on participation: a heterogeneous political environment could highlight the stakes, and increase participation (Kotler-Berkowitz 2005), or discourage participation Mutz (2002). For our purposes, the key factor is not the impact of heterogeneity on

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[18] This effect is likely to be slight for voting, however, as it is a short-duration, intentionally non-disruptive activity;   much larger effects would be expected for behaviors such as engaging in political protest.

participation, but of participation on heterogeneity. It seems relatively unlikely that

participation would increase the future heterogeneity of discussion.[19,20]

Sample Econometric Model, Incorporating Dynamic Interactions

As with voting behavior research in the rational choice tradition, a plethora of

models has been developed for social interactions and voting. For my purposes however,

a sample model can suffice to illustrate how dynamic interactions can be explicitly

modeled. For example, consider the political discussion model of Mutz (2002). In that

paper, she provides empirical tests of this model:

$$Pr\_Vote = probit(B_o + B_1 \, Political\_Network\_Diversity$$

$$+ \; B_2 \, Frequency\_Political\_Discussion + B_3 \, Political\_Network\_Size$$

$$+ B_4 \, Overall\_Political\_Interest + B_5 \, Education + B_6 \; Partisanship + B_7 \, Age$$

$$+ B_8 \, Income + B_9 \, Race + B_{10} \, Gender)$$

A simple extension into dynamic interactions occurs when one additional piece is

added: the individuals can change their political discussion networks to avoid conflict

over time. As noted above, this factor has been discussed and substantiated separately in

the literature, but does not appear to have been explicitly combined with a model of

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[19] Unless it leads to polarized individuals seeking out political combatants – which would nevertheless trigger a positive cycle of (combative) political discussion and turnout over time.

[20] Another potential exception to this positive feedback cycle exists in people reacting negatively to social pressure – being less likely to participate via social psychological "reactance" (though again, our concern is with the impact of participation on pressure, and not vice versa). The limited work in political science on reactance and social pressure for electoral mobilization (Mann 2010) indicates that reactance is not a major factor in the effectiveness of mobilization, however.

political discussion and voting. As with the dynamic analysis of the Civic Voluntarism

Model, I will leave this equation in a stylized form at the moment:

$$\text{Political\_Network\_Diversity}_{i,t} = f(\text{Vote}_{i,1..t-1}, \text{Vote}_{i..k\,(k!=i),1..t-1}, \text{Political\_Network\_Diversity}_{i,t-1}, ?)$$

The result is a feedback loop, in which the act of voting is both a function of, and

helps to determine, the diversity of one's political interactions.

Mobilization and Participation

Core Theoretical Argument

An assortment of theoretically diverse researchers has examined the direct impact

that one person can have on another individual's participation by *asking* them to

participate – i.e. mobilization. This factor was briefly discussed in Chapter 1, and a quick

summary should suffice to place cycles of mobilization in the same context as other

feedback loops discussed in this chapter.

Strong evidence exists for the causal impact of direct mobilization across a range

of political behaviors, including voting, political volunteering (Verba et al. 1995), and

recruitment into dissident organizations. Each individual can signal her intention to

participate, modifying other people's beliefs about the likelihood of political success

(Lohmann 1994; Schelling 1971; Fowler and Smirnov 2003). Household members may

also influence the expectations and norms of behavior for others in their household

(Nickerson 2008).

The short term impact of mobilization on voting appears empirically robust, as

cited in Chapter 1 and found in the work of Rosenstone and Hansen (1993), Verba et al. (1995), Abramson and Claggett's (2001) and Goldstein and Ridout's (2002), and Green and Gerber (2004). In addition to the strong findings demonstrating the impact of mobilization on turnout, a separate set of research findings analyze the impact of turnout, and various predictors of turnout, on mobilization. Rosenstone and Hansen (1993) argue that those who are mobilized are simply those who are most likely to answer, in part due to previous turnout (i.e., that organizers are strategic). Verba et al. (2000) argue similarly: "rational prospectors would…want to maximize the probability that the people they ask to get involved will be high in participation potential…Firstly, and most obviously, the recruiter would want to know whether an individual has been active in the past (p. 256-7)."   They find solid support for this argument, especially when recruitment occurs by someone who directly knows the target.

Dynamic Interactions

Extending models of mobilization and participation into dynamic interactions over time simply entails putting the two sides of the literature together – the impact of mobilization on turnout, and the impact of turnout on mobilization – as demonstrated in Chapter 1. If these two components are correct, a positive feedback cycle exists between the two. Researchers have noted this likely cyclic effect in passing, but have yet to analyze it empirically. For example, Abramson and Claggett (2001) warn: "Since past recruitment efforts may have induced past participation, the total effect of recruitment, past and present, on current participation may be larger (p. 913)." That cycle, they note, would cause significant problems in the empirical estimation process.

Sample Econometric Model, Incorporating Dynamic Interactions

I analyze the theoretical and empirical implications of this particular cycle in depth in Chapter 4, but a brief analysis can help further the more general discussion of the dynamics of participation at this stage. Rosenstone and Hansen's (1993, p273) seminal work of mobilization's impact on turnout provides a good basis for that discussion:[21]

$$Pr\_Vote = probit(B_o + B_1\ Income +\ B_2\ Education + B_3\ Unemployment + B_4\ Age$$

$$+\ B_5\ Efficacy + B_6\ Partisanship + B_7\ Candidate\_Support$$

$$+\ B_8\ Years\_In\_Community + B_9\ Church\_Attendance + B_{10}\ Homeowner$$

$$+\ B_{11}\ Employed + B_{12}\ Closeness\_Of\_Election + B_{13}\ Registration\_Restrictions$$

$$+\ B_{14}\ Gender + B_{15}\ South + B_{16}\ Race + B_{17}\ Mobilized\_By\_Party)$$

While Rosenstone and Hansen (1993), and other authors, *do* provide clear specifications of the likely impact of turnout on mobilization, in keeping with the earlier presentations, I will temporarily leave that equation in a generic form:

$$Mobilized\_By\_Party_{i,t} = f(Vote_{i,1..t-1},?) \qquad where\ \partial\ Mobilized\_By\_Party_{i\ i,t}\ /\ \partial\ Vote_{i,1..t-1} > 0$$

Once again, this stylized form highlights a simple feedback loop between voting and a factor that partially determine it: mobilization.

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[21] Some variables dropped for compactness; 31 regression variables were used in all, in the full model.

Personal Voting History, Habit, and Internal Efficacy

Core Theoretical Argument (including Dynamic Interactions)

While strong empirical results indicate that prior turnout is a major predictor of future turnout, relatively little theoretical development has occurred to explain this regularity until recently. Numerous researchers employ lagged participation as a control variable to remove confounding influences in the analyses, but otherwise do not consider the theoretical meaning of this control variable (e.g., Abramson and Claggett 2001). Previously, a detailed examination of turnout history would have required multi-year panel data, which is expensive to collect and rarely representative. However, with the spread of field experiments, researchers have now begun to posit and test theories about participation as a habit – in which the mere act of participation leads to future participation (Gerber et al. 2003; Green and Shachar 2000).[22] This literature provides a rare example in which the cyclic interaction of an individual-as-decision maker and the micro-context of that decision (here, internal habits and tendencies) have been discussed.

A second, less common, example of cyclic interactions in the voting literature occurs in Finkel's work on efficacy (1985). Finkel argues that individual political participation and belief in political efficacy are reciprocal; each reinforces the other. Previous authors had demonstrated that an individual's belief in the government's responsiveness to the public ("external efficacy") and in their personal capacity to affect policy change ("internal efficacy") increase the probability that the individual will

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[22] The theoretical work on participation history as a habit is distinct from the significant theoretical apparatus developed on early socialization. From Campbell et al. (1960), to Campbell (2006), and Green, Palmquist, and Schickler (2002), scholars have examined how experiences during one's formative years leave a lasting impression on one's political decision making process. Again, this larger literature on how parents and the social environment of youth shape life-long participation is outside of the scope of this discussion.

participate politically. He finds that increased electoral participation is associated with a subsequently increased belief in the "external efficacy" of participation, after controlling for prior belief, but participation is not found to increase an individual's belief in "internal efficacy". As expected from prior research, he verifies that perceived political efficacy increases the probability of participation.

Connecting the two streams of research, in the habit literature, researchers recognize that "habit" may merely be a proxy for other factors that change in the person's environment. For example, Gerber et al. (2003) offer four hypotheses about the formation of habits:

- voting alters psychological factors in the voter, encouraging future turnout, citing Finkel (1985) on efficacy, or a possible increase in one's sense of duty;

- voting increases future outreach and information from the parties, similar to the discussion on political information and mobilization, above;

- voting changes "conative attitudes", or positive and negative feelings about the act itself, citing Fishbein and Ajzen (1975),

- voting subtly changes the self-identity of voters, coming to regard voting as something that "people like me do on election day", and similar to Schuessler's (2000) model of Expressive Choice.

Each of these underlying processes could generate positive feedback cycles, as could other explanations of habit formation.

Sample Econometric Model, Incorporating Dynamic Interactions

Gerber et al. (2003) provide one model of habit, though other similar varieties exist in the literature. Their econometric model is (p547):

$$Pr\_Vote = two\_stage\_least\_squares(B_o + B_1\ Number\_Of\_Individuals\_In\_Household$$

$$+\ B_2\ Voting\_Ward + B_3\ Age + B_4\ Age^2 + B_5\ Registered\_MajorParty\_Voter$$

$$+ B_6\ Treatment\_To\_Induce\_Voting + B_7\ Voted\_In\_Previous\_Midterm\_Election$$

$$+ B_8\ Voted\_In\_Previous\_General\_Election)$$

In each case, the underlying mechanisms of habit – such as self-efficacy, "conative attitudes" or self-expression – form a cycle in which they both influence and are influenced by the act of voting.

The Odd Man Out: the Michigan School approach

Starting with Campbell et al. (1960) researchers in the Michigan School tradition have argued that individuals have an enduring *personal* attachment to a political party. Early socialization creates that attachment, which drives future political participation.[23] A vast literature expounds upon the Michigan School perspective (see Niemi and Weisberg (2010) for a summary; see Green et al. (2002) for a recent expansion).

The Michigan School tradition was long dominant in American political science, but unlike the range of other models reviewed here, does not appear to have an easy extension into dynamic interactions. This should not be surprising, since the core model

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[23] The Michigan school considers both the act of turnout, and, especially, which party individuals support. For clarity of presentation, I focus on the former.

focuses on an unchanging affiliation over time. Nevertheless, countless researchers have

"added on" to the social-psychological model with additional factors that are more

suggestive of dynamic changes, and can be analyzed within this framework. These

additions, which cover a hodge-podge of variables (including prior participation, civic

skills and efficacy) have been covered in other sections of this chapter; see Niemi and

Weisberg (2010) for a description of these models.

An Aside, on Political Intermediaries

While rarely addressed in the American political behavior literature, another

pathway exists by which individuals could influence their own and each other's future

participation: via the intermediary of political institutions and policies. Individual and

collective political action leaves a legacy of political institutions, which can be

supportive, hostile, or simply uninterested in the aims and methods of future political

participants. Rational choice institutionalism (see Weingast 2002) examines the

formation of these institutions and how they shape the options and incentives confronting

political actors. For example, North and Weingast (1989) describe how the institution of

checks upon the King's power changed in the political structure of 17th century Britain

and allowed the government to credibly commit to property rights. The political

opportunity structure (POS) tradition in political sociology also discusses in detail how

structural changes shape individual and group dissent.

Unfortunately, these studies all lack one vital piece: a clear understanding of how

individuals, precisely, influence political outcomes. As Lichbach points out (1995), the

precise production of policy from dissent is woefully underspecified. For voting, the

simplified production function is well known, especially in majoritarian democracies. Once proportional representation systems (Lijphart 1999; Powell 2000), checks and balances, and other veto players are also considered, it rapidly becomes difficult to trace the precise impact that an individual voter has on political outcomes.[24] Where less complex third party institutions are considered, these relationships and their development over time can bear fruit. In cases where the production function is not well specified, relatively little work has been done on how one's own participation influences that of others via intermediary institutions.

Since the focus of this work is on the individual's dynamic micro-context, I will conclude the discussion of political intermediaries here, but note that political intermediaries could provide an interesting avenue for future research.

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[24] If there were, opposing activists would exploit it, deadlock would result, and the function would no longer be meaningful. The one exception, where empirical regularity has been found is between dissent and repression: more dissent leads to more repression (Davenport et al. 2005). Unfortunately, the degree, duration, timing and type of resulting repression are not as well specified.

Why Bother: The Challenges of Non-Dynamic Models of Dynamic Processes

The previous section demonstrated how four research traditions in American political science involve implicit or explicit dynamic processes. Here, I revisit the obvious question asked in Chapter 1: does that matter?

Revisiting the Methodological Issues of Models that Ignore Dynamic Interactions

In Chapter 1, I discussed three primary reasons why models that have underlying dynamic processes, but do not analyze them explicitly, are problematic:

1. The long term impact of an independent variable on voting behavior will be underestimated if its indirect (and time-delayed) role is not explicitly analyzed.

2. The functional forms most often used to model voting behavior and its determinants create unrealistic projections of long term behavior, when dynamic interactions are present. They could predict (in isolation of other factors) that the voting population would grow to include all people, no one, or asymptotically approach a steady-state level of participation without a clear theoretical interpretation.

3. If the underlying temporal dynamics are incorrectly specified, or if they incorporate complex functional forms that violate assumptions of stationarity, then the commonplace statistical tools used to estimate the models will provide biased results (de Boef and Keele 2008).

In the following sections, I examine additional implications of these challenges, and lay the foundation for a potential solution.

Additional Implications of these Methodological Challenges

The three methodological challenges listed above do not mean that no work can be done in the area, nor ever could. It is fully possible that a clever and highly skilled methodologist could build a model that was testable against its null hypothesis using existing means. However, a related two-fold issue arises:

First, even if high quality panel data on the interaction between voting behavior and the political environment were available, proper dynamic econometric techniques are beyond the reach of all but a narrow segment of the political science community. For the rest of us, there is no effective counter argument, i.e., the resulting model could only be tested against other methodologically clever applications of the current tools. The resulting discourse may be insightful, diverse, and ultimately lead to an accurate depiction of the world. Or it may not. We will not know. The effect of this methodological challenge is to weed out theories on methodological grounds, and not on theoretical ones. To an extent, this must always occur – some level of methodological rigor is required to apply empirical rigor to the theoretical models. In this case, only a handful of commonly accepted models of dynamic political behavior over time exist, though many authors discuss dynamics theoretically. That fact should provide us with a hint that this methodological barrier is more difficult to overcome, in practice, than those that exist in other areas of empirical political science.

Unless there are major advances in *non*-specialized econometric techniques, the

dangers of applying current methodological tools are vast even for the most clever and skilled. If the underlying model is incorrectly specified, not only will the econometric results be spurious, but researchers may not know there is a problem. Except in certain noteworthy cases (autocorrelation tests), we do not have good tools to warn us of danger. The problem is not that the current tools aren't up to the task; sometimes, they are. Instead, they cannot reliably say when the theorist is wrong across the range of potential exotic dynamic models, and provide an imperfect signal about the value of their application. The common counter argument is that we can generate other theories to provide alternative explanations. As noted above, these theories face other, methodological criteria that lead them to mount a less than stellar offense.

Moreover, work in computational social science, and, separately, in comparative political science and political sociology, indicate that the dynamics of political behavior are likely to be far more complex than these techniques can handle. As will be discussed shortly, computational social science models regularly find that political behavior is a contingent, path-dependent (and non-stationary) phenomenon. Existing methodological techniques would falter, at least without significant theoretical elaboration of the underlying non-stationary dynamic process. Researchers need to elicit new observable implications that *are* amenable to empirical testing or to perform clever transformations of the process into a stationary one (e.g., second and higher order Markov representations). How then can we distinguish between appropriate uses of our limited, but still powerful, econometric tools for studying dynamic processes, and inappropriate cases?   The problem is one of understanding the process, and not the use of sophisticated tools to provide that understanding. Proper use of the tools assumes understanding of the

dynamic interactions, and it is understanding that we lack. This challenge, a lack of theoretical work to help understand dynamic political interactions, is linked to another set of theoretical problem with static models.

Other Theoretical Challenges with Static Models of Dynamic Processes

Turning our attention temporarily from voting behavior to the study of political conflict, dynamic interactions have been extensively studied in two interrelated fields – the qualitative, comparative, case-study study tradition and the political-opportunity-structure (POS) tradition in political sociology. In the former, dynamic interactions over time are a fundamental, if at times implicit, part of the "story" to be told; events unfold over time, and often they are contingent upon earlier events, with a level of complexity and nuance that is unlikely to be captured by existing econometric models. In the latter, there is often an explicit discussion of cycles of contention and the contingent nature of political events on prior political events. Tilly and Tarrow (2006), for example, reject simple (and statistically tractable) cause-effect relationships in contentious politics, drawing explicit contrast with statistical approaches, "in contentious politics, no complex outcome ever results from the operation of a single causal process (p31)."

In both literatures, researchers look for the particular combination of mechanisms and pivotal events driving a particular historical outcome. The models built from these approaches are far more open ended, and less structured than common models of voting behavior. The approach provides relief for some of the myopia of statistical and formal modeling – by allowing for the discussion of events that any commonsense description of political behavior would include, but that would require works of magic to incorporate in

formal or statistical models. Soule (1997) provides a useful example, in which tactics used by political protesters evolved over time in a highly-contingent, non-linear (and non-stationary) fashion.

Similar lessons about historical contingency, complex emergent behavior, and non-stationary processes arise from the computational social science literature. Computational social scientists such as Scott Page, Leigh Tesfatsion, and Cathleen Carley use a variety of computer-based approaches to directly simulate social processes and study their dynamics, without reliance on closed form mathematical solutions or statistical models. For example, Miller and Page (2007) describe dynamic models of political parties jockeying for power. Dean et al. (2000) provide an early model of the Anasazi, in which simple household settlement rules generated compelling macro-patterns of behavior that fit the historical record. Learning from such experiences, computational social scientists have critiqued the *theoretical* consequences of existing econometric and formal modeling tools – the loss of theoretical flexibility, the inability to model complex processes, and the lack of a shared language among researchers to discuss such processes.[25]

While the contentious politics, political case study, and computational social science literatures rarely model the dynamics of voting behavior, they can inspire similar critiques of existing voting studies. In the previous sections, I have drawn out particular cases in which dynamic interactions lurk within major models of voting behavior; numerous others could be envisioned, especially if the door were opened to develop

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[25] See de Marchi (2005) and Miller and Page (2007) for two excellent reviews of the limitations of traditional methods, and the new theoretical frontiers opened up by computational tools such as dynamic social network analysis and agent-based modeling.

entirely new models of such interactions. Yet, addressing these dynamic complexities, and showing that they are worth the trouble, is not so straightforward.

Three Potential Methodological Answers

Three related methodological approaches appear promising to develop comprehensible, generalizable, dynamic models. The first is to accept the statistical and data limitations of modeling dynamics, and approach complex dynamics like an unobservable inner process. Start with a conceptual model of a dynamic process, and provide a detailed mathematical operationalization (a la Chong 1991 or Lohmann 1994). Then, determine the range of implications, and select new, testable implications for which the available methodological tools and data are sufficient. The validity of the model is then based on the empirical testing of these observable implications. This path is certainly not novel; it is central to many scientific endeavors. It warrants a mention though, lest the pessimistic discussion above seem to imply that well-earned wisdom about dynamic processes from these models is irrelevant. It requires an explicit awareness of the limitations of current statistical methods, and that care to be taken not to blindly use methods that are inappropriate for the hypothesized process (de Boef and Keele 2008).

Second, researchers can approach the modeling of dynamic processes as a deductive exercise, in which (unlike many dynamic models) the assumptions are simple, easily understood, and readily accepted. The value placed on the model's outcomes, as non-intuitive and as difficult to test uniquely as they may be, is thus based on the validity of the assumptions. The data requirements are thus less demanding. Schelling's (1971)

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thought experiments on segregation and on auditorium seating provide examples of these clear, fascinating, models built on first principles.

A third approach would be to concentrate on the structure of the dynamic process, and look for regularities across dynamic processes. The output would be dynamic mechanisms similar to those employed in game theoretic models (credible commitment, principal agent models, etc.) that can be readily understood and reused in other substantive contexts. Tilly and Tarrow (2006) have embarked on a similar path, but have failed to provide the connective tissue and insight on how particular mechanisms produce observable, testable outcomes. In the case of the protest movements, for example, potentially generalizable dynamic processes would include the dynamic interaction between movements and governments as they of learn each other's' capabilities and shift tactics (building on Lichbach 1987; Moore 1998), and mobilization appeals change over time as prior successes draw in diverse pools of activists, changing the targeting and message of future mobilization appeals.

In the latter two cases, simulation modeling can help the discovery and modeling process, but does not provide a panacea. Rather than delve into a full analysis of the value and limitations of simulation modeling (see Miller and Page 2007), a few comments can be made. The great practical weakness of simulation models of dynamics is their methodological strength – the flexibility to model arbitrary complex processes. Researchers have too often been tempted into embracing the complexity of the processes they seek to understand – and generating models for whom the observable implications are unclear, the assumptions are too numerous or too arbitrary to be widely accepted, or the resulting mechanisms are too specific to be generalized. In other words, complex

models that fail to provide any of the three potential solutions to complexity proposed above. In Operations Research, a long tradition of simulation modeling has provided practical, widely accepted solutions to narrow problems such as queuing behavior and building egress. In part, they have succeeded because of their narrow, practical focus, with self-imposed constraints. As Robert Frost is reported to have said "the self-imposed restrictions of meter in form and of coherence in content work to a poet's advantage; they liberate him from the experimentalist's burden—the perpetual search for new forms and alternative structures (PoetryFoundation.org 2012)." In confronting the wide open space of complex dynamic processes, perhaps a few self-imposed restrictions can help modelers find their own form of coherence.

A Proposed Solution

To meet these methodological and theoretical challenges, I offer a three-stage approach to studying the dynamic interactions between an individual political participant and her micro-context. First, use a simple theoretical framework to help identify particular dynamic processes, and contextualize them so that potential interactions and confounding influences can be found. This framework draws directly from the existing literature on political behavior in American political science, but has strong parallels to research in contentious politics. The framework also provides an initial set of concepts with which to discuss particular processes of interest, drawing especially on the complex adaptive systems literature. Second, develop a concrete statistical model of the specific process of interest, building on existing non-dynamic models and testing its empirical implications. Third, extend the model for novel, testable, hypotheses via simulation

modeling.

The resulting simulation model is freed from the constraints of autoregressive stationarity, but still grounded in existing, well-known models, and made amenable to empirical testing and falsification. The aim is not to find a single, comprehensive model to "cover" all political dynamics, but rather to build up a set of methodological tools, theoretical concepts, and substantive findings that can support further research into specific dynamic interactions. In the subsequent chapters of this dissertation, I develop this theoretical framework and a methodology (Chapter 3) to identify and test regularities across dynamic processes. I then provide two specific econometric and simulation models of dynamic interaction (voter mobilization in Chapter 4 and peer pressure in Chapter 5), and discuss the results in the context of potential further research (Chapter 6).

Chapter 3: Theoretical Framework and Methodology

In the previous Chapter, I discussed how four major research traditions in the study of American voting behavior implicitly or explicitly incorporate dynamic interactions between the voter-as-decision-maker and the micro-context of that decision over time. I also discussed how these dynamic interactions pose challenges for statistical estimation, and began to propose a solution: the careful use of simulations to open the doors to the explicit modeling, estimation, and application of dynamic processes.

As I touched upon briefly at the end of that Chapter, simulation models are not a perfect tool, and many modelers have gone astray by generating complex models of political behavior that are difficult to empirically test or to benchmark against the existing literature (Leombruni and Richardi 2005). To avoid that unfortunate outcome, I believe that it behooves the simulation modeler to understand well the existing literature, and start new modeling efforts with well-developed, and well-substantiated, empirical models.

In this Chapter, I further analyze the four sample models with dynamic interactions from Chapter 2. I demonstrate how one can identify their core dynamic processes, and learn from the System Dynamics literature about what to expect from these mathematical forms, regardless of the substantive interpretations one hopes to apply to them. Next, I return to the substance of the voting models, and consider three pathways of dynamic interaction that recur in the literature. In the final section, I use these lessons – on the mathematics of dynamic interactions, and on a typology of

dynamic voter interactions – to develop a methodology by which researchers can rigorously study dynamic interactions among voters and the micro-context of their decision-making.

The Dynamic Updating of Existing Voter Models

As a first step, Table 2 summarizes each of the models of voting behavior that served as examples in the previous chapter.

Table 2: Sample Voting Behavior Models

Model	Determinants of Voting	Main Temporal Variable
CVM (Weak Rational Choice)	$Pr\_Vote = B_o + B_1\,Vocabulary + B_2\,Income + B_3\,Religious\_Attendance + B_4\,Political\_Interest + B_5\,Political\_Information + B_6\,Efficacy + B_7\,Partisanship + B_8\,Eligiblity\_To\_Vote$	Political Information
Political Disagreement	$Pr\_Vote = probit(B_o + B_1\,Political\_Network\_Diversity + B_2\,Frequency\_Political\_Discussion + B_3\,Political\_Network\_Size + B_4\,Overall\_Political\_Interest + B_5\,Education + B_6\,Partisanship + B_7\,Age + B_8\,Income + B_9\,Race + B_{10}\,Gender)$	Political Network Diversity
Mobilization	$Pr\_Vote = probit(B_o + B_1\,Income + B_2\,Education + B_3\,Unemployment + B_4\,Age + B_5\,Efficacy + B_6\,Partisanship + B_7\,Candidate\_Support + B_8\,Years\_In\_Community + B_9\,Church\_Attendance + B_{10}\,Homeowner + B_{11}\,Employed + B_{12}\,Closeness\_Of\_Election + B_{13}\,Registration\_Restrictions + B_{14}\,Gender + B_{15}\,South + B_{16}\,Race + B_{17}\,Mobilized\_By\_Party)$	Mobilized By Party
Habit	$Pr\_Vote = two\_stage\_least\_squares(B_o + B_1\,Number\_Of\_Individuals\_In\_Household + B_2\,Voting\_Ward + B_3\,Age + B_4\,Age^2 + B_5\,Registered\_MajorParty\_Voter + B_6\,Treatment\_To\_Induce\_Voting + B_7\,Voted\_In\_Previous\_Midterm\_Election + B_8\,Voted\_In\_Previous\_General\_Election)$	History of Voting

In each case, the model can be reorganized in terms of factors that update over time *because of participation itself* and "everything else". For example, mobilization is the main variable that updates over time in the third model. While income, education,

and unemployment status also may change over a particular individual's lifetime, they are very unlikely to change because of prior political participation. Such variables are exogenous to the dynamic participation process, while mobilization is endogenous. In cases where the researchers employed more than one potentially endogenous variable, such as Rosenstone and Hansen's use of (potentially endogenous) political efficacy as a control variable for mobilization, I focus on the single, primary variable for purposes of analytical clarity. I will return to the role of multiple overlapping interactions later on.

In Chapter 1, I presented a stylized mobilization model, and organized it in terms of mobilization, prior participation, and other exogenous factors. Here, I will apply a slightly more nuanced analysis to mobilization and to each of the other three research traditions. If we reorganize the mobilization function given in Table 2 around the dynamic updating process, and adding in subscripts to show differences over individuals and time, the mobilization function becomes:

$$\text{Pr\_Vote}_{i,t} = \text{probit}(B_o + B_1\, C_i + B_2\, X_{i,t} + B_3\, \text{Mobilized\_By\_Party}_{i,t}) \qquad \text{where } B_3 > 0$$

Where C_i represents the various variables that are effectively constant over the period of study for a given person (e.g., education), and $X_{i,t}$ represents exogenous variables that may vary over time – but in a manner unrelated to mobilization or prior voting behavior (e.g., age, income). In addition to the impact of mobilization on turnout, we also have the impact of prior turnout on current mobilization.

In the previous chapter, it was left intentionally vague:

$$\text{Mobilized\_By\_Party}_{i,t} = f(\text{Vote}_{i,1..t-1}, ?) \quad \text{where } \partial \text{ Mobilized\_By\_Party}_{i\,i,t} / \partial \text{ Vote}_{i,1..t-1} > 0$$

For analytical clarity, I will again focus on a single historical, endogenous determinant of mobilization: voting in the last election cycle. We can then rewrite the mobilization equations as:

$$\text{Mobilized\_By\_Party}_{i,t} = f(\text{Vote}_{i,\,t-1}, C_i, X_{i,t}) \qquad \text{where } \partial \text{ Mobilized\_By\_Party}_{i\,i,t} / \partial \text{ Vote}_{i,t-1} > 0$$

Where we assume (or appropriately expand) the vectors C_i and $X_{i,t}$ to cover all of the additional non-endogenous variables used to explain both mobilization and participation. The mobilization function provides the other half of the positive feedback cycle discussed in the previous chapter, i.e., the equation for how the individual's micro-context for decision making updates over time. Each of the other feedback equations can be similarly reorganized. Table 3 provides the new versions.

Table 3: Voting Behavior Models Reorganized to Highlight Temporal Variable

Model	Voting Equation	Update Equation
CVM (Weak Rat. Choice)	$\text{Pr\_Vote} = B_o + B_1 C_i + B_2 X_{i,t} + B_3$ Political_Information	Political Information$_{i,t}$ = $f(\text{Vote}_{i,\,t-1}, C_i, X_{i,t})$
Political Agreement	$\text{Pr\_Vote} = \text{probit}(B_o + B_1 C_i + B_2 X_{i,t} + B_3$ Political_Network_Homogeneity)	Political Network Homogeneity$_{i,t}$ = $f(\text{Vote}_{i,\,t-1}, C_i, X_{i,t})$
Mobilization	$\text{Pr\_Vote}_{i,t} = \text{probit}(B_o + B_1 C_i + B_2 X_{i,t} + B_3$ Mobilized_By_Party$_{i,t}$)	Mobilized_By_Party$_{i,t}$ = $f(\text{Vote}_{i,\,t-1}, C_i, X_{i,t})$
Habit	$\text{Pr\_Vote} = 2\text{SLS}(B_o + B_1 C_i + B_2 X_{i,t} + B_3$ Voted_In_Previous_Election)	Voted In Previous Election = $\text{Vote}_{i,\,t-1}$

I have reversed the definition (and thus the sign) of the key variable in Mutz's

(2002) model, political diversity, from "political disagreement" to "political agreement",

to standardize the functions further. Now, in each function, the key endogenous variable

has been found empirically to have a positive impact on voting behavior ($B_3 > 0$), and

prior voting behavior has been found or has been posited to have a positive impact on that

endogenous variable, either directly or through an intermediary factor (i.e.,

$\partial\text{Mobilized\_By\_Party}_{i\,i,t} / \partial\text{Vote}_{i,t-1} > 0$).

These four systems of equations can be simplified further into the following

stylized version, adding a straightforward interpretation of how the probability of voting

translates into actual vote behavior:

$$\text{Pr\_Vote} = g(B_o + B_1\,C_i + B_2\,X_{i,t} + B_3\,u_{i,t}) \qquad \text{where } \partial\text{Vote}_{i,t} / \partial u_{i,t} > 0$$

$$u_{i,t} = f(\text{Vote}_{i,\,t-1}, C_i, X_{i,t}) \qquad \text{where } \partial u_{i,t} / \partial\text{Vote}_{i,t-1} > 0$$

$$\text{Vote}_{i,\,t-1} = 1 \text{ if random}(0,1) >= \text{Pr\_Vote}_{i,\,t-1} \text{ and } 0 \text{ if random}(0,1) < \text{Pr\_Vote}_{i,\,t-1}$$

Where $u_{i,t}$ represents the endogenous variable that updates over time.

This system of equations is a simple positive feedback cycle, establishing what is

called in the System Dynamics literature a "causal loop". In fact, a cursory review of this

model from a System Dynamics perspective quickly yields the conclusion that the current

model is woefully insufficient. For those with familiarity with the relevant mathematics,

the problem is clear, and the next section can be skipped. For everyone else, it is

worthwhile to step through the analysis to understand not only the problem, but how to

resolve it, and how to address similar (less obvious) problems in a systematic manner.

Analyzing the Sample Model from a System Dynamics Perspective

In reorganizing each of the sample models, I have intentionally focused attention on the dynamic aspects of voting behavior – illustrating the "causal loops" by which current voting decisions can influence future voting decisions. The structure of such loops, as distinct from their substantive meaning and context, has been well studied in the System Dynamics field. Before diving into the lessons from this literature, a brief introduction to System Dynamics is warranted.

System Dynamics is an interdisciplinary approach to studying complex, dynamic problems (Forrester 1961). It studies the relationships between entities in a system to understand how the structure of those relationships influences the behavior of those entities within the system.[26] Systems Dynamics modeling is particularly common in the Operations Research and Management Science communities, where it is used to model business processes, such as take up rates of new products or inventory levels at a warehouse, and ecological problems such as resource dependency and extinction.

Development of a System Dynamics model often starts with identification of the essential quantities (stocks) in the system, and the relationships by which those quantities increase or decrease over time (flows). These stocks and flows are formalized as a set of interrelated, non-linear equations (generally differential equations). As with any other modeling technique, the researcher seeks to exclude extraneous information and provide a parsimonious model that reproduces the behavior of interest. The system of equations is then encapsulated in a simulation package such as VenSim or DYNAMO. The model

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[26] For more information about the field see Kirkwood (1998) or the System Dynamics Society (2012).

is then calibrated to real world data, and simulations are executed to study behavior of the model under diverse scenarios and to further test the applicability of the model against its observable implications.[27] The method is especially useful where non-linear relationships and circular causality (causal loops) are present; simpler linear modeling and equation solving find often such conditions are intractable.

Historically, System Dynamics simulation models were calibrated by hand, but in the last decade new techniques have been developed to perform automatic calibration and confidence interval estimation in a manner very similar to maximum likelihood estimation of econometric equations (Oliva 2003). As part of the study of System Dynamics, researchers have identified commonly recurring elements such as positive and negative feedback loops, delays and smoothing, and behaviors such as oscillating processes, goal seeking behavior, and S-shaped growth over time, caused by these common structures. The common elements and behaviors are driven by the system structures themselves, and provide a general toolbox for understanding new problems. They provide tools to understand the behavior of systems, abstracted away from substantive meaning of the systems themselves.[28]

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[27] Like all simulation models, the output of Systems Dynamics models is a set of logical implications from their assumptions. Automated tools then allow for the comprehensive exploration of those logical implications and for testing against the *applicability* (not "accuracy") of those assumptions and implications against the real world.

[28] The differential or difference equations underlying a system dynamics model could also be analyzed using other tools, such as dynamical systems theory, or Markov models (though requiring a stronger set of assumptions). I find that the particular representations and terms used in System Dynamics well illustrate the problems of dynamic interactions in voting behavior – but I do not mean to imply that other analyses of the same underlying systems of equations would not be appropriate. While there are clearly important differences between the techniques, there is no *a priori* reason barring a dynamical systems approach when a System Dynamics one is also feasible.

System Dynamics Versions of Existing Voting Behavior Models

I will demonstrate the value of the System Dynamics approach for studying

dynamic political interactions by converting one of the sample econometric models, the

Civic Volunteerism Model, into a System Dynamics one. For ease of representation, and

to avoid the complexities of probabilistic individual-level models (e.g., Mosekilde and

Rasmussen 1983), I will consider how the Civic Volunteerism Model would predict the

aggregate level of voter turnout in the United States, given its members' skills, resources

and level of engagement in politics.

Start with the main Civic Volunteerism equation above, in which we consolidated

the independent variables into Political Information, constant personal characteristics (C),

and everything else (X). The impact of political information on turnout was given

previously as:

$$\text{Pr\_Vote} \ = \ B_o + B_1\,C_i + B_2\,X_{i,t} + B_3\,\text{Political\_Information}$$

We can approximate this individual-level equation at the societal level by

calculating the expected percentage of people voting in each election. If we assume that

the exogenous variables $X_{i,t}$ do not vary systematically over time for a given person, and

that each population is homogenous, then the simplified aggregate equation is:[29]

$$\text{Percent\_Of\_Peoeple\_Voting}_t = C + B_1\,\text{Average\_Political\_Information\_Per\_Person}_t$$

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29 The assumption of non-time-varying characteristics is a reasonable assumption for many of the variables
used by Verba et al. (1995) such as education. This is potentially invalid for income and job_level,
however, since for many people they increase with age. The assumption of a homogenous population (i.e.,

For the moment, the assumption of homogenous populations is a very strong one. Later on, I will address this assumption by studying heterogeneity across populations (since the individuals within the populations are independent of each other in this model, the expected result is the same), and show that the core findings are invariant to the assumption that C is homogenous.

In terms of the impact that voting has on Political Information, I will start with a simple linear relationship – each additional voting experience teaches participants more about the voting process, marginally decreasing costs, and thus marginally increasing the probability of continued future voting. Voting this builds a stock of experience, which provides political information and voting in the future:

$$\text{Average\_Political\_Information\_Per\_Person}_t = \sum_{s=0}^{t-1} \text{Percent\_Of\_Peoeple\_Voting}_s$$

In this simple model, the stock of experience is cumulative, and does not decay over time.

This system of two equations, implemented in the System Dynamics package VenSim, is illustrated in Figure 2 on the next page, where C is represented as the "population's exogenous characteristics", and B_1 is the "coefficient of political information".

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characteristics not varying in i) is not a realistic one, naturally – and it useful here to demonstrate the approach and is required for tractable System Dynamics modeling. It will be relaxed later when I apply a hybrid agent-based modeling / System-Dynamics approach that incorporates heterogeneity.
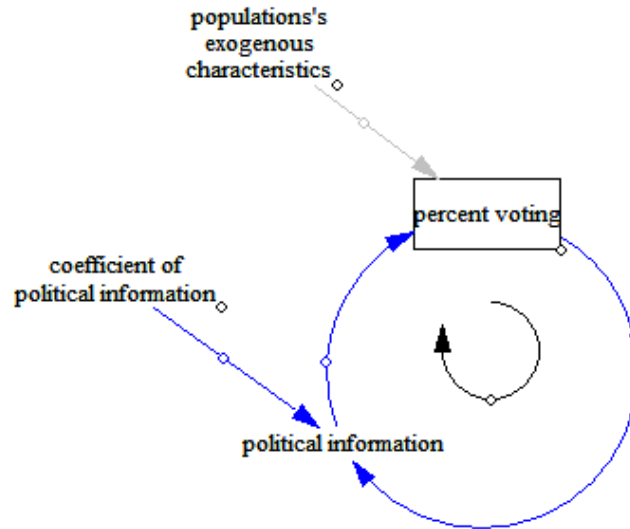
**Figure 2: System Dynamics Representation of the
Aggregated Political Information Model (Civic Volunteerism)**

Once expressed as a System Dynamics simulation, we can systemically study the behavior of this model for different characteristics of the population (C). For example, fixing B_1 at 0.1, and providing the starting conditions of

$$Average\_Political\_Information\_Per\_Voter_0 = 0$$

Then systematically varying the exogenous characteristics of the populations, c, we can plot how the probability of voting in each successive election changes over time across a diverse set of characteristics. The results of that simulation are shown in Figure 3, on the next page.

Change in Percent Voting Over Time
Political Information Model (Aggregated)
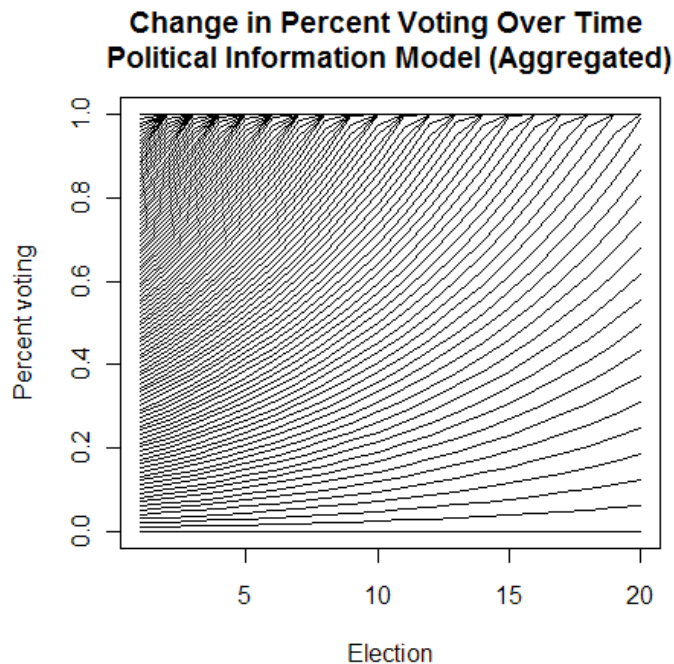
Figure 3: Simulation Results for Aggregated Political Information Model, across
100 different populations of individuals with varying exogenous characteristics

Each line represents a simulated population, which varies according to the single parameter, C (the exogenous, non-time varying default vote propensity). The results are clear even for this simple test: the percent of people voting increases over time, except in one special case. I.e., no matter what the inherent propensity of individuals is to vote, the feedback loop of political information comes to dominate their behavior. Given sufficient time, each population will increase to 100% participation.

The one case in which it does not dominate is the line at the bottom – in which the initial propensity to vote is zero, and thus no one ever tries, never increases their political information, and thus never changes over time.

I selected the society-level civic volunteerism model, and its political information feedback loop, because it was structured in a manner that allowed for easy demonstration of this problem with a minimum of algebraic manipulation. However, similarly problematic outcomes are produced by each of the models discussed above.

Moving from the political information model to Mutz's (2002) political agreement model, a new set of behaviors occurs. While numerous alternative operationalizations of the political agreement model could be developed, here I explore one stylized variant; this model is discussed in greater detail in Chapter 5. First, we replace the linear relationship with a probit function, as given in the sample Political Agreement model above. Second, we rename "Average Political Information Per Person" to the "Effect Of Prior Participation", to reflect a more general interpretation of the model. Third, we cap the maximum effect of prior participation using a logistic curve, as fits the concept of "political homogeneity" used in the political agreement model. The stylized cycle is:

$$Percent\_Of\_Peoeple\_Voting_t = probit\ (C + B_1\ EffectOfPriorParticipation_t)$$

$$EffectOfPriorParticipation_t = logit(\sum_{s=0}^{t-1} Percent\_Of\_Peoeple\_Voting_s)$$

Figure 4, on the next page, demonstrates sample paths through this cycle.[30]

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[30] Since the probit model has a different effective range than the prior linear one (in which linear values were directly interpreted as percentages), additional parameters affect the shape of these curves. With these parameters, the function is $Percent\_Of\_Peoeple\_Voting_t = probit\ (scale * (offset + C + B_1\ EffectOfPriorParticipation_t))$. In this case, an offset of 0.5 was used, and a scale factor of 5.

Change in Percent Voting Over Time
Probit with Capped Effect (Aggregated)
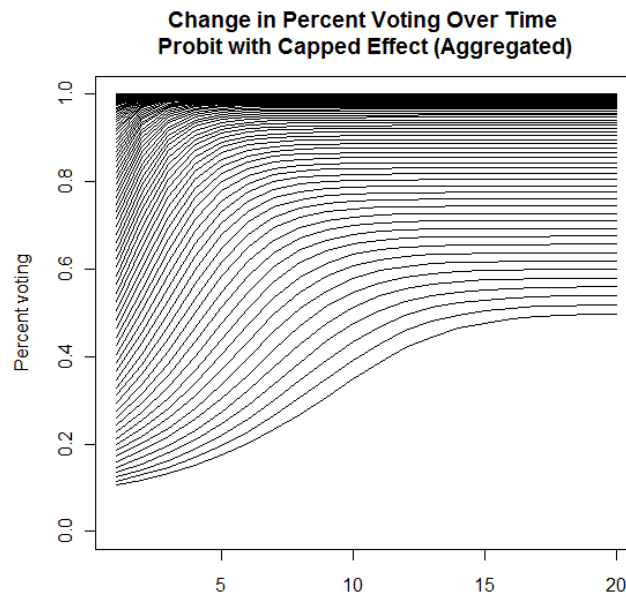
Figure 4: Revised feedback model, with a capped, non-linear (probit) relationship

As before, the effect of prior participation steadily grows over time until the cap on maximal impact is reached. Depending on the initial conditions of the model, either: a) the population reaches full participation or b) the population significantly increases participation over time due to the feedback process alone -- and without any additional perturbation or change in the electoral environment. While the first case is more dramatic, both are clearly unrealistic. The particular shape of the curve and magnitude of the effect depends on the parameters of the model – but the potential for significant error in predicting voting behavior remains.

The mobilization model is discussed in greater detail in Chapter 4. However, a brief comment can be made for both the mobilization and habit models. In one operationalization employed in the literature, the feedback cycle is presented as a simple, single-step influence: the last cycle's participation affects current mobilization/habit, and current mobilization/habit affects current participation.

This model is a first-order serial autocorrelation model, various specifications of which are well studied in the literature:

Percent_Of_Peoeple_Voting$_t$ = f(C, EffectOfPriorParticipation $_t$)

EffectOfPriorParticipation $_t$ = Percent_Of_Peoeple_Voting$_{t-1}$

Where the voting function, f, is linear, and no other time-varying parameters are considered, then this model either a) rapidly explodes into full participation, or b) implies that each year of participation is shaped by not only last cycle's participation, but all prior years of participation (with decreasing force). In the latter case, the cumulative impact of a single year of participation is greater than the parameter B_1 would indicate, and needs to be carefully analyzed. In the case of non-linear voting functions (as are now the norm in the literature), or when authors expand from a first-order model into moving averages or other multi-year relationships, then the dynamics and interpretations of these models rapidly become very difficult. In each case, however, there is a core question: what does it mean theoretically, and empirically, to have a positive feedback cycle in the model, and how can the complexities of the model be rigorously studied?

The Problem with Positive Feedback

As noted above, for those familiar with feedback dynamics or AR(1) processes, these odd behaviors – unconstrained rapid growth or rapid growth up to a constraint – are not a particularly surprising result. System Dynamics models such as these are well studied and documented. An unbalanced feedback loop, i.e., one that is not somehow countered by an opposing relationship, will eventually dominate any system. If the

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feedback mechanism is limited in magnitude, as with the upper cap on political homogeneity above, it will eventually meet its maximum output – ignoring all other variations in the system (i.e., heterogeneity among voters). Moreover, the initial starting point and the particular parameters of the growth are less relevant than the structure, namely, that explosive growth may eventually occur no matter what, given enough time.

The more surprising result is that this fact, well known in System Dynamics, has not been explored further (and resolved) in the voting behavior literature, even when habit, prior participation or internal efficacy has been explicitly modeled in econometric research, each of which sets up a positive feedback loop. Similarly, it appears not to have been covered in the limited theoretical discussion of mobilization's impact on turnout. Clearly there is a theoretical piece missing in the model, since, as any observer of American elections knows, turnout is not growing over time to include the entire population or to a predetermined maximum amount. Individuals are not steadily increasing their intentions to vote (or strength of habit, or feelings of self-efficacy, etc.) over time.

Voting behavior researchers are neither foolish nor blind; research into dynamic interactions is only starting to develop, with excellent experimental work occurring in the field of voting habits, in particular. For most researchers, dynamics are simply not part of the picture – or when they are, they are considered only to "control" for their effects on contemporaneous variables. Rather, these results show the value of thinking in terms of dynamic systems. In particular, by intentionally highlighting the dynamic aspects, we can abstract away from the substantive (and theoretical) specifics, and learn from the well-developed System Dynamics literature, to build better models and more accurate

understandings of political behavior. For example, further lessons can be drawn from even this simple test case.

Handling Positive Feedback

In each of the four models considered, positive feedback establishes secular growth in voting behavior over time. This is clearly unrealistic. There appear to be three ways out of this problem in terms of voting:

1. **Balance the positive feedback cycle at the individual level**. At the level of each individual voter, there may be countervailing forces that stop a person's voting behavior from increasing over time due to increasing efficacy, habit, mobilization, political information, or social influence. One possibility is that everything decays over time – interest in politics, habits, etc. People become distracted or disinterested. Other individual level constraints include scarce attention or time for political activity.

2. **Balance the positive feedback cycle at the societal level.** One obvious factor is aging of the population – while each person's experience over time could push them to be more active as they gain experience, the population as a whole constantly loses active voters and gains new (potential) voters with no prior experience, i.e., the system has an outlet to avoid this extreme behavior.[31] Similarly, internal migration

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[31] It does not limit the unrealistic and unconstrained growth in propensity to vote within each individual's lifetime – for that, balancing at the individual level is required.

from people buying new houses and changing jobs can disrupt existing habits, one's sense of confidence in knowing how to go about voting, etc. Immigration can also play a role if the incoming population has a lower average turnout rate (see McDonald and Popkin 2001). Other societal constraints include resource constraints for voter mobilization – as is discussed in Chapter 4.

3. **Show that no positive feedback cycle is relevant in practice**, either because the initial magnitude of the impact itself is minimal, or the maximal impact over time is inconsequential. Given the strong empirical results found for each of the four models of voting behavior examined above, this is not likely to be the case.

The System Dynamics literature indicates that balancing process can avoid explosive growth from a positive feedback cycle, provides mathematical insight (beyond the scope of this discussion) the how each cycle and balancing process would function in practice. Which form of balancing that occurs in practice is not an analytical matter, though, but rather a theoretical one. There is unlikely to be any overarching mechanism that will always resolve this issue and make dynamic political participation models more realistic; instead, each dynamic model must be constructed, and tested, on a case by case basis; I will delve into that process in more detail shortly. First, however, regardless of how feedback plays out in any given model, its existence raises further methodological concerns, and reason to mistrust current econometric results, even for ostensibly static personal characteristics.

Methodological Implications of System Structure

If any feedback loops are in place, and even if nothing else more complex is involved, then System Dynamics research provides additional insight into the methodological challenges of estimating dynamic models of voting behavior, discussed in Chapters 1 and 2.[32] In short, most current econometric techniques used for voting behavior assume the separability of the independent variables, and a strict, single, causal link between independent and dependent variables. That is not the case when (one or more) feedback loops are present. There are omitted variables causally linking the independent variables (but not fully explaining them – hence substituting them is insufficient and adding them into the model would cause serious multi-collinearity problems), and there is bidirectional causality, over time. Autocorrelation tools can thankfully handle the econometric problems when the underlying structure is known (or correctly guessed). However, knowing the autocorrelative relationships is challenging – and the System Dynamics framework given here helps to identify those relationships and place them at the core of the analysis, instead of relegating them to nuisance parameters or interference to be minimized using technical tricks.

Second, when some form of balancing is in place, an additional complexity arises. By limiting the impact of a given variable such as habit under certain scenarios, the balancing process breaks the common assumption about universal domain implicit in many econometric models. The voting habit may have little impact in certain scenarios

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[32] Unless the true empirical relationship is a simple one, such as first-order autocorrelation. In that case, the problem is one of interpretation, rather than estimation – since robust techniques have been developed to estimate in the presence of those factors. The interpretation problem, namely handling the enduring effects of prior participation across multiple cycles, is briefly discussed above and is more thoroughly considered in Chapter 4.

(such as busy mothers with numerous competing habits), but a strong impact in other scenarios (retired grandfathers).[33] These complexities can be readily handled with existing econometric techniques, by including interaction effects. However, the researcher must already know that they are there for theoretical reasons; in absence of specification, the assumption of universal domain applies. A System Dynamics approach to modeling voting behavior does not suggest that these interactions will necessarily occur; rather, it provides a methodology to help the researcher think about them in the theory-building process and incorporate them when relevant.

Building a Theoretical Framework

Drawing inspiration from these sample models, and the analysis of their feedback processes, we can develop an overall framework that can help researchers develop and test new models of dynamic political behavior. This framework can then provide structure and linkages to the existing literature, to help simulation modelers better ground and test their work and to avoid the unrealistic predictions that a pure feedback process would generate.

Four Pathways of Influence on the Turnout Decision

The literature on political participation provides a wealth of rationales for why an individual might engage in political behavior. Without re-examining the literature

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[33] Interestingly, balancing processes also can change the interpretation of regression coefficients for dynamic processes. The most "important" variable driving voting behavior, such as habit, would be statistically insignificant or of low magnitude when it is balanced, and suddenly jump to statistical significance and high magnitude in other scenarios.

research on political participation, we can draw on the earlier discussion in Chapter 2 and the models analyzed in this chapter to trace out pathways by which external or historical factors could influence that decision over time.

In particular, four broad pathways are discussed in the literature that can directly influence on the individual decision to participate:

1. **Exogenous Factors**
    a. **Personal Traits.** An individual can participate due to inherent personal characteristics, such as an enduring sense of partisanship (Campbell et al. 1960) that motivates action, civic duty (Blais 2000), or rationally applied policy preferences that determine the "value" of participation (Downs 1957; Fiorina 1981). These characteristics are generally treated as exogenous and unchanging, though the information that triggers a sense of duty or valuation of an election are variable, as is discussed in item #2.
    b. **Environmental Traits.** The decision to participate is clearly related to the political environment of the election – the most obvious example being the wide difference in turnout between presidential and non-presidential elections. Similarly, the closeness of the election and incumbency of the candidate can have significant impacts on turnout. Like certain personal traits, the characteristics are also treated as exogenous and immutable (at least with respect to a given election.)
2. **Mobilization and Persuasion.** Political parties and other actors in an individual's political micro-environment can actively (and often intentionally) influence the decision to participate by direct mobilization (Rosenstone and Hansen 1993; Verba et

al.1995), evoking a sense of duty (Blais 2000) or personal expression (Schuessler 2000) or by providing information about the costs and benefits of participation (Downs 1957).

3. **Personal Adaptation.** An individual can influence his or her own future participation via the act of participating itself – by forming a habit (Green et al. 2003) or building a sense of internal efficacy (Finkel 1985), or gaining skills and information that lowers the costs of participation (Verba et al. 1995).

4. **Social Influence.** Individuals can influence each other's choice to participate via group-level pressures and descriptive and prescriptive norms (Huckfeldt and Sprague 1995; Gerber and Rogers 2009), often through the intermediary of political discussion (McClurg 2003), bonds of reciprocal trust (Putnam 2000), or passive information transfer (Huckfeldt and Sprague 1995).

Naturally there are other factors that influence the participation decision – e.g., whether an individual grew up in a household that voted – but these factors arguably must have their impact on the *individual* decision to participate through one of these four channels.

Even if we remain agnostic about the particular mechanism occurring within an individual's head, these four pathways of influence can help organize an analysis on interdependent political participation. Figure 5, on the next page, illustrates these four pathways, how they feed into the individual decision to participate (solid lines). In three of the pathways, i.e. not including exogenous personal and environmental characteristics, the act of participation can provide feedback that shapes their future impact on the

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individual's participation (dashed lines). For example, political campaigns can learn

what types of appeals drive participation, individuals can build civic skills through

current participation that enable future participation, or friends can target nonvoters for

pressure before the next election.
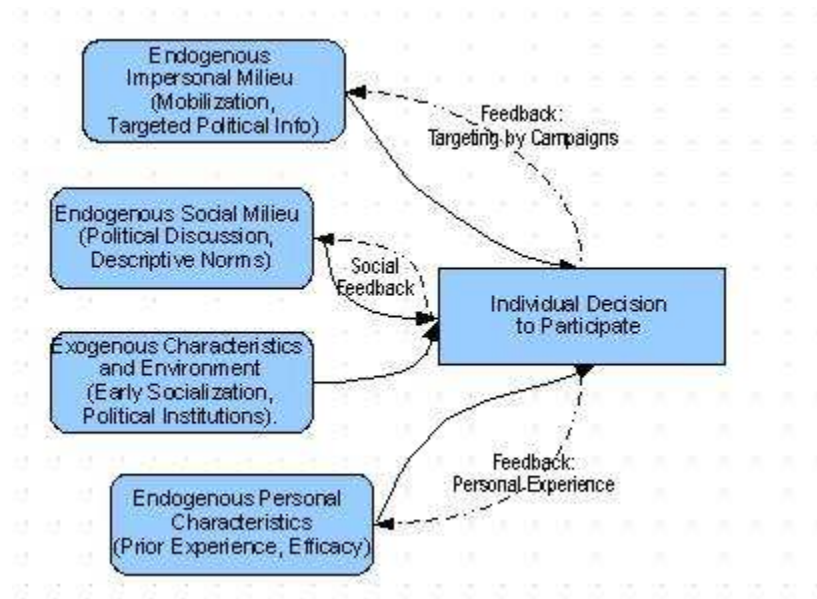
Figure 5: Four pathways of influence on the turnout decision

Various dynamic cycles of participation and adaptation can be identified and

contextualized within this framework: mobilization is just one possible mechanism by

which the individual decision to participate influences the individual's institutional milieu

(in this case, the mobilizer), which in turns shapes future participation decisions.[34]

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[34] Assuming that the mobilizer and individual are still in place for the next election cycle. For the individual, naturally the cycles of influence stop upon death or another "exit" from the potential voter pool (e.g,, felony conviction). For the mobilizer, this points to the importance of political parties as *durable* mobilizers that can learn from previous cycles of mobilization. If the mobilization were transitory (mobilization by a single, independent candidate), or there were no way to learn from previous cycles (no voter files or records of prior mobilization), this cycle would not be relevant.

Similarly, cycles of norm formation and participation can be studied. Descriptive norms are one mechanism by which the individual participation choice affects others' decisions to participate and thus the social milieu for future participations decisions. By embedding these individual processes within the overall theoretical framework, we can also gain insight into potential confounding variables that should be controlled for, and more complex interactions that may arise among multiple processes.

Balancing Feedback

While each of these feedback cycles clearly applies to a particular context, e.g., turnout affects efficacy, they also provide counter-arguments to each other. To better understand this, one can separate the micro-context (feedback cycle) from the substantive variable that is updated by the cycle. Consider updates that involve one's social network (the micro-context). In a circle of friends, social pressure can lead to voting, which leads to social expectation, and more future pressure. It can also lead to voting which leads to efficacy and to lower costs to future participation. It can lead to voting, which builds up political skills and resources to ease future participation. Or, finally, it can be a conduit of information that focuses individual attention to further supporting information in the future. Whenever a particular cycle of interest is identified (e.g., social pressure leading to voting leading to more social pressure), there are numerous other potential cycles that cross the various research traditions and may amplify or balance the initial cycle. Thus, one must be particularly careful in analyzing these scenarios to incorporate or exclude these alternatives.

The System Dynamics literature can help guide the specification of the precise

feedback mechanisms at work in a given interaction, and their net influence on political behavior, to avoid the obvious problems with unconstrained positive feedback discussed above. For example, for theoretical reasons, social influence may be believed to have positive feedback (activists support each other), negative feedback (via a desire to be different than one's peers), contingently cause discontinuities in behavior (by introducing a person to whole new group of political friends via a chance occurrence), or have strong attractors (regardless of initial conditions, social groups may segregate into all-participants or no- participants). The net influence on the political behavior may be a straightforward but non-linear extension of the single-step process, or a surprising emergent result that could not be intuited from the individual components. In building models with dynamic interactions between actors, two key lessons from complex adaptive systems should be kept in mind:

- start with small and simple models, and
- small, simple models can result in behavior that is astoundingly complex and non-obvious.

While this general guidance from the System Dynamics literature is very useful, more is needed to develop specific dynamic political participation models. In the next section, I outline a stepwise process for identifying, modeling, and testing these dynamic models, building on System Dynamics insights and simulation methods.

A Methodology for Analyzing Dynamic Processes

While the theoretical model presented above can help contextualize a particular dynamic political process, it does not provide guidance on how to study that process and drive new testable insights from it. In fact, as discussed in Chapter 2, the presence of such dynamic processes increases the complexity of studying political behavior – since the assumptions of stationarity and separability used in traditional econometric techniques are violated, and hence new techniques are required.

In other words, to estimate dynamic models, a different approach may be needed. In this section, I present a three-step process for modeling, estimating, and testing dynamic models of political participation. As noted in the previous chapter, only one of the primary dynamic cycles of political participation has received significant attention in the political science literature – the influence of current participation on future participation via the updating of (internal) personal characteristics such as habit and efficacy. In this section, I use examples from the two relatively unexplored pathways for dynamic feedback (mobilization and social influence) to make the methodological approach more concrete. In the next two chapters, I then apply this methodology in practice: to mobilization by political parties and to the influence of descriptive norms.

Step 1: Develop a Theoretical Model, Leveraging the Framework

The theoretical framework above helps us tease out dynamic relationships at work in a simulation of interest and look for competing explanations. First, however, we must address a major challenge to modeling dynamic processes: their complexity and degrees of freedom.

Handling the Complexity of Dynamic Models

In Operations Research, a long tradition of simulation modeling using System Dynamics has provided practical, widely accepted solutions to narrow problems such as queuing behavior and building egress. In part, they have succeeded because of their narrow, practical focus, with self-imposed constraints. However, in modeling dynamic political phenomena such as voting, there are no well accepted constraints or narrow definitions of the problem – as the study of the dynamics of political participation is still quite young.

Theoretically, the realm of possibility for the simulation modeler of voting behavior is endless and overwhelming. Researchers have too often been tempted into embracing the complexity of the processes they seek to understand – and generating models for which the observable implications are unclear, the assumptions are too numerous or too arbitrary to be widely accepted, or the resulting mechanisms are too specific to be generalized (e.g. Leombruni and Richardi 2005). While there are a few simulation models of voter-politician interaction (Gainsborough et al. 2008), and of political conflict (Miller and Engemann 2004, Epstein 2006), none has achieved any significant following in political science, in part due to these concerns.

Even with the parsimonious theoretical framework described above, it is all too easy to imagine the range of overlapping, potentially confounding influences on voting behavior that may make the model more accurate (in theory) but would also make it unmanageable and unfalsifiable. To avoid this danger, the researcher should be aware of these dangers and strive to make the dynamic model as parsimonious as possible, i.e., while countless pathways are possible, it is unhelpful to analyze them all at once. As with

any form of modeling, the researcher must rely on theoretical arguments to exclude large swaths of the universe of possible explanations. Moreover, if the researcher can develop a dynamic model that closely tracks existing non-dynamic work, then the leap into the dynamic world, while perhaps less exciting, would be far easier for other researchers to follow and analyze (and attempt to falsify) on their own.

Identifying and Contextualizing the Dynamic Process

With the potential for open-ended, overly complex dynamic models, researchers can benefit from a series of questions to structure the initial creative, model-building process. I suggest two stages: to identify and clearly specify the particular dynamic process, and then to analyze its practical and theoretical significance in the context of the wider dynamic environment.

First, given an initial behavior of interest (voting) and a factor that appears to influence the behavior (Get-out-the-vote calls from the political party), one can ask the following questions:

1. **What "type" of factor is it?**   Does it influence behavior through personal characteristics (e.g., information remembered about the elections), social pressure (e.g., friends expect you to vote), or direct mobilization (e.g., you are pressured or persuaded to commit to vote).

2. **How does this factor change over time?** Once the "type" is identified, the framework provides some guidance on how the factor may change over time. For

example, phone calls by campaigns change across election cycles because the targeting criteria and data used by political parties changes. Similarly, individual evaluations of voting' value changes with personal experience of the voting process.

3. **Is there a feedback cycle between political behavior and the factor that influences it?**   In particular, look to the micro-environment of the individual's decision-making environment. Impersonal, institutional factors that influence voting (such as majoritarian versus proportional representation systems) are very unlikely to be changed by the *individual* decision to participate. However, the climate of political discussion at one's office place could change over time. The latter is likely to show feedback cycles; the former is not. If no such cycle exists, then existing tools and methods are (more likely to be) appropriate, and one can skip the rest of this process.

Second, one can analyze the dynamic process in more detail, to search for alternative explanations and to determine if traditional empirical estimation is feasible. This process helps put the particular dynamic process in context, and provide an initial test for the unique value of further research on the process. It can also help constrain the impulse to employ the kitchen sink approach of modeling – by tracing the unique contribution of this particular model, one can either reasonably put aside the tangled web of related issues for further research, or change the focus of the research to cover the most interesting (and presumed powerful) mechanism. Again, a series of questions, using the theoretical framework, can help:

1. **How important is the feedback cycle?** Specifically, what is the expected change in (the probability of) the political behavior if the person went from receiving the minimum possible impact of the given factor to the maximum possible influence? For example, how much more likely is a person to vote if they are called by the political party every day, versus never? That maximum marginal effect is also the upper bound on the impact of the feedback cycle over time. If the maximum effect is not of practical interest, then neither is the feedback cycle, and traditional methods can be used to explore the rest of the model.

2. **What factors would mitigate the impact of the feedback cycle?** If the maximum effect of the variable is very large, then the simple System Dynamics model shown in Figure 2 suggests that a positive feedback cycle, in isolation, could dominate the political behavior. Since this rarely happens in practice, something else must be mitigating the impact – such as an opposing feedback loop that balances out the positive one, either at the societal or individual level. Boundary conditions on the interaction, resource constraints, and inflow/outflow of the population are potential factors. If either strong path dependence or balancing feedback cycle is present, then traditional econometric methods are likely to be inappropriate.

3. **What competing explanations are possible, if a feedback cycle is surmised?** For any process of interest, competing explanations are always possible. The framework above can help identify, and disentangle, these explanations. For example, when

studying a feedback cycle between mobilization by political campaigns and voter

turnout, the framework warns us that participation is likely to have multiple effects on

the individual – changing the individual's assessment of the value of voting,

providing information and skills for voting, and perhaps changing the person's

network of political discussants. Each of these 'other' impacts of participation could

amplify or negate the 'direct' impact that mobilization has on participation and

participation has on mobilization.

Step 2: Implement Model in Computer Program

Formalizing the Model

Once a parsimonious theoretical model of the dynamic process has been

developed, then empirically minded researchers can translate and test it. With more

traditional models, developing a "testable form" of the model often entails squeezing the

behavior of interest into a single linearized statistical function, at the expense of more

nuanced or readily interpretable representations. With this linearized function, one would

then use a technique such as generalized least squares or maximum likelihood estimation

to estimate the model's parameters and determine statistical significance. However, for

dynamic models, traditional econometric forms (e.g., linearized models for use with

generalized least squares) are often insufficient – since the tools used to estimate their

parameters rely on assumptions that may be violated.

Instead of searching for a linearized representation of the dynamic theoretical

model, look for the most natural mathematical formalization. One possible formalization

of a dynamic process would be a set of interdependent difference equations, as are used

in the dynamical systems and System Dynamics arenas. Difference equations, differential equations and discrete state transition matrices are often used to represent such processes. For this purpose, the particular formalization is not relevant – as long as it effectively captures the theory and can be represented mathematically.

Once that mathematical representation has been found, one can implement it as a computer program that takes model parameters as inputs and produces point predictions about political behavior as outputs.[35] The resulting computer program is a simple simulation model.

So, thus far, the process is exactly the same as is used when a researcher seeks to estimate a linearized econometric model, except that the mathematical (and therefore simulation) representation of the model need not be as rigidly constrained in its functional form. The next step however, may appear a bit more exotic – more exotic than it really is.

Estimating the model parameters

In order to estimate the parameters of the computer (mathematical) model, an empirical researcher in political science would generally use maximum likelihood estimation techniques to find the values of those parameters that minimize prediction error relative to a known dataset. With dynamic models, we must accomplish the same thing. However, instead of using regression techniques, we can use optimization

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[35] To illustrate, difference equations could be readily implemented in a language such as R or MATLAB, in which the parameters are variables read from a file or otherwise specified at the start of the program. The particular language employed and structure of the program is irrelevant – as long as it faithfully represents the mathematical model.

techniques to search though the space of possible parameter values - determining the parameters that minimize prediction error relative to a given dataset.

The optimization process is well studied and has a long standing and extensive literature, though one not typically referenced in political science. Techniques such as Newton's Method, which uses gradients in parameter space to determine successive approximations of the "best" parameters, are reasonably well known (but have serious flaws when used for complex problems). Other techniques that are less well known in political science but widely used in Operations Research include Simulated Annealing, Genetic Algorithms, Tabu search and quadratic programming. Each technique has its benefits and limitations; two summaries of optimization algorithms can be found at Glover et al. (2003) and Mohan and Deep (2009). For our purposes though, we need not constrain the particular optimization algorithm that is used – as long as it is appropriate for the particular mathematical formalization of the theoretical model.[36]

Once an optimization algorithm is selected, the researcher would then connect optimization software (such as those implemented in libraries in R, Matlab, etc.) to the computer representation of the dynamic model. With the help of a scoring function that uses a known dataset and a set of model parameters to test, one then can estimate the error generated by those parameters relative to the known dataset. The optimization software executes the scoring function numerous times with different sets of parameters, searching for the parameter set that produces the smallest error.

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[36] Certain optimization techniques are only appropriate for particular functional forms – e.g., quadratic programming is appropriate for quadratic functions with linear constraints. Other techniques such as genetic algorithms assume a particular structure to the parameter space, but can be used on any functional form.

To some political scientists, this procedure may sound similar to maximum likelihood estimation, in which a log-likelihood function is optimized to estimate model parameters. In some MLE scenarios, a closed form optimization of the log-likelihood function is possible. In other cases, MLE also relies on numerical optimization. While there are differences in the procedure (specifically in how likelihood is defined versus the simulation scoring function, and constraints made on the likelihood function), in both cases numerical optimization is used to estimate the best parameters for a given dataset. The similarity has its roots, as Oliva (2003) argues, because estimating a simulation model in this manner is actually a subset of the MLE technique. In political science, however, this application of the MLE method to simulations is not widely used despite the widespread application of MLE for econometric estimations.

Determining Confidence Intervals and Statistical Significance

With point estimates of the model parameters in hand, researchers can then determine the confidence intervals around these estimates and test for statistical significance. For a simulation model, this process entails a form of Monte Carlo simulation: executing the simulation model repeatedly with the same input parameters to determine the variation in the output predictions. Unlike a traditional Monte Carlo simulation however, the output is the parameter estimates, and the input is the known dataset. The probability distribution of the dependent variable is unknown (and need not be assumed); one can use bootstrapping techniques to repeatedly sample from the known dataset, estimate the parameters on that subset, then generate an estimate of the probability density function across the resulting parameter estimates. From that

probability distribution, one can determine confidence intervals, and test null hypotheses against a particular parameter having no effect on the model.

From start to finish, this process allows empirical estimation (calibration) and hypothesis testing of dynamic models of arbitrary functional form. To recap, the suggested methodology is:

1. Implement the core model in a simulation, limiting the set of open parameters to only what is absolutely necessary.
2. Use numerical optimization to calibrate the parameters of the model against existing, well-studied datasets.
3. Use Monte Carlo simulations of the model (simulations where nothing varies except for random noise, or bootstrapping, etc.) to estimate the confidence intervals of those parameters.
4. Test parameters against the null hypothesis of zero (i.e., a statistical significance test) or, better, against externally validated values when available.

Steps 2-4 are effectively a maximum likelihood test, and replicate the maximum likelihood estimation and hypothesis testing process from normal statistical analyses in a manner adapted for dynamic models. This places the seemingly exotic simulation model on the same playing field as a traditional econometric model, and clears the way for more rigorous testing against new data.

Limitations of the estimation and hypothesis testing process

There are two key limitations to keep in mind during the optimization process; both are shared with MLE, but can be more troublesome in a simulation environment. First, as with any econometric model, limiting the number of parameters used in the model is vital. At a minimum, the optimization process becomes more difficult (and may not converge to any result) as the number of parameters increases. Moreover, interpretation of the simulation model's parameters becomes exceedingly difficult, as is the case with econometric models (Achen 2005), but even more so in a simulation environment where the functional form is unrestricted and hence the interpretation of marginal changes in variables is less-standardized.[37]

Second, broadly speaking there are two forms of optimization – deterministic and heuristic. Certain optimization algorithms deterministically provide an exact solution, i.e. the global optimum, when the scoring function meets specific requirements (otherwise, they would provide no solution whatsoever). Heuristic algorithms do not place such restrictions on the scoring function,[38] but sacrifice the guarantee of finding the global optimum. When a heuristic algorithm is used, within a simulation estimation or in a traditional MLE, then the confidence intervals around a particular point estimate contain both the variation in the underlying data and the variation caused by the inexactness of the optimization procedure itself. In general, this means that tests of statistical significance would be harder to pass (i.e., the added "error" makes the tests more

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[37] Though, as with logit models, there are ways to estimate the practical significance of a particular model parameter under sensible scenarios using simulation models.

[38] Though certain algorithms are "better suited" for some types of problems than others, misapplication leads to lower accuracy and efficiency, rather than the inability to produce a solution at all.

conservative). While both forms of optimization could be used, traditional MLE usually

employs a global exact optimization technique whenever possible. Simulation-based

parameter estimation would generally use heuristic optimization – because the same

modeling challenges that lead a researcher to use a simulation model also make it

difficult to optimize the model. Thus the rough tradeoff between using a tractable

econometric model and an intractable simulation model is this: accuracy of estimation

(econometric), versus the freedom to tackle otherwise intractable problems (simulation).

Heterogeneity, Stochasticity and Flavors of Simulation Modeling

Thus far, I have left the particular form of simulation model that one could

employ open ended, to focus on the general tradeoffs in using simulations versus

econometric models. In the preceding chapter, I used System Dynamics models as

examples, since they are easy to conceptualize and have served as a tried and true method

of modeling complex dynamic systems for over fifty years. However, each simulation

technique has its limitations, and some are more appropriate than others to for a particular

theoretical problem.

When modeling voter behavior, a particularly challenging issue arises for all

simulation modeling techniques – how to handle the heterogeneity of voters and their

stochastic voting decisions. Significant analytical squeezing, stretching, and simplifying

are required to fit heterogeneity and stochasticity into a System Dynamics package.

Similarly, while any functional form can be used to generate the core simulation model to

formalize, estimate, and test the theoretical model developed in Step 1, common methods

such as difference equations and state transition matrixes place strong restrictions on the

resulting mathematical model.

Over the last fifteen years, a simpler way has appeared that allows for a more direct translation of the theoretical model into its mathematical form, without restricting the functional form. That method, agent-based modeling, is predominant in the computational social science literature, and is slowly making inroads into mainstream political science. Like any simulation model, the modeler specifies the components of the system, the rules by which the components interact, and executes the model to explore outcomes. The outcomes are always logical deductions – there is nothing in the model that was not programmed in.

Agent-based models differ from other simulation models more in how they are used than in their mathematical basis. The modeler identifies individual agents (hence the name) who interact autonomously in the system according to specified rules. The rules are not bounded by the normal constraints of utility maximization or analytic tractability that are employed in econometric models, but instead can encapsulate any theoretically interesting process. The agents are often heterogeneous and adapt their behavior over time (See Miller and Page 2007). Agent-based models are thus well suited to complex systems of individuals interacting among themselves, and are structured so that the modeler can intuitively specify the underlying theory from the perspective of the individuals themselves. Arguably, this helps the modeler to develop new and innovative theories, and analyze problems that otherwise would be too complex to analyze with other analytical tools.

In subsequent chapters, I will continue to use the conceptual framework derived from System Dynamics (e.g. feedback loops, systems of interrelated components), but

employ agent-based modeling in order to supply a simple, intuitive formalization of the theoretical concepts that can nevertheless be rigorously tested using the methods described above.[39]

Step 3: Test Against New Observable Facts

In much of the empirical work in political science, a journal article stops when the model has been formalized and estimated, and statistical significance of parameters of interest has been established. Numerous attempts have been made to require that the research process be extended – to test the estimated models against new (out of sample) empirical data and to determine whether the findings still hold. However, considerable data collection and econometric work is often required to fulfill this goal, and, perhaps not surprisingly, a significant percentage of new research efforts do not include this step.

In the case of dynamic models of political behavior, the problem of collecting additional data for out-of-sample testing is even more acute. Currently, researchers have very few panel data sets from which to draw in order to conduct any form of dynamic modeling. Finding an additional dataset, that contains similar coverage and operationalization of the core conceptual variables is indeed challenging. The methodology presented here is not designed to generate new panel datasets; it cannot solve the data collection problem. However, it can help ease the constraint of limited data in another manner, by making it easier to generate new predictions of the model that are more readily and convincingly tested.

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[39] This approach is known as "systems thinking" in the literature (Meadows 2008), in which system-dynamics insights are applied and tested more broadly than the particular mathematical setting (differential and difference equations) in which they were originally conceived.

The simulation provides a test-bed for exploring the predictions of the theoretical model in novel contexts and conditions. Under this approach, the simulation models would search for non-obvious implications of the model, such as new extensions that apply the model to a new problem for which there is data, and can serve as a test for the model's underlying assumptions. For example, an individual-level (agent-based) simulation model can allow researchers not only to compare the model's predictions about individual behavior (i.e., against a hard-to-find panel dataset), but also to analyze aggregate patterns of voting, and how those patterns of voting change over time. These novel predictions can then be compared to existing aggregate data (which is generally much easier to find than individual level panel datasets), and used to test the model's core assumptions. It is precisely this approach that I take in the next chapter, on the dynamics of mobilization over time.

Chapter 4: Dynamics of Mobilization and Participation

Introduction

Dynamic interactions between political participants and their micro-environment are perhaps most overt in the case of voter mobilization – where, in each election cycle, political parties intentionally target individuals based on their prior participation. In previous chapters, I presented a theoretical framework to contextualize dynamic political behaviors, and a stepwise process for identifying, formalizing, and testing models of those behaviors. Along the way, I have used mobilization and voting as one example of a "feedback loop" between the individual and the micro-environment. Here, I develop that argument in much greater detail, formalizing and testing a fully specified model, starting with a more thorough review of the literature on mobilization and participation.

Theoretical Background

Static and Short Term Models of Mobilization and Voting

Within American political science, numerous well developed lines of research exist on political participation and mobilization, many of which are driven by 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 2010), but a few gross generalizations can be made. While each type of political behavior has a different profile, researchers have found that those who are most likely to be politically active are well educated, wealthy, white (e.g., Verba et al. 1995), politically interested and 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 that a variety of immutable personal traits and malleable attitudinal and behavioral characteristics lead to political engagement, in line with the theoretical framework presented above.

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 organizers consider many of the same personal characteristics that are involved in the individual choice to become politically active – though perhaps with different weighting. For example, Rosenstone and Hansen (1993) found that mobilizers consider many of the factors that determine individual participation – including education, race, prior participation. Brady, Schlozman and Verba (1999) present a similar concept as "rational prospecting" of good targets for mobilization. However, Gershtenson (2003) cautions that the profile of who is asked changes over time as parties adapt to changing

circumstances. Across the literature on mobilization, however, numerous authors have found that when mobilizers ask, potential voters do respond.

As noted in Chapter 2, the impact of mobilization on political participation is well substantiated. The initial research on the topic consisted of survey work and statistical studies of existing datasets measuring same-year mobilization and voting. Rosenstone and Hansen (1993) analyzed changes over time for multiple political activities, ranging from writing letters to elected officials, to attending local political meetings, to making campaign contributions. For example, they estimate that mobilization increases voter turnout by 7.8%[40], and a similar increase in voting arises from dynamic personal characteristics, such as feelings of efficacy. Their model, while widely cited, has not spawned an extensive theoretical and empirical literature. In one of the few other survey-based studies of mobilization, Verba, Schlozman and Brady (1995) examine political participation and find strong evidence that interpersonal mobilization increases voting, and mixed results for formal mobilization by political parties. Goldstein and Ridout (2002) critique Rosenstone and Hansen's (1993) broader claims, but confirm mobilization's effect on individual voter behavior.[41] Abramson and Claggett (2001) also find substantively the same role for mobilization and efficacy on voter turnout as Rosenstone and Hansen (1993).

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[40] Looking beyond voting, they found that mobilization increased campaign work by 4.8% and financial contributions to campaigns by 6.6%.

[41] Goldstein and Ridout (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.

Experimental Studies

A bevy of recent field work in American political science has moved beyond observational studies to demonstrate experimentally the impact of mobilization on voting, both on directly targeted individuals and their households (e.g., Green and Gerber 2004; Nickerson 2008). The wave of modern field experiments on mobilization arose from Yale University, starting with the studies in 1998 by Gerber and Green (2000) on the effectiveness of diverse methods of voter contact. The authors, in conjunction with the League of Women Voters, conducted a non-partisan campaign to encourage individuals to vote via phone, mail, and door-to-door canvassing. They found that while voter turnout increased substantially after canvassing, no change occurred after the get-out-the-vote telephone calls.

Subsequent research has examined the role of multiple mailings (Green and Gerber 2004), the effectiveness of mobilization in subgroups of interest (e.g., youth and women; see Green and Gerber 2004) such as Asian Americans (Wong 2005). They have also looked for consistency across multiple urban locations (2000), and across partisan and non-partisan messages (i.e. legislative elections in New Jersey in 1999), again providing more generalized results. Additional modes of contact have been considered, including personal phone calls, robo-calls, email (Green and Gerber 2004), and personalized letters. Researchers have examined the role of the organizer, including whether the organizer is of the same race as the targeted individual (Michelson 2003). Message content has been examined - including messages emphasizing civic duty vs. high stakes of the election vs. community solidarity (see Green and Gerber's 1998 and 1999 New Haven experiments; Green and Gerber (2004)). Nickerson (2008) provides an

example of mobilization of other household members. Overall, the issues studied range from very practical, detailed questions about mailing styles and TV ads (Vavreck and Green 2006), to studies that touch on larger, more theoretically interesting questions of the role of social accountability (Gerber, Green and Larimer 2008) and descriptive norms of voter turnout (Gerber and Rogers 2009).

This growing body of experimental literature verifies the impact of certain forms of mobilization on turnout, both on directly targeted individuals and their households. For particular campaign tactics, the results are relatively well established: door-to-door canvassing is by far the most effective (7% boost in participation). Other methods still can have an impact though, from personal calls (3% boost), to leaflets (1.5% boost), down to direct mail (0.5%) (note: robo-calls and email showed no impact; all statistics from Green and Gerber 2004). The results also show that partisan messages, on the whole, are more effective than non-partisan messages. Contacts with those who voted in the past are generally more effective than contacts with those who have failed to do so. Stepping back from these specific results, one can draw the general conclusions that mobilization's impact has been well substantiated, but that one must be careful to differentiate between specific forms of mobilization, since their impact varies widely.

Limitations

While these studies are clearly relevant to the dynamics of mobilization, they generally employ statistical analyses of a single interaction between organizers and the mobilized. The long term impact of current participation on the likelihood of future mobilization and participation has received surprisingly little attention, given its

importance for understanding political mobilization. After one such analysis of short-term recruitment effects, Abramson and Claggett (2001) warn: "Since past recruitment efforts may have induced past participation, the total effect of recruitment, past and present, on current participation may be larger" (p913).

Unfortunately, research into multi-election cycle dynamics 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 only 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 by using specially targeted survey and field experiments, respectively. Their work however, analyzes only two cycles of mobilization and participation, again due to challenges in data collection. Quantitative research into multi-round mobilization and participation remains limited. While multi-round mobilization has not yet been tackled in survey work or field experiments, there is no *a priori* reason why creative solutions could not be found to employ experimental methods with sufficient funding and a consistent research design over multiple election cycles.

Below, I present a model that specifically seeks to estimate the total effect of recruitment, past and present, on voting and demonstrates how the approach outlined above can tackle such complex dynamic interactions. This study diverges from existing research in three ways. 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 functions (and hence, who is mobilized). In the terminology of systems dynamics, these form an important constraint on the positive feedback in place between mobilization and participation. 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 voter turnout on work by Abramson and Claggett (2001), Rosenstone and Hansen (1993), Goldstein and Ridout (2002) and Verba et al. (1995).

Step 1: Develop the Theoretical Model

Given the growing body of literature on mobilization and voting, and the methodological and data limitations noted above, I start with a somewhat novel approach to building and testing a dynamic model of this process. First, I start with existing models of single-step voter mobilization and turnout. Then, I delve deeper into the dynamics of mobilization, looking at how the positive feedback between mobilizers and mobilized requires further theoretical elaboration and causes problems of estimation and interpretation. Finally, I examine how a simulation built to estimate the dynamic model can be extended into multiple cycles of mobilization and voting – providing new, testable predictions about the medium and long-term impacts of mobilization.

A Simple Cycle of Mobilization and Participation

Voter mobilization and participation are messy, complex processes. Each political organizer and each potential voter 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 will first step back from the details of these processes and present a stylized theoretical model of mobilization; after the outline is clear, I will return to the gritty details to see how they influence the overall picture. This model centers on a three-stage "cycle of mobilization", describing a simple positive feedback process within the general theoretical model presented above:

- Step 1: **Organizers select whom to ask,** based on their political agenda, the inherent and exogenous traits of the targeted individuals (race, gender, etc.), and the mutable personal characteristics 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 traits (race, gender, etc.), their mutable personal characteristics (experience, etc.), and 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 adapt, learning of individual participation via voter files and adjusting future mobilization drives accordingly.

- Cycle: **Repeat Steps 1-3.**

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This cycle is repeated, and individuals' traits evolve over their lifetimes. A simple graphical representation of this cycle, a simplification of the overall framework provided in Chapter 3, is shown in Figure 6:
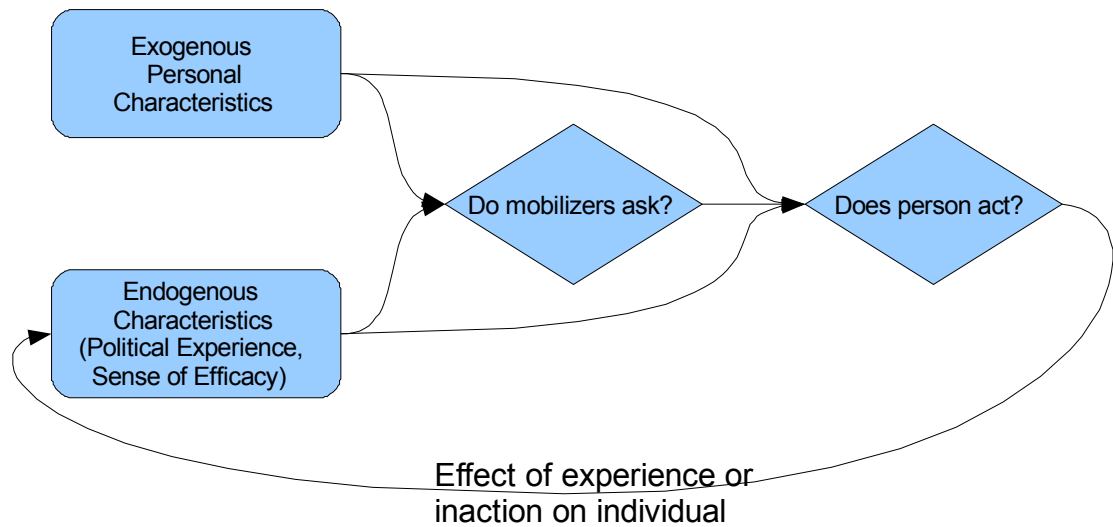
Figure 6: Cycle of Mobilization and Participation

Initial Mathematical Representation

This theoretical model can be more rigorously represented, and the assumptions made more explicit, by expressing it in mathematical form. I presented an initial formulation of the decision to vote in Chapter 3, using the following notation to summarize Rosenstone and Hansen's (1993) voting model:

$$Pr\_Vote_{i,t} = probit(B_o + B_1 C_i + B_2 X_{i,t} + B_3 Mobilized_{i,t})$$

Where: C_i represents the variables that are effectively constant over the period (e.g., education), $X_{i,t}$ represents exogenous personal characteristics that may vary over time – but in a manner unrelated to mobilization or prior voting behavior (e.g., age, income).

Building on this formulation for voting, we can develop a more fully articulated set of equations for each of the three stages of the cycle of mobilization and participation. First, some additional notation is helpful. I will refer to the vector of relevant mutable historical characteristics (prior participation) for individual i at time t as $H_{i,t}$. We will discuss mobilization in detail as a feedback mechanism, which is represented as $M_{i,t}$. Finally, exogenous personal traits, $X_{i,t}$ (discussed above), and environmental traits, such as the overall level of participation and interest in the campaign, L_t will also be included. In summary, we have:

C_i: the vector of constant personal traits for individual i

$X_{i,t}$: exogenous personal characteristics for individual i at time t

L_t: the political climate or level of participation at time t

$H_{i,t}$: mutable historical characteristics, such as prior participation for i at time t

$M_{i,t}$: mobilization of individual i at time t

Using this notation, we can define the functions that make up the cycle as follows:

- A mobilization function, $M_{i,t} = m(C_i, X_{i,t}, H_{i,t}, L_t)$, which determines whether individual i is asked to participate at time t.

  o m is a binary function; either an individual is asked to participate or is not.

  o m is stochastic; personal characteristics are not destiny.

- $\partial m_{i,t} / \partial C_i > 0$, $\partial m_{i,t} / \partial X_{i,t} > 0$, $\partial m_{i,t} / \partial H_{i,t-1} > 0$. Each static and mutable characteristic within the vectors C_i, $X_{i,t}$ and $H_{i,t}$ is measurable and can be expressed on a numeric scale, where increasing values indicate increased likelihood to be mobilized. That is, some individuals are more likely to be asked than others, according to their meaningful personal characteristics.

- A participation function, $P_{i,t} = p(C_i, X_{i,t}, H_{i,t}, M_{i,t}, L_t)$, which determines whether the individual i participates at time t.

  - p is also a binary, stochastic function, which is monotonically increasing in C_i, $X_{i,t}$, $H_{i,t}$ and L_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, $H_{i,t+1} = u(C_i, X_{i,t}, H_{i,t}, M_{i,t}, P_{i,t}, L_t)$ which determines how an individual's endogenous characteristics change given participation (or the lack thereof) and the passage of time. Individuals are shaped by their experiences, updating their personal habits (Gerber et al. 2003), or feelings of efficacy (Finkel 1985), etc.

  - u is monotonically increasing in $P_{i,t}$ with interest and skills decaying over time. Both prior participation, $P_{i,t}$ and the vector of historical characteristics, $H_{i,t}$ (potentially influenced by prior cycles of participation, $P_{i,1..t}$) shape the update function.

The models employed by existing research on mobilization each can be readily

expressed in this notation. For example, Goldstein and Ridout (2002)'s model can be

written as:[42]

$M_{i,t}$ = logit(B_o +
   C_i [B_1 Gender$_i$ + B_2 Education$_i$ + B_3 Black$_i$ + B_4 South$_i$] +
   $X_{i,t}$ [B_5 Age$_{i,t}$ + B_6 Age$_{i,t}^2$+ B_7 Income$_{i,t}$ + B_8 Union$_{i,t}$ + B_9 Partisanship$_{i,t}$] +
   $H_{i,t}$ [B_{10} $P_{i,t-1}$] +
   L_t [B_{11} HouseCompetitiveness$_t$ + B_{12} SenateCompetitiveness$_t$
      + B_{13} PresidentialCompetitiveness$_t$ + B_{14} GubernatorialElection$_t$]

$P_{i,t}$ = logit(B_o +
   C_i [B_1 Gender$_i$ + B_2 Education$_i$ + B_3 Black$_i$ + B_4 South$_i$] +
   $X_{i,t}$ [B_5 Age$_{i,t}$ + B_6 Age$_{i,t}^2$ + B_7 Income$_{i,t}$ + B_8 Partisanship$_{i,t}$ + B_9 Married$_{i,t}$
      + B_{10} InterestInPolitics$_{i,t}$ + B_{11} Efficacy$_{i,t}$] +
   $H_{i,t}$ [B_{12} $P_{i,t-1}$] +
   $M_{i,t}$ [B_{13} Mobilized$_{i,t}$]
   L_t [B_{14} HouseCompetitiveness$_t$ + B_{15} SenateCompetitiveness$_t$
      + B_{16} PresidentialCompetitiveness$_t$
      + B_{17} GubernatorialElection$_t$ + B_{18} ContestedPrimary$_t$ + B_{19} PerceptionOfCloseness$_t$]

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

Their model can be condensed into the simpler cycle of mobilization and

participation:

$M_{i,t}$ = logit(B_m + B_{cm} C_i + B_{xm} $X_{i,t}$ + B_{hm} $H_{i,t}$ + B_{lm} L_t)
$P_{i,t}$ = logit(B_p + B_{cp} C_i + B_{xm} $X_{i,t}$ + B_{hp} $H_{i,t}$ + B_M $M_{i,t}$ + B_{lp} L_t)
$H_{i,t}$ = $P_{i,t-1}$

Where (B_{cm}, B_{xm}, B_{hm}, B_{lm}), and (B_{cp}, B_{xp}, B_{hp}, B_{lp}) are vectors of coefficients for the

relative weight of variables for constant personal characteristics, mutable but exogenous

personal characteristics, mutable historical personal characteristics, and the overall level

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[42] One could classify various variables such as education as Constant or mutable but Exogenous, depending on the time frame of the analysis and the empirical change in the population over time. In addition, the concept of overall Level of participation, and its components such as Senate Competitiveness could be disaggregated into separate temporal and spatio-temporal elements. I leave those complexities for further analysis, and instead focus on the core cycle of participation over time that occurs regardless of these modeling choices.

of participation in the <u>m</u>obilization and <u>p</u>articipation process, respectively, and B_m and B_p are constants that establish the y-intercepts.

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 Ridout (2002) both use a lagged dependent variable to analyze participation. This technique is common in political science to handle estimation problems with time series cross-sectional data (Beck 2001; Beck and Katz 1995).[43] Since it is well documented that mobilization is correlated with prior participation, serious estimation bias can occur without this control.[44] Their model is:

$$
\begin{aligned}
M_{i,t} = \text{logit}(B_o + \\
\quad C_i \quad [B_1\,\text{Gender}_i + B_2\,\text{Education}_i + B_3\,\text{Black}_i + B_4\,\text{South}_i\,] + \\
\quad X_{i,t}\,[B_5\,\text{Age}_{i,t} + \; B_6\,\text{Income}_{i,t} + B_7\,\text{Union}_{i,t} + B_8\,\text{Partisanship}_{i,t} + B_9\,\text{EmploymentStatus}_{i,t} \\
\qquad + B_{10}\,\text{Log(YearsInCommunity)} + B_{11}\,\text{Homeowner} + B_{12}\,\text{ReligiousAttendance} \\
\qquad + B_{13}\,\text{IdeologicalExtremity} + B_{14}\,\text{GroupMember}] + \\
\quad H_{i,t}\,[B_{15}\,P_{i,t-1}\,] + \\
\quad L_t \quad [B_{16}\,\text{ElectoralVotes}_t + B_{17}\,\text{SenateElection}_t + B_{18}\,\text{PresidentialCompetitiveness}_t \\
\qquad + \; B_{19}\,\text{GubernatorialElection}_t\,]
\end{aligned}
$$

$$
\begin{aligned}
P_{i,t} = \text{logit}(B_o + \\
\quad C_i \quad [B_1\,\text{Gender}_i + B_2\,\text{Education}_i + B_3\,\text{Black}_i + B_4\,\text{South}_i] + \\
\quad X_{i,t}\,[B_5\,\text{Age}_{i,t} + \; B_6\,\text{Income}_{i,t} + B_7\,\text{Union}_{i,t} + B_8\,\text{Partisanship}_{i,t} + B_9\,\text{EmploymentStatus}_{i,t} \\
\qquad + B_{10}\,\text{Log(YearsInCommunity)} + B_{11}\,\text{Homeowner} + B_{12}\,\text{ReligiousAttendance} \\
\qquad + B_{13}\,\text{IdeologicalExtremity} + B_{14}\,\text{GroupMember} + B_{15}\,\text{PoliticalEngagement} \\
\qquad + B_{16}\,\text{CandidateAffect}] + \\
\quad H_{i,t}\,[B_{17}\,P_{i,t-1}\,] + \\
\quad M_{i,t}\,[B_{18}\,\text{Mobilized}_{i,t}\,] + \\
\quad L_t \quad [B_{18}\,\text{ElectoralVotes}_t + B_{19}\,\text{SenateElection}_t + B_{20}\,\text{PresidentialCompetitiveness}_t \\
\qquad + \; B_{21}\,\text{GubernatorialElection}_t\,]
\end{aligned}
$$

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

---

[43] 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 the scope of this work but deserves further attention.

[44] 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. However, there are problems with this solution – as discussed in the next section.

Which, after dropping insignificant terms (following their own presentation of the model), becomes:

$$M_{i,t} = \text{logit}(B_o +$$
$$C_i \; [B_1 \; B_2 \, \text{Education}_i] +$$
$$X_{i,t} \, [B_3 \, \text{Age}_{i,t} + \; B_4 \, \text{Partisanship}_{i,}] \; +$$
$$H_{i,t} \, [B_5 \, P_{i,t-1}]$$
$$P_{i,t} = \text{logit}(B_o +$$
$$C_i \; [B_1 \, \text{Education}_i \; +$$
$$X_{i,t} \, [B_2 \, \text{Age}_{i,t} + B_3 \, \text{Union}_{i,t} + B_4 \, \text{ReligiousAttendance}$$
$$+ \, B_5 \, \text{PoliticalEngagement} + B_6 \text{CandidateAffect}] +$$
$$H_{i,t} \, [B_7 \, P_{i,t-1}] +$$
$$M_{i,t} \, [B_8 \, \text{Mobilized}_{i,t}]$$

Rosenstone and Hansen's model, first analyzed in Chapter 3, can be specified as:

$$M_{i,t} = \quad \text{probit}(B_o + (B_o + B_1 \, \text{Income} + \; B_2 \, \text{Education} \ldots + (B_3 * H_{i,t}))$$
$$P_{i,t} = \quad \text{probit}(B_o + B_1 \, \text{Income} + \; B_2 \, \text{Education} + B_3 \, \text{Unemployment} + B_4 \, \text{Age} + B_5 \, \text{Efficacy}$$
$$+ \, B_6 \, \text{Partisanship} + B_7 \, \text{Candidate\_Support} + B_8 \, \text{Years\_In\_Community}$$
$$+ \, B_9 \, \text{Church\_Attendance} + B_{10} \, \text{Homeowner} + B_{11} \, \text{Employed}$$
$$+ \, B_{12} \, \text{Closeness\_Of\_Election} + B_{13} \, \text{Registration\_Restrictions} + B_{14} \, \text{Gender} + B_{15} \, \text{South}$$
$$+ \, B_{16} \, \text{Race} + B_{17} \, \text{Mobilized})$$
$$H_{i,t} = \quad P_{i,t-1}$$

Mobilization Over Time

Each of these models has a notable deficiency, however. From a System Dynamics perspective, they incorporate a feedback loop that has not been carefully analyzed. In particular, they employ a single-step model in which mobilization is both correlated with lagged participation (it is a key determinant in mobilization) and also plays a similar, but independent, role as lagged participation does – creating a first-order serial autocorrelation (mobilization is strongly correlated with lagged mobilization since the same personal characteristics, observed and unobserved, affect both). In Chapter 1, I introduced this problem with a simplified version of the mobilization model; here, I discuss the implications in more detail with the full model.

The first-order serial autocorrelation relationship, implicit in these mobilization

models, raises two concerns. First, the models are generally presented without this acknowledgement, which hides the multistage dynamics that all first-order serial autocorrelation models have. Second, depending on its parameters, a first-order serial autocorrelation model would imply that the impact of prior mobilization exponentially grows over time (unlikely), or has a long-term, but time-decaying, effect. The relationship becomes even more complex when we consider the impact of prior mobilization on prior participation, and of prior participation on other feedback cycles, such as habit and personal efficacy, identified in Chapter 3. In short, the net impact of a single instance of mobilization is greater than the simple regression estimation employed by these authors would imply – the regression coefficient provides the effect for the first year, but not for subsequent time periods. Alternatively, from the perspective of a single election – current and prior years of mobilization both influence voter turnout *at the same time,* directly and via proxies such as prior participation. One such relationship is displayed in Figure 7:
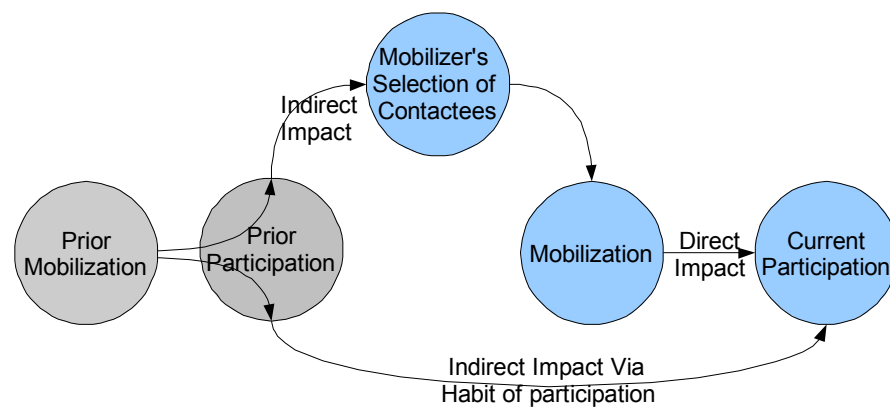
Figure 7: Impact of prior mobilization on political participation

Given these relationships, interpreting the regression coefficient on mobilization in these models is a challenging task.[45]   Rather than try to untangle the various influences (known and unknown) that could be at work, I will present an alternative means of estimating these influences below, using simulation modeling. Other challenges with these models still need to be discussed first, however.

Given that prior mobilization, prior participation, current mobilization, and current participation are all correlated with each other and with an enduring set of known and unknown variables, one would expect significant multicollinearity to arise in the estimation process. Statistically significant relationships, when found, would be a powerful and conservative test of the real strength of the relationship (the real relationship would be crisper, since it must overcome multicollinearity to be considered statistically significant).

Finally, consider what these models imply about the logic of political campaigns in the aggregate. Prior participation is modeled as a determinant of current mobilization. Thus, if citizens were especially excited about a particular presidential election, and turned out more than normal, these models predict that in the next (midterm) election mobilizers would magically spend more money. They would also be more successful at mobilizing individuals than normal, simply because prior year turnout was high.

The logical problem becomes even more apparent if we consider what would happen if the very specific functional form used in these models was incorrect – and the true relationship between current mobilization and prior mobilization is something different than a one-period lag (via prior participation). Drawing on the discussion in

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[45] Interpreting the coefficient is challenging when we move beyond the simple linear model in Chapter 1.

Chapter 3 on feedback processes, a variety of dynamics could occur, depending on

whether mobilizers employed a moving average of individual's prior participation history

over time to guide their outreach, or additional information about voters' participation

over time simply increased their value to mobilizers, leading to an unconstrained

feedback loop. In these alternative functional forms, if mobilizers have any impact on

participation, then as participation increases, so does the strength of mobilization over

time, and so does participation, etc. Up to 100% of the population could eventually be

mobilized by their political parties.[46] Substantively, this is also incorrect. The solution to

this logical problem is to consider more carefully the mobilization strategies of political

parties; doing so also solves the problem of positive feedback over time.

A balanced budget amendment

Existing models of political party mobilization do not explicitly incorporate a

budget constraint – i.e. an upper limit on how many people political parties are willing to

pay to contact. Moreover, they provide no rationale for *why* an organizer would select

one person over another given this constraint. The resulting models can provide useful

insights; but are not, conceivably, applied in practice.

Instead, political parties have budget constraints, and so political organizers must

employ a decision rule, implicit or explicit, that guides their choice of whom to mobilize,

given their limited resources and their goal to secure political gains. In the practitioner

literature (e.g., Guzzetta 2006), a range of pragmatic rules are suggested. Practitioner

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[46] For some functional forms, mobilization would steadily increase over time to a fixed limit, as discussed
in Chapter 3. With or without a limit on the final level of mobilization, the problem is the same –
mobilization doesn't increase on its own, simply because of prior participation.

views on targeting for maximal effectiveness range widely from "swing voters" or "core voters" to focusing on particular (politically loyal) ethnic groups. Treatment responsiveness, i.e., the determinants of an individual's change in turnout propensity due to a campaign contact (treatment), is a key question for field campaigns, but has insufficient systematic study in the field.

In the initial version of the model, I will assume that political parties employ a simple rule: 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, and thus some noise should be incorporated. The specification uses a scoring function to determine who is contacted for mobilization:[47]

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

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.
$u_{i,t}$ = stochastic error in calculating each individuals' lift

That is, mobilizers target those who are most likely to change their behavior in support of their candidate due to the request to participate, subject to error. If we recognize that mobilizers are usually only interested in members of their own party, and

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[47] 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.

that changes in party affiliation (and support in the ballot box) are relatively uncommon, then we can simplify this equation as follows:

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

Where each political campaign's pool of mobilizable individuals entails members of their party.

Step 2: Formalizing and Testing the Model

Econometric Model

The three-step theoretical model requires additional elaboration before it is tested empirically. Namely, the specific determinants of the participation function, P, and the history update function, H, are required.

In previous sections, I demonstrated how existing models of mobilization and participation can be expressed in this three-step structure. In particular, Abramson and Claggett (2001) use a standard set of personal and demographic variables in their model of mobilization, including age, partisanship, education, and income. They also control for one known dynamic process – changing levels of efficacy. Rather than diverge from the current literature, I will use Abramson's and Claggett's (2001) participation function directly in this model, so as to focus on (and provide a clearer comparison with) the true innovations of the model.

In terms of the participation function, numerous authors employ lagged

participation as a simple mechanism by which historical experience affects current participation. There are significant problems with interpreting this model, especially when mobilization is included, because of its correlation with lagged participation. In keeping with the current literature, I will also use a one-period lag for participation as my update function,[48] but I will leverage tools from simulation modeling to provide a much clearer interpretation of the resulting parameters. I also described above how problems can occur in the positive feedback cycle between mobilization and participation (in the first-order autocorrelation model as well as in other formulations); I break that positive feedback cycle by constraining the budget that mobilizers have to invest in their mobilization campaign.

The resulting three equations are substantially similar to the exiting literature, but will be analyzed and interpreted within a simulation framework. This allows us to focus on the novel features of the model – an explicit analysis of the dynamics of mobilization and participation over time, and a more realistic decision function for mobilizers under budget constraints. As will be shown below, the results are significantly different, despite their common core.

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[48] For the purposes of benchmarking the simulation model against known (if flawed) results. As described in Chapter 3, this process allows one to verify the *method* before leveraging the flexibility in modeling afforded by the simulation structure to correct the underlying *assumptions* to something more realistic.

The full specification is:[49]

$$M_{i,t} = \text{TopN}[(P_{i,t|m=1} - P_{i,t|m=0}) + u_i]$$
$$P_{i,t} = \text{logit}(B_o +$$
$$C_i\ [B_1\,\text{Education}_i +$$
$$X_{i,t}\,[B_2\,\text{Age}_{i,t} + B_3\,\text{Union}_{i,t} + B_4\,\text{ReligiousAttendance}$$
$$+ B_5\,\text{PoliticalEngagement} + B_7\text{CandidateAffect}] +$$
$$H_{i,t}\,[B_8\,P_{i,t-1}\,] +$$
$$M_{i,t}\,[B_9\,\text{Mobilized}_{i,t}\,]$$
$$H_{i,t} = P_{i,t-1}$$

Simulation Implementation

These three equations, and in particular the mobilization function, are difficult to

estimate using standard regression techniques because of the budget constraint placed on

mobilization. As discussed in Chapter 3, an alternative means to estimate them can be

found in the literature on optimization (Oliva 2003) – in which a simulation model is

developed that implements the functions, and their parameters are estimated in a manner

analogous to maximum likelihood estimation (MLE). To recap, the procedure uses

optimization techniques to search the space of possible parameter values, determining the

parameters that minimize prediction error relative to a given dataset. In return for

gaining the ability to estimate otherwise inestimable models, one sacrifices deterministic

outcomes and the guarantee of finding the globally (versus locally) optimal parameters.

In this case, because I can compare the results of the procedure against an existing model

estimated with traditional techniques, I can gauge the risks in this tradeoff.

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[49] Employing the second, simplified version of Abramson and Claggett's participation function – with insignificant terms removed. Their initial version applied the "kitchen sink" approach adding in numerous unrelated variables.

I implemented the simulation using the R programming language (R Development Core Team 2012). The simulation code is included in the Appendix, and has three main components:

1. The voter participation function.

2. The mobilization function described above, selecting individuals who would show the greatest "lift" from mobilization, subject to random error.

3. The scoring function that compares the predicted values against historical values in the supplied dataset.

Following Abramson and Claggett (2001), I employed the 1990-1992 ANES panel to estimate the model – the most recent ANES panel dataset in which the necessary information on both participation and recruitment by political parties is available. In order best to leverage their work as a baseline for the simulation model, the encoding of variables follows directly from Abramson and Claggett (2001), and is described in the Appendix. The mobilization budget (i.e., N in the equation above), was set at the observed number of individuals in the ANES 1992 data that were mobilized in practice (25% of the population).

The structure of the simulation itself is straightforward. At the center of the simulation is the participation function, using exactly the same assumptions and functional form as in standard regression techniques. The mobilization code consists of calling the participation function with and without mobilization of each individual (to calculate the "lift" from mobilization), and selecting the top N individuals based on lift and random noise. No new assumptions are added. The update function also follows the

function above; a trivial copying of one value to another.

These three functions are then surrounded by control logic that accepts a set of
parameter values ($B_o...B_9$), and the dataset of individual demographics and characteristics
from the ANES 1990-1992 panel as input, and outputs the predicted voting behavior of
each individual. Finally, the optimization routine applies sets of parameter values to this
control logic, comparing the output to the observed voting behavior from the ANES
1990-2 panel, and adjusting the parameters until the optimal fit is found between the
predicted and observed voting behavior.

Test 1: Estimating Model Parameters and Testing Statistical Significance

In order to estimate the parameters and generate confidence intervals around each
estimate, I employed the "Flexible Modeling Environment" (FME) package in R
(Soetaert and Petzoldt 2010; see discussion in Chapter 3) to control the optimization
process, and the Levenberg-Marquardt algorithm for the optimization itself. The
Levenberg-Marquardt algorithm is a commonly used algorithm for non-linear least-
squares optimization, in which an initial parameter set is used to determine the localized
change in model error from marginal changes in each parameter (i.e., the gradient of
model error, in parameter space). Levenberg-Marquardt uses a combination of a strict
gradient descent and the Gauss-Newton algorithm (roughly, projecting the lowest error
point in parameter space and jumping to it), to iteratively traverse the parameter space
and find the error-minimizing parameter coefficients. The FME package then conducts
additional simulations around the error-minimizing coefficients to determine the degree
of precision (standard errors) for these estimates.

To test the sensitivity of the optimization to its starting parameters, and to assess the risk of converging to a local, rather than global, maximum, I conducted the optimization first using the Abramson and Claggett (2001) (logit regression) parameters, which one would expect to be close to the error-minimizing true parameters. I then conducted the optimization using sets of arbitrary starting points. The estimated parameters were not significantly different in each case, pointing towards the stability of the procedure. The results are provided in Table 4, below.

Table 4: Estimation of budget constrained voter mobilization function

Variable	Ave. Predicted Probability Change	Estimate	Std. Error	t value	Pr(>|t|)
Intercept		-2.75	0.35	-7.93	0.00
Age	0.16	0.02	0.00	5.04	0.00
Education	0.37	3.63	0.40	9.13	< 2e-16
Union member	0.10	1.00	0.18	5.42	0.00
Religious attendance	0.05	0.65	0.22	2.95	0.00
Political engagement	0.32	1.42	0.18	7.75	0.00
Presidential candidate affect	-0.07	-0.01	0.00	-2.18	0.03
Mobilized	0.05	0.47	0.16	3.04	0.00
Turnout in 1990	0.36	3.58	0.47	7.66	0.00

I calculate the impact of each of these parameters by analyzing the average marginal change in the probability of voting across the individuals in the original dataset, as advocated by researchers such as Hanmer and Kalkan (2009). This entails calculating predicted probabilities for each individual in the data, with the maximum and the minimum value for each variables, rather than using a single stylized individual with "average" values across all other variables, as has been common practice in the field.

The results provide evidence in support of the budget-constrained mobilization model, with dynamic interactions between the mobilizer and the mobilized: one finds that the impact of recruitment by political parties on voting is statistically significant at the 1% level, and we cannot exclude the null hypothesis of no effect. The average change in the predicted probability of voting, across the individuals in the ANES dataset, due to voter mobilization is 5%.

This result on its own would indicate that the simulation optimization technique can gain traction on (i.e., effectively optimize) the budget-constrained model of participation. However, given the tradeoffs in using a simulation approach versus as standard MLE or regression, how similar are the results to prior estimations?

Test 2: Comparing Results Against the Benchmark, Non-Simulation Model

To verify the validity of the initial data processing and simulation estimation, I replicated Abramson and Claggett's work with a standard logit analysis of the unconstrained single-lag voter participation model. Following Abramson and Claggett directly, I estimated the participation function in isolation, using the observed mobilization data in the 1992 ANES dataset instead of the mobilization equation.[50]

The results were generated using the Zelig package (Imai, King, and Lau 2010) in the R statistical language, and are provided in Table 5, on the next page.[51]

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[50] Abramson and Claggett estimate mobilization and participation separately, with no empirical connection between the two, as do all other known researchers in the field. Either way, however, a standard logit analysis could not estimate the budget constrained mobilization function.

[51] In addition, I performed a simulation optimization of the original (unconstrained) Abramson and Claggett model – as a narrow test of the MLE simulation estimation versus the logit estimation. Very minor parameter differences occurred across the variables.

Table 5: Logit estimation of benchamark voter mobilization model

	Ave. Predicted Probability Change	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)		-2.08	0.34	-6.19	0.00
Age	0.15	0.02	0.01	3.64	0.00
Education	0.30	2.63	0.42	6.28	0.00
Union member	0.08	0.73	0.26	2.81	0.00
Religious attendance	0.07	0.76	0.28	2.72	0.01
Political engagement	0.29	1.16	0.20	5.73	0.00
Presidential candidate affect	-0.16	-0.01	0.00	-2.70	0.01
Mobilized	0.06	0.55	0.24	2.25	0.02
Turnout in 1990	0.34	2.94	0.28	10.64	< 2e-16

The parameter coefficients are not strikingly different between the Abramson and

Claggett model and the revised simulation model. Most notably, the coefficient on

recruitment is 15% smaller in the simulation estimation than in the original (non-budget

constrained) model. This translates into an average difference in predicted probability of

20% from the baseline; these differences are well within the standard error of the two

estimation processes. All other substantive variables are similar in coefficient and

predicted probability.

These similar results should not be surprising – the only differences between the

two models are the estimation technique and the use of a budget constrained mobilization

function. The estimation technique should produce the same results – and indeed,

appears to – since the optimal parameters are still optimal whether a logit regression or a

MLE-type optimization was used to find them. The budget constraint itself should have

no effect in a single-step election cycle – since the constraint was explicitly set to mimic

the observed number of people mobilized in the 1992 ANES dataset. Finally, the

individuals selected by the budget constrained mobilization function, according to their

'lift', should be very similar to the observed pattern of mobilization (if the assumption of

selection via lift is correct). Indeed they are, but not perfectly so, given random noise in

the process. Thus, the results of this test support the approach used for estimating and

modeling mobilization and participation but provide no stunning results otherwise. More

importantly, they provide a platform for a proper estimation of mobilization's total (direct

and indirect) impact.

As discussed above, it is in *subsequent* election cycles that the assumptions

underlying a non-budget constrained mobilization process produce illogical results; I

explore multiple election cycles below. However, before conducting a novel analysis of

multiple cycles, I needed to ensure that the model used in that analysis is solid. This

comparison between the benchmark model and the simulation helps substantiate that

conclusion that when the benchmark model was converted into a budget constrained

simulation model, its core characteristics were not changed, and we can safely expand

into more novel terrain.

Test 3: Estimating the Total Effect of Mobilization, including Indirect Impacts

In addition to the direct impact that mobilization can have on participation in the

first year, mobilization can have subsequent, indirect impacts on participation. The first

part is captured by the estimation process; the latter is not. As I discussed above,

mobilization can influence participation via a variety of routes, including building the

habit of participation (Green and Shachar 2000) and increasing one's sense of efficacy

(Finkel 1985) – and thus having a lasting, indirect impact on participation in future years. For example, consider an individual who would not otherwise 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 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).

The direct impact is conceptually straightforward: it is provided by the coefficient on current-year mobilization and the marginal change in predicted probabilities it causes. Exactly how that marginal change should be calculated is not as obvious, however. As discussed above, I analyze the marginal change in predicted probabilities for each individual in the dataset, rather than using a single stylized individual with "average" values for each independent variable. In so doing, an underlying assumption about the data generating process was exposed. Specifically, calculating marginal changes in predicted probabilities across the entire population, whether with the fine-tuned approach advocated by Hanmer and Kalkan (2009) or with an "average" individual, is unrealistic in the case of a budget-constrained mobilization process: because only a subset of specific individuals will actually be mobilized. Political campaigns do not randomly select

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individuals and achieve an average marginal impact on voting; rather they target specific individuals who are likely to give the greatest "bang for the buck". The impact on those individuals is significantly greater. In fact, running the predicted probability analysis again for the overall population and for the subset mobilized, one finds:

- The average direct impact of mobilization across the entire population: 6%

- The average direct impact of mobilization across the subset of individuals who are likely to be mobilized: 9%.

Since indirect impacts of mobilization are only relevant for those individuals who are actually mobilized, I employ the larger calculation of direct impact, below, based on that subset of individuals. This is essential for providing a more accurate (and lower) estimate of the indirect impact.

While the indirect impact was easily calculated in the illustrative linear model presented in Chapter 1, the simulation model provides a more robust way to analyze indirect impacts on an otherwise intractable budget constrained version. To calculate the indirect impact of mobilization, I first executed the simulation model without mobilization, and determined the probability of participation for each individual, $P_{i|m=0}$ in the following election cycle. I executed the simulation again with mobilization, and found the total impact of mobilization for each individual mobilized, $P_{i|m=1} - P_{i|m=0}$. I subtracted the direct impact of mobilization from the total impact of mobilization (direct and indirect), to discover the indirect impact.
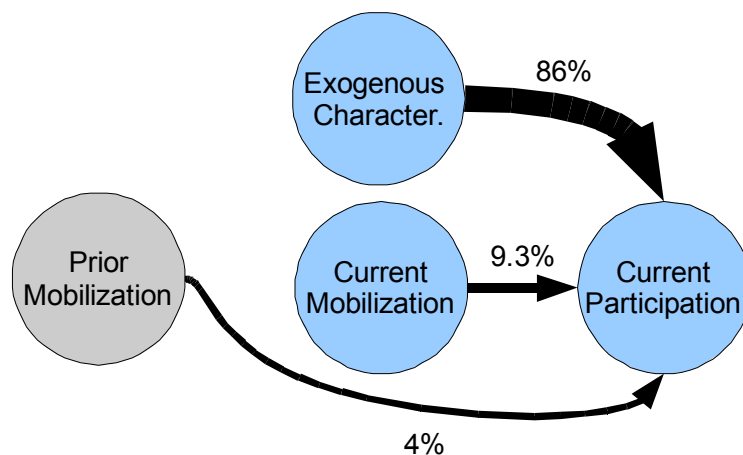
Figure 8: Direct and indirect impacts of prior mobilization on voting

A summary of the results is displayed in Figure 8.[52] For voting behavior, the

average direct impact of mobilization *on the individuals who were actually mobilized* was

9.3%,[53] and the average total impact of mobilization, direct and indirect, per individual

mobilized was 13.3%.[54] 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.[55]

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[52] I am grateful for the help of Ozan Kalkan in estimating a GEE version of this model (and verifying the results using that alternative econometric approach) for the 2009 Political Methodology conference.

53 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). The difference comes from the assumed prior state of the world. In a world where no mobilization has ever occurred (and thus future participation levels have not been affected), mobilization has a larger direct than indirect impact. Where mobilization has already occurred, the indirect effects are larger. That is, the estimate given in the text is a conservative figure for the actual indirect impact of mobilization.

54 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)/0.25.

55 This is again a conservative estimate. The model, as designed, examines one possible route for indirect impacts to occur – from mobilization to participation to subsequent participation. If changes in internal

If nothing else, these results indicate that the role of mobilization has been substantially underestimated in current, single-round, empirical analyses of mobilization and participation. If mobilization were simply a minor factor in overall turnout and political participation, then a 40% 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. The role of mobilization in the rise and decline of turnout over time deserves reconsideration.

Perhaps most interestingly however, the indirect impact has profound effect on other political behaviors and on long term voting behavior over time, as I discuss in the next section.

Step 3: Extending the Model into New Observable Facts

Moving beyond the basic analysis that was used to estimate model parameters and test for statistical significance, numerous options are available for extension and further testing.

Extension 1: Incorporating Other Political Behaviors

Abramson and Claggett's (2001) analysis, along with that of Rosenstone and Hansen (1993) and Verba et al. (1995), each demonstrate how the study of voter

efficacy or social networks were included in the model, then one would expect mobilization to have an increased indirect effect.

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mobilization can be extended into other political behaviors. Notably, the ANES 1990-2 panel, used by Abramson and Claggett (2001) and the analysis presented above, provides data on two other behaviors of interest: campaign contributions and volunteering for the campaigns. A quick replication of the estimation process on budget constrained campaign contribution and volunteering models verifies statistical significance for the central variables (mobilization and lagged participation), in keeping with prior (unconstrained) models. Replicating the analysis of the indirect effects of mobilization also shows interesting results.

Even larger indirect impacts occur for campaign contributions and campaign volunteering than for voting behavior. Figure 9 displays the results for political 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.
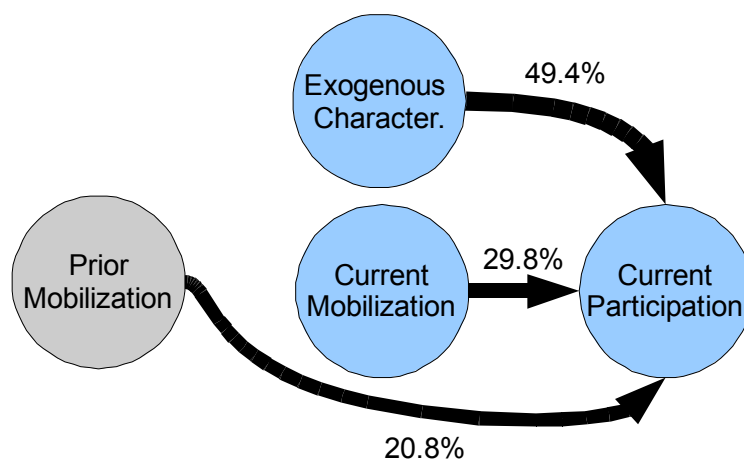
Figure 9: Direct and indirect impacts of mobilization on political volunteering

Extension 2: A Multi-Cycle Simulation Model

In addition to increasing aggregate levels of participation, mobilization may 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.

Building on the simulation developed in previous sections, I extend the simulation to cover multiple future elections. Specifically, I add one step at the end of the simulation's logic:

4. Using the ANES data, I 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.

In the previous version, an optimization algorithm fed sets of parameters to mobilization, participation, and update functions in order to find the optimal values. In this case, the optimization algorithm is replaced by a few lines of code that take the optimized parameters, and the initial ANES dataset, and apply the mobilization, participation, and update functions repeatedly, updating $m_{i,t}$ and $p_{i,t}$ each round. This method allows us to focus on the changes that mobilization cause in the voting behavior

of the population, but has a number of limitations. For example, real wages are assumed to be stagnant; education, partisanship, and the demographic profile of the population are similarly static. Further research should be considered on each of these factors, but is outside of the scope of this work.

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, 26 time slices starting with the original ANES data and continuing through 25 subsequent biannual elections.[56] 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 with 1097 individuals, 26 elections, and two dependent variables for each election (mobilization and participation). I first ran the simulation for voting behavior and voter mobilization then expanded to incorporate campaign contributions and political volunteering as well. The outcomes are most striking for these latter two political behaviors, with interesting differences from voting behavior.

Multiple cycles of mobilization for campaign contributors and political volunteers 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, its impact is considerable. Roughly 33% of individuals in the

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[56] Births and deaths (entry and exit) were not modeled in this analysis, and should be considered in future research.

population are mobilized more than 95% of the time.[57] 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 6, on the next page, 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.

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. That is, 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.

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[57] Nearly all of those individuals who are called upon to make a contribution in 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.

Table 6: Impact of Mobilization on Campaign Contributions

Frequency with which Individuals are Mobilized	Participation with Mobilization	Participation without Mobilization
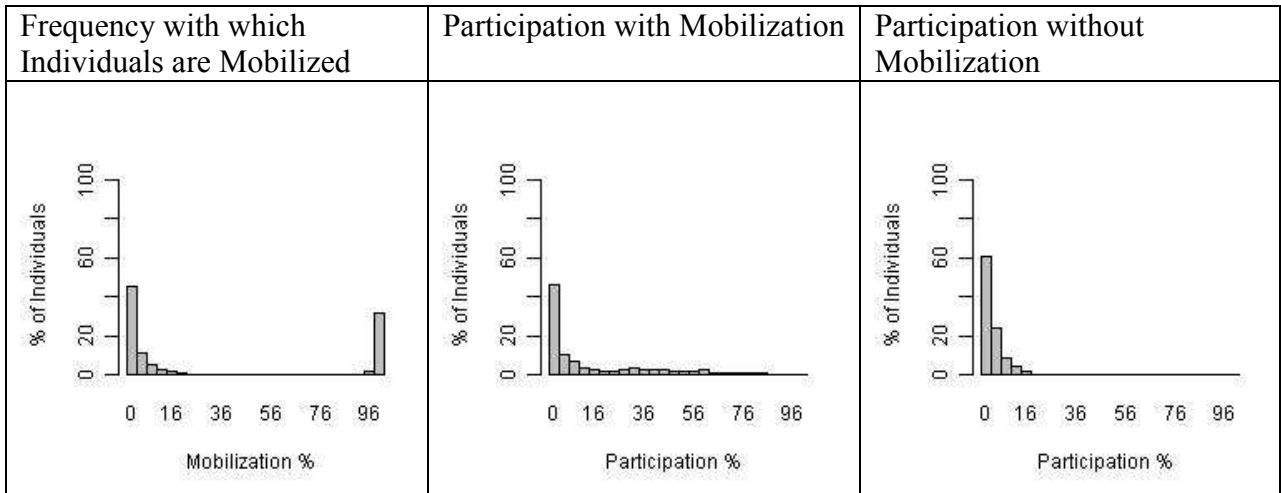
For voting, the impact of multiple rounds of mobilization is rather different. Because voting is a significantly more common activity than volunteering or making campaign contributions, the group of individuals targeted by Get Out The Vote efforts is intermixed with those who would have participated 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.

In order to test the robustness of these findings, one can examine 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 the specializing effect of mobilization clearly separates the smaller, high-participation group from the rest of the population. As the effectiveness of mobilization increases, the gap widens. The next two sections consider other variants on the assumptions and parameters used in the benchmark model.

Extension 3: 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 examined the case where the starkest results should be expected – mobilization for campaign contributions, in which well-targeted mobilization created the greatest divisions between participators and non-participators. In this version of the simulation, the organizers are unable to accurately assess 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 of mobilization scores, is shown in Figures 10 and 11, on the next page. Inefficient mobilization leads to a broader swath of individuals contacted, as one would expect. Even with such a large

amount of noise in the process, however, mobilization (and participation) favor a group of high-participation individuals.
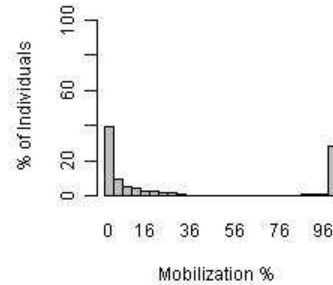
**Figure 10: Normal Mobilization
for Campaign Contributions**
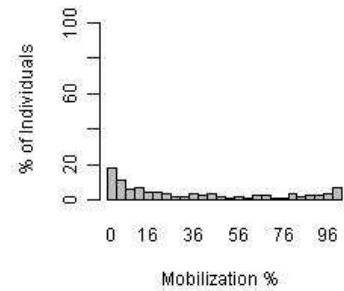
**Figure 11: Noisy Mobilization
for Campaign Contributions**

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.

Micro-targeting uses the detailed demographic and behavioral data to generate individual turnout (and support) propensity scores for each individual in a target population, across a set of potential contact methods and messages (Issenberg 2010). These scores are then used by political and advocacy campaigns to prioritize whom to

contact, how to contact them, and when. The seed data used to generate micro-targeting

models is often gathered from preliminary field experiments. After the campaign is

conducted, and assuming sufficient data gathering was conducted, results of the field

campaign are then fed back into the micro-targeting models for greater accuracy and

intelligent targeting of the next round of field experiments. According to anecdotal

reports, micro-targeting, and associated field experiments, were used for hundreds of

millions of contact efforts in the 2008 elections (Issenberg 2010).

The result is an increasingly accurate targeting process, aimed specifically at

individuals with the greatest potential lift from mobilization.[58] 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, often focusing on groups of individuals who seemed to be the

most likely supporters.

Extension 4: An Alternative Mobilization Function - Likely Supporters

Goldstein and Ridout (2002) provide another possible critique of the "efficiency"

assumption used in the benchmark model. They argue that historically organizers have

not efficiently targeted high "lift" individuals in their Get Out The Vote campaigns, and

actually targeted those individuals who were already the most likely to cast a vote for the

candidate. This inefficiency is due to fears that the mobilization effort will either

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[58] 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.

energize opponents or, alternatively, fail to turn out the campaign's strongest supporters. The resulting mobilization function is:

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

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 Ridout (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.[59]

Opportunities for Further 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

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[59] 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.

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 whom 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.

<u>Conclusion</u>

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 provided a simple three stage model, building on Chapters 1 and 3, that helps delineate dynamics of this mobilization process over time, and estimates its parameters.

I then examined the implications of this dynamic model of mobilization and participation. 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.

Chapter 5: Dynamics of Social Conformity and Participation

Introduction

Potential voters continually interact with each other: socially, at work, and through everyday casual encounters. A growing literature discusses how various forms of interpersonal interaction – political discussion, personal conflict, and norm setting – can shape the voting decision. In this chapter, I examine the role of social conformity on the decision to turn out to vote, using the theoretical framework presented in Chapter 3. I develop a full model of social conformity among voters, estimate its parameters versus empirical data, and project novel testable predictions of the model. In the process, I analyze the influence of conformity in the empirical and theoretical context of other, often confounding, social influences.

The core argument, like in Chapter 4, is that static models of voting are imperfect predictors of individual behavior over time, and a parsimonious dynamic model can better capture the underlying process. The result is greater empirical accuracy and conceptual clarity, resulting from a slightly more complex model that requires the novel estimation technique offered in Chapter 3.

<u>Theoretical Background</u>

Since the 1950s, the preponderance of research in political science has examined the isolated individual, and how personal characteristics shape political behavior (e.g., Campbell et al. 1960 or Downs 1957; see Zuckerman 2005 for an excellent history). Intuitively, however, the individual is embedded in a social context, and social relationships can play an important role in political behavior, from shaping political opinions to spurring political participation. As one scholar notes (Zuckerman 2005), core lessons concerning the influence of social interactions on individual action date back to classical Greek philosophy and are found throughout the Bible. Scholars in political science underwent periods of "rediscovery" in the 1930s and 1950s, providing renewed attention to the social interactions. One such rediscovery is underway now, with a slew of interdisciplinary research centers (e.g., CASOS 2012), publications (e.g., Diani and McAdam 2003), and conferences (e.g., University of Michigan 2011; INSNA 2012) examining the social logic of politics.

Three lines of quantitative research have recently blossomed on the manifold role of social networks in political behavior. In political science, research into social networks and voting behavior has recently grown quite rapidly (e.g., Fowler 2005; Nickerson 2008). A related branch of research, with roots in geography, studies autocorrelation across a network of spatial interaction, and is examining issues of spatial concentration in political behavior (Gimpel et al. 2004), such as political contributions by ethnic minorities (Cho 2003). A complementary, but largely disjoint, research tradition has arisen on the role of social networks in social movements, building on field studies in

comparative political science and sociology; for example, Diani and McAdam's edited volume (2003) examines relational approaches to understanding social movements, including the diffusion of protest cycles across various networks (Oliver and Myers 2003). The political science literature generally employs statistical, simulation, and formal modeling; the spatial autocorrelation literature primarily employs (statistical) spatial regression; the sociology literature is rich in detailed case studies and qualitative theory. This chapter follows the spirit of the burgeoning political science literature, but draws connections and lessons from all three traditions on the core question – how social conformity affects the likelihood of political participation.

Social Networks and Conformity in Political Science

In the political science literature on social networks, researchers have posited that a variety of types of social influences affect political behavior, ranging from political discussion, to casual observation, to organizational membership; the empirical results have been mixed, if not contradictory. One of the most common types of social influence considered is the role of political discussion in prompting individuals to participate. McClurg (2003) finds that informal, politically oriented, discussion has a major (positive, monotonically increasing) impact on participation. Alternatively, mere observation of peers' political expressions can drive participation: Huckfeldt and Sprague (1995) posit that informal observation, including of neighbor's lawns signs and bumper stickers, has a strong causal role in political participation, and find significant empirical support. Putnam (2000) focuses on the role of memberships in formal organizations, arguing that such interactions build a sense of generalized reciprocal trust, or social capital, which

motivates participation in the voting booth.

Within these models, often multiple mechanisms are considered for a single form of social interaction such as political discussion, ranging from the avoidance of conflict, to the diffusion of political information, to social conformity. The empirical and theoretical challenges of discriminating between and testing for these mechanisms can be seen in the debate over "cross-pressuring" ties, or diversity of political opinions within one's social interactions. Putnam (1995a; 1995b; 2000) posited, and found support for, a simple positive relationship between increased social ties and turnout, across various diverse social contexts, based on his model of social capital. Other scholars have critiqued this finding, stating that the impact of social interactions is conditioned on whether there is diversity (or conflict) across those interactions. Kotler-Berkowitz (2005) finds that diversity in social contacts increases turnout, employing a model of information and opportunities for participation. Other empirical scholars have found empirical support for exactly the opposite result, that diversity decreases turnout, based on a model of political conflict and dissonance. According to Alesina and Ferrara (2000), individuals prefer to interact with others who are similar, and, when confronting diversity, tend to withdraw and not form the formal organizations that are considered necessary for political interaction. According to Mutz (2002), cross-pressures lead to lower participation, because a conflicted social environment leads to political ambivalence and raises impossible-to-meet social accountability pressures.

Stepping back from the particular research studies conducted to date, we can identify a set of underlying mechanisms that can be examined across the various forms of social interaction. For example, Alesina's and Ferrara's (2000) desire to avoid

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confrontation could be applied to informal observation of lawn signs, as well as direct

political discussion. Kotler-Berkowitz (2005) focus on information gleaned from social

interaction. Putnam (2000) discusses, among other mechanisms, a generalized sense of

trust built though positive social interactions. Gerber and Rogers (2009) discuss

"descriptive norms", or the tendency to mimic the actions of others around you - due to

expectations of appropriate behavior or perhaps to a desire to avoid conflict. Schuessler's

work on Expressive Choice (2000), while not directly applied to issues of social

interaction, provides another potential explanation – that social interactions provide the

opportunity (and expectation) to express one's personal identity in political terms. Each

of these is based on a fundamentally different understanding of how individuals make

decisions in a social environment.

It may be that further theoretical elaboration will resolve such diverse findings

and provide the necessary micro-foundation that explains each in turn. The study of

social interactions in political science is still quite new however, and there has yet to be a

thorough and convincing analysis of when the various possible mechanisms are relevant,

and how they interact. Two formal modeling efforts provide some insight into the

underlying complexities, however. Siegel (2009) provides a set of formal network

models, in which the network context differentially responds to increased

interconnections.[60] Without an understanding of the particular network structure in

which a person is embedded, he found that it is difficult or impossible to forecast the

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[60] Similar to Cho and Rudolph (2008)'s observation, Siegel (2009) argues that the addition of a new social tie can increase or decrease participation depending on the existing 'base' rate for the individual.   Adding a tie to a non-participating individual dilutes the aggregate motivation to participate, and vice versa for a tie to a participating individual.

specific impact that social interactions will have on behavior. Fowler's (2005) model of turnout in a "small world" (Watts and Strogatz 1998) examines a narrower set of theoretical possibilities, using the network parameters estimated from Huckfeldt and Sprague's data (1995, 2000) and finds a similar dependence of the network's behavior to its specific network characteristics. Abstract models of localized influence, as in the Voter Model used in physics, find similar conclusions – delving in great detail into the role of network structure in the properties of system convergence (and unit level conformity) over time.

In this Chapter, I seek to address these challenges in my study of the role of social conformity in voting behavior, by controlling for the influence of other social processes identified above, and analyzing conformity in the specific context of two empirically observed social networks.

Participation and Spatial Autocorrelation

Spatial econometrics analyzes how spatial dependence, the interaction between "nearby" units, can cause artifacts in traditional estimation techniques and how these artifacts can be mitigated (e.g., Anselin 2003). While the technique has a significant history in geography and in econometrics, it is still somewhat new to political science, and warrants a brief overview before discussing its application to voting behavior. Spatial econometrics is used when the value of the dependent variable in a regression model for a given unit is correlated with that of other nearby units – and thus normal regression techniques will generally underestimate the variance in the data, calculating inappropriately high significance levels, and potentially biasing coefficient estimates

(Ward and Gleditsch 2008; Beck et al. 2006).[61] By explicitly modeling the spatial autocorrelation, one can produce more accurate inferences about the causal role of independent variables and one can gain an understanding of the structure of the spatial interaction itself.

Issues of spatial dependence and spatial interactions are increasingly being applied to political science phenomena (Ward and Gledistch 2008; Franzese and Hays 2007; Gimpel et al. 2004). For example, this approach has been used to study neighborhood effects in interstate violence (Gartzke and Gleditsch 2004), and the spatial distribution of lynchings in the US South (Tolnay et al. 1996); in both cases spatial auto-correlation was found to be present. Of particular relevance here is the study of autocorrelation across networks of interaction (Doreian 2001; Leenders 2002a, 2002b).[62] In these analyses, the pattern of interaction between units can be expressed as a (non-spatial) network – a computer network, social network, etc. For example, Gould (1991) applied a network autocorrelation model to mobilization in the Paris Commune, a "process in which a district's resistance level is a function of a set of exogenous variables *and of the resistance levels of all the other districts,* weighted by the strength of its links with them…This specification implies that each district simultaneously influences and is influenced by each other district in the network (p721)."

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[61] Other models of spatial dependence include autocorrelation in the error term and in the independent variables. See Anselin 2003 for a review.

[62] Spatial autocorrelation models and network autocorrelation models employ the same underlying mathematical techniques; they differ in how the "neighborhood" of interacting units is defined. In spatial autocorrelation, neighboring units are usually geographically contiguous. In network autocorrelation, units can interact across social connections, electronic connections (e.g. a computer network), or geographically contiguous locations. For a discussion of the mathematical linkages between spatial autocorrelation and network effects, see Doreian (2001). Physical proximity is often used as a proxy for social networks due to data limitations (see Huckfeldt and Sprague 1995), but any form of network can be examined from an autocorrelation perspective.

Voting behavior can present similar estimation problems that can be mitigated by spatial and network auto-correlation techniques. In a traditional statistical analysis of voting, voters are treated as independent of one another, though temporal autocorrelation for each person across election cycles is often considered. If, in reality, voters condition their behavior on the characteristics or behavior of other voters, the assumption of independence causes statistical artifacts. While a small number of political scientists have analyzed this problem with respect to spatial autocorrelation (see Gimpel et al. 2004 for an early example), the same problems arise with social interactions between voters – network autocorrelation. For example, if one potential voter gets into a political argument with another potential voter, then each of the verbal combatants may become more (or less) inclined to go vote. If the interpersonal spark that turned political interest into political action is not incorporated into the analysis, then personal variables (such as partisanship) will appear more significant than they should. In a dataset containing a sparse random sample of a large population, in which individuals are sampled without their political discussants, then this interaction would be an omitted variable influencing the included variable of partisanship. In a denser dataset where political discussants are likely to be included, then network (spatial) autocorrelation and misestimation occurs.

One challenge facing researchers who employ spatial or network autocorrelation techniques is to specify, beforehand, the correct unit of interaction – researchers must already have an understanding of whether interactions occur over neighboring streets, census blocks, cities, or counties, for example. Further, the substantive meaning of a positive spatial autocorrelation result can be challenging in the context of voting. Mathematically, spatial autocorrelation models provide an estimate of the global

equilibrium of the interaction (Anselin 2003), after an unspecified number of cycles of interaction. Similarly, the common form of interaction is assumed to be a diffusion process – values of interest from one unit spreading out to influence other units based on distance – which requires careful thought to apply to interactions between voters (see Cho and Rudolph, 2008 for one example).

While understudied and still imperfectly adapted to voting behavior, spatial and network autocorrelation models provide a valuable tool to check the assumptions of existing voting behavior models (e.g., Gimpel et al. 2004). They also help untangle existing debates in the field. Cho and Rudolph (2008) provide a possible rationale from a spatial perspective on the apparently contradictory results of cross pressures: the impact of cross-pressures could depend on the "base" level of participation in a local region. A low or high "base" could occur because of personal characteristics of the individuals, or localized dynamics within a tightly knit group, or both. Whatever the base participation level may be, it influences voters in the region and surrounding regions to regress toward that mean.

Limitations

Three problems arise in applying research on social influence to political science phenomena such as voting. First, as noted above, there are potentially multiple, overlapping processes. While authors have demonstrated the statistical significance of various processes, disentangling their interactions is a daunting task. Second, network structure has a major impact on the outcome of social interactions, and researchers need to have an understanding of that network structure before running econometric analyses

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of social interaction. The spatial autocorrelation literature provides a mathematical basis for expressing that network structure; Siegel (2009) vividly demonstrates how changes in the underlying network structure affect results of otherwise identical theoretical models. Too many authors employ a generic "networks approach" or "social approach" and attempt to generalize their findings from a particular network configuration into more general social ties.

A third problem arises in the application of social influence models without additional theoretical checks and balances; in the terminology of Chapter 3, a simple feedback loop can result, in which the predicted outcomes are wildly unrealistic. As with mobilization and other dynamic processes, one must look outside of the core interaction for concurrent constraints on the model that limit unrealistic outcomes. In the case of social interactions, "extraneous" factors (the social requirements of one's job, family, and entertainment), provide grist for political discussion and interaction and fundamentally shape the social interaction process and underlying network structure.[63]

In this paper, I seek to explore one particular mechanism of social influence on participation, recognizing the necessity of accounting for diverse, and potentially overlapping, concurrent mechanisms. The top level result has strong similarities to the spatial autocorrelation literature – in specifying a social transition process – but also provides a (theoretical) micro-foundation that allows for ready elaboration and testing without the methodological tools and assumptions of the spatial autocorrelation literature.

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[63] A related critique of social network research focuses on these "other" factors. The critique states that social processes are merely predicated on some prior, non-social and presumably more "solid" event or personal characteristic – such as ethnicity, gender, or early partisanship. While accurate, this argument is not compelling on its own – since causally prior events always exist. It is in the social interaction that we find a feedback loop creating changes in behavior over time.

I pursue an analysis of localized conformity which is related to the larger discussion in the literature about the importance of a norm of civic duty in voting behavior (Blais 2000, Knack 1992); I see this individual level analysis as providing a micro-foundation to this higher level analysis. Similarly, this work is strongly related to that of Green, Gerber and Larimer (2008) finding that social expectation affects individual level voting; unlike their experimental work, I posit a specific mechanism for the individual-to-individual interaction, and extend the model to consider unanticipated consequences for society.

In the process of developing and testing the model, I seek to address each of three limitations in the existing literature identified above. To address the challenge of multiple, overlapping processes, I employ a simulation model, first presented in Chapter 3, which analyses descriptive norms alongside alternative social processes, in an intuitive manner that allows for their individual impact to be considered. To address the importance of known network structure, I employ datasets that provide the actual structure of social interaction for two groups of voters. In the next two sections, I also address the issue of social feedback loops, and develop models that build in additional constraints for a more realistic portrayal of voter behavior.

Step 1: Develop the Theoretical Model

The primary goal of this chapter is to develop an understanding of how social conformity affects voting behavior. However, given the diverse and overlapping social processes described in the literature, I will first develop a clearer understanding of how social and political processes interrelate with each other. This broader conceptual model

of social processes can also provide a foundation for analyzing dynamic cycles at work in multiple social interactions, in the spirit of Chapter 3's theoretical framework.

Cycles of Social Interaction and Participation

Similar to the cycle of mobilization, we can highlight the dynamic, adaptive, nature of social interaction and voting in a stylized cycle – a three-stage "cycle of social influence" – of which a cycle of social conformity is one process:

- Step 1: **Individuals interact with their social environment,** in a particular *context* of interest, such as workplace political discussion or informal observation of lawn signs.

- 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.), and their social experiences as filtered through a particular psychological *mechanism (*rational evaluation based on available information, conformity to descriptive norms, avoidance of conflict, etc.).

- Step 3: **The act of participation changes the individual and her social environment**, via changes in the social network (new friends or enemies) and personal characteristics (partisanship, political information and interest). These updated characteristics and environment shape social interactions in the next cycle, which in turn leads to increased (or decreased) participation.

- Cycle: **Repeat Steps 1-3.**

Figure 12, below, provides one way to visualize this generic cycle.
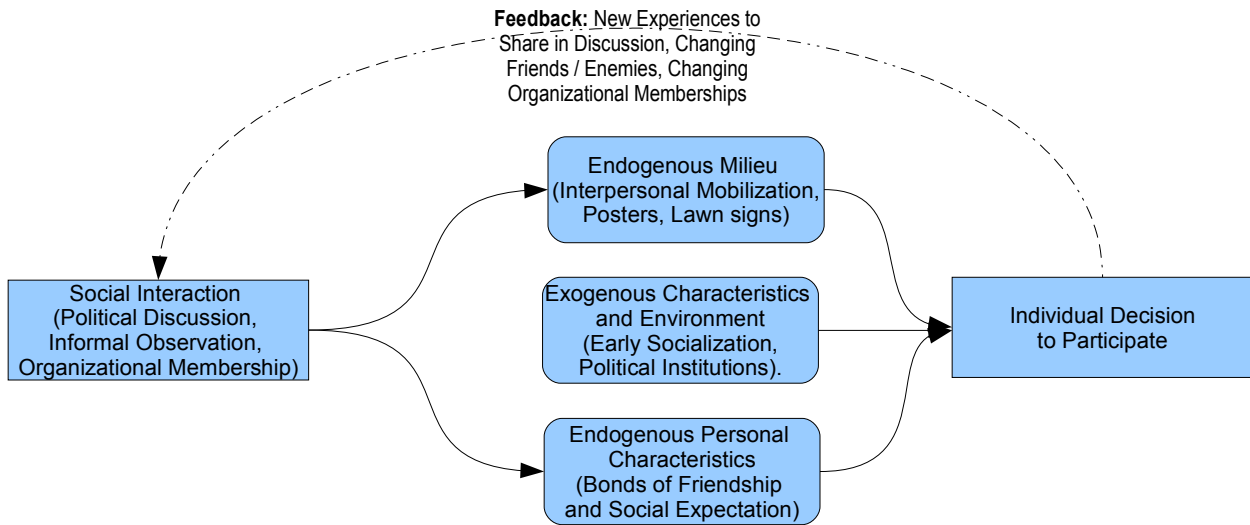
Figure 12: A general dynamic process of social interaction

This framework helps contextualize current models of social-political interaction, from descriptive norms (Gerber and Rogers 2009) to social capital (Putnam 2000). For example, McClurg's (2003) work demonstrates how political conversation (Step 1) increases the likelihood of an individual's participation (Step 2), controlling for the social milieu and exogenous personal characteristics, which then would influence future political conversations (Step 3).

Theoretical Model

Here, I will focus on one such cycle of social interaction, which is driven by social conformity. The underlying theoretical mechanism is straightforward, in which individuals have a tendency to model their behavior on the behavior of their peers. This process is also known as descriptive norms in the literature, as individuals try to follow

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their understanding of socially appropriate behavior, which they determine by (a description of) what others are actually doing. Descriptive norms have been the subject of significant research in social psychology (Cialdini, Kallgren and Reno 1991; Reno, Cialdini, and Kallgren 1993), and recently have been shown to have substantively significant effects on voter turnout in experimental research by Gerber and Rogers (2009).

Descriptive norms of political participation would be based on an individual's perception of whether others intend to participate. I assume that this perception is formed through observation, especially through direct political discussion with other individuals. While an individual may, at some level, be aware of the national turnout rate, feelings of social accountability and expected behavior weigh most heavily on an individual when they are tied to the person's direct peer group; i.e., in the common usage, they are tied to a person's social network. I will refer to this perceived vote intention of peers as the "local participation rate", to distinguish it from the overall participation rate; all local participation rates are relative to a particular individual observing them.

With this definition of descriptive norms, based on the local (perceived) rate of voter participation, we can delineate a dynamic interaction that occurs between the individual and his or her social network:

- Step 1: **Individuals observe the local participation intention of their social network,** through direct political discussion with their peers.
- Step 2: **Individuals decide whether or not they intend to vote**, based on their own political agenda, the overall political climate, their exogenous characteristics, their endogenous traits, and whether or not they expect their peers to participate.

- Step 3: **The decision to participate changes the individuals *and their peers*,** leading to an increased (or decreased) likelihood of presenting others with the intention to participate during the next cycle. All individuals in the system are thus updated, creating new local participation rates for the next round.

- Cycle: **Repeat Steps 1-3.**

An updated version of Figure 12, specific to this cycle is given in Figure 13.
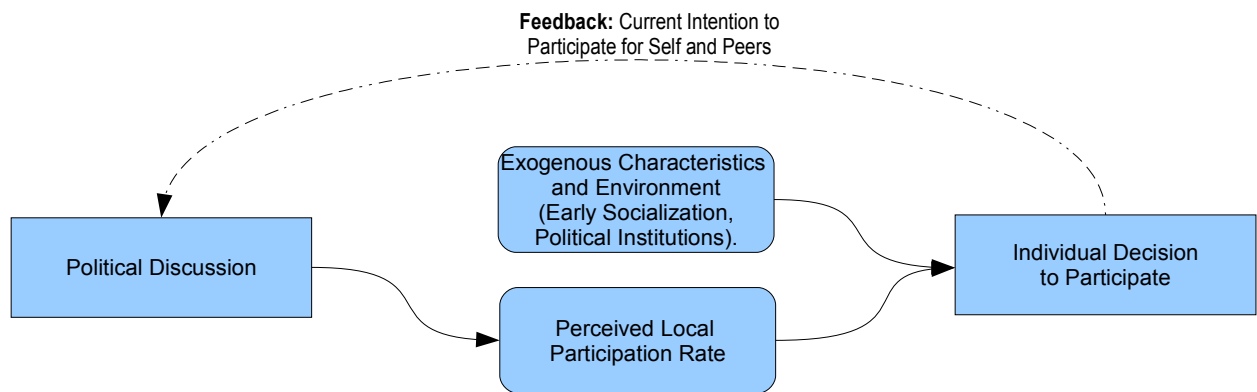
Figure 13: Specific dynamic process, of descriptive norms and intent to participate

This specific cycle expresses the key mechanism of interest – the two-way process of conforming to one's peers. In the next section, I translate this cycle into a mathematical form that can be estimated and tested. However, it is important to remember that this process is just one of many possible social cycles that could be occurring at a given time (per Figure 12); I will return to examine descriptive norms within the soup of potentially confounding social processes shortly.

Initial Mathematical Representation

To formalize this cycle and make the assumptions more explicit, I start with a basic representation of descriptive norms and voting behavior.

Assume that each individual i, i:1..N, has a turnout intention, T, which can range from 0, no intention to vote, to 1, perfect certainty. That intention to vote is determined by two factors: the individual's desire to conform to the perceived local participation rate of her peers, LPR, and the person's inherent but exogenous desire to vote (or not), X. Assume that the individual has disutility in deviating from her exogenous turnout intention X, and, simultaneously, disutility in deviating from the turnout intention of her peers, the LocalParticipationRate, and that the level of discomfort increases with the square of the distance from these two ideal points (i.e., the discomfort increases and accelerates with greater social and personal deviations from these ideals). This utility function can be represented as:

$$U(T) = 1 - \gamma_1 (T - X)^2 - \gamma_2 (T - LPR)^2$$

And the utility maximizing level of turnout intention can be determined as:

$$\partial U / \partial T = 0 = 2\gamma_1 (T - X) - 2\gamma_2 (T - LPR)$$

$$T(2\gamma_1 + 2\gamma_2) = 2\gamma_1 X + 2\gamma_2 LPR$$

$$T = 2(\gamma_1 X + \gamma_2 LPR) / (2\gamma_1 + 2\gamma_2)$$

Cleaning up the notation, this model can be represented as:[64,65]

$$T = \alpha_1 X + \alpha_2 LPR$$

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[64] In an environment where all individuals interact with each other, and can strategically change their preference to maximize utility, this simple scenario can be represented as an assurance game, with well-known outcomes. Here, interaction is limited to members of the individual's social network.

With the Turnout Intention (T) as the individual's optimal (intended) probability of turning out to vote, Local Participation Rate (LPR) is a function of the turnout intention of one's peers, and X as the exogenous turnout intention of the individual if there were no social influences. Assuming that the individual weighs all social ties equally, LPR can be calculated as the average perceived turnout intention of the peers.

Turnout intentions, and local participation rates, would change over time as the individuals interact with one another. In each interaction, the individual would learn the current turnout intentions of their peers (which they had formed in the prior period), and adjust his turnout intentions accordingly.[66] Their peers would do the same, creating a new set of intentions and local participation rates at the end of each interaction.

Highlighting the Feedback Process

The relationship between the individual's turnout intention and that of her peers drives the dynamic interaction illustrated in Figure 13. One's voting intentions affect one's peer's intentions, which reflect back to the individual affecting future voting intentions. Putting aside the individual's exogenous interests in voting (X), this core cycle can be represented as:

$T \sim LPR$

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[65] Note, one can use the same approach to model political attitudes more generally, in which each individual has a vector of political attitudes (e.g., turnout intention, party allegiance, etc.) that adjust according to the individual's desire to conform to the local attitudes of his peers.

[66] In this stylized model, I assume that people can change their own attitudes to fit the norm, but cannot significantly change the people with whom they interact. I assume that most interactions are exogenous, at least in the short term – they are required by work, by where one lives, and by the family the person is born into. Further research could relax this assumption.

This simple model has been well explored in the literature, and from a practical perspective it often predicts unrealistic outcomes, such as utterly homogeneous behavior. In this extreme, the feedback cycle between individuals and their peers leads both sides to converge on the same behavior (such as everyone votes or no one votes.). Johnson and Huckfeldt (2005) provide a useful summary of this type of model and its unrealistic results in a political context.

In order for the model to realistically predict voting behavior, either this feedback cycle must have no practical significance (i.e., a cycle is present but has little importance), or some other constraint must exists on the social feedback process. The individual's exogenous characteristics (X) are one such constraint and limit the homogenizing influence of social conformity. Political science research on social influences generally includes controls for such 'extraneous factors', for good theoretical reasons and to focus on the unique impact of the social influence of interest. By adding them to their models, researchers also avoid unrealistic edge solutions. My model also employs theoretically relevant control variables, with the pleasant side-effect of making the core social process more realistic.

Another constraint on the homogenizing power of social conformity is network structure, or the specific types of connections that are present between individuals. Johnson and Huckfeldt (2005), Centola and Macy (2007) and others find that models of pure diffusion or pure norms can resist corner solutions under particular forms of social network structures. For example, the grouping of individuals into relatively insular cliques can result in heterogeneity across cliques, even if it is suppressed within cliques. I examine the role of various network structures in the last section of this chapter.

Indirect Impacts Over Time

A cycle of dynamic (social) interactions over time sets up the opportunity for a complex pattern of serial autocorrelation, in which prior social interactions have an enduring impact across multiple future interactions and voting cycles; a similar statistical challenge as arose with cycles of mobilization in Chapter 4. The serial autocorrelation is unlikely to be a simple first-order process, because the impact of prior social interactions is mediated through a very specific social structure that generates each cycle's local participation rate. The direct and indirect (time-delayed) impact of social interactions is displayed in Figure 14.
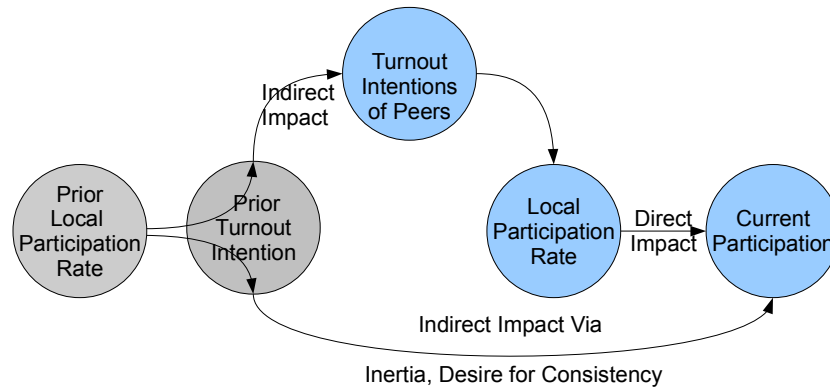
Figure 14: Impact of prior social interaction on political participation

Two indirect impacts are identifiable. First, the indirect impact via one's peers is shown on the top line, as has been the focus of the discussion thus far. Second, we would expect that turnout intention would be serially correlated, in which prior turnout intentions provide inertia (or the basis for habit) for future turnout intentions. This second indirect impact is very similar to the pathway considered in Chapter 4, as mobilizers build the habit (or inertia) of voting in their targets.

While these processes set up potentially complex statistical relationships, they can be estimated using the same tools employed to estimate the mobilization model – the optimization of a simulation model that captures the underlying econometric functions.

Step 2: Formalizing and Testing the Model

Econometric Model with Controls

The next step in developing the econometric model is to specify factors beyond the local participation rate that influence voting and might bias the estimation of social conformity's role if not included. Like other researchers, I will (partially) control for personal traits that are exogenous to the participation choice, drawing from the rich literature on individual determinants of political participation cited above. For example, some of the variables incorporated in the literature include personal resources (age income, education), engagement (interest, efficacy, ideological extremity), and demographic factors (race, gender). A range of underlying theoretical models provide rationale for these variables, including resource mobilization models (Verba et al. 1995), Michigan-style social-psychological models (Campbell et al. 1960), or rational choice models of relative costs and benefits (Downs 1957; Fiorina 1981; etc.). These ontologically individual models provide overlapping and often competing interpretations; for my purposes however, it is unnecessary to adjudicate between these interpretations. The variables are effectively nuisance parameters for this *social* model of descriptive norms; the resulting functional form follows Seigel (2009), employing nuisance variables to control for these factors and focusing the analysis on the social dynamics.

The resulting econometric model of turnout intention is:

Local Participation Rate$_{i,t}$ = $\sum_{j:1..K}$(TurnoutIntention$_{j,t-1}$) / (K)

TurnoutIntention$_{i,t}$ = Logistic(B$_o$
    + B$_1$Local Participation Rate$_{i,t}$
    + Personal Factors *[= B$_2$Race$_i$ + B$_3$Marital Status$_{i,t}$ + B$_4$Gender$_i$*
      + B$_4$Employment Status$_{i,t}$ + B$_5$Household Income$_{i,t}$ + B$_6$Age$_{i,t}$ + B$_7$Education$_{i,t}$
      + B$_8$Political Interest$_{i,t}$ + B$_9$Partisan Extremity$_{i,t}$ + B$_{10}$ Ideological Extremity$_{i,t}$]
    + History *[= B$_{11}$ TurnoutIntention$_{i,t-1}$]*)
H$_{i,t}$ =   TurnoutIntention$_{i,t-1}$

It requires one statistical estimation process, for turnout intention. This estimation requires an unusual dataset, however. It should have direct information about the prior turnout intention of one's peers,[67] and prior turnout intention of the individual, along with current turnout intention for the individual. It should also include information on other, potentially competing, social processes.

Competing Social Processes

Further improvements can be made by untangling the overlapping impacts of various social processes. First, social capital is commonly discussed, and can be operationalized as participation in organized social groups (per Putnam 2000). Second, network heterogeneity can be operationalized as the number of individuals in a person's local network that disagree with the individual on their choice of political candidate.[68] As above, I will not assume a particular model of how diversity affects participation.

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[67] Since knowledge is one's peers intentions is necessarily based on PRIOR events, the prior turnout intention of one's peers can be measured as the CURRENT understanding of the PRIOR turnout intention of one's peers.

[68] Note also that the operationalization of diversity impacts the empirical outcome. As Mutz (2002) points out, cross-cutting pressures have often been examined as cross-cutting group memberships, but she finds that direct metrics of social pressure often lead to contradictory results. Following Mutz, I employ a direct measure of cross-cutting social pressure – presidential preferences of one's discussants.

Researchers have found positive (Kotler-Berkowitz 2005), negative (Mutz 2002), or

neutral effects from network heterogeneity. Instead, I treat the competing processes as

nuisance variables, to be revisited in future research focused on discriminating between

these multiple processes. Third, increased information arising from social contact, and

subsequently lower costs to participation, can be operationalized as the number of

political discussants an individual has (following McClurg 2002). Unfortunately, the

South Bend dataset does not facilitate analysis of this competing process, as the

researchers required that respondents provide a fixed number of discussants (3), and is

not included in this analysis. Finally, Chapter 4 provides evidence that mobilization can

also provide an effective trigger for turnout, and thus should also be included as a control.

The resulting model, incorporating both immutable personal traits and potentially

confounding processes of social influence and mobilization is:

$$
\begin{aligned}
\text{TurnoutIntention}_{i,t} = \text{Logistic}(B_0 \\
+ B_1 \text{Local Participation Rate}_{i,t} \\
+ B_2 \text{Race}_i + B_3 \text{Marital Status}_{i,t} + B_4 \text{Gender}_i + B_4 \text{Employment Status}_{i,t} \\
+ B_5 \text{Household Income}_{i,t} + B_6 \text{Age}_{i,t} + B_7 \text{Education}_{i,t} + B_8 \text{Political Interest}_{i,t} \\
+ B_9 \text{Partisan Extremity}_{i,t} + B_{10} \text{Ideological Extremity}_{i,t} \\
+ B_{11} \text{Social Group Memberships}_{i,t} + B_{12} \text{Network Heterogeneity}_{i,t} \\
+ B_{13} \text{Mobilization}_{i,t} \\
+ B_{14} \text{TurnoutIntention}_{i,t-1})
\end{aligned}
$$

From Turnout Intentions to Voting Behavior

While Turnout Intention is theoretically interesting for its feedback effects, the

practical significance of this research for political scientists hinges on an additional

relationship:

$$\Pr(\text{Vote}) \sim \text{TurnoutIntention}$$

Political scientists are most interested in how social conformity affects the

likelihood that an individual will actually turn out to vote, rather than whether they *plan*

to turn out to vote. Thus, the second model of interest is:

Pr(Vote) = Logistic(B_0
    $+ B_1$Local Participation Rate$_{i,t}$
    $+ B_2$Race$_i + B_3$Marital Status$_{i,t} + B_4$Gender$_i + B_4$Employment Status$_{i,t}$
    $+ B_5$Household Income$_{i,t} + B_6$Age$_{i,t} + B_7$Education$_{i,t} + B_8$Political Interest$_{i,t}$
    $+ B_9$Partisan Extremity$_{i,t} + B_{10}$Ideological Extremity$_{i,t} + B_{11}$Social Group Memberships$_{i,t}$
    $+ B_{12}$Network Heterogeneity$_{i,t} + B_{13}$Mobilization$_{i,t}$
    $+ B_{14}$ TurnoutIntention$_{i,t-1}$)

And thus the dataset used to estimate these models would ideally have data on

actual voting behavior, as well as on turnout intentions.

Data Sources

Following Siegel's (2009) analysis, I assume that the underlying network

structure over which social interactions occur is of great practical significance of those

interactions. Rather than attempting to model the range of possible network structures, I

examined datasets that provide detailed information voters and their discussants. Data on

these social interactions and on voter turnout is scarce, but some suitable datasets are

available.

Huckfeldt and Sprague have two datasets that provide detailed social data for

South Bend, Indiana (circa 1984) and St. Louis-Indianapolis study (circa 1996-1997).

The South Bend data (Huckfeldt and Sprague 1985) is a three-wave panel study of 2,158

individuals around the 1984 presidential elections, capturing demographic and attitudinal

variables before, during and immediately after the national conventions. The

interviewers gathered a list of individuals with whom the respondents most frequently

discussed politics; they then conducted follow-up interviews with 924 of their discussion partners. The St. Louis-Indianapolis Study (Huckfeldt and Sprague 2000; Huckfeldt and Sprague 2002) has interviews with 2,612 individuals, and follow-up interviews with 1,740 of their political discussants. Individuals were drawn from the list of registered voters, and cross-sectional waves of interviews occurred before, during, and after the elections; topics included standard demographic and attitudinal questions plus additional questions on political and community involvement and perceptions of the political preferences of frequent discussants. Both data sets have been used by a series of researchers, such as Fowler (2005), to analyze network influence and can provide a baseline for comparison against existing models.

For this study, I analyze both datasets, working around their limitations to ask two related questions: how does the perception of others' voting intentions affects one's own *voting intentions*, and how does the perception of others' *turnout behavior* affects one's own *turnout behavior?* Both datasets include the desired information about personal and demographic factors that are treated as exogenous factors in the model including race, marital status, gender, income, age, education, partisanship, and ideological extremity. They also include information that allows us to control for alternative explanations of social influence, including mobilization, network heterogeneity and membership in social groups (political capital). The South Bend data contains self-reported voting behavior for the individual and his discussants, as well as two prior measurements of turnout intentions for the individual; the St. Louis dataset contains both self-reported voting behavior and intentions for the individual and the individual's discussants, but unfortunately is cross-sectional and no data is available on prior turnout intentions.

The coding of each variable for each of the two datasets is available in the Appendix. In employing these datasets, I seek to measure the influence on voting behavior of each individual's *perception* of their discussant's behavior, and not the discussant's own statement of their behavior or validated turnout data. While these two are generally quite similar (Huckfeldt and Sprague 1995), perceptions are more appropriate for descriptive norms, and I employ only the primary interviewees' perceptions of their peers' behavior, and not their peers' self-reported behavior.

Working with the strengths of each dataset, the two sources are mapped onto two empirical tests of the theoretical model, as follows:

- With the South Bend panel dataset, I analyze the impact of the perceived turnout intentions of one's peers on one's own voting behavior, controlling for one's own prior turnout intentions.
- With the St. Louis pre-election data, I analyze the impact of the perceived turnout intentions of one's peers on one's own turnout intentions.

Note: in addition to these two datasets, I analyze a related dataset in the Appendix, for further verification of the results. The data is drawn from the two post-election cross sections from the St. Louis study (Huckfeldt and Sprague 2000), and provide information on the role of peer turnout intentions on individual voting behavior. Unlike the South Bend panel, those post-election cross sections for St. Louis do not include a control variable for the individual's prior turnout intentions, and are thus not included in the main body of the paper.

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Simulation Implementation

I implemented two simulations, one focusing on conformity of turnout intentions, and one on conformity of turnout behavior, built around the St. Louis and South Bend datasets, respectively. As in Chapter 4, the simulations follow the underlying models' equations precisely, with the addition of a scoring function that compares the individual-by-individual predictions of the models to the original South Bend and St. Louis data. The simulation is then optimized with respect to the scoring function, to determine optimal parameters that minimize error against the observed data. This approach allows for accurate estimation of models with significant violations of standard regression assumptions (such as circular and non-linearizable feedback loops), but sacrifices the certainty that the resulting parameters are global, rather than local, optima. The resulting process is analogous to a non-deterministic Maximum Likelihood Estimation (see Chapter 3 for a more detailed description). As in Chapter 4, I implemented the simulations using the R programming language (R Development Core Team 2012).

Test 1: Estimating Model Parameters and Testing Statistical Significance

For each of the two simulation models, I use the "Flexible Modeling Environment" (FME) package in R (Soetaert and Petzoldt 2010) to estimate the parameters of the model and generate confidence intervals around each estimate. I use the FME package's implementation of the Levenberg-Marquardt algorithm for the optimization itself.

After the estimation (optimization) process is complete, I calculate the impact of each of these parameters by analyzing the average marginal change in the probability of

voting across the actual individuals in the original dataset, as advocated by researchers

such as Hanmer and Kalkan (2009). This entails calculating predicted probabilities for

each individual in the dataset with the maximum and the minimum value in each of the

variables, rather than using a single stylized individual with "average" values across all

other variables, as has been common practice in the field. The estimation of the first

model on the St. Louis dataset, examines how one's turnout intentions conform to the

turnout intentions of one's peers, and is presented in Table 7.

Table 7: Simulation estimation of the impact of the Local Participation Rate on Turnout Intentions (St. Louis dataset)

Variable	Ave. Predicted Probability Change	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	NA	-1.08	0.67	-1.60	0.11
White	-0.03	-0.25	0.31	-0.80	0.42
Married	0.03	0.23	0.20	1.16	0.25
Female	0.04	0.35	0.18	1.99	0.05
Employed	-0.05	-0.47	0.23	-2.03	0.04
Age	0.09	0.01	0.01	1.42	0.15
Household Income	0.05	0.01	0.00	1.13	0.26
Education	0.05	0.38	0.45	0.84	0.40
Political Interest	0.08	0.62	0.26	2.38	0.02
Partisan Extremity	0.27	0.62	0.10	6.24	0.00
Ideological Extremity	0.03	0.10	0.08	1.23	0.22
Group Membership	0.08	0.13	0.08	1.66	0.10
Mobilization	0.00	0.01	0.19	0.03	0.97
Heterogeneity (% Agree)	-0.07	-0.58	0.25	-2.34	0.02
LPR (% Plan to Vote)	0.06	0.49	0.26	1.90	0.06

In this model, the turnout intentions of one's peers have a statistically and

practically significant impact on one's own intentions – increasing the probability of

intending to vote by 6%.

The second model, on social conformity in actual voting behavior, provides an alternative measure of the impact of social conformity, and is presented in Table 8.

Table 8: Simulation estimation of the impact of the Local Participation Rate on Turnout Behavior (South Bend dataset)

Variable	Ave. Predicted Probability Change	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	NA	-3.49	0.60	-5.78	0.00
White	-0.05	-0.96	0.26	-3.63	0.00
Married	-0.03	-0.52	0.24	-2.19	0.03
Female	-0.01	-0.10	0.20	-0.53	0.60
Employed	0.03	0.44	0.24	1.78	0.08
Age	0.20	0.05	0.01	6.36	0.00
Household Income	0.01	0.00	0.01	0.38	0.70
Education	0.11	1.76	0.51	3.43	0.00
Political Interest	0.13	1.74	0.25	6.93	0.00
Partisan Extremity	0.04	0.21	0.09	2.22	0.03
Ideological Extremity	-0.10	-0.55	0.12	-4.57	0.00
Group Membership	0.08	0.20	0.07	2.79	0.01
Mobilization	0.02	0.25	0.18	1.36	0.17
Heterogeneity (% Agree)	0.03	0.54	0.23	2.38	0.02
Prior Turnout Intention	0.19	2.43	0.26	9.39	0.00
LPR (% Voted)	0.08	1.15	0.28	4.18	0.00

This model also indicates a statistically and practically significant role for social conformity – leading to an 8% bump in reported voter turnout. In terms of the underlying theory of social conformity, both pieces of evidence are encouraging.

The higher impact, by 33%, witnessed in the second model is intriguing – indicating that voting behavior is more influenced by conformity pressures than turnout intentions. One might suspect that the populations surveyed in the two datasets, from South Bend in 1984 and St. Louis in 1996 vary in important ways, leading to greater

social conformity pressures. However, the post-election cross sections from St. Louis focusing on voter behavior offer very similar results to the 1984 South Bend data (results provided in the Appendix). Alternatively, one could argue that the *intention* to vote may be less influenced by social pressures than self-reported *voting behavior*.[69] In part, this could be because of differences in the timing of the turnout intention and voting behavior datasets; the turnout intention data is collected before (sometimes, many months before) the election, and the voting behavior datasets are collected after the election. It is likely that most discussion of whether one should vote or not occurs directly before the election, rather than in the previous months.

Test 2: Comparing Results against the Benchmark, Non-Simulation Model

As in Chapter 4, I will use the simulation model to extend the analysis into future periods and generate testable hypotheses that would not have been feasible using a standard regression model. Those extensions are discussed in the next section. However, I first want to ensure that the novel simulation implementation aligns with the more standard methods employed in the literature.

As a benchmark, I employed a logit regression; this is an imperfect vehicle because of the assumed presence of network autocorrelation, but it is nevertheless an appropriate benchmark as it (or uncorrected probit analyses) is used in the existing research on similar models (e.g., Huckfeldt et al. 2000). Estimations were performed

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[69] One might also ask whether the inclusion of the control variable for prior voting intention – possible in the South Bend panel study but not in the cross-sectional St. Louis dataset – is behind the change in predicted probabilities. When this control variable is removed, the following estimation results occur (with a logit regression implementation): Ave Predict Probability Change = 20%, Coefficient Estimate: 1.77, Std. Err 0.33. That is, the effect of social conformity increases further, rather than falling in line with the St. Louis dataset.

using the R statistical package, with the Zelig library (R Development Core Team 2012; Imai, King, and Lau 2010). The table below provides a test of the model in which the Local Participation Rate is a predictor of turnout intentions.

Table 9: Logit regression of the impact of the Local Participation Rate on Turnout Intentions (St. Louis Dataset)

Variable	Ave. Predicted Probability Change	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	NA	-1.62	0.77	-2.09	0.04
White	-0.03	-0.27	0.33	-0.81	0.42
Married	0.02	0.17	0.23	0.73	0.46
Female	0.05	0.44	0.21	2.16	0.03
Employed	-0.03	-0.25	0.26	-0.97	0.33
Age	0.10	0.01	0.01	1.53	0.13
Household Income	0.06	0.01	0.01	1.25	0.21
Education	0.01	0.10	0.51	0.20	0.84
Political Interest	0.05	0.43	0.30	1.41	0.16
Partisan Extremity	0.30	0.69	0.11	6.36	0.00
Ideological Extremity	0.06	0.17	0.09	1.79	0.07
Group Membership	0.10	0.17	0.08	2.01	0.04
Mobilization	0.01	0.07	0.22	0.33	0.74
Heterogeneity (% Agree)	-0.04	-0.37	0.28	-1.30	0.19
LPR (% Plan to Vote)	0.08	0.63	0.30	2.07	0.04

In this logistic regression, the key variable of interest – the local participation rate – is statistically significant at the 95% level, and corresponds to an average change in the predicted probability of intending to vote of 8%. This is comparable to the 6% lift seen in the simulation model, but noticeably higher. The change in impact may be caused by bias of the logistic regression (due to violation of regression assumptions on data with network autocorrelation) or by error in the simulation estimation process (since the

optimization process cannot guarantee results that are the global maxima).

Table 10 provides the results of a similar logistic regression, in which I estimated the impact of the local participation rate on self-reported turnout behavior.

Table 10: Logit estimation of the impact of the Local Participation Rate on Turnout Behavior (South Bend Dataset)

Variable	Ave. Predicted Probability Change	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	NA	-3.39	0.77	-4.39	0.00
White	-0.04	-0.53	0.31	-1.69	0.09
Married	-0.02	-0.34	0.30	-1.12	0.26
Female	0.00	-0.03	0.25	-0.12	0.90
Employed	0.03	0.35	0.30	1.18	0.24
Age	0.20	0.04	0.01	4.26	0.00
Household Income	0.06	0.01	0.01	1.53	0.13
Education	0.05	0.65	0.59	1.11	0.27
Political Interest	0.10	1.19	0.29	4.11	0.00
Partisan Extremity	0.04	0.18	0.12	1.46	0.14
Ideological Extremity	-0.08	-0.37	0.14	-2.58	0.01
Group Membership	0.08	0.17	0.09	1.94	0.05
Mobilization	0.02	0.30	0.23	1.29	0.20
Heterogeneity (% Agree)	0.03	0.33	0.30	1.12	0.26
Prior Turnout Intention	0.19	1.94	0.25	7.86	0.00
LPR (% Voted)	0.15	1.60	0.36	4.50	0.00

The local participation rate is again statistically significant. The average change in the predicted probability of voting, for the individuals in the original dataset, is 15%, markedly higher than the 8% lift seen for the simulation model. As mentioned above, we would expect some differences between the two methods for two reasons. First, the underlying econometric assumptions differ, and we have strong reason to believe they are violated in the case of the logistic regression. Second, the estimation process differs, and

is less exact for the simulation model, compared to the ideal case of a logistic regression in which its assumptions all hold.

In both cases, however, social conformity pressures are a significant, positive, predictor of individual turnout, even after controlling for a host of individual and alternate social factors. These results line up with the simulation model, providing a measure of confidence that the methodology is solid, and affords further extension into new observable facts.

Test 3: Estimating the Total Effect of Social Conformity, including Indirect Impacts

In addition to the direct impact of social conformity on one's voting intention and voting behavior, conformity can indirectly impact future actions via two routes. These routes are illustrated in Figure 14, at the beginning of Step 1 of this analysis. They can be summarized as follows:

- Social conformity first influences the individual to vote (or plan to vote), as a direct impact. That personal decision then is relayed to one's peers, and becomes part of *their* social conformity pressures. Their decision to vote (or plan to vote) then is relayed back to the individual, becoming part of an updated set of social conformity pressures, and again influencing the individual's decision, but in an indirect manner.

- Social conformity first influences the individual to vote (or plan to vote), as a direct impact. That personal decision shapes the individual's longer term habits, and influences future voting decisions indirectly.

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I estimated the first type of indirect impact using the St. Louis pre-election dataset, since it provides the most detailed information about the main respondent's discussants and their own turnout intentions. This indirect impact can be calculated by determining how important conformity, applied to one's peers (by one's peers' peers, including oneself), is to one's own decisions. The estimation process is:

1. Estimate the simulation model of turnout intention and its determinants using the main respondents in the data, as presented in the previous section.

2. For each discussant in the data, apply the estimated model to predict their turnout intention with and without the influence of social conformity.

3. For each main respondent in the data, determine the average turnout intention of their discussants, with and without the influence of social conformity. The result is each individual's Local Participation Rate (with and without conformity pressures on the discussants).

4. For each main respondent in the data, apply the estimated model to predict their turnout intention, given the two possible Local Participation Rates (when their peers are under the influence of social conformity, and when they are not.)

5. Calculate the average change in turnout intentions due to social conformity pressures on one's peers – which is the indirect impact of that conformity on the individual.

The resulting indirect impact of conformity on turnout intentions, an average increase in 0.4% in intentions, is very modest, and does not warrant much future attention. However, when the same analysis is applied to voting *behavior* on the post-election data, the average increase in turnout is 1.7%, which is practically very

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significant, and could determine the outcome of a presidential election.

It is somewhat more challenging to calculate the other type of indirect impact, in which the prior local participation rate affects prior turnout intentions and those turnout intentions affect current participation above and beyond the current participation rate (i.e., through habit or inertia). Ideally, one would trace the same individuals through the initial social conformity process, through the formation of turnout intentions, to later rounds of social conformity pressures, to the final decision to vote. However, neither the South Bend nor St. Louis datasets alone provide the full set of information required: an estimate of the local participation rate's impact on turnout intention, and the impact of prior intentions on current intentions.

Instead, we can roughly estimate the average indirect impact using the results of the analyses of the two individual, but separate, datasets. The process is as follows:

1. Estimate the impact of the Local Participation Rate on turnout intentions – using the St. Louis, pre-election dataset. These results are presented in Table 7.

2. Estimate the impact of prior intentions on voting *behavior* – using the South Bend dataset. These results are presented in Table 8.

3. Calculate the combined impact of both factors.

The resulting indirect impact, a 1.14% increase in turnout due (=6% * 19%) is also practically significant, and could be consequential in a presidential election. No firm conclusions should be drawn from this analysis though, given the rough procedure used to estimate the impact. The results do warrant further attention though, if a suitably detailed panel dataset can be found.

In total, social conformity's direct and indirect impact on voting behavior, if supported by further tests, could be very substantial – adding up to an 11% boost in overall turnout.

Step 3: Extending the Model into New Observable Facts

Extension 1: A Multi-Cycle Simulation Model, in a Fragmented Society

Social conformity has an important role in shaping individual turnout intentions and turnout behavior, as evidenced in the prior section. However, we have only considered the short term impact thus far – of direct and indirect (2-cycle) changes in behavior. How might social conformity affect behavior in the long term?

Given the literature on models of pure conformity and the extreme outcomes they predict (described in the introduction to this chapter), clearly other dynamics are at work in the case of voting. Johnson and Huckfeldt (2005) and Siegel (2009) both demonstrate the importance of network structure to how individuals interacting over a network adapt their behavior over time in response to conformity pressures. Unfortunately, the two datasets used in the analyses thus far, the South Bend and St. Louis studies, do not provide a complete network of discussants.[70] Instead, the St. Louis and South Bend datasets are both "snowball" studies, in that the researchers initially queried a set of individuals, then asked for their political discussants, and interviewed as many of those discussants as was feasible. The researchers then stopped, and did not interview the discussants of the discussants, or the discussants of those discussants, etc. These second,

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[70] Nor do there appear to be any other publically available, full-network, datasets of voter behavior and intentions over time.

third, and higher order discussants influence the voting decisions of their peers, but are not included in the dataset, and the network of social influence is thus "incomplete".

Given this limitation, we can nevertheless analyze the multi-cycle impact of social conformity by studying specific scenarios supported by the data. Namely, though information on discussion partners is lacking, we can construct a stylized society of fragmented groups of individuals, who communicate with like-minded individuals from the data, and no one else.[71] We would expect that environment to have two impacts on the model: on the expected local participation rate, and indirectly on behavior. The local participation rate would tend towards 0 or 1, as individuals constructed their political discussion networks to avoid disagreement. Second, we would expect that the indirect effects of conformity, i.e., mirroring one's views through one's peers and one's peers' peers, would have little impact: in homogeneous groups, the individuals start the process already conforming to their peers' behavior.

A simple extension of the simulation model provides a test of this thought experiment. I classify the individuals in the dataset into deciles of turnout probability, according to the estimated parameters for the simulation model of turnout. I randomly draw individuals from each decile. Then, I draw political discussants from the same decile, up to the number of discussants that the selected individuals indicated on the survey, and setup a group of intercommunicating, but otherwise fully isolated, individuals

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[71] Such a society could arise, in theory, if individuals actively shape their discussion networks to avoid disagreement, select neighborhoods of likeminded individuals, and receive their news about broader social expectations from carefully chosen online and traditional media outlets. Whether this is, in fact, occurring has been an ongoing debate in the American popular press.

for each set of discussants. Finally, I simulate multiple electoral cycles with and without

the influence of social conformity.[72]

The South Bend panel dataset provides the richest base for this extension of the

model, since it provides information on both the formation of turnout intentions before

the election and then afterwards on the decision to vote, given the intentions of one's

peers. I initialize the population of the simulation with the South Bend dataset, for the

1984 elections. For each subsequent election, I first assume that an individual's

probability of voting in the prior election carries over to become the pre-election (and

pre-social influence) turnout intention of that person in the next round, then I estimate

conformity's influence, and I determine the likelihood that the individual will vote in that

election. I repeat this process ten times, taking this isolated-version of the South Bend

population through a simulated journey to 2024. The result can be seen in Figure 15, on

the next page.

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[72] To simulate a world without social conformity playing a role, one cannot drop the term associated with conformity – that would simulate a world in which none of one's peers ever participated. Instead, one should assume that one's peers have the same participate rates as the individual would have had based on her non-social independent variables. Using the simplified notation from Step 1, start with $T = \text{logit}(\alpha_o + \alpha_1 X + \alpha_2 LPR)$. Then, set LPR to the participation rate that the individual would have had normally, ie $\text{logit}(\alpha_o + \alpha_1 X)$. Substituting into the original equation $T = \text{logit}(\alpha_o + \alpha_1 X + \alpha_2 \text{logit}(\alpha_o + \alpha_1 X))$. This places turnout intentions at the level of participation from a "neutral" social environment, rather than a completely discouraging one ($\alpha_2 = 0$). Discouraging environments are examined in the next section.
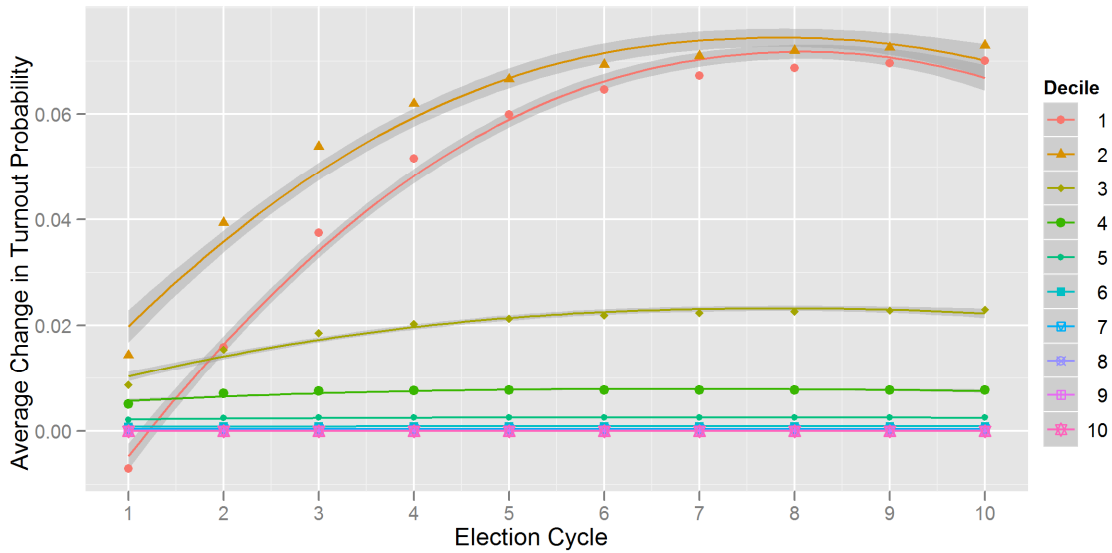
Figure 15: Average change in turnout over time in "Isolated" Populations, due to social conformity

Figure 15 demonstrates that long-term changes in turnout intentions do occur among these isolated populations, and they vary depending on the level of initial participation each isolated populations starts with. However, these changes are very slight. The average across all groups is small – only a 1.4% increase across all time periods, and a less than 1% increase for the first time period. The average impact found using the original South Bend dataset was significantly greater, at 8%.

The change in turnout intentions across the groups also varies considerably. With each group, discussants were drawn from the population of individuals whose initial predisposition to vote was within the same decile. The homogeneity of those groups varied substantially, though. The higher-deciles of turnout were nearly homogeneous, with a variance in the initial probability of participation of 6×10^{-5}%; the lowest decile of turnout was somewhat less homogeneous. The highest groups showed nearly no change in turnout intentions. The 1st and 2nd decile of initial turnout, with a greater internal heterogeneity, saw a the maximum change in voting intentions over time at 7%, just

under the average impact found using the original South Bend dataset.[73]

This result fits with one's expectations – within (relatively) homogenous groups, dynamic social pressures have little practical significance. Instead, the structure of the group itself (homogeneous) has already incorporated the power of conformity. This result only holds for truly homogeneous groups, however. The power of conformity applied by an otherwise homogenous group on a heterodox member could still be very powerful, as I will explore shortly.

Extension 2: Everyone Else is Voting (Or Not)!

Cialdini's, Kallgren's and Reno's (1991) work on peer comparisons and consumer behavior, and subsequent work on voter behavior (Gerber et al. 2008), points towards another interesting extension of the model. In their seminal work in the field, Cialdini, Kallgren and Reno informed individuals of the average energy consumption of their neighbors. They found that individuals that had previously consumed more than the average significantly decreased energy consumption. Those that consumed less than the average would increase their consumption (i.e., conform to the reference value given by the experimenters), unless a simple message of social approval was given (e.g., "Congratulations!").

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[73] Two other factors could also be at work with this variation across the groups. First, in the South Bend dataset, the majority of the individuals have over a 90% predicted probability of voting (the underlying turnout is based on self-reports, which are known to be excessively high). Individuals who fall into the highest deciles by initial turnout probability have the smallest capacity to increase *further* due to social effects over time. However, this cannot be well separated from their social context; they have the *greatest* capacity to decrease their probability of turnout, if they were placed in a contrary social milieu that discouraged participation. Second, the underlying model employs a logistic curve, which is most responsive to changes near 50%, and least responsive near 0% and 100%.

That research spurred the development of the private company OPower, which provides these messages to consumers as a service to public utility companies. OPower applies an even rosier comparison – if the individual consumes less than the average, the companies' materials will shift the comparison from averages to instead reference another group that is consuming even less than the individual. The result is the construction of a socially positive reference group: the individual is (almost) always compared to a group that is doing better than themselves, and the individual faces a norm that pushes them to improve regardless of their starting point.

This research has three potential parallels in voting behavior. First, political parties and their PACs can attempt to encourage (or suppress) targeted segments of the population who they expect to vote in their favor with this form of intentionally constructed "peer" pressure. Second, a less devious version of this process occurs naturally when individuals move to areas dominated by opposing views. That is, when a non-voter is immersed in a context with people who unfailingly vote, this extreme form of peer pressure would result.[74] Campbell (2006) explores a similar premise for civic-minded individuals moving into cities with heavy political polarization. A third context might be experimental field studies by political scientists, if Institutional Review Board (IRB) issues could be resolved (see Gerber et al. 2008 for a less controversial but related line of experimental research).

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74 One could similarly analyze social pressure on voter preferences – e.g., the immersion of Democrat in a strongly Republican context. We'd expect both strong peer pressure in the short term, and the pressured person to adjust their network to avoid such stark conflict. Both topics – voter preferences and self-selection in political discussants – should be explored in further research.

What would be the effect of such extreme peer contexts? Figure 16 provides the result on an initial examination. In this extension to the model, each member of the South Bend dataset was placed in both a simulated "100% voting" and "0% voting" context. As before, the individuals were divided into deciles to better identify the variation in responsiveness to peer pressure across the population.
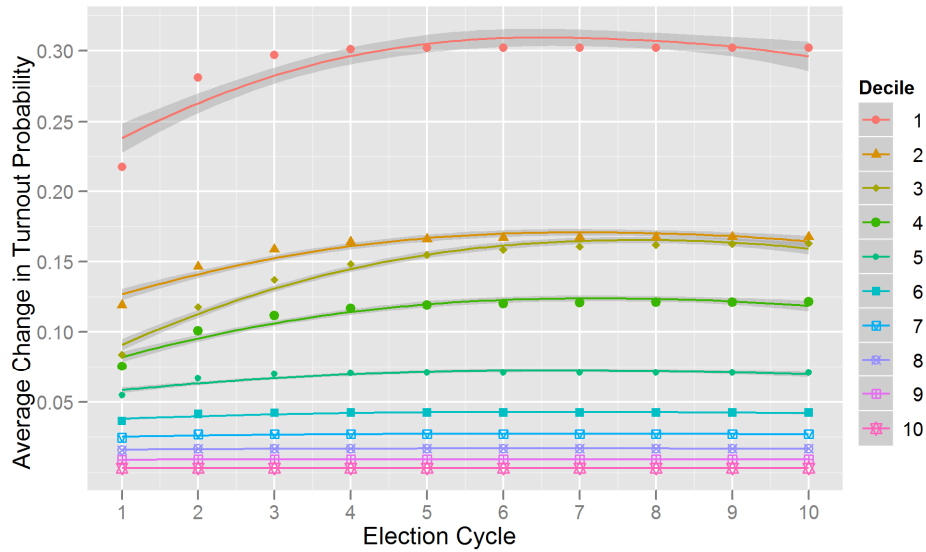
Figure 16: Average change in turnout over time for individuals placed in all-voter vs. no-voter contexts

Comparing Figure 16 and Figure 15, clearly these extreme peer pressures have significantly more effect than pressures that occur in relatively homogeneous groups. The average impact across all individuals by the end of the simulation is an impressive 9.2% change in turnout. Those individuals who always vote – in the upper deciles of initial turnout – are unmoved, even by this extreme peer pressure. More interestingly though, consider the results for those groups that are most effected by peer pressure – individuals from the first decile, who had an average initial turnout level of 62% in this

dataset. These voters are normally the least decisive about voting, and tailored peer pressure can trigger a tremendous 30% change in turnout. A 30% change in the turnout of a targeted group, if predisposed to vote for one candidate or another, could naturally have a very significant impact on the outcome of elections.

Discussion and Conclusion

This analysis indicates that a commonsense mechanism of social influence, peer pressure, can have a strong impact on voter turnout, even when a wealth of more complex models found in the literature is considered. That impact can range from a minor 1% increase in turnout among relatively homogeneous groups, to an average increase of 8% across a broad dataset of potential voters, to a 30% increase among carefully targeted populations. The impact of peer pressure occurs both immediately, as some others have already identified (e.g., Gerber and Rogers 2009), and over time through indirect channels, as has yet to be well analyzed in the literature.

While pursuing these empirical results, I provided a stylized theoretical model, in which one could identify and analyze alternative dynamic social interactions. These dynamic interactions each contain a social feedback loop, that researchers can analyze using the tools presented in Chapter 3. In this Chapter, I provided a demonstration of those tools, developing a simulation model to encapsulate the dynamic process of peer pressure, optimization techniques to estimate the model's parameters and test for statistical significance, and then extensions to the simulation to explore the model's broader implications.

Numerous avenues of future research appear promising, given this base. One path entails examining additional implications of the current model. For example, an alternative specification of the Local Participation Rate could be investigated, that incorporated the frequency of interaction with each discussant, or the ideological fervor of the discussant (Huckfeldt and Sprague 1995, Cho and Rudolph 2008). Two such metrics would be:

$$\sum \text{discussant\_participates} * \text{frequency\_of\_contact\_with\_discussant}$$
$$\text{or}$$
$$\sum \text{discussant\_participates} * \text{discussant\_ideological\_or\_political\_extremity}$$

Another interesting avenue of research entails leveraging related models on norm formation. Bendor's and Swistak's (2001) work in the evolution of norms in an evolutionary game theory context is particularly promising. The framework outlined here could be combined with formal evolutionary game theory to study more rigorously the interaction between individual exogenous characteristics and norm formation in a population.

Finally, in the discussion of indirect impacts of the model, I mentioned a number of limitations in light of the scant available empirical data. With appropriate panel data and a more complete understanding of the full social network of interacting individuals, one could gain more accurate estimates of these processes.

Chapter 6: Discussion

The preceding chapters sought to accomplish four tasks: identifying an understudied theoretical mechanism, that of dynamic interactions; describing the theoretical and statistical challenges that can arise when they are present; offering a methodology that can help tackle these challenges; and applying the methodology to two such interactions, between individual voters and political campaigns and between voters and their political discussants. In this chapter, I step back from the analyses themselves and ask how well each of these tasks has been accomplished, and what tradeoffs were made along the way to introduce and study this underappreciated mechanism. Then, I consider the broader implications of the dynamic interactions, and consider potential next steps for this line of research.

Review of the Methodology and Major Findings

Problem

In Chapters 1 and 2, I identified a theoretical mechanism that applies to a surprisingly broad swathe of current research in voting behavior: dynamic interactions between individuals and the micro-context of their decision to vote, in which a single factor both influences, and is influenced by, the act of voting. I illustrated how these interactions can occur in four areas of political science research on voting – analyses of social interactions, (weak) rational choice analyses of the costs and benefits of voting, the

growing base of experimental work on habit formation, and the diverse literature on political party mobilization. These interactions setup "feedback cycles" that pose both theoretical and statistical challenges if not analyzed appropriately.

Drawing on well-established work on auto-regressive processes and on System Dynamics, I outlined three major statistical issues that can occur:

1. Underestimating the net indirect impact of these mechanisms on voting behavior, by ignoring their indirect impacts,

2. Unintentionally incorporating unrealistic assumptions about long term trends in voting behavior,

3. Biasing the estimation process and offering misleading results, under specific conditions of non-stationarity or complex autoregressive relationships.

While researchers may be able to employ advanced econometric techniques to mitigate some of the problems, these issues raise another practical concern:

4. Modeling processes with dynamic interactions using current methods requires challenging econometric techniques, hard to find panel datasets with sufficient detail, and/or unintuitive model formulations. All of these limit the exploration and understanding of these processes in practice.

Methodology

In Chapter 3, I proposed a methodology to confront these four challenges: employing simulation models to instantiate dynamic processes in an intuitive format that can be rigorously estimated, and can provide novel testable predictions that ease the

requirement for extensive panel data. The methodology consisted of three broad steps:

1. **Developing a Theoretical Model**

    a. The researcher would identify a dynamic process of interest, including the specific feedback process and the means by which that feedback process was constrained or shaped to avoid unrealistic predictions.

    b. This step could potentially leverage the theoretical framework presented in Chapter 3 on the dynamics of voting behavior, which provides an overall context for many of the dynamic processes evident in the current literature on voting behavior.

2. **Implementing the Model in a Computer Simulation**

    a. The researchers would then instantiate the theoretical model in mathematical form, and convert that mathematical form into a computer simulation. The simulation should be a direct representation of the mathematical model, with no new assumptions or additional variables; the simulation serves as a wrapper, feeding parameters and input data to the mathematical representation, executing the mathematical functions, and recording the output.

    b. While any mathematical and simulation vehicles could potentially be appropriate, I argued that agent-based models offer a great degree of flexibility and intuitiveness, especially when modeling individual-level phenomenon such as voting.

    c. The researchers would then estimate the model parameters by using optimization techniques to find most error-reducing parameters that fit a

known dataset, like the ANES, in a process similar to Maximum Likelihood

Estimation.

d. Finally, researchers would determine confidence intervals around, and the

statistical significance of, these parameter estimates by using Monte Carlo

simulations to approximate their distribution functions.

3. **Testing the Model Against New Observable Facts**

a. Finally, with the calibrated simulation model in hand, researchers would

explore the model's behavior in detail to find novel predictions and

unanticipated outcomes that can be tested against out-of-sample empirical

data.

Dynamics of Mobilization

In Chapter 4, I then applied this methodology to the issue of dynamic interactions

between individual voters and political campaigns attempting to mobilize them.   A

feedback cycle is established as the political campaigns both increase turnout, and target

their mobilization efforts based on prior turnout.   Some existing models of mobilization

and voting behavior have explicitly incorporated this process, especially Abramson and

Claggett (2001), but have not analyzed its long terms impact.   In the extreme, this

dynamic interaction drives the model to predict that eventually political campaigns seek

to mobilize everyone in the population.

I argue that a more realistic, but still parsimonious, model of mobilization

incorporates the fact the political campaigns have limited resources, and only seek to

mobilize the "best" individuals (by a variety of metrics). The dynamic process, and

especially the budget constraint, set up complex autoregressive relationships and a functional form that is difficult to estimate with standard econometric techniques. The theoretical model can be readily translated into a simulation model, however, and estimated using parameter optimization against empirical datasets, such as the ANES.

The result of the estimation process yields parameter estimates (and predicted probabilities) that are quite similar to the less-complex econometric models used in the existing research, providing some initial evidence in support of the simulation model. The independent variable of interest – budget constrained voter mobilization – has both statistical (1% level) and practical (5% average increase in the probability of voter turnout) significance. Moreover, the simulation model generates intriguing new predictions about political behavior and mobilization that warrant further attention and testing:

1. The indirect impact of mobilization. If mobilizers are successful at prompting an individual to vote, they change the likelihood that the individual would be mobilized again, and thus participate again. This indirect impact adds an additional 43% to the direct impact of mobilization on turnout. For the population that is likely to be mobilized, that corresponds to an additional 4 percentage point increase in turnout.[75]

2. This model can be applied to other political behavior such as campaign contributions and political volunteering, with more striking results. The indirect impact of mobilization on volunteering is a 21 percentage point increase in participation, which is an additional 70% of mobilization's direct impact.

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[75] The average increase due to mobilization across the entire population is considerably lower. However, in practice, it is not the entire population that is mobilized – but only a particularly responsive subset.

3. Over multiple election cycles, mobilization appears to increase the participation

   levels of a narrow, unrepresentative, portion of the population. In mobilizing

   campaign contributions, for example, 33% of the population receives over 95% of the

   requests to contribute, and they account for 89% of the donations made.

These findings raise interesting questions about the strategic investments that

political parties make in mobilization and building their base of participants over time.

They also extend the model's predictions into novel territory, facilitating empirical

testing using new datasets, such as field experiments on mobilization and survey data on

political contributions and volunteership.

Dynamics of Social Conformity

In Chapter 5, I analyzed the changing pressures for conformity between

individuals and their political discussants. As individuals decide whether or not to vote,

they take into account the behavioral expectations of their peers – in short, if all of one's

friends vote, you are more likely to do so as well. The communication, and the setting of

expectations is two way, however – as individuals formulate their own turnout intentions,

they communicate those intentions to their peers, who adjust their own behavior and

intentions, and who then feedback their (updated) intentions back to the first individual.

The result is a form of feedback loop, as intentions flow from the individual to peers and

back to the individual (as well as from peers to their other peers, back to them, back to

the individual, etc., throughout all layers of the discussion network).

This feedback cycle is an example of network autocorrelation, and one in which

traditional econometric techniques falter.[76]   The feedback cycle also presents serious

problems for empirical analysis, in that detailed information about individual voters, their

turnout, political discussions with others, and the turnout of peers is required.   Using two

such suitable datasets, I developed two related models – one on changes in individual

voting *behavior* at election time given the (perceived) behavior of others, and one on

changes in individual turnout intentions given the (perceived) intentions of others, before

the election.   In each case, I used the theoretical framework from Chapter 3 to identify

two potentially confounding alternative dynamic processes, and control for them:

mobilization, and disagreement / conflict among one's peers.   Both models were

instantiated as agent-based simulations, and estimated using the optimization procedure

provided in Chapter 3.

The results of the estimation process broadly confirmed the simulation models –

on both models, conformity pressures were found to be both statistically (1%, 10%

levels), and practically (8%, 6% average change in predicted probability of turnout)

significant.   The models were also readily extended to generate novel testable

predictions:

1. The indirect impact of conformity pressures on voting behavior can increase turnout

    in the next round of discussion by 1.7 percentage points.

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[76] There are also specialized techniques for handling network autocorrelation, which can accurately estimate the net impact of network effects at equilibrium. In Chapter 5, however, I sought to explicitly model the step-by-step process of network updating, and used simulation modeling instead to achieve this.

2. In a society of insular, relatively homogenous groups, peer pressure *per se* has little effect; since the individuals enter the groups because their preferences are already aligned.

3. Irregular voters can be highly susceptible to peer pressure – real or experimentally constructed – in which pressures to conform can change individual turnout rates by up to 30%.

Benchmarking this model against standard econometric techniques, however, leads to a puzzling problem. While the results (parameter estimates and predicted probability changes) are similar, there are notable differences. And, these differences reveal a limitation to the methodology that should be considered further.

Assessment of the Methodology

In employing a new technique – simulation modeling and parameter optimization – to study dynamic processes, one would expect tradeoffs against existing methods. Many of the expected tradeoffs were outlined in the initial chapters, and warrant a review based on the experience of applying the methodology in Chapters 4 and 5. The methodology offers these benefits:

1. Researchers can model processes that are would otherwise be difficult to express as normal econometric models, such as budget constraints on the mobilization process that affect who is targeted, especially constraints that change from year to year.

2. Researchers can estimate models that, subtly or obviously, would violate the

assumptions of most econometric models, such as complex path-dependent (and non-stationary) processes.

3. Researchers can directly convert their intuitive theoretical model of a dynamic process into a simulation model that instantiates the same theoretical concepts. This is particularly valuable when the theoretical model is about interacting individuals, with heterogeneous autonomous people interacting with each other over time. The development of the simulation does not require a long "formalization" process in which the characteristics of people and their interactions are abstracted away. In an agent-based model, the theoretical concepts can become the analytical model directly.

However, at the same time:

1. By not requiring a detailed formalization process, researchers employing simulation models in this manner also are not required to ground their models in well-established methods and clearly articulate the underlying assumptions of their models. I have presented a practical approach to counter this, by explicitly starting with existing (non-simulation) models of voting behavior and benchmarking the results against known empirical results.

2. Until a significant body of well-understood and tested simulation models is developed for voting behavior that can be used for benchmarking, researchers are stuck benchmarking their models against existing econometric models. The further one moves into models that are econometrically intractable, the more difficult that becomes.

3. The parameter estimation process cannot guarantee that the global optimum is found,

meaning that estimated parameters may be inaccurate. While techniques exist to mitigate this problem (e.g. cross-validation using untouched data, verification with different initial parameters and algorithms), they cannot remove this problem altogether.

4. Expertise in programming (rather than advanced econometric techniques) is currently required. Thus, it is unclear whether this methodology currently provides a net benefit for political scientists without advanced technical skills. New simulation modeling tools are being developed (e.g., NetLogo and RePast) that allow non-programmers to develop and explore these types of models. However, no non-technical systems appear to exist yet that can facilitate the parameter estimation and hypothesis testing process.

In the Chapter 5, both the benefits and the risks of this approach were particularly well on display. First, the simulation estimation found statistical and practical significance on a dataset that one would strongly expect has network-autocorrelation problems, and was able to sidestep these problems to generate an intuitive and testable model. Second, the estimation process generated parameter predictions that were similar to, but noticeably different from a simplified econometric model used to "benchmark" it. Because the simulation estimation process cannot guarantee optimal parameter values, it is unclear whether the difference between the two models was due to a faulty econometric model (violation of the assumptions), an "ineffective" simulation optimization (unable to find true parameters), or some combination of the two. The benchmark process provides useful support for the simulation model when the outcomes

are the same, but is clearly not as useful when the outcomes are different than the benchmark. It can provide supportive evidence, but cannot falsify the simulation model.

Assessment of the Findings and Next Steps

The two analyses conducted here, on mobilization and social conformity, both provide insights into their specific processes and raise interesting questions about the dynamics of political participation more generally.

In terms of mobilization and conformity, as discussed above, the indirect impacts of these factors are both statistically and practically significant – ranging from a 1.7% to a 4% increase in turnout, enough to swing the result of an election. The long term impact of targeted mobilization, the creation of cadres of often-mobilized activists, raises questions about whether political campaigns are effectively using their mobilization funds to build their parties in the long term, and whether the unevenness of participation undermines the concept of a participatory democracy. The long term impact of peer pressure, however, is much more complex. Targeted use of peer pressure or intentionally constructed peer comparisons can lead to significant increases in turnout – even up to a 30% increase. However, in an increasingly fragmented society, where individuals surround themselves with likeminded peers and media outlets, external peer pressure has a rapidly diminishing impact.

More broadly though, these findings, and the models that produced them, provide a foundation for a host of new research questions, ranging from the role of "shocks" to the mobilization process, to the effects of an aging population on turnout behavior over

time, to the effects of individual migration from high-turnout areas to low-turnout areas (and vice-versa). These models can be directly extended and tested in these new contexts, allowing the researcher to build on the simulation modeling and calibration that has already been conducted and to focus on the more exciting parts of research – exploring the unknown and testing the insights found therein.

Appendices

Appendix A: Estimation Code for the Dynamics of Mobilization Simulation

This appendix provides the simulation used to estimate the Dynamics of

Mobilization model from Chapter 4. The simulation is written in the R programming

language, with user-defined parameters to establish the characteristics of individuals as

well as the mobilization, participation, and update functions. The central algorithm of the

model is as follows:

```
# Define the Budget Constrained mobilization and voting model: returns each
# individual's predicted probability of voting.  Takes two input variables: the vector of
# current parameters, and the dataset of ANES individuals.

Constrained_Model <- function(p,x)
{
        # Calculate lift from mobilization
        y_m0 = logistic(p[1] + p[2]*x$Age + p[3]*x$Education + p[4]*x$Union.member
        + p[5]*x$Religious.attendance
        + p[6]*x$Political.engagement + p[7]*x$Presidential.candidate.affect
        + p[8]*0 + p[9]*x[,historyvar])

        y_m1 = logistic(p[1] + p[2]*x$Age + p[3]*x$Education + p[4]*x$Union.member
        + p[5]*x$Religious.attendance
        + p[6]*x$Political.engagement + p[7]*x$Presidential.candidate.affect
        + p[8]*1 + p[9]*x[,historyvar])

        # Select individuals for mobilization with the greatest lift
        diffValue = y_m1 - y_m0
        mob <- as.numeric(diffValue > quantile(diffValue,c(1-0.25)))

        # Determine probability of participation, based of mobilization & other factors
        y = logistic(p[1] + p[2]*x$Age + p[3]*x$Education + p[4]*x$Union.member
        + p[5]*x$Religious.attendance + p[6]*x$Political.engagement
        + p[7]*x$Presidential.candidate.affect
        + p[8]*mob + p[9]*x[,historyvar])

        # return the results, to inform the optimization algorithm
        return(data.frame(y=y,diffValue=diffValue, mob=mob))
```

}

# Define the vector of residuals between observed and predicted data
# (this algorithm requires raw residuals, and internally calculates the sum of the squared
# residuals)
Residuals <- function(p) (dtaC$Turnout-Constrained_Model(p,dtaC)$y)

Call the optimization routine from the FME packages; uses the Levenberg-Marquardt
algorithm, with arbitrary but non-zero starting parameters
P <- modFit(f=Residuals,p=c(-1,1,1,1,1,1,1,1), method="Marq")

# Print out the results for review
print(P)

That's it. The optimization process returns the estimated error-minimizing parameters,
then calculates re-simulates the model around those parameters to determine confidence
intervals for those estimates.

Chapter 4 employed the ANES's 1990-1992 panel dataset, 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.

Variable Codings, identical to Abramson and Claggett (2002) where relevant:

Age: Actual age in years.

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.

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

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.

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.

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.

Mobilized: Indicates whether individual was contacted the political parties or "someone else" to "talk to you about supporting specific candidates in this last election".

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.

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, 0.8, 0.6, 0.4, 0.2 and 0 respectively Those who reported that they never attend religious service except for weddings, baptisms or funerals were also coded 0.

Sex: Female was coded 1 and male 0.

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.

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

Turnout in 1990: Indicates the self-reported behavior of the individual in the 1990 elections.

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

Appendix C: Analysis of St. Louis Post-Election Data

In addition to the two datasets used in the main text, another similar dataset is available to test the role of peer turnout on one's own voting behavior. In the main text, I employed the cross-sections of the St. Louis dataset that occurred before the 1996 elections, to test turnout intentions, and the panel over time of the South Bend dataset that occurred around the 1984 elections, to test turnout behavior.

I did not employ the cross-sections of the St. Louis dataset that occurred *after* the 1996 elections, in order to simplify the overall presentation. The St. Louis post-election dataset allows one to test the role of peer turnout on one's own turnout. It is similar to the South Bend dataset, but is slightly inferior in that it does not provide a control variable for the individual's prior turnout intentions. I replicated the analysis from the body of the text on this data; those results are presented in Table A.1, on the next page.

Table A.1: Logit regression of the impact of the Local Participation Rate on

Turnout Behavior, with Post-Election St. Louis Dataset

Variable	Ave. Predicted Probability Change	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	NA	-4.19	0.84	-4.96	0.00
White	-0.03	-0.38	0.37	-1.02	0.31
Married	0.01	0.10	0.25	0.40	0.69
Female	0.02	0.16	0.23	0.69	0.49
Employed	-0.01	-0.08	0.29	-0.26	0.79
Age	0.20	0.03	0.01	3.52	0.00
Household Income	0.06	0.01	0.01	1.46	0.14
Education	0.15	1.39	0.60	2.30	0.02
Political Interest	0.07	0.72	0.33	2.21	0.03
Partisan Extremity	0.27	0.76	0.13	6.05	0.00
Ideological Extremity	0.00	0.01	0.10	0.13	0.90
Group Membership	0.09	0.18	0.09	1.91	0.06
Mobilization	0.06	0.60	0.25	2.39	0.02
Heterogeneity (% Agree)	0.00	0.05	0.30	0.18	0.86
LPR (% Voted)	0.13	1.12	0.32	3.52	0.00

The cross-sectional St. Louis post-election dataset offers similar results as the South Bend panel study which was collected nearly 12 years later. Most importantly for the analysis, the average change in the predicted probability of voting are quite similar – with a 13% predicted change on the St. Louis dataset, and a 15% change on the South Bend dataset (both results are statistically significant at the 1% level). Other variables, that were not statistically significant in one or more of the datasets (Mobilization, Percent Agree), do show significant variation across the two analyses. That should not be surprising given their high standard errors, however.

Appendix D: Analysis of Imputed Data on Social Conformity

In the main text, I dropped cases that were missing any of the independent variables, and then used that trimmed dataset for the analyses: simulation estimation, benchmark logistic regressions, and calculation of indirect effects. In the St. Louis dataset, 401 of 1344 individuals with data for the dependent variable were dropped; in the South Bend dataset, 503 of 1510 individuals were dropped.

This greatly simplified the simulation process, and the presentation of the simulation results. However, this approach is not ideal when confronting missing data. A more appropriate method is to apply multiple imputation, in which a model is fitted to the available data and applied to estimate the missing information, and the process is repeated multiple times to gauge the stability of resulting values (King et at. 2001).

I applied multiple imputation to the original South Bend and St. Louis datasets, using the Amelia II package in R (Honaker et al. 2011).   I then replicated the benchmark logistic regressions on these imputed datasets. The results were substantially the same as for the trimmed datasets, both in coefficient estimates and statistical significance, and are displayed in Tables A.2 and A.3, on the next two pages.

Table A.2: Logit regression of the impact of the Local Participation Rate on Turnout Intentions, with Multiple Imputation of St. Louis Dataset

Variable	Estimate	Std. Error	t-stat	p-value
Intercept	-2.22	0.60	-3.67	0.00
White	-0.08	0.23	-0.34	0.73
Married	0.05	0.19	0.29	0.78
Female	0.30	0.17	1.78	0.07
Employed	-0.10	0.21	-0.51	0.61
Age	0.02	0.01	2.37	0.02
Household Income	0.01	0.00	1.99	0.05
Education	0.28	0.40	0.70	0.48
Political Interest	0.48	0.24	2.06	0.04
Partisan Extremity	0.67	0.09	7.61	0.00
Ideological Extremity	0.20	0.08	2.65	0.01
Group Membership	0.14	0.07	2.10	0.04
Mobilization	0.09	0.18	0.52	0.60
Heterogeneity (% Agree)	-0.37	0.26	-1.41	0.16
LPR (% Planning to Vote)	0.62	0.30	2.07	0.04

The parameters of interest on the imputed and non-imputed datasets are nearly identical. For example, the coefficient on LPR is 0.63 vs. 0.62 on the two datasets, 0.07 vs. 0.09 for mobilization, 0.62 on both for discussant network diversity. The standard errors for these variables are also nearly identical.

Table A.3: Logit regression of the impact of the Local Participation Rate on Turnout Behavior, with Multiple Imputation of South Bend Dataset

Variable	Estimate	Std. Error	t-stat	p-value
Intercept	-3.77	0.54	-7.00	0.00
White	0.00	0.21	-0.02	0.99
Married	-0.10	0.21	-0.46	0.64
Female	0.01	0.17	0.04	0.97
Employed	0.03	0.23	0.15	0.88
Age	0.03	0.01	5.35	0.00
Household Income	0.01	0.01	1.84	0.07
Education	0.04	0.41	0.10	0.92
Political Interest	1.06	0.20	5.24	0.00
Partisan Extremity	0.26	0.09	2.76	0.01
Ideological Extremity	-0.14	0.10	-1.39	0.17
Group Membership	0.13	0.06	1.99	0.05
Mobilization	0.15	0.17	0.89	0.38
Heterogeneity (% Agree)	0.52	0.22	2.37	0.02
Prior Turnout Intention	1.59	0.19	8.43	0.00
LPR (% Voted)	1.77	0.24	7.43	0.00

As with the St. Louis dataset, the parameters of interest on the imputed and non-imputed data are very similar. For example, the coefficient on LPR is 1.77 vs. 1.60 on the two datasets, 1.59 vs. 1.94 for prior vote intentions.   In both cases, these analyses indicate that the results presented in the main body of the paper would not have significantly changed if they had been conducted on imputed data.

Appendix E: Variable Coding, St. Louis Dataset

Dependent Variable:

Variable Meaning: Vote Intention

Original Variable(s): V3, NUV2.

Coded Variable(s): WillVote

Coding: 1 whenever the individual indicated a specific preference, and 0 when the individual specifically intended not to vote, and NA otherwise. To counteract social desirability influences, and to retain as much of the sample as possible for analysis, when individuals indicated that s/he did not know whether sh/e would vote, the individual was coded as unlikely to vote (0).

Main Independent Variable:

Variable Meaning: Local Participation Rate (Perceived, Intended Turnout)

Original Variable(s): V3, NUV2.

Coded Variable(s): PercentVoting

Coding: Gives the percent of the individuals' political discussants that the individual believed would vote. To retain as much of the sample as possible for analysis, when individuals indicated that s/he did not know whether a discussant would vote, that discussant is counted as a likely non-voter.

Other Independent Variables:

Coded Variable(s): White; Dummy variable for whether individual is White

Original Variable(s): D14

Coding: 1 for white, NA for Don't know or Refused, 0 otherwise.

Coded Variable(s): Married; Dummy variable for whether individual is married

Original Variable(s): D1

Coding: 1 for married, NA for Don't know or Refused, 0 otherwise.

Coded Variable(s): Female; Dummy variable for whether individual is female

Original Variable(s): D2 (Gender)

Coding: 1 for female, NA for Don't know or Refused, 0 otherwise.

Coded Variable(s): Employed; Dummy variable for whether individual is employed

Original Variable(s): D7 (Employment Status)

Coding: 1 for employed, NA for Don't know or Refused, 0 otherwise.

Coded Variable(s): Age (in 1996)

Original Variable(s): D13 (Year of Birth)

Coding: 1996 – Year of Birth, unless Don't know or Refused (coded as NA)

Coded Variable(s): HouseholdIncome; Household Income, in Thousands

Original Variable(s): D16-20

Coding: >75k: 87.5   >50k: 62.5   >35k: 42.5

               >25k: 30.0   >15k: 20.0   <15k: 7.5

Coded Variable(s): Education, [0,1] variable for highest level of schooling

Original Variable(s): D11 (Years of Schooling)

Coding: 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 but no four year college degree was coded .6,

                A college degree or more, but no advanced degree was coded .8,

                An advanced degree was coded 1.

Coded Variable(s):   PoliticalInterest; Respondent's General Level of Interest in Politics

Original Variable(s): P1

Coding: # Coded as: very = 1; somewhat = .5; not = 0

Coded Variable(s): PartisanExtremity; [0,1] Level of Partisan Intensity

Original Variable(s): PT2B,P3, P4, P5 (Self-identification on partisan spectrum)

Coding: Absolute Value of: 4 - (ANES 1-7 scale of intensity)

Coded Variable(s): IdeologicalExtremity; [0,1] Level of Ideological Intensity

Original Variable(s): P8B, P9, P10, P11 (Self-identification on ideology spectrum)

Coding: Absolute Value of : 4 - (ANES 1-7 scale of intensity)

Coded Variable(s): Mobilization

Original Variable(s): PO1 (Contact By Political Parties)

Coding: Yes = 1; No= 0; Don't know or refused = NA;

Coded Variable(s): GroupMembership

Original Variable(s): O1A, O1B, O2, O3, O4, O5

Coding: Count of the number of times the individual said they were a member of a

particular type of organization (each question, O1A, O1B, O2, O3, O4, O5, corresponds

to a membership).

Coded Variable(s): SizeOfNetwork

Original Variable(s): N[1…5] (Respondent names a political discussant)

Coding: Count of individuals named

Coded Variable(s): FrequencyOfPoliticalTalk

Variable Meaning: How often discuss politics

Original Variable(s): N[1…5]J

Coding: Maximum value, across political discussants, of the following per-discussant

coding: Never 0; Rarely 0.33; Sometimes = .66; Often = 1

Coded Variable(s):   PercentAgree, Level of Political Agreement with Network

Original Variable(s): N1J, N2K, N3K, N4K, N5K

Coding: Sum of individuals agreeing ("often" or "sometimes") / # of individuals in

network

Appendix F: Variable Coding, South Bend Dataset

Note – the coding of the St. Louis and South Bend datasets are nearly identical. All of the independent variables, except for prior voting intentions, are available in both datasets and employed similar or identical wording. The text below provides the variable names used in this dataset, along with the (duplicated) descriptions.

The data collection occurred in 3 waves, as given in the first letter of most variable names: A, B, or C. Where information on a particular topic was available in more than one wave, the first answer (wave) that a particular respondent gave was used.

Dependent Variable:

Variable Meaning: Self Reported Voting Behavior

Original Variable(s): C27, C28.

Coded Variable: Voted_84

Coding: 1 whenever the individual indicated a specific preference, and 0 when the individual specifically intended not to vote, and NA otherwise. To counteract social desirability influences, and to retain as much of the sample as possible for analysis, when individuals indicated that s/he did not know whether sh/e voted, the individual was coded as unlikely to have voted (0).

Main Independent Variable:

Variable Meaning: Local Participation Rate (Perceived, Intended Turnout)

Original Variable(s): C149, C150, C151

Coded Variable(s): PercentVoted

Coding: Gives the percent of the individuals' political discussants that the individual believed would vote. To retain as much of the sample as possible for analysis, when individuals indicated that s/he did not know whether a discussant would vote, that discussant is counted as a likely non-voter.

Other Independent Variables:

Variable Meaning: Pre-Election Turnout Intention

Original Variable(s): B187

Coded Variable(s): WillVote

Coding: 1 whenever the individual indicated a specific preference, and 0 when the individual specifically intended not to vote, and NA otherwise. To counteract social desirability influences, and to retain as much of the sample as possible for analysis, when individuals indicated that s/he did not know whether sh/e would vote, the individual was coded as unlikely to vote (0).

Coded Variable(s): White; Dummy variable for whether individual is White

Original Variable(s): A139, B230, C217

Coding: 1 for white, NA for Don't know or Refused, 0 otherwise.

Coded Variable(s): Married; Dummy variable for whether individual is married

Original Variable(s): A101, B201, C177

Coding: 1 for married, NA for Don't know or Refused, 0 otherwise.

Coded Variable(s): Female; Dummy variable for whether individual is female

Original Variable(s): RSex

Coding: 1 for female, NA for Don't know or Refused, 0 otherwise.

Coded Variable(s): Employed; Dummy variable for whether individual is employed

Original Variable(s): A105, B50, C181

Coding: 1 for employed, NA for Don't know or Refused, 0 otherwise.

Coded Variable(s): Age (in 1985)

Original Variable(s): A134, B225, C212 (Year of Birth)

Coding: 1985– Year of Birth, unless Don't know or Refused (coded as NA)

Coded Variable(s): HouseholdIncome; Household Income, in Thousands

Original Variable(s): A142,B249, C232

Coding: >50k: 70.0   >40k: 45.0

              >30k: 35.0   >20k: 25.0   >15k: 17.5

              >10k: 12.5   >5k: 7.5   <5k: 2.5

Coded Variable(s): Education, [0,1] variable for highest level of schooling

Original Variable(s): A102,B202,C178

Coding: 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 but no four year college degree was coded .6,

Four years of college degree was coded .8,

More than a college degree was coded 1.

Coded Variable(s):   PoliticalInterest; Respondent's General Level of Interest in Politics

Original Variable(s): A30, B137, C2

Coding: # Coded as: very interested / yes / a great deal = 1; somewhat / some = .5; not interested / no / only a little / none at all = 0

Coded Variable(s): PartisanExtremity; [0,1] Level of Partisan Intensity

Original Variable(s): A72-A75; B236-B239

Coding: Absolute Value of: 4 - (ANES 1-7 scale of intensity)

Coded Variable(s): IdeologicalExtremity; [0,1] Level of Ideological Intensity

Original Variable(s): A65-A67, B233-B235, C220-C222

Coding: Absolute Value of : 4 - (ANES 1-7 scale of intensity)

Coded Variable(s): Mobilization

Original Variable(s): A33,A34,B139,B140, C16

Coding: Boolean indicating if political parties, or "anyone" has "come around to talk to you" about registering or voting.   Yes = 1; No= 0; Don't know or refused = NA;

Coded Variable(s): GroupMembership

Original Variable(s): B30, B31, B32, B33, B34, B42, B43,

Coding: Count of the number of times the individual said they were a member of a particular type of organization

Coded Variable(s):   PercentAgree, Level of Political Agreement with Network

Original Variable(s): C170, C171, C172

Coding: Sum of individuals agreeing ("often" or "sometimes") / # of individuals in network.

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