Partisan Messages, Unconditional Strategies and Coordination in American Elections*

Walter R. Mebane, Jr.†

February 8, 2005

*Previous versions of parts of this paper were presented during 2003 and 2004 at meetings of the Midwest Political Science Association, the Political Methodology Society, and the American Political Science Association, at sessions of the Empirical Implications of Theoretical Models program at Duke University and at Washington University, and at seminars at Princeton and New York Universities. I thank Jim Alt for hospitality when I worked on this paper while visiting at the Center for Basic Research in the Social Sciences at Harvard University during the spring of 2004, Marc Ratkovic, Israel Waismel-Manor and Jonathan Wand for helpful comments, and Jasjeet Sekhon for stimulating discussion. This work is supported by NSF grant SES-0214965.

†Professor, Department of Government, Cornell University, 217 White Hall, Ithaca, NY 14853–7901 (Phone: 607-255-2868; Fax: 607-255-4530; E-mail: wrm1@cornell.edu).

Abstract

Partisan Messages, Unconditional Strategies and Coordination in American Elections

I use evolutionary models to study how partisan messages and cuing contribute to—or perhaps substitute for—strategic coordination by voters in American presidential elections. Cuing means imitating another voter's strategy: a cue tells a voter what to do, not what to think. Using National Election Studies data from 1976–96 to simulate and estimate models of replicator dynamics shows that voters respond to messages from other voters who are partisans. About 70 percent of voters use an unconditional strategy, which means their vote decisions do not depend on their current evaluations of policies or other factors. About 30 percent of voters use a coordinating strategy that involves systematic attention to the separation of powers and to other voters. Voters seem to evaluate their strategies and make changes only sporadically. In most elections, what the coordinating voters do determines what happens.

Introduction

Many questions concerning people's strategies, organizational involvements and social positions as voters in American elections may be construed as questions about information. Do voters know enough to to coordinate their voting decisions with one another, to send and receive meaningful messages, to anticipate the consequences of their choices? These questions point in two directions. One is a concern with whether voters are competent to make such decisions, and the other asks whether voters really need to make such decisions.

Competence is the more familiar version of the information concern. The conventional wisdom from generations of research and experience seems to prove that few if any voters are sufficiently attentive and informed that it is reasonable to describe them as optimal electoral strategists. Converse (1964) classically questioned whether most people know enough about public policies to make any judgments at all about them. By and large the image of an ignorant and passive public remains ascendant (Althaus 2003; Alvarez and Brehm 2002; Delli Carpini and Keeter 1996)

The necessity question points to institutions and processes voters are involved in and asks whether the messages and cues the institutions provide substitute for complicated decisions by the voters (Sekhon 2004). Here there are two strands of work, one emphasizing how messages originate with political parties and interest groups (McKelvey and Ordeshook 1985; Forsythe, Myerson, Rietz, and Weber 1993; Zaller 1992), the other focusing on how messages flow through social networks (Huckfeldt and Sprague 1995). The distinction between parties and interest groups is not all that great, as we may think of parties as election-oriented organizations that interest groups or activists struggle to control (Aldrich 1995; Miller and Schofield 2003).

Clearly voters who are individually incomptent may collectively comprise an electorate that is more adept, not so much because of the wonders of aggregation (Feddersen and Pesendorfer 1997) but because of the organizing power of informed signals voters may receive and because of the networks through which the signals are conveyed. Indeed, when voters face uncertainty they may rely on informative party signals, and the fact that voters find the signals useful may in turn encourage the parties to present the voters with significantly distinctive alternatives (Snyder and Ting 2002). Voters who rely on such signals may not make precisely the same choices as they would make if they were individually fully informed (Bartels 1996;

Feddersen and Pesendorfer 1997; Schattschneider 1960), but their choices are certainly different from and often better than the ones they would make absent such cues.

The questions about information present a challenge to work such as Mebane (2000) and Mebane and Sekhon (2002), which argues that at election time the American electorate is involved in a situation of large-scale strategic coordination. The claim is that American electors (i.e., voters and nonvoters) in presidential and House elections act according to a Nash equilibrium of a game they are all involved in, with all electors being informed by rational expectations about the election outcome. The equilibrium features policy moderation and institutional balancing between the president and the legislature, as in Alesina and Rosenthal (1995), Alesina and Rosenthal (1996) and Iannantuoni (2003). Mebane (2000) and Mebane and Sekhon (2002) find that models in which such strategic coordination is assumed fit National Election Studies (NES) data from years 1976 through 1998 better than do models that assume there is no equilibrium behavior but, instead, at best, nonstrategic spatial voting.

The information challenge to such work is primarily a challenge to resolve a major ambiguity: how much of the strategic coordination that appears to occur is due to individuals' personal competence, and how much does it reflect the institutions and partisan environment in which elections take place? The same ambiguity also affects other theoretical and empirical work that supports an image of strategic electorates, and not only in the United States. Among the affected work is Cox (1997), who analyzes many aspects of party systems using assumptions that there is strategic voting based on rational expectations about electoral outcomes. Also implicated are models of economic performance evaluations such as Alesina, Roubini, and Cohen (1997) and Erikson, Mackuen, and Stimson (2002), each claiming in a different way that voters' rational expectations about the economy strongly affect both public opinion and government policy. In all these cases it is unlikely that individuals are acting independently to produce the apparent strategic equilibria or dynamics.

In this paper I use a collection of evolutionary models to study what may happen when individuals are presented with partisan messages. The models implicitly embed individuals in networks that let them adjust their behavior in response to messages that may originate in a wide variety of places. A theme in the models is the idea that in a complicated informational environment people pay the most attention to messages that seem to relate to and perhaps even come from people like themselves. Such messages may appear to be more trustworthy (Lupia and McCubbins 1998) or perhaps simply more relevant to the person's concerns than others. They may involve immediate social relations such as family, friends and neighbors (Huckfeldt and Sprague 1987, 1995; Huckfeldt, Johnson, and Sprague 2005) or wider social networks (Berelson, Lazarsfeld, and McPhee 1954).

If considerations of similarity help limit the scope of the connections through which individuals receive messages, a consequence may be that the networks that convey effective partisan messages are thin, with most people linked to only a few others—few, that is, relative to the size of the whole electorate. Theoretical work such as Ellison and Fudenberg (1995) suggests that such restricted connections between people may produce outcomes that are collectively superior to those produced by denser networks or more frequent and extensive communications. A thinner network may slow the proliferation of responses to random misinformation. Because political information is always subject to bias and noise, the ideal of a political order in which everyone is fully aware of and responsive to the same common pool of information may not be as desirable as Converse (1964) and work in that tradition may suggest.

Abstracting from all details of how people may in reality be in contact with or learn from others, the models I introduce represent only the essential behavioral idea that when a voter encounters someone who has similar attributes, the voter may decide to imitate the voting strategy the other person is using. To imitate someone's strategy, I shall say, is to take a cue from them. This concept of cuing differs from the idea that a cue is an informational shortcut (Popkin 1991). Here a cue tells a voter what to do, not what to think. The less satisfied a voter is with his current strategy, the more likely he is to take cues from someone else. Specific models add various forms of partisan messaging to this baseline of imitation. I use NES data to try to assess which of the models best describes voters' behavior in presidential elections.

The models I use specify several forms of replicator dynamics (Weibull 1995). The replicators are differential equations that approximate stochastic processes of adaptation or learning that individuals are assumed to undergo during the campaign period. I consider an environment in which voters may use the coordinating strategy of Mebane (2000), or they may use one of four strategies that imply unconditional voting behavior. A voter who uses an unconditional strategy always makes the same choice regardless of the characteristics of the alternatives and regardless of the current electoral environment. Voters may imitate the strategies used by other voters whom they happen to encounter. Because voters are more likely to keep their strategy when they are satisfied with it, surviving strategies tend not to produce bad results. The evolutionary framework allows a mix of strategies to be sustained in a diverse population (Samuelson 1997). By using replicator dynamics to combine imitation with partisan signaling, I can connect the implausibly demanding equilibrium results of Mebane (2000) to a somewhat more realistic image of individual electors. As we will see, models such as the coordinating model of Mebane (2000) can fit the data well even when in fact only a small proportion of the electorate is behaving strategically.

I tie the analysis closely to observed voter behavior in two ways. First, I simulate the replicators numerically, using NES data from presidential election years 1976–1996. Second, I estimate choice models that include the possibility that unconditional strategies are used. These estimates are based on approximations of the relationship the simulations identify between voters' political evaluations and the probability of using each unconditional strategy. The links between estimation and simulation are intricate, because the simulations depend on sets of model parameter estimates derived from the same NES data. Indeed, one question that helps to determine whether the partisan signals come from other voters is whether the iteration between the estimation and simulation steps may be in a certain sense closed. A principal methodological contribution of the paper is that I present new ways to use data-based criteria to choose among simulated evolutionary models.

To foreshadow the results, I find there is a persistent heterogeneity among the strategies voters use. Most voters act unconditionally: they vote unconditionally for one party both for president and for the House of Representatives, or they unconditionally vote a split ticket that includes a vote for the House incumbent. A relative few act with full sophistication, using the coordinating strategy. For voters who use an unconditional strategy, beliefs about policy, performance or other factors do not affect the vote. Voters receive messages from other voters—from a subset of strong partisans—but notwithstanding changes that occur in their opinions about policies and other political matters, they only sporadically change their voting strategies. In most American presidential elections, the coordinating voters are the decisive voters, so that in the aggregate, what those voters do determines what happens.

Models

The models consider voters who make choices simultaneously for president and for a House candidate. Only votes cast for the two major parties, denoted D and R, are considered. For each election period there are n voters. Each voter $i = 1, \ldots, n$ chooses one of the four pairs of presidential and House votes in the set $\mathcal{K} = \{RR, RD, DR, DD\}$. The expected loss for voter i from making choice $ph \in \mathcal{K}$ is a combination of two components: $\lambda^i_{ph} = x^i_{ph} - \epsilon^i_{ph}$. Each element of the vector $x^i = (x^i_{RR}, x^i_{RD}, x^i_{DR}, x^i_{DD})'$ is a parametric function of observed attributes such as policy positions, party identification, economic evaluation, and House district incumbency status. The vector $\epsilon^i = (\epsilon^i_{RR}, \epsilon^i_{RD}, \epsilon^i_{DR}, \epsilon^i_{DD})'$ is random, with a generalized extreme value (GEV) distribution.

A voter may use any of a variety of strategies to decide how to vote. Using an optimizing strategy, denoted s_O, the vote choice $Y \in \mathcal{K}$ minimizes the expected loss:

$$Y^i_O = \arg\min_{ph \in \mathcal{K}} \lambda^i_{ph}$$

There are also four strategies that involve unconditional voting rules, denoted s_{DD}, s_{RR}, s_{DR} and s_{RD}. According to these strategies, the voter always makes the choice indicated by the subscript. A voter may also use a mixed strategy in which each of the foregoing strategies is used with some probability.[1] To be specific, let $S = (s_O, s_{DD}, s_{RR}, s_{DR}, s_{RD})'$ denote a vector of $m = 5$ pure strategies, and let $\rho^i = (\rho^i_O, \rho^i_{DD}, \rho^i_{RR}, \rho^i_{DR}, \rho^i_{RD})' = (\rho^i_1, \ldots, \rho^i_m)'$ be the vector that indicates the probability that voter i uses each of the strategies in S, $0 \leq \rho^i_j \leq 1$, $\sum_{j=1}^m \rho^i_j = 1$. Naturally, different voters may use different strategies.

In general the probabilities ρ^i are functions of time. Time here refers to dynamics occurring during a single election, presumably toward the end of the campaign period, in the weeks or few months before election day. To analyze the dynamics of ρ^i as time progresses, I exploit a duality available in evolutionary game theory (e.g. Weibull 1995, 69–72), which entails associating each of the n voters with a continuum of voters who all have the same attributes x^i. Each of the voters in each of these continua uses a pure strategy, but all the voters who have the attributes x^i may not use the same strategy. Now ρ^i indicates the proportion of the voters in continuum i that are using

[1] Although s_O depends on the values of λ^i, s_O is a pure strategy.

each of the strategies in S. Alternating between the probabilistic and the proportional interpretations of ρ^i is reasonable in the case of interest here, where n will immediately correspond to the small number of respondents in an election survey sample (i.e., the NES) that is drawn from a much larger electorate. We may assume that each voter in the electorate who has the same attributes as a surveyed voter uses one of the pure strategies, but we do not know which strategy each voter who happens to be included in the survey sample is using.

I assume that over time the random vector ϵ^i changes in a natural way according to a leader process (Resnick and Roy 1990). This means that from time to time each component ϵ^i_{ph} of ϵ^i undergoes an increment in response to new information about the choice alternatives. The variations in ϵ^i mean that every alternative in $\mathcal{K}$ is best for voter i some of the time. If the attributes x^i are constant, then the proportion of the time that alternative ph is the best choice is the same as the probability that the vote is $ph \in \mathcal{K}$ according to s_O, assuming an observer who knows x^i but not ϵ^i (Resnick and Roy 1990).

Replicator dynamics specify how ρ^i changes in response to the payoffs associated with each strategy. I treat time as continuous, which means the replicators are systems of ordinary differential equations for the time derivative of ρ^i, denoted $\dot{\rho}^i$. To avoid clutter I suppress explicit statement of the time index.

I consider two forms of replicator, corresponding to two conceptions of what a presidential election campaign is. One idea is that a campaign period is unlike other times, so that it begins at a particular moment, proceeds in an unstable manner and then ends. Election day is a kind of deadline and not necessarily a point where the campaign processes have reached any kind of dynamic equilibrium. The other idea is that while the campaign period may represent a heightening of activity and attention, it is not utterly unlike other times. Here election day is just a day not much different from any other, representing a kind of slice through a process that is in a steady state.

The first form is the simplest possible replicator (Weibull 1995, 188–189), expressed by

$$\dot{\rho}^i_j = \rho^i_j(u^i_j - \bar{u}^i)\,, \quad \bar{u}^i = \sum_{k=1}^{m} \rho^i_k u^i_k\,, \tag{1}$$

where $u^i_j > 0$ denotes the payoff voter i expects from using strategy $s^i_j \in S$, and $\bar{u}^i$ is the expected payoff given that ρ^i is used. Here payoffs are defined in terms of the expected losses associated with each alternative. Using the indicator function $I_X = 1$ if X is true, otherwise $I_X = 0$,

$$u_j^i = -\sum_{ph\in\mathcal{K}} \lambda_{ph}^i I_{[s_j^i=ph]} \ .$$

Weibull (1995, 152–161, 187–189) shows how (1) may be derived from a model of pure imitation driven by dissatisfaction. In that model, a voter who is more dissatisfied is more likely to review his strategy, and when a voter decides to change strategies he switches to the strategy used by the first voter he encounters who has the same attributes.

In the replicator of (1), a strategy that produces above average expected payoffs becomes more likely to be used, and a strategy that produces below average expected payoffs becomes less likely. A strategy that is persistently below average is effectively eliminated, in the sense that ρ_j^i approaches zero. Because the average expected payoff changes over time as the mix of strategies changes, and because the performance of a strategy in general depends on what other strategies are being used, a strategy that has above average performance at one time may not perform as well at a later time.

Because s_O always selects the best alternative, almost surely $u_O^i > \bar{u}^i$ and hence $\dot{\rho}_O^i > 0$. But each unconditional strategy sometimes selects the worst alternative, in which case $u_{ph}^i < \bar{u}^i$ and $\dot{\rho}_{ph}^i < 0$, so if the dynamic of (1) begins with $\rho_j^i > 0$ for all j and then runs for an indefinitely long period of time only s_O survives. That is, as time increases, $\rho_O^i \uparrow 1$. To obtain other values of ρ^i using (1), it is necessary to choose a particular termination time; i.e., election day's date matters.

The other form of replicator I consider includes a concept of reversion that allows the model to achieve a stochastic steady state with, persistently, $\rho_O^i < 1$. The idea is that at any particular time only a fraction μ of the voters who have attributes x^i are involved in the processes of imitation that (1) represents. The remaining $1-\mu$ of the voters are tending to fall away from using s_O, falling away more the more that ρ_O^i exceeds a threshold value η. This reversion to one of the unconditional strategies may be thought to be due to the difficulty of using s_O. For instance, perhaps it is time consuming to use s_O, so beyond a certain point the opportunity costs are too great. A similar consideration may apply to a single voter when ρ_O^i is viewed as a probability: the personal cost of sustaining a high value of ρ_O^i may be too great. In any case, the idea is that a voter who abandons s_O picks up one of the unconditional strategies completely at random.

These ideas lead to the following replicator. For $0 < \mu < 1$ and $0 < \eta < 1$,

$$\dot{\rho}^i_{ph} = \mu\rho^i_{ph}(u^i_{ph} - \bar{u}^i) + (1-\mu)(\rho^i_O - \eta)/4\,, \quad ph \in \mathcal{K} \tag{2a}$$

$$\dot{\rho}^i_O = \mu\rho^i_O(u^i_O - \bar{u}^i) + (1-\mu)(\eta - \rho^i_O)\,. \tag{2b}$$

The stochastic steady state to which (2a-b) converges is described by the following.[2]

Remark 1 *Over an indefinitely long period of time, the dynamic of (2a-b) maintains $\rho^i_O \in (\eta, 1)$ and $\rho^i_{ph} > 0$, $ph \in \mathcal{K}$. As μ is closer to zero, the upper bound on ρ^i_O is closer to η. If s_{ph} typically has $(u^i_{ph} - \bar{u}^i) < 0$, then eventually ρ^i_{ph} becomes and remains relatively small. If s_{ph} typically has $(u^i_{ph} - \bar{u}^i) > 0$, then eventually $\rho^i_{ph} \approx 1 - \rho^i_O$ with ρ^i_{ph} slightly smaller than $1 - \eta$. If there are two alternatives ph and ph^* such that typically either $u^i_{ph} > \bar{u}^i$ or $u^i_{ph^*} > \bar{u}^i$, then ρ^i_O may eventually stay near values substantially larger than η.*

That is, in the steady state ρ^i_O remains less than 1, substantially less if μ is small. Indeed, if one alternative typically gives the best payoff, then ρ^i_O remains just larger than η, and ρ^i_{ph} corresponding to that typically best u^i_{ph} remains just smaller than $1 - \eta$. If two alternatives typically alternate in giving the best payoff, then ρ^i_O can be much larger than η. Unconditional strategies that choose alternatives that typically give inferior payoffs do not disappear but are rarely used.

To represent partisan signaling in these models I allow the expected payoffs u^i to change over time in response to a stream of messages each voter receives. The payoffs represent judgments about such matters as the voter's perceptions of the policy positions the parties and candidates are taking, the voter's own preferences regarding those policies and the voter's beliefs and preferences regarding economic performance. Parties send messages about such matters during presidential campaigns. In the absence of messages, (1) derives from the idea that voter i imitates voters who have the same attributes (Weibull 1995, 187–189). Having a different u^i in (1) means the voter takes cues from a different set of voters than if there were no messages. The same intrepretation applies to (2a-b). People who support different parties receive different cues.

[2] In (2a-b), as in (1), $\sum_{j=1}^{m} \dot{\rho}^i_j = 0$ maintains $\sum_{j=1}^{m} \rho^i_j = 1$.

I let the messages come from voters who are strong partisans in the NES sense of partisanship: each message to a self-identified Democrat (including Independent Democrats) corresponds to the observed attributes of a randomly selected strong Democrat, and each message to a self-identified Republican corresponds to the observed attributes of a randomly selected strong Republican. To be precise, let every unit of time to be divided into 30 equal intervals. Thus each unit of time can be considered a simulated "month" (or *sim-month*) composed of 30 simulated "days" (*sim-days*). At each sim-day I draw a new vector of observed attributes, denoted x^V, by sampling from the x^i vectors observed among either strong Democrats or strong Republicans, depending on the partisanship of voter i. For pure Independents, x^V is drawn from the attributes of pure Independents. In each case the voters from whom x^V is drawn are restricted to be in a House district with the same incumbency status[3] as voter i. I compute $\bar{x}^i = (x^i + x^V)/2$ and consequently expected losses $\bar{\lambda}^i = \bar{x}^i - \epsilon^i$. The payoffs used in (1) and (2a-b) are then

$$u_j^i = -\sum_{ph \in \mathcal{K}} \bar{\lambda}_{ph}^i I_{[s_j^i = ph]} \ .$$

Subject to one condition, this form may represent a situation where the messages voters receive come from other voters. The condition relates to the fact that the models depend on values for the parameters that are used to compute the attributes x^i. The next section of this paper describes a method for using NES data to estimate the parameters in a way that takes the replicator dynamics into account; i.e., the estimates depend on a previous run of the replicator. A sharp question is whether the model can be closed in the sense that the parameter values that drive the replicator reproduce themselves in the subsequent estimation. The messages used in the model would then have the same characteristics as the strongly partisan voters, being generated by the same data and the same parameter values. A model that is not closed I will say is open. Failure to close the model—or failure to find a closed model that fits the data as well as an open model—would make it doubtful that the model represents signaling that originates among voters, because of the need to stipulate an external source. The most likely external source is just the parties. An open model is most likely a model with unified party signaling in another guise. A

[3]Either a Democrat incumbent is running for reelection, a Republican incumbent is running, or there is an open seat.

necessary condition for a messaging model to represent messages that originate with other voters is therefore that the model must be closed.

All told then, I will consider the six classes of models shown in Table 1. The three unstable models, based on (1), depend on the choice of a duration for the replicator to run and to some extent on the initial conditions. The steady state models, based on (2a-b), do not depend on a particular duration but do depend on the choice of values for μ and η. I consider open baseline models in which there is no messaging and in which there is messaging, each using both the unstable and the steady state replicator. The open models feature two sets of parameter values: the ones used to run the replicator and the ones produced by the subsequent estimation step. I also consider closed versions of the messaging models.

*** Table 1 about here ***

Estimation

To estimate the parameters of the evolutionary models using cross-sectional NES data, I define a likelihood for each voter's stated vote choices using the cross-sectional distribution of the probabilities ρ^i that each replicator generates.[4] Given x^i but treating ϵ^i as unknown, we can define the probability π^i_{ph} that the vote is $ph \in \mathcal{K}$ according to s_O:

$$\pi^i_{ph} = \frac{e^{-x^i_{ph}}}{G(x^i)} \frac{\partial e^{-G(x^i)}}{\partial e^{-x^i_{ph}}} \tag{3}$$

where $G(x^i)$ defines the joint cumulative distribution function of ϵ^i,

$$e^{-G(x^i)} = \Pr(\epsilon^i_{RR} < x^i_{RR}, \epsilon^i_{RD} < x^i_{RD}, \epsilon^i_{DR} < x^i_{DR}, \epsilon^i_{DD} < x^i_{DD})$$

(McFadden 1978). The particular definition of $G(x^i)$ depends on the correlation structure assumed for ϵ^i (see, e.g., (8) in Appendix B). Voter i chooses $ph \in \mathcal{K}$ either by using s_O or by using s_{ph}, so given x^i and ρ^i the overall probability of choosing ph is $g^i_{ph} = \rho^i_O \pi^i_{ph} + \rho^i_{ph}$. Using the g^i_{ph} values as probabilities in a multinomial choice model, the component of the log-likelihood for a voter i who chooses alternative ph is $\log g^i_{ph}$.

[4] Readers who are not interested in the methods used to estimate the models may wish to skip this section.

The ideal approach to estimating such a model is not feasible. Ideally we would run the replicator for each voter using each trial set of the parameter values that define x^i. This method is not feasible because the computations to run the replicator so frequently are too extensive.

Instead, I adopt a two-step method. First I use one set of x^i values, based on a fixed set of parameters, to run the replicator and hence determine ρ^i for all voters. Then I use the distribution of the ρ^i values to estimate new values for the parameters that define x^i. The ρ^i values used in the second step are not the fixed numbers determined in the first step but instead are the values of functions that approximate the cross-sectional distribution of the replicator results. This allows the ρ^i values used for each i to change with the new parameter values as x^i also changes, in a way that is compatible with the cross-sectional distribution determined by the replicator. If the new x^i values fall within the range of x^i values used to estimate the approximating function, we can be confident that the results of the two-step method are close to what the ideal approach would have produced.

I use a set of quadratic polynomials to approximate the cross-sectional relationship between the x^i values and ρ^i. I regress the logits $\log(\rho^i_{ph}/\rho^i_O)$, $ph \in \mathcal{K}$, on the following vector:

$$Z^i = \left[1, x^i_{RR}, x^i_{RD}, x^i_{DR}, (x^i_{RR})^2, (x^i_{RD})^2, (x^i_{DR})^2, (x^i_{DD})^2, x^i_{RR}x^i_{RD}, x^i_{RR}x^i_{DR}\right]' \ . \tag{4}$$

Because of symmetries in the particular definition of x^i I ultimately use, every linear or quadratic function of elements of x^i is a linear function of Z^i. For each logit I estimate the vector A_{ph} cross-sectionally in the following model by ordinary least squares:

$$\log(\rho^i_{ph}/\rho^i_O) = A'_{ph}Z^i + v^i_{ph} \ , \tag{5}$$

where v^i_{ph} has mean zero and variance σ^2_{ph}.[5] Using the estimates $\hat{A}_{ph}$ and a vector $\tilde{Z}$ having the

[5]In each year 1976–1996 I estimate the regressions (5) separately for each of three groups of voters: all Democrats, including leaners; all Republicans, including leaners; and pure Independents. With this partitioning of voters, the regressions (5) are highly accurate for most voters. Finer groupings of voters produce inferior results, due to the limited range of Z^i values.

form of (4), I compute m approximate strategy probabilities $\tilde{\rho}_j(\tilde{Z})$:

$$\tilde{\rho}_O(\tilde{Z}) = \left[1 + \sum_{ph\in\mathcal{K}} \exp(\hat{A}'_{ph}\tilde{Z})\right]^{-1} \tag{6a}$$

$$\tilde{\rho}_{ph}(\tilde{Z}) = \tilde{\rho}_O(\tilde{Z})\exp(\hat{A}'_{ph}\tilde{Z}), \quad ph \in \mathcal{K} \; . \tag{6b}$$

Using these approximate probabilities I define choice probabilities

$$\tilde{g}^i_{ph} = \tilde{\rho}^i_O \pi^i_{ph} + \tilde{\rho}^i_{ph}, \quad ph \in \mathcal{K} \; , \tag{7}$$

where $\tilde{\rho}^i_O = \tilde{\rho}_O(\tilde{Z}^i)$, $\tilde{\rho}^i_{ph} = \tilde{\rho}_{ph}(\tilde{Z}^i)$, and $\tilde{Z}^i$ is (4) with x^i defined using the current parameter estimates. Let $y^i_{ph} = 1$ if i chooses ph, otherwise $y^i_{ph} = 0$. Using sampling weights ϕ^i,[6] the log-likelihood is

$$L = \sum_{i=1}^{n} \phi^i \sum_{ph\in\mathcal{K}} y^i_{ph} \log \tilde{g}^i_{ph} \; ,$$

where n is the number of voters in the NES sample. I refer to this as an approximated evolutionary dynamics (AED) model. To estimate the model I keep the values $\hat{A}_{ph}$ used in (6a) and (6b) constant while finding new values for the parameters of x^i to maximize L. Using this likelihood, estimates of the parameters of x^i map through (3), (6a), (6b) and (7) to give an approximation of the choice probabilities induced by the replicator.[7]

I evaluate each replicator numerically for each voter in the survey sample, with a new, statistically independent value of ϵ^i being used each sim-day. The natural interpretation of this setup is that each voter considers a new set of random information about the choice alternatives each day, although it remains to be determined what relationship simulated time bears to voters' actual experiences. To focus on each replicator's expected path of evolution, I repeat each simulation at least ten times for each i and use the mean of ρ^i over the replications at each time in (5). Replicator (1) begins with a low probability of using s_O and equal probabilities of using each unconditional strategy: the initial conditions are $\rho^i_O = 1/10$ and $\rho^i_{ph} = 1/4 - 1/40$.

[6] The sampling weight is the reciprocal of the probability that i is included in the NES sample, rescaled for convenience so that the sum of the weights equals the original sample size.

[7] I use code written in **R** (R Development Core Team 2003) to obtain maximum likelihood estimates.

Replicator (2a-b) begins with $\rho_O^i = \eta$ and $\rho_{ph}^i = (1-\eta)\pi_{ph}^i$.[8]

For the steady state models, simulating the replicator and estimating an AED model for a large set of η and μ values would involve an inordinate amount of computing. I use a screening procedure that tends to make the steady state AED model produce a distribution of $\tilde{\rho}^i$ that is similar to the distribution given by a target model. I use a set of twenty observations from each year to choose values of η and μ that produce a distribution of ρ^i from simulating (2a-b) that is close to the distribution produced in the target model. I use the simulated steady state ρ^i values from sim-month 36 to compare the distributions; by sim-month 36, inspection shows that all of the specifications have reached steady-state values. I then estimate the steady state AED model using the chosen η and μ values. To smooth variations around the long-run steady-state mean, for each i in the AED model I use multiple ρ^i values to estimate A_{ph} in (5)—in particular, the six ρ^i values for sim-months 31 through 36. Experience shows this method produces steady state AED model $\tilde{\rho}^i$ distributions broadly similar but hardly identical to the target model.

I compare the AED models to one another in terms of how well each fits the survey data, and I also compare them to a choice model based on assuming that all voters use s_O. Because the AED models do not nest the model based solely on s_O, I use a nonnested hypothesis test to compare them. The models use the same data, the same definitions of the variables and the same functional form specifications to define x^i and π_{ph}^i, $ph \in \mathcal{K}$, but the likelihoods are the same only on the boundary of the evolutionary models that occurs when $\rho_O^i = 1$. In (1), ρ_O^i can get arbitrarily close to 1.0 but never equals 1.0. In (2a-b), ρ_O^i is strictly less than 1.0. Likewise, the alternative AED models based on either different replicators or the same replicator at different simulated times are not nested. I use Vuong's statistic (Vuong 1989, eqns. 5.6–5.8), here denoted V, to compare how well the models fit the data. V has a standard normal distribution if the models fit the data equally well.

Simulated and Estimated Dynamics

To support comparisons between the evolutionary models and the results of Mebane (2000), I simulate the replicators using the same data as Mebane (2000), namely, NES data from the six presidential elections of 1976–1996. I specify the optimizing strategy, s_O, to be the coordinating

[8] Examples of the *Mathematica* (Wolfram Research 2003) code used to run the simulations appear in Appendix C.

strategy Mebane defines, and I define x^i exactly as in Mebane (2000). I generate a sequence of ϵ^i values that have the same GEV distribution used in Mebane (2000). The definitions of x^i and G are described in detail in Appendix B. Details regarding the specification of the replicators and regarding model selection also appear in Appendix B.

Comparing the various models shows that having an explicit model of messaging substantially improves the fit to voters' behavior, and that closed models that represent the idea that the messages originate with other voters fit the data well. Table 2 reports the log-likelihood value for the coordinating model and each of the AED models, along with the results of the nonnested tests between every pair of models. The unstable and the steady state models without messaging (UN and SN) fit the data about equally well and slightly but not significantly better than the coordinating model. But the coordinating model and the UN and SN models all fit significantly worse than the unstable open model (UO). These results suggest that if the coordinating model somehow implicitly captures the messaging and cuing that occurs during presidential election campaigns, it does not provide as good a representation as the explicit treatment in the UO model. The steady state open model performs poorly, fitting the data worse than all the other models. The unstable closed model (UC) fits the data well, indeed slightly but not significantly better than the UO model. The fit of the steady state closed model (SC) is worse than both the UC and UO models, although not significantly so, but the SC model fits significantly better than the models without messaging and better than the coordinating model.

*** Table 2 about here ***

The results favor the closed models: UC among the unstable models and SC among the steady state models. The relative success of the closed models is compatible with the idea that voters receive and respond to partisan messages that originate with other voters. Of course the fact that the models are compatible with voter origination does not contradict the possibility that there is unified party signaling that simply gets filtered through strongly partisan voters. Whatever the ultimate origin of the messages, the results suggest the messages do not diverge from the considerations brought to bear by strong partisans who use s_O in their voting decisions.

Between the two closed models, UC fits the data better than SC does. Because the gap between UC and SC is not all that large, it is likely that presidential campaigns fall somewhere between the alternative conceptions that motivate (1) and (2a-b). For most people, perhaps, the campaign period is unique and terminates on election day, while for others an active contest between the parties never really ends.

The fact that SC does so well makes it interesting to consider what its characteristics suggest about the learning processes the models are supposed to represent. The most striking feature of SC is the low value of μ it seems to imply. Having $\mu = .02$ suggests that at any particular time only one in fifty voters is involved in the processes of imitation that (1) represents. Imitation, in this case, is not producing very frequent or rapid changes in voters' strategies. Relatively few voters appear to be using s_O: considering all voters in all years, the mean of $\tilde{\rho}^i_O$ in the SC AED model is .29 with standard deviation .03. The small value of μ suggests that the 71 percent of voters who are using an unconditional strategy rarely reappraise the strategy. While every voter continually receives a stream of messages in the model, the fact that $\mu = .02$ means that roughly 98 percent of the time voters are not doing anything to update their strategies in response to that information. Their opinions about the payoffs associated with each strategy may fluctuate, as new messages arrive and random events occur, but mostly they do not reevaluate their strategies, and mostly they do not change them.

Of course, SC does not fit the data quite as well as UC, so most likely there is more dynamism among voters during the campaign period than the SC model would suggest. But an image of thin interactions and rare changes in voters' strategies is probably closer to the truth than one of ubiquitous cuing and great volatility.

Estimated Strategy Distribution

The distribution of $\tilde{\rho}^i$ implied by the best fitting AED model—the UC model—confirms the impression that voters mostly do not use s_O. Over all voters in all years, the mean of $\tilde{\rho}^i_O$ in the UC AED model is .28 with standard deviation .02. Table 3 shows the mean value of $\tilde{\rho}^i$ by voter party identification and House incumbent status, computed using the UC AED model parameter estimates. Table 3 shows mean values of $\tilde{\rho}^i_O$ ranging from .26 to .31. The highest values of $\tilde{\rho}^i_O$ occur for strong partisans when either a House incumbent of their same party is running or there is an open seat. The lowest values of $\tilde{\rho}^i_O$ occur for pure Independents.

*** Table 3 about here ***

The use of unconditional straight-ticket strategies depends strongly on the status of the House incumbent. Strong, weak and leaning partisans are all highly likely to vote a straight ticket for their party unconditionally when a concordant House incumbent is running. For Democrats in such circumstances the mean of $\tilde{\rho}^i_{DD}$ ranges from .61 to .63, and for Republicans the mean of $\tilde{\rho}^i_{RR}$ ranges from .64 to .67. With an open seat, these means drop more for Republicans than for Democrats. With an open seat, for Republicans the mean of $\tilde{\rho}^i_{RR}$ ranges from .48 to .57 while for Democrats the mean of $\tilde{\rho}^i_{DD}$ ranges from .53 to .58. But when a House incumbent from the opposite party is running, it is Democrats whose propensity to give unconditional support to their party shrinks most. In this circumstance the mean of $\tilde{\rho}^i_{DD}$ ranges from .32 to .43 for Democrats, and the mean of $\tilde{\rho}^i_{RR}$ ranges from .42 to .54 for Republicans. For each status of the House incumbent it is strong partisans who always have the highest mean probability of unconditionally supporting their party. Partisans almost never unconditionally vote a straight ticket for the other party when a concordant House incumbent is running, and they rarely do so otherwise. Pure Independents are relatively unlikely to use either s_{RR} or s_{DD}, but between the two s_{RR} is more likely. For pure Independents, the mean of $\tilde{\rho}^i_{RR}$ ranges from .16 to .33 while the mean of $\tilde{\rho}^i_{DD}$ ranges from .05 to .22. For pure Independents s_{RR} or s_{DD} are each least likely when a House incumbent of the other party is running.

Unconditional strategies to vote a split ticket are most likely when there is a House incumbent to attract votes from supporters of the other party. But Democrats facing such an incumbent are more likely to split their tickets to vote unconditionally for that incumbent than Republicans are: with a Republican incumbent, the mean of $\tilde{\rho}^i_{DR}$ among Democrats ranges from .27 to .36; with a Democrat incumbent, the mean of $\tilde{\rho}^i_{RD}$ among Republicans ranges from .14 to .22. Democrats are slightly more likely than Republicans are to vote an unconditional split ticket for the other party's House candidate when there is an open seat. In that case the mean of $\tilde{\rho}^i_{DR}$ among Democrats ranges from .09 to .13 while the mean of $\tilde{\rho}^i_{RD}$ among Republicans ranges from .07 to .11. Partisans are unlikely to use an unconditional split-ticket strategy that involves voting for the other party's presidential candidate. The mean probabilities for that range from .01 to .09.

Coordinating Strategy Parameters

The UC AED model parameter estimates show that with one important exception the UC model and Mebane's (2000) coordinating model support the same conclusions about how voters behave when using s_O. Table 4 reports the UC AED model parameter estimates, with 95% confidence intervals.[9] For convenience the table also shows the point estimates for the coordinating model. Most of the coordinating model point estimates fall within the 95% confidence interval for the corresponding parameter in the UC AED model. The coefficients for the dummy variables that indicate House incumbent status differ slightly: the coordinating model's estimate for the effect of having a Democratic incumbent running (c_{DEM}) is slightly below and the estimate for the effect of having a Republican incumbent running (c_{REP}) is slightly above the UC model's 95% intervals. The coefficients for party identification differ considerably. The coefficients that distinguish pure Independents (c_I) and Republicans (strong, weak and leaners, respectively c_{SR}, c_R and c_{IR}) from Strong Democrats are substantially smaller in the UC model than in the coordinating model. Indeed, the confidence intervals of the coefficients for weak Democrats (c_D), Independent Democrats (c_{ID}), pure Independents, Independent Republicans and weak Republicans substantially overlap one another.[10] The intercept parameters for each year ($c_{P0,76}$ through $c_{P0,96}$ and $c_{H0,76}$ through $c_{H0,96}$), which indicate the baseline for Strong Democrats, are of smaller magnitude in the UC model than in the coordinating model. This result conveys a picture startlingly different from the coordinating model and indeed from the one usually seen in analysis of NES data: usually all Republicans have baselines sharply different from all Democrats. The UC AED model results suggest that for voters who use s_O there are essentially three different starting points in terms of raw partisanship: strong Democrats and strong Republicans have distinctive baselines, and everyone else is the same.

*** Table 4 about here ***

The estimated UC AED model parameters agree with Mebane's (2000) estimates regarding the way voters who use s_O respond to the separation of powers between the president and the legislature in policymaking. The policy outcomes voter i expects in the coordinating model are $\alpha\theta^i_P + (1-\alpha)[\bar{H}\theta^i_R + (1-\bar{H})\theta^i_D]$, where θ^i_R and θ^i_D are respectively the policy positions of the Republican and Democratic parties, θ^i_P is either θ^i_R or θ^i_D depending on which party controls the

[9] In light of the complications parameter estimates on a boundary of the parameter space induce in the asymptotic distribution of the estimates (Moran 1971; Self and Liang 1987), I follow Mebane (2000) and bootstrap the score vectors to estimate quantiles of the distribution implied by $\alpha_{D,76} = \alpha_{D,84} = \rho_{D,84} = \rho_{D,92} = \rho_{R,80} == \rho_{R,96} = 1$. The notable asymmetry of some of the confidence intervals primarily reflects the nonlinearity of the model. The confidence intervals are estimated with the vectors $\hat{A}_{ph}$ and functional form (6a-b) treated as known.

[10] The standard errors reported in Mebane (2000, Table 2) show such overlap does not occur in the coordinating model.

presidency, α measures the power of the president ($0 \leq \alpha \leq 1$), and $\bar{H}$ is the proportion of votes Republicans are expected to win nationally in the legislative election ($\bar{H}$ satisfies a fixed point constraint). There are 12 different estimates for α, one for each party in each of the six election years. The UC AED model estimates are all close to the coordinating model estimates: in every year the winning presidential candidate was expected to be more powerful than the legislature.[11] The models produce the same value in each year for $\bar{H}$ (to two significant figures). Seven parameters (q, b_P, b_{HP}, b_H, b_{PH}, b_{E0} and b_{E1}) determine the weight policy positions have in each voter's decision making, and all have similar estimates in the two models. The large, positive values for b_P and b_H mean that voters who use the coordinating strategy act as if their votes measurably affect the presidential and legislative election outcomes, and the fact that b_{HP} is positive while b_{PH} is zero reflects the existence of a presidential coattail effect.[12] The models also produce the same values for an additional quantity that affects the weight policy considerations have, namely $\bar{P}$, which is the probability that the Republican will win the presidency ($\bar{P}$ is also subject to a fixed point constraint).

The UC AED model conveys the same impression as the coordinating model regarding voters' reactions to economic conditions when using s_O. The estimates for the coefficents of the variable that measures subjective retrospective evaluations ($c_{P1,76}$, $c_{H1,76}$, etc.) suggest that those who think economic conditions have gotten worse usually reduce their support for candidates of the incumbent president's party.

Discussion

First consider the fact that the UC and SC models seem to fit the data so similarly, despite the fact that (1) and (2a-b) are so different. That $\tilde{\rho}^i_O$ in the UC AED model varies so little across conditions of partisanship and House incumbent status supports the notion that s_O is simply too difficult or too costly for most voters to use most of the time. There is no reason why the cost of using s_O should vary substantially with whether an incumbent is running or with a voter's policy preferences. So, by and large, the distribution of such costs should not be related to partisanship and House incumbent status. In that case, the cost-induced upper bound on ρ^i_O should be

[11] Mebane's (2000) model also includes 12 parameters that measure how positions each voter states for the parties and presidential candidates combine to produce θ^i_R and θ^i_D. The models agree regarding those parameters' estimates.

[12] For details see Mebane (2000, 50).

roughly the same among voters in all the partisanship and incumbent status categories, and that is the pattern in Table 3. The UC AED model thereby inductively confirms one of the ideas that motivate (2a-b), without the idea being formally built in. Even though (1) is unstable, the UC AED model estimates point strongly to a key concept that implies steady state behavior.

So despite the fact that the SC AED model fits slightly worse than the UC model, it is reasonable to take seriously what the SC model suggests about the heterogeneity of different voters' experiences during presidential campaigns. The small value of μ in the SC model suggests that at any given time during a campaign only a small percentage of voters are evaluating their strategies and making changes in imitation of others they encounter. That form of cuing happens only sporadically. On the other hand, if we take from the UC model a campaign duration of 60 sim-days, then $\mu = .02$ suggests that reevaluation occupies roughly one $(.02(60) = 1.2)$ sim-day. If we boldly map sim-days directly onto days, that may suggest that for each voter typically there is one day during the campaign period on which the voter makes up his or her mind what strategy to use.[13] For voters who decide to use an unconditional strategy, that decision is effectively the vote choice decision. Rare changes due to cuing would be consequential changes, as voters would tend to stick with the strategies they adopt.

The persistent heterogeneity of strategies for each i has two sharply divergent interpretations, depending on how one resolves the basic ambiguity regarding ρ^i: does ρ^i represent a mixed strategy for each voter i, or does ρ^i measure the proportion of voters with attributes x^i who are using each of the five strategies in S?

Concluding that ρ^i represents a mixed strategy means that almost every voter has the personal competence to use s_O and at any given time may do so. In this case, drawing on Samuelson (1997), it is in a formal sense reasonable to treat the SC AED model parameter estimates as calibrating a Nash equilibrium wherein each voter's gains from using s_O are balanced by the costs represented by η in (2a-b). The results then suggest that in equilibrium every voter sometimes works hard to be vigilant and make the best decision, but mostly voters are doing what is easy and voting without having to make any decisions at all. Given the distribution of $\tilde{\rho}^i_O$,

[13] It is interesting that the 60 sim-day duration of the best fitting unstable model roughly matches the period from Labor Day to election day that is traditionally the time when the presidential general election campaign occurs. Too many features of the model are arbitrary to believe the result validates the reality of the model's timing. Nonetheless, the correspondence is intriguing.

the probability of a voter's being vigilant is typically less than 0.3. The SC model is more suitable for interpretation as a Nash equilibrium solution than the UC model is, because nothing about the formulation of (1) has voters taking into account the fact that the election will happen at a particular date. Strictly speaking, the only Nash equilibrium solution of (1) occurs in the limit when $\rho^i_O = 1$ for all i. That is, with (1) the only Nash equilibrium is the coordinating model. In that light, the fact that the UC model (for sim-month two) fits the data slightly better than the SC model does may be evidence that the situation on election day is not a Nash equilibrium for all voters. But the fact that the SC model fits the data as well as it does may mean that the discrepancy from a Nash equlibrium configuration is small.

Concluding instead that ρ^i measures the proportion of voters who are using each of the five strategies is compatible with the idea that only a few voters are personally competent to use s_O. Such an interpretation would be firmly in line with the tradition that runs through Converse (1964, 1990), wherein most people are not thought to know enough to think coherently about politics, let alone to make optimal electoral decisions. The voters who use s_O take into account not only one another but also the majority of voters who are voting unconditionally.[14] So the success of the SC AED model may indicate there is approximately a Nash equilibrium among the voters who use s_O but not among the whole electorate.

The interpretation of ρ^i as measuring proportions implies a story about the voting behavior of most voters that is incompatible with the behavioral model of Campbell, Converse, Miller, and Stokes (1960). The more than 70 percent of voters who use an unconditional strategy according to the UC AED and SC AED models do not begin with a baseline of party sentiment from which they may depart in response to short-term considerations of policy, performance, personality or whatnot. The nature of the unconditional strategies is such that voters who use them do not make new voting decisions at election time at all. The commitment to use an unconditional strategy might be described as a "standing decision" (Key 1966), but it is a decision more radically habitual than most believe is entailed by being a party identifier (compare Green, Palmquist, and Schickler 2002). If a voter uses an unconditional strategy, the voter's beliefs about policy, performance or other factors have no effect on the vote cast. A voter whose decisions depend on assessing variable considerations is not using an

[14]This refers to the fact that in the AED models $\bar{P}$ and $\bar{H}$ are fixed points. See Appendix B.

unconditional strategy. In view of the value of μ in the SC AED model, it is a question whether the frequency with which voters reconsider their strategies and, possibly, change them through imitation is high enough to correspond to the contingent variability Campbell et al. (1960) and the succeeding literature attribute to all voters.

In both the UC and SC models, the mix of strategies occurs in an environment that presents voters with a stream of partisan messages. In a precise technical sense, the messages come from anyone who is a strong party identifier, but if we step back a bit from the exact way the simulations are formulated we arrive at an interesting connection to the idea that the parties are nothing more than the electon-oriented face of activists and interest groups. Consider the interpretation of ρ^i as measuring proportions. In that case Table 3 shows that only about 30 percent of strong partisans use s_O. It is reasonable to think that only those who are themselves using information about policy positions and economic performance in their own voting decisions are likely to be the originators of the information. Those who are not using the information are most likely, at best, simply passing it along. So only about 30 percent of the strong partisans would be candidates for being message originators. Over all six election years, about 38 percent of voters are strong partisans, implying that the message originators are limited to about 11 percent of voters. In contemporary parlance, this 11 percent might be described as comprising each party's vocal "base"—the voters politicians and party leaders are loath to offend. If the base were unconditionally loyal to the party they favor, politicians would not need to be so careful to minister to them. In the UC and SC models, the greatest risk for politicians is not that these voters will personally switch to support the other side, even though, as users of s_O they might readily do that in response to undesirable policy stances. The greatest risk is that they will start to send messages that cue the unconditional voters to follow them out of the party.

Mostly voters do not use s_O, but the proportion who do is ample to make the coordinating voters the decisive voters in most American presidential elections. This means that the AED model estimates support the aggregate implications of the theory of policy moderation and institutional balancing developed by Alesina and Rosenthal (1995) as strongly as the coordinating model estimates of Mebane (2000) do. The estimates for all of the parameters that matter for that theory are effectively the same in both models. The electorate may be characterized as engaged in large-scale strategic coordination, as defined by Mebane (2000), even though more than 70 percent of the electorate is voting unconditionally for one party or the other, or unconditionally voting a split ticket.

Voters do not act in isolation. They communicate with others. Many voters look to others for guidance about what they should do. But the low value for μ in the SC AED model suggests that such cuing interactions are relatively infrequent, too rare, perhaps, for presidential elections to be subject to bubbles and fads such as more prevalent imitation would tend to produce. During the campaign many voters effectively never change their voting strategies—strategies that specify unconditional voting behavior—notwithstanding changes that occur in their opinions about the issues, the economy and other volatile factors. For most voters, most of the time, those opinions shift with the partisan messages they receive. The messages may not be particularly meaningful apart from their function as markers for cues the voters follow on the sporadic occasions when they reevaluate their strategies. A subset of voters originate the messages, which both reflect and structure the competition between the parties.

Such an electorate, in such a comprehensively partisan environment, is the one represented by the evolutionary models I have investigated, in light of the empirically derived estimates of the parameters of those models. Embedded in that electorate is a subsystem of voters who behave like optimal strategists, taking into account the institutions of American government and the strands of policy debate, warily eyeing and counterbalancing one another. Beyond presidential elections and the coordinating model, I imagine such an arrangement generally describes what happens in electoral systems and in the dynamics of national political economies. Most actors act unconditionally, a relative few act with full sophistication, and information flows through networks from the one group to the other. In the aggregate, it may be that what the more sophisticated actors do dominates, because they are more volatile and because the messages they originate tend, eventually, to drag the others along. But close inspection of many individuals may leave one unimpressed with their competence. To focus on the individuals in isolation, however, without developing a clear picture of all that ties them together, is a mistake.

Appendix A

Proof of Remark 1: In (2a-b), ϵ^i varies over time, but each value of ϵ^i persists during a finite period of time. Because $\mu(1 + u^i_O - \bar{u}^i) \geq 1$ implies $\dot{\rho}^i_O > 0$, and because, for each value of ϵ^i,

$(u^i_O - \bar{u}^i)$ decreases as ρ^i_O increases, eventually $1 > \mu(1 + u^i_O - \bar{u}^i)$. Define $\nu^i_O = \eta(1-\mu)/(1-\mu(1+u^i_O - \bar{u}^i))$. If $1 > \mu(1+u^i_O - \bar{u}^i)$, then $\mathrm{sgn}(\dot{\rho}^i_O) = \mathrm{sgn}(\nu^i_O - \rho^i_O)$. If $\rho^i_O < 1$, then almost surely $u^i_O > \bar{u}^i$ and therefore $\nu^i_O > \eta$. Hence ρ^i_O eventually becomes and remains larger than η. Because $\rho^i_O = 1$ implies $\nu^i_O = \eta$, ρ^i_O stays below 1.0. As μ is closer to zero, the upper bound on ρ^i_O is closer to η.

Consider the situation with $\rho^i_O > \eta$. If $u^i_{ph} < \bar{u}^i$, then $\mathrm{sgn}(\dot{\rho}^i_{ph}) = \mathrm{sgn}(\nu^i_{ph} - \rho^i_{ph})$, where $\nu^i_{ph} = (1-\mu)(\eta - \rho^i_O)/(4\mu(u^i_{ph} - \bar{u}^i)) > 0$. This bounds ρ^i_{ph} above zero. If typically $u^i_{ph} < \bar{u}^i$, then eventually ρ^i_{ph} tends to stay near ν^i_{ph}, and the more negative $(u^i_{ph} - \bar{u}^i)$ typically is, the smaller ν^i_{ph} is. If $u^i_{ph} \geq \bar{u}^i$, then $\dot{\rho}^i_{ph} > 0$, but $(u^i_{ph} - \bar{u}^i)$ decreases as ρ^i_{ph} increases. If typically $u^i_{ph} > \bar{u}^i$, then eventually $\rho^i_{ph} \approx 1 - \rho^i_O$, and because in this eventuality typically $u^i_O - \bar{u}^i \approx 0$ whenever $u^i_{ph} > \bar{u}^i$, ν^i_O is typically just slightly larger than η and ρ^i_{ph} eventually remains slightly smaller than $1 - \eta$. If there are two alternatives $ph \in \mathcal{K}$ and $ph^* \in \mathcal{K}$ such that typically either $u^i_{ph} > \bar{u}^i$ or $u^i_{ph^*} > \bar{u}^i$, then typically $u^i_O - \bar{u}^i$ does not approach zero so that, if μ is not very small, ν^i_O may be substantially larger than η and ρ^i_O may stay near values substantially larger than η. $\square$

Appendix B

The following definition of x^i_{ph} is the same as the definition of x_{phi} given by Mebane (2000, eqs. (6a–d)), using this paper's convention that individuals are indexed using a superscript i, and using γ_D and γ_R to denote the parameters Mebane (2000) denoted ρ_D and ρ_R. The variables mentioned in the formulas have the following meanings (see Mebane (2000) for full details). θ^i, ϑ^i_{PD}, ϑ^i_D, ϑ^i_{PR} and ϑ^i_R are the voter's average placement on several policy items of, respectively, self, the Democratic presidential candidate, the Democratic party, the Republican presidential candidate and the Republican party. EC^i is the voter's evaluation of the national economy over the past year. $\mathrm{PP}^i = 1$ if the president is a Republican and $\mathrm{PP}^i = -1$ if the president is a Democrat. $\mathrm{DEM}^i = 1$ if a Democrat is running for reelection in the voter's congressional district, otherwise $\mathrm{DEM}^i = 0$. $\mathrm{REP}^i = 1$ if a Republican incumbent is running in the voter's, otherwise $\mathrm{REP}^i = 0$. $\mathrm{PID_D}^i$, $\mathrm{PID_{ID}}^i$, $\mathrm{PID_I}^i$, $\mathrm{PID_{IR}}^i$, $\mathrm{PID_R}^i$ and $\mathrm{PID_{SR}}^i$ are dummy variables that correspond to levels of the NES seven-point scale measure of partisanship, using "Strong

Democrat" as the reference category. I discuss $\bar{H}$ and $\bar{P}$ below.

$$
\begin{aligned}
\theta_D^i &= \gamma_D \vartheta_{PD}^i + (1-\gamma_D)\vartheta_D^i \,, \qquad 0 \le \gamma_D \le 1 \,, \\
\theta_R^i &= \gamma_R \vartheta_{PR}^i + (1-\gamma_R)\vartheta_R^i \,, \qquad 0 \le \gamma_R \le 1 \,, \\
\tilde{\theta}_D^i &= \alpha_D \theta_D^i + (1-\alpha_D)[\bar{H}\theta_R^i + (1-\bar{H})\theta_D^i] \,, \qquad 0 \le \alpha_D \le 1 \,, \\
\tilde{\theta}_R^i &= \alpha_R \theta_R^i + (1-\alpha_R)[\bar{H}\theta_R^i + (1-\bar{H})\theta_D^i] \,, \qquad 0 \le \alpha_R \le 1 \,, \\
\beta^i &= (1 + \exp\{-b_{E0} - b_{E1}\mathrm{EC}^i\})^{-1} \,, \\
w_P^i &= (1-\beta^i)|\theta^i - \tilde{\theta}_R^i|^q - \beta^i|\theta^i - \tilde{\theta}_D^i|^q \,, \\
w_H^i &= q(\theta_D^i - \theta_R^i)[(1-\alpha_R)\bar{P}(1-\beta^i)|\theta^i - \tilde{\theta}_R^i|^{q-1}\,\mathrm{sgn}(\theta^i - \tilde{\theta}_R^i) \\
&\qquad + (1-\alpha_D)(1-\bar{P})\beta^i|\theta^i - \tilde{\theta}_D^i|^{q-1}\,\mathrm{sgn}(\theta^i - \tilde{\theta}_D^i)] \,, \\
z_{RR}^i &= -c_{P0} - c_{H0} - c_{REP}\mathrm{REP}^i - (c_{P1} + c_{H1})\mathrm{PP}^i\mathrm{EC}^i \\
&\qquad - c_D\mathrm{PID_D}^i - c_{ID}\mathrm{PID_{ID}}^i - c^i\mathrm{PID_I}^i - c_{IR}\mathrm{PID_{IR}}^i - c_R\mathrm{PID_R}^i - c_{SR}\mathrm{PID_{SR}}^i \,, \\
z_{RD}^i &= -c_{P0} + c_{H0} - c_{DEM}\mathrm{DEM}^i - (c_{P1} - c_{H1})\mathrm{PP}^i\mathrm{EC}^i \,, \\
z_{DR}^i &= c_{P0} - c_{H0} - c_{REP}\mathrm{REP}^i + (c_{P1} - c_{H1})\mathrm{PP}^i\mathrm{EC}^i \,, \\
z_{DD}^i &= c_{P0} + c_{H0} - c_{DEM}\mathrm{DEM}^i + (c_{P1} + c_{H1})\mathrm{PP}^i\mathrm{EC}^i \\
&\qquad + c_D\mathrm{PID_D}^i + c_{ID}\mathrm{PID_{ID}}^i + c^i\mathrm{PID_I}^i + c_{IR}\mathrm{PID_{IR}}^i + c_R\mathrm{PID_R}^i + c_{SR}\mathrm{PID_{SR}}^i \,, \\
x_{RR}^i &= (b_P + b_H b_{PH})w_P^i + (b_H + b_P b_{HP})w_H^i + z_{RR}^i \,, \\
x_{RD}^i &= (b_P - b_H b_{PH})w_P^i + (b_P b_{HP} - b_H)w_H^i + z_{RD}^i \,, \\
x_{DR}^i &= (b_H b_{PH} - b_P)w_P^i + (b_H - b_P b_{HP})w_H^i + z_{DR}^i \,, \\
x_{DD}^i &= -(b_P + b_H b_{PH})w_P^i - (b_H + b_P b_{HP})w_H^i + z_{DD}^i \,.
\end{aligned}
$$

In Mebane (2000), all voters use the coordinating strategy and, in equilibrium, each voter has rational expectations about the way everyone else will vote. $\bar{P}$ and $\bar{H}$ measure these expectations. $\bar{P}$ is the probability that the Republican will win the presidency. $\bar{H}$ is the proportion of votes Republicans are expected to win nationally in House races. Formally, $\bar{P}$ and $\bar{H}$ are complicated functions of π_{ph}^i, $ph \in \mathcal{K}$. See Mebane (2000) for details. In equilibrium, $\bar{P}$ and $\bar{H}$ are fixed points of the relationship between voters' behavior and voters' beliefs about the election outcome.

In the AED models, $\bar{H}$ and $\bar{P}$ are computed as in Mebane (2000), except using $\tilde{g}_{ph}^i$ instead of

π^i_{ph}. This implies that the existence of the replicator is treated as common knowledge for voters using s_O. AED model estimates satisfy a fixed-point condition involving $\bar{H}$ and $\bar{P}$. When simulating the replicators I do not impose the fixed point constraint. Instead, the numerical values for $\bar{P}$ and $\bar{H}$ computed using the coordinating model or using the estimates of a previous AED model are used, depending on the model parameters used to compute x^i.

Mebane (2000) uses

$$G(x) = e^{-x_{RR}} + \left(e^{-x_{RD}/(1-\tau)} + e^{-x_{DR}/(1-\tau)}\right)^{1-\tau} + e^{-x_{DD}} \ , \tag{8}$$

where $0 \leq \tau < 1$ (Mebane 2000, 41–42). To sample from this distribution,[15] I combine standard type 1 extreme value variates (Johnson, Kotz, and Balakrishnan 1995, 24) with variates from the bivariate extreme value distribution $\exp[-(e^{-x_{RD}/(1-\tau)} + e^{-x_{DR}/(1-\tau)})^{1-\tau}]$ produced using the method of Nadarajah (1999), which generates unit Fréchet bivariate values that I transform to have standard type 1 marginals. For background see Kotz, Balakrishnan, and Johnson (2000) and Mari and Kotz (2001).

When running (1) or (2a-b) for the open models (UN, UO, SN and SO), I use the parameter estimates for the best coordinating model reported in Mebane (2000) to compute x^i. For the UN and UO models I run (1) for 12 sim-months and estimate the AED model using the simulation results from the end of each sim-month. Of the 12 UN models, the largest L value is obtained for sim-month eleven, and of the UO models the largest is obtained for sim-month two. These two models are also better than the models of the same type for the other sim-months according to V, although the differences are not always statistically significant. Therefore in the text I focus on these two models.

For the UC model, I initially used the UO AED model parameter estimates to compute x^i in (1), but the resulting UC AED model does not satisfy the conditions for closure: the 95% confidence intervals for several parameters substantially fail to include the corresponding parameter values that were used to run (1). Using these initial UC AED model parameter estimates to compute x^i and run (1) and then using the resulting $\tilde{\rho}^i$ distribution to estimate the UC AED model eliminates the disparity.[16]

[15] I use $\tau = 0.392$ as estimated in Mebane (2000).

[16] The 95% confidence intervals of the iterated UC AED model contain the initial UC model parameter values used

For the SC model, I use the UC AED model's parameter estimates to compute x^i when running (2a-b). The resulting SC AED model satisfies the conditions for closure.[17]

I use the screening procedure for choosing η and μ to match simulations of each of the steady state models to the distribution of $\tilde{\rho}^i$ produced by the corresponding unstable AED model. Matching SN to the UN AED model gives $\eta = .2$, $\mu = .9$, matching SO to the UO AED model gives $\eta = .32$, $\mu = .45$, and matching SC to the UC AED model gives $\eta = .3$, $\mu = .02$.

Appendix C

Following is *Mathematica* code used to simluate (1) for the initial UC model using 1976 NES data. Each of the files called `randsi.dat`, `i` $= 1, \ldots, 10$, contains 10,000 pseudorandom vectors independently generated with the GEV distribution (8). File `obsS76.dat` contains the x^i vectors for the UO AED model estimates.

```
AppendTo[$Echo, "stdout"];

randmats = Table[rands[i], {i, 10}];
Do[
  fname = "rands" <> ToString[i] <> ".dat" ;
  randmats[[i]] = Import[fname, "Table"]; , {i, 10}
];

mix := 1/2;

getpty[obsmat_, k_] := obsmat[[k,5]];

getinc[obsmat_, k_] := Module[{fdem,frep},
  fdem = obsmat[[k,6]];
  frep = obsmat[[k,7]];
  inc = If[fdem==1, 1, If[frep==1, 2, 3]]; (* 1 Dem, 2 Rep, 3 Open *)
  Return[inc];
];

idx[t_] :=  1 + IntegerPart[30 N[t]];
x[1][t_] := obs[[1]] * mix + rands[[idx[t], 1 ]];
x[2][t_] := obs[[2]] * mix + rands[[idx[t], 2 ]];
x[3][t_] := obs[[3]] * mix + rands[[idx[t], 3 ]];
```

to run (1), except the initial model has $\hat{c}_{IR} = 1.42$ while the upper bound of the iterated model's 95% interval for c_{IR} is 1.41.

[17] The 95% confidence intervals of the SC AED model contain the UC AED model parameter values used to run (2a-b), except the UC AED model has $\hat{c}_{REP} = 1.22$ while the upper bound of the SC AED model's 95% interval for c_{REP} is 1.19.

```
x[4][t_] := obs[[4]] * mix + rands[[idx[t], 4 ]];
x[5][t_] := Max[x[1][t], x[2][t], x[3][t], x[4][t]] ;
xavg[t_] := (x[1][t] r[1][t] + x[2][t] r[2][t] +
             x[3][t] r[3][t] + x[4][t] r[4][t] + x[5][t] r[5][t]) ;

runsim[n_] := NDSolve[{
 r[1]'[t] == r[1][t] (x[1][t] - xavg[t]),
 r[2]'[t] == r[2][t] (x[2][t] - xavg[t]),
 r[3]'[t] == r[3][t] (x[3][t] - xavg[t]),
 r[4]'[t] == r[4][t] (x[4][t] - xavg[t]),
 r[5]'[t] == r[5][t] (x[5][t] - xavg[t]),
 r[1][0] == 1/4-1/40, r[2][0] == 1/4-1/40,
 r[3][0] == 1/4-1/40, r[4][0] == 1/4-1/40,
 r[5][0] == 1/10},
 {r[1], r[2], r[3], r[4], r[5]},
 {t, 0, n}, AccuracyGoal -> Infinity, MaxSteps -> Infinity];

simit[time_, obsmat_, m_] := Module[{pty, inc, ridx, oidx, tlim, swrk},
  smix := 0;
  obs = obsmat[[m, {1, 2, 3, 4}]];
  tlim = time 30;
  pmat = Table[pvec[i], {i, tlim}];
  Do[
    pty = getpty[obsmat, m];
    inc = getinc[obsmat, m];
    ridx = Random[Integer, {1, ptyinccount[[pty, inc]][[1]] }];
    oidx = ptyincindx[[pty, inc]][[ridx]];
    pty2 = Switch[pty,
           1, 1,
           2, 1,
           3, 1,
           4, 4,
           5, 7,
           6, 7,
           7, 7];
    ridx2 = Random[Integer, {1, ptyinccount[[pty2, inc]][[1]] }];
    oidx2 = ptyincindx[[pty2, inc]][[ridx2]];
    pmat[[i]] = smix * obsmat[[oidx, {1, 2, 3, 4}]] +
              (1-smix) * obsmat[[oidx2, {1, 2, 3, 4}]];
  , {i, tlim}];
  swrk = Table[sol[i], {i, 10}];
  Do[
    rands = randmats[[k]];
    Do[
      rands[[i]] = rands[[i]] + pmat[[i]] * (1-mix) ;
    , {i, tlim}];
    swrk[[k]] = runsim[time];
  , {k, 10}];
```

```
  Return[swrk];
];

states = Table[Table[st[i][j], {i, 683}, {j, 5}], {im, 12}];

obsmat = Import["obsS76.dat", "Table"];

ptyincindx = Table[{}, {i, 7}, {j, 3}];
ptyinccount = Table[{}, {i, 7}, {j, 3}];
Do[ ptyinccount[[i, j]] = {0};, {i, 7}, {j, 3}];
nrows = Length[obsmat];
Do[
  pty = getpty[obsmat, k];
  inc = getinc[obsmat, k];
  ptyinccount[[pty, inc]] = ptyinccount[[pty, inc]] + 1;
  ptyincindx[[pty, inc]] = Append[ptyincindx[[pty, inc]], k] ;
  , {k, nrows}
];

esumtabs[k_, sols_, sols2_, sols3_] :=  Module[{},
  Return[Evaluate[
      ( Sum[Table[r[i][k], {i, 5}] /. sols[[j]], {j, 10}]
      + Sum[Table[r[i][k], {i, 5}] /. sols2[[j]], {j, 10}]
      + Sum[Table[r[i][k], {i, 5}] /. sols3[[j]], {j, 10}])
        / 30]];
];

time := 12;
Do[
  sols = simit[time, obsmat, m];
  sols2 = simit[time, obsmat, m];
  sols3 = simit[time, obsmat, m];
  Do[
    states[[im, m]] = esumtabs[im, sols, sols2, sols3][[1]];
    , {im, 12}];
    FortranForm[states] >> "stateSS.76.out";
  , {m, 683}];
```

To simluate (2a-b) for the steady state model, the function `runsim` is defined as follows. The parameter `mu` in the program equals $1 - \mu$ in (2a-b).

```
runsim[n_] := NDSolve[{
 r[1]'[t] == (1-mu) r[1][t] (x[1][t] - xavg[t]) + mu (r[5][t] - eta)/4,
 r[2]'[t] == (1-mu) r[2][t] (x[2][t] - xavg[t]) + mu (r[5][t] - eta)/4,
 r[3]'[t] == (1-mu) r[3][t] (x[3][t] - xavg[t]) + mu (r[5][t] - eta)/4,
 r[4]'[t] == (1-mu) r[4][t] (x[4][t] - xavg[t]) + mu (r[5][t] - eta)/4,
 r[5]'[t] == (1-mu) r[5][t] (x[5][t] - xavg[t]) + mu (eta - r[5][t]),
```

```
r[1][0] == (1-eta) props[[1]],
r[2][0] == (1-eta) props[[2]],
r[3][0] == (1-eta) props[[3]],
r[4][0] == (1-eta) props[[4]],
r[5][0] == 1 - (1-eta) (props[[1]]+props[[2]]+props[[3]]+props[[4]]) },
{r[1], r[2], r[3], r[4], r[5]},
{t, 0, n}, AccuracyGoal -> Infinity, MaxSteps -> Infinity];
```

The `props` vector contains the choice probabilities from the coordinating model.

References

Aldrich, John. 1995. *Why Parties: The Origin and Transformation of Political Parties in America*. Chicago: University of Chicago Press.

Alesina, Alberto and Howard Rosenthal. 1995. *Partisan Politics, Divided Government, and the Economy*. New York: Cambridge University Press.

Alesina, Alberto and Howard Rosenthal. 1996. "A Theory of Divided Government." *Econometrica* 64 (November): 1311–1341.

Alesina, Alberto, Nouriel Roubini, and Gerald D. Cohen. 1997. *Political Cycles and the Macroeconomy*. Cambridge, MA: MIT Press.

Althaus, Scott L. 2003. *Collective Preferences in Democratic Politics: Opinion Surveys and the Will of the People*. New York: Cambridge University Press.

Alvarez, R. Michael and John Brehm. 2002. *Hard Choices, Easy Answers: Values, Information and American Public Opinion*. Princeton, NJ: Princeton University Press.

Bartels, Larry M. 1996. "Uninformed Votes: Information Effects in Presidential Elections." *American Journal of Political Science* 40 (February): 194–230.

Berelson, Bernard R., Paul F. Lazarsfeld, and William N. McPhee. 1954. *Voting: A Study of Opinion Formation in a Presidential Campaign*. Chicago: University of Chicago Press.

Campbell, Angus, Philip E. Converse, Warren E. Miller, and Donald E. Stokes. 1960. *The American Voter*. New York: Wiley.

Converse, Philip E. 1964. "The Nature of Belief Systems in Mass Publics." In David E. Apter, editor, *Ideology and Discontent*, .New York: Free Press. Pages 206–261.

Converse, Philip E. 1990. "Popular Representation and the Distribution of Information." In John Ferejohn and James Kuklinski, editors, *Information and Democratic Processes*, .Urbana: University of Illinois Press.

Cox, Gary W. 1997. *Making Votes Count: Strategic Coordination in the World's Electoral Systems*. New York: Cambridge University Press.

Delli Carpini, Michael X. and Scott Keeter. 1996. *What Americans Know about Politics and Why It Matters*. New Haven: Yale University Press.

Ellison, Glenn and Drew Fudenberg. 1995. "Word-of-Mouth Communication and Social Learning." *Quarterly Journal of Economics* 110 (February): 93–125.

Erikson, Robert S., Michael B. Mackuen, and James A. Stimson. 2002. *The Macro Polity*. New York: Cambridge University Press.

Feddersen, Timothy and Wolfgang Pesendorfer. 1997. "Voting Behavior and Information Aggregation in Elections with Private Information." *Econometrica* 65 (September): 1029–1058.

Forsythe, Robert, Roger B. Myerson, Thomas A. Rietz, and Robert J. Weber. 1993. "An Experiment on Coordination in Multi-candidate Elections: The Importance of Polls and Election Histories." *Social Choice and Welfare* 10: 223–247.

Green, Donald P., Bradley Palmquist, and Eric Schickler. 2002. *Partisan Hearts and Minds: Political Parties and the Social Identities of Voters*. New Haven: Yale University Press.

Huckfeldt, Robert, Paul Johnson, and John Sprague. 2005. "Individuals, Dyads, and Networks: Autoregressive Patterns of Political Influence." In Alan S. Zuckerman, editor, *The Social Logic of Politics: Personal Networks as Contexts for Political Behavior*, .New York: Temple University Press chapter 2.

Huckfeldt, Robert and John Sprague. 1987. "Networks in Context: The Social Flow of Political Information." *American Political Science Review* 81 (December): 1197–1216.

Huckfeldt, Robert and John Sprague. 1995. *Citizens, Politics and Social Communication: Information and Influence in an Election Campaign*. New York: Cambridge University Press.

Iannantuoni, Giovanna. 2003. "Divided Government and Dominance Solvability." *European Journal of Political Economy* 19: 715–733.

Johnson, Norman L., Samuel Kotz, and N. Balakrishnan. 1995. *Continuous Univariate Distributions* volume 2. New York: Wiley second edition.

Key, Jr., V. O. 1966. *The Responsible Electorate: Rationality in Presidential Voting, 1936–1960*. Cambridge, MA: Harvard University Press.

Kotz, Samuel, N. Balakrishnan, and Norman L. Johnson. 2000. *Continuous Multivariate Distributions* volume 1. New York: Wiley second edition.

Lupia, Arthur and Mathew D. McCubbins. 1998. *The Democratic Dilemma: Can Citizens Learn What They Need to Know?*. New York: Cambridge University Press.

Mari, Dominique Drouet and Samuel Kotz. 2001. *Correlation and Dependence*. London: Imperial College Press.

McFadden, Daniel. 1978. "Modelling the Choice of Residential Location." In Anders Karlqvist, Lars Lundqvist, Folke Snickars, and Jörgen W. Weibull, editors, *Spatial Interaction Theory and Planning Models*, .New York: North-Holland. Pages 75–96.

McKelvey, Richard D. and Peter C. Ordeshook. 1985. "Elections with Limited Information: A Fulfilled Expectations Model Using Contemporaneous Poll and Endorsement Data as Information Sources." *Journal of Economic Theory* 36 (June): 55–85.

Mebane, Walter R., Jr. 2000. "Coordination, Moderation and Institutional Balancing in American Presidential and House Elections." *American Political Science Review* 94 (March): 37–57.

Mebane, Walter R., Jr. and Jasjeet Singh Sekhon. 2002. "Coordination and Policy Moderation at Midterm." *American Political Science Review* 96 (March): 141–157.

Miller, Gary and Norman Schofield. 2003. "Activists and Partisan Realignment in the United States." *American Political Science Review* 97 (May): 245–260.

Moran, P. A. P. 1971. "Maximum-likelihood Estimation in Non-standard Conditions." *Proceedings of the Cambridge Philosophical Society* 70 (3): 441–450.

Nadarajah, S. 1999. "Simulation of Multivariate Extreme Values." *Journal of Statistical Computing and Simulation* 62: 395–410.

Popkin, Samuel L. 1991. *The Reasoning Voter: Communication and Persuasion in Presidential Campaigns*. Chicago: University of Chicago Press.

R Development Core Team. 2003. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. Vienna, Austria. ISBN 3-900051-00-3.
URL `http://www.R-project.org`

Resnick, Sidney and Rishin Roy. 1990. "Multivariate Extremal Processes, Leader Processes and Dynamic Choice Models." *Advances in Applied Probability* 22: 309–331.

Samuelson, Larry. 1997. *Evolutionary Games and Equilibrium Selection*. Cambridge, MA: MIT Press.

Schattschneider, E. E. 1960. *The Semi-Sovereign People: A Realist's View of Democracy in America*. New York: Holt, Rinehart and Winston.

Sekhon, Jasjeet S. 2004. "The Varying Role of Voter Information across Democratic Societies." Paper presented at the 2004 Political Methodology summer meeting, Stanford, CA, July 29–31.

Self, Steven G. and Kung-Yee Liang. 1987. "Asymptotic Properties of Maximum Likelihood Estimators and Likelihood Ratio Tests Under Nonstandard Conditions." *Journal of the American Statistical Association* 82 (June): 605–610.

Snyder, Jr., James M. and Michael M. Ting. 2002. "An Informational Rationale for Political Parties." *American Journal of Political Science* 46 (January): 90–110.

Vuong, Quang H. 1989. "Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses." *Econometrica* 57 (March): 307–333.

Weibull, Jörgen W. 1995. *Evolutionary Game Theory*. Cambridge, MA: MIT Press.

Wolfram Research. 2003. *Mathematica 5*. Champaign, IL: Wolfram Research. Computer program.

Zaller, John. 1992. *The Nature and Origins of Mass Opinion*. New York: Cambridge University Press.

Table 1: Classes of Evolutionary Voting Models

	Replicator Dynamics	
Messages	Unstable (1)	Steady State (2a-b)
None	UN	SN
Open	UO	SO
Closed	UC	SC

Table 2: Evolutionary Voting Model Fits and Nonnested Tests

	Model Type						
	s_O	UN	UO	UC	SN	SO	SC
${s_O}^a$	−3186.0						
UN^b	0.5	−3181.7					
UO^c	3.1	2.5	−3155.3				
UC^d	3.2	2.4	0.3	−3154.5			
SN^e	0.7	0.0	−2.8	−2.8	−3181.4		
SO^d	−1.0	−1.3	−5.3	−4.9	−1.4	−3199.8	
SC^g	3.2	2.4	−0.7	−0.8	2.9	4.2	−3159.4

Notes: Diagonal values show the log-likelihood (L) for each model. Off-diagonal values show the statistic (V) for the non-nested test of fit between the row and column models. $V > 0$ means the row model has the better fit, while $V < 0$ means the column model has the better fit.
[a] Coordinating model of Mebane (2000). [b] Sim-month eleven, x^i in (1) from the s_O model.
[c] Sim-month two, x^i in (1) from the s_O model. [d] Sim-month two, x^i in (1) from iterated UC estimates. [e] $\eta = .2$, $\mu = .9$, x^i in (2a-b) from the s_O model. [f] $\eta = .32$, $\mu = .45$, x^i in (2a-b) from the s_O model. [g] $\eta = .3$, $\mu = .02$, x^i in (2a-b) from the UC AED model.

Table 3: Probability of Use of Strategies with the Unstable Closed AED Model, 1976–96

	Strategies				
Democratic Incumbent	s_{RR}	s_{RD}	s_{DR}	s_{DD}	s_O
Strong Democrat	.00	.03	.03	.63	.31
Democrat	.00	.04	.05	.61	.29
Independent Dem.	.00	.04	.05	.62	.29
Independent	.16	.26	.11	.22	.26
Independent Rep.	.42	.22	.05	.03	.28
Republican	.44	.21	.05	.03	.28
Strong Republican	.54	.14	.02	.01	.28
Open Seat	s_{RR}	s_{RD}	s_{DR}	s_{DD}	s_O
Strong Democrat	.01	.03	.09	.58	.30
Democrat	.01	.04	.13	.53	.29
Independent Dem.	.01	.03	.12	.55	.29
Independent	.33	.17	.13	.10	.27
Independent Rep.	.48	.11	.09	.03	.29
Republican	.48	.10	.09	.03	.30
Strong Republican	.57	.07	.05	.01	.30
Republican Incumbent	s_{RR}	s_{RD}	s_{DR}	s_{DD}	s_O
Strong Democrat	.01	.01	.27	.43	.27
Democrat	.03	.02	.37	.32	.26
Independent Dem.	.03	.02	.36	.34	.26
Independent	.32	.04	.31	.05	.29
Independent Rep.	.64	.02	.05	.00	.29
Republican	.64	.02	.06	.00	.29
Strong Republican	.67	.01	.02	.00	.30

Note: Each row shows the average value of $\tilde{\rho}^i$ among voters who have the indicated combination of party identification and House incumbent status, using the maximum likelihood estimates of the UC AED model for sim-month two.

Table 4: Parameter Estimates for the Unstable Closed AED Model

	UC AED			s_O[a]		UC AED			s_O
parameter	MLE	lower	upper	MLE	parameter	MLE	lower	upper	MLE
τ	.28	.15	.43	.39	c_D	.97	.73	1.22	.90
q	1.04	.92	1.20	1.03	c_{ID}	.86	.56	1.13	.77
b_P	4.93	3.66	5.80	3.92	c_I	1.12	.83	1.41	1.92
b_{HP}	1.90	1.18	3.07	1.88	c_{IR}	1.13	.82	1.41	2.82
b_H	5.93	4.00	9.21	5.16	c_R	1.25	.97	1.52	2.88
b_{PH}	.05	−.18	.13	.02	c_{SR}	1.95	1.63	2.25	3.54
$\alpha_{D,76}$	1*	.54	1.00	1*	c_{DEM}	1.08	1.03	1.12	1.02
$\alpha_{D,80}$	.40	.13	.54	.40	c_{REP}	1.22	1.18	1.24	1.32
$\alpha_{D,84}$	1*	.63	1.00	.77	$c_{P0,76}$	−.73	−.92	−.55	−1.05
$\alpha_{D,88}$	.67	.41	.93	.67	$c_{P0,80}$	−.59	−.85	−.34	−.85
$\alpha_{D,92}$	.98	.77	1.00	.98	$c_{P0,84}$	−.19	−.38	.01	−.65
$\alpha_{D,96}$	.83	.67	1.00	.83	$c_{P0,88}$	−.52	−.72	−.30	−.90
$\alpha_{R,76}$	.64	.31	1.00	.76	$c_{P0,92}$	−.48	−.75	−.22	−.89
$\alpha_{R,80}$	.96	.76	1.00	.95	$c_{P0,96}$	−.87	−1.08	−.63	−1.14
$\alpha_{R,84}$	.45	.34	.63	.54	$c_{H0,76}$	−.52	−.71	−.38	−.94
$\alpha_{R,88}$	.74	.55	.87	.74	$c_{H0,80}$	−.50	−.71	−.27	−.91
$\alpha_{R,92}$	.56	.30	.79	.56	$c_{H0,84}$	−.42	−.59	−.26	−.87
$\alpha_{R,96}$	.09	.00	.52	.10	$c_{H0,88}$	−.60	−.76	−.40	−1.06
$\gamma_{D,76}$	.93	.55	1.00	.99	$c_{H0,92}$	−.30	−.47	−.07	−.76
$\gamma_{D,80}$	.86	.47	1.00	.86	$c_{H0,96}$	−.41	−.57	−.21	−.85
$\gamma_{D,84}$	1*	.45	1.00	.97	$c_{P1,76}$	.21	−.13	.51	.22
$\gamma_{D,88}$	.91	.55	1.00	.78	$c_{P1,80}$	.65	.29	.97	.42
$\gamma_{D,92}$	1*	.40	1.00	1*	$c_{P1,84}$	.57	.24	.90	.48
$\gamma_{D,96}$	.75	.44	1.00	.74	$c_{P1,88}$	.37	−.01	.79	.29
$\gamma_{R,76}$	.61	.10	1.00	.65	$c_{P1,92}$	.36	.00	.69	.35
$\gamma_{R,80}$	1*	.64	1.00	1*	$c_{P1,96}$	.83	.42	1.21	.68
$\gamma_{R,84}$	.82	.40	1.00	.78	$c_{H1,76}$	.25	−.03	.49	.22
$\gamma_{R,88}$	.63	.17	1.00	.63	$c_{H1,80}$	.03	−.23	.27	.04
$\gamma_{R,92}$	.52	.14	.90	.56	$c_{H1,84}$	.02	−.19	.24	.01
$\gamma_{R,96}$	1*	.45	1.00	1*	$c_{H1,88}$	.30	.06	.60	.28
b_{E0}	.37	.15	.60	.31	$c_{H1,92}$	.24	.05	.48	.22
b_{E1}	.61	.25	.97	.48	$c_{H1,96}$	.36	.07	.63	.32

Notes: Maximum likelihood estimates. Asterisk indicates a boundary-constrained parameter. AED results show the point estimate and the lower and upper bounds of the 95% confidence interval. Pooled NES survey data, 1976–96, $n = 4,859$. [a] Coordinating model point estimates are the same as in Table 2 of Mebane (2000).