The Swing Voter's Curse in the Laboratory[1]

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Abstract

This paper reports the first laboratory study of the swing voter's curse and provides insights on the larger theoretical and empirical literature on "pivotal voter" models. Our experiment controls for different information levels of voters, as well as the size of the electorate, the distribution of preferences, and other theoretically relevant parameters. The design varies the share of partisan voters and the prior belief about a payoff relevant state of the world. Our results support the equilibrium predictions of the Feddersen-Pesendorfer model, and clearly reject the notion that voters in the laboratory use naive decision-theoretic strategies. The voters act as if they are aware of the swing voter's curse and adjust their behavior to compensate. While the compensation is not complete and there is some heterogeneity in individual behavior, we find that aggregate outcomes, such as efficiency, turnout, and margin of victory, closely track the theoretical predictions.

Introduction

Voter turnout has traditionally proven difficult to explain. Rational models highlight the fact that the incentives to participate in an election depend on the probability of being pivotal. If voting is costly, then significant turnout in large elections is inconsistent with equilibrium behavior (see Ledyard [1984] and Palfrey and Rosenthal [1983, 1985]). If voting is costless, then abstention is a dominated choice. However, this is also inconsistent with observed behavior. Voters often selectively abstain in the same election–Feddersen and Pesendorfer [1996] report that almost 1 million voters participated in the 1994 Illinois gubernatorial contest but abstained on the state constitutional amendment listed on the same ballot, even though the amendment was listed first. Crain, et al. [1987] report that in the 1982 midterm elections turnout levels averaged 3% higher for the Senate contests in those states with such contests than the House races that were on the same ballot. In seven of the 219 races they studied, the difference in turnout was larger than the margin of victory in the House race, suggesting that voters were abstaining even in close contests.[1] Assuming that voting is virtually costless when already in the ballot booth, this seems irrational.

Feddersen and Pesendorfer [1996] show that these large abstention rates can be explained even if the cost of voting is zero if there is asymmetric information, thereby rationalizing such behavior. They draw an analogy between the voters' problem and the "winner's curse" observed among bidders in an auction (see Kagel and Levin [2005] and Thaler [1996]).[2] A poorly informed voter may be better off in equilibrium to leave the decision to informed voters because his uninformed vote may go against their choice and could decide the outcome in the wrong direction. The voter, therefore, may rationally "delegate" the decision to more informed voters by abstaining even if voting is costless. Feddersen and Pesendorfer [1996] name this phenomenon the *Swing Voter's Curse.*

This theory explains some empirical facts, but it remains–along with rational theories of voting more generally–highly controversial (see Feddersen [2004] for a recent discussion). Empirical evidence has been produced both in favor and against rational voter theories, especially when compared to the assumption that voters act naively and ignore strategic considerations.[3] None of these results, however, are conclusive, partly because field data sets are not rich enough to identify all the variables that may affect voters' decisions. This is especially true for tests of rational theories of voting based on asymmetric information, such as the Swing Voter's Curse.

This paper reports the first laboratory study of the swing voter's curse. Our results, however, provide insights on the larger "pivotal-voter" literature. This literature includes the earlier

[1] They omitted states with gubernatorial contests to focus on the choice whether to vote in both the Senate and House races. Wattenberg, et al. [2000] report that in the 1994 California election 8% of those who voted for governor abstained in state legislative elections and over 35% abstained on state supreme court judicial retention votes. They note that the pattern of abstention appears independent of ballot order, with the abstention of those who voted in the governors' race only 2% on two ballot propositions which were seven ballot positions below the judicial retention elections.

[2] By this term, economists refer to the phenomenon in which bidders in a common value auction overbid with respect to what would be optimal in equilibrium. This occurs because they do not realize that, conditional on winning, the expected value of the object is lower than ex ante. A bidder wins precisely when his or her estimated value of the object for sale is inflated relative to other bidders' estimates, and hence relative to actual value.

[3] Feddersen [2004] reviews this literature. Matsusaka and Palda [1999], based on an extensive study of turnout decisions using both survey and aggregate data, contend that strategic theories of voter turnout provide little explanatory power in explaining voter choices and that turnout decisions appear to be random. Coate, et al. [2006] propose a simple model of expressive voting better, and argue that it explains turnout in local Texas referenda better than the standard pivotal voting model.

models with symmetric information and costly voting (Ledyard [1984], Palfrey and Rosenthal [1983]); asymmetric information and costly voting Palfrey and Rosenthal [1985]); and the broader theoretical literature that focuses on information aggregation in elections with common or private values and asymmetric information (Austen-Smith and Banks [1996], Battaglini [2005], Feddersen and Pesendorfer [1997, 1999] and others).

To overcome the problems with field data, we design a laboratory experiment that provides a sharp test of the theoretical predictions of the Feddersen-Pesendorfer model. The laboratory setting allows us to control and directly observe the level of information of different voters, as well as preferences, voting costs, and other theoretically relevant parameters. Our attempt to test the pivotal voting model of turnout and behavior using laboratory experiments is significantly different from previous experiments which have primarily focused on cases where information is symmetric and voting is costly.[4] Much less experimental work has been done with models with asymmetric information. Guarnaschelli, McKelvey, and Palfrey [2000] test Feddersen and Pesendorfer Jury's model (Feddersen and Pesendorfer [1998]) and focus on information aggregation in small committees. They rule out abstention by assumption, and therefore do not provide evidence on participation. Battaglini, Morton, and Palfrey [2005] study sequential voting in a similar model but allow abstention. However, all voters are equally well informed.

A significant non-experimental empirical literature on turnout exists and a number of these studies attempt to test the pivotal voter model on large elections or a variant of the model as augmented by group and/or ethical motivations for voting (see, for example, Hansen, et al. [1987], Filer, et al. [1993], Shachar and Nalebuff [1999], Coate and Conlin [2004], Noury [2004], and Coate, et al. [2006]). None of these studies are able to evaluate the role of asymmetric information in explaining abstention and test the swing voter's curse.

A number of researchers have used variations in voter information in field studies to evaluate the effect of information on the choice to abstain which suggest support for the swing voter's curse (see, for example, Palfrey and Poole [1987], Wattenberg, et al. [2000], and Coupe and Noury [2004]). The main finding is that turnout is positively correlated with voter information levels, but this work cannot identify the causal relationship since the demand for political information may be derived from the decision to participate. Recently researchers have examined the impact on turnout of changes in political information where political information is arguably an exogenous variable. McDermott [2005] and Klein and Baum [2001] present evidence that respondents to surveys during elections are more likely to state preferences when information is provided to them. Gentzkow [2005] shows that decreases in voter information associated with the advent to television in U.S. counties is correlated with decreasing voter turnout. Lassen [2005] examined turnout in a Copenhagen election where residents of four of the city's fifteen districts were provided with detailed information about the choices in an upcoming referendum. He finds that voters provided with more information were more likely to participate.

Lassen argues that there are two possible explanations for the relationship between information and turnout–the swing voter's curse theory of Feddersen and Pesendorfer and a decision-theoretic model first suggested by Matsusaka [1995] in which voters are more likely to turnout

[4] See Schram and Sonnemans [1996], Cason and Mui [2005], Grosser, et al. [2005] who have studied strategic voters participation in laboratory experiments, focusing on environments with symmetric information and homogeneous costs. One problem with these early works is that, under these assumptions, voting models may have many equilibria. Levine and Palfrey [2007] have recently conducted expeirments based on a model with heterogeneous costs which has a unique equilibrium. They find support for the three primary predictions of the rational model: (1) turnout declines with the size of the electorate (the size effect); (2) turnout is higher in elections that are expected to be close (the competition effect); and (3) turnout is higher for voters who prefer the less popular alternative (the underdog effect).

the more confident they are in the correctness of their choices. Gentzkow also notes that his results support a number of theories that argue that information increases turnout including simple decision-theoretic ones as well. Lassen concludes (p. 116): "The natural experiment used here does not allow for distinguishing between the decision-theoretic and game-theoretic approaches ....; this may call for careful laboratory experiments, as the predictions of the models differ in only subtle ways that can be difficult to accomodate in even random social experiments, but the results reported in this article can serve as a necessary first step in motivating the importance of such experiments ..."

The upshot of these studies is that the available natural experiments cannot analyze the data to distinguish between these two approaches and we take the next step in the study of the swing voter's curse in this paper. In our experimental design we are able to investigate 240 different elections which vary between all voters uninformed to over 70 percent informed. Thus, we can consider the effect of information on aggregate turnout levels as well as the margin of victory, considerations that are difficult to make using natural experiments. We are also able to consider a variety of degrees of partisan balance and information distribution as well. Finally, we can consider how different individuals choose depending on the information available and the partisan balance. With this wide array of observations we can show that the game theoretic model is a better predictor of behavior than the decision-theoretic approach.

THE MODEL

We consider a game with a set of N voters who deliberate by majority rule. There are two alternatives A, B and two states of the world: in the first state A is optimal and in the second state B is optimal. Without loss of generality, we label A the first state and B the second. A number $n \leq N$ of the voters are *independent voters*. These voters have identical preferences represented by a utility function $u(x, \theta)$ that is a function of the state of the world $\theta \in \{A, B\}$ and the action $x \in \{A, B\}$:

$$u(A, A) = u(B, B) = 1$$
$$u(A, B) = u(B, A) = 0$$

State A has a prior probability $\pi \geq \frac{1}{2}$. The true state of the world is unknown, but each voter may receive an informative signal. We assume that signals of different agents are conditionally independent. The signal can take three values a, b, and ϕ with probability:

$$\Pr(a\,|A) = \Pr(b\,|B) = p \text{ and } \Pr(\phi\,|A) = \Pr(\phi\,|B) = 1 - p$$

The agent, therefore, is perfectly informed on the state of the world with probability p, and has no information with probability $1 - p$. The remaining $m = N - n$ voters are *partisan voters*. We assume that the partisans strictly prefer policy A in all states. For convenience we assume that m is even, n is odd and $m \leq n - 3$.[5]

After swing voters have seen their private signal, all voters vote simultaneously. Each voter can vote for A, vote for B, or abstain. In any equilibrium, the independent voters who receive an informative signal always strictly prefer the state that matches their signal; and the partisans

[5] These assumptions are made only to simplify the notation. In Feddersen and Pesendorfer [1996] m is random variable; however, since they focus the analysis on the limit case in which $n \to \infty$, the realized fraction of partisan voters is constant by the Law of Large Numbers in their model.

always strictly prefer state A: in any equilibrium, therefore independents would always vote for the state suggested by their signal, and partisans would always vote for A. We can therefore focus on the behavior of the uninformed agents. Let σ^i_A, σ^i_B, and σ^i_ϕ be respectively the probability that an uninformed agents votes for A, B and abstains. An equilibrium of this game is symmetric if agents with the same signal use the same strategy: $\sigma^i = \sigma$ for all i. We analyze symmetric equilibria in which agents do not use weakly dominated strategies and we will refer to them simply as equilibria.

THE VOTING EQUILIBRIUM

In this section we characterize the equilibria of the voting game, and the equilibrium is unique for the experimental parameters. With respect to Feddersen and Pesendorfer [1996] and other previous results in the literature, we do not limit the analysis to asymptotic results that hold as the size of the electorate grows to infinity, but focus on results that hold even for a finite number of voters. This allows us to test the model directly with an electorate of a size that can be managed in a laboratory. Formal proofs of all the results appear in an Appendix.

No Partisan Bias

We first consider the benchmark case in which all the voters have the same common value, so $m = 0$.

Lemma 1 *Let $m = 0$. If $\pi = \frac{1}{2}$, then $\sigma_A = \sigma_B$; if $\pi > \frac{1}{2}$, then $\sigma_A \geq \sigma_B$.*

The intuition of this result is as follows. If the uniformed voters are voting for, say B, with higher probability, then if pivotal it is more likely that alternative A has attracted more votes from informed voters. If this is the case, then conditioning on the pivotal event, alternative A is more attractive to an uninformed independent, and none of them would vote for B, a contradiction.

Though this result provides testable predictions, it can be made more precise:

Proposition 1 *Let $m = 0$. If $\pi = \frac{1}{2}$, then $\sigma_A = \sigma_B = 0$; if $\pi > \frac{1}{2}$, then $\sigma_A \geq \sigma_B = 0$.*

This is a particular form of the Swing Voters' Curse. To see the intuition behind it, suppose the prior is $\pi = \frac{1}{2}$. If an uninformed voter were to choose in isolation, he would be indifferent between the two options A or B. When voting in a group, however, he knows that with positive probability some other voter is informed. By voting, he risks voting against this more informed voter. So, since he has the same preferences of this informed voter and he is otherwise indifferent among the alternatives because he has no private information on the state, he always finds it optimal to abstain. When the prior is $\pi > \frac{1}{2}$, the problem of the voter is more complicated. In this case the swing voter's curse is mitigated by the fact that the prior favors one of the two alternatives. As before, the voter does not want to vote against an informed voter. However, he is not sure that there is an informed voter: and if no informed voter is voting, he strictly prefers alternative A since this is ex ante more likely. Thus although the voter never finds it optimal to vote for B, he may find it optimal to vote for A. The higher is π, the higher is the incentive to vote for A; the higher is p (i.e. the probability that there are other informed voters), the lower is the incentive to vote. For any p, if $\pi > \frac{1}{2}$ is not too high, the voter abstains.

From Proposition 1 we know that when $\pi \geq \frac{1}{2}$ a voter would never vote for B if $m = 0$, so $\sigma_B = 0$. Given this, the expected utility of an uninformed voter from voting for A, and therefore σ_A, can be easily computed. Let u_A and u_ϕ be respectively the expected utilities of voting for A and abstaining for an uniformed voter, expressed as functions of σ_A. The net utility of voting for A is:

$$\begin{aligned} u_A - u_\phi &= \frac{1}{2}\left[\pi \Pr\left(P_0 \left| A\right.\right) - (1-\pi)\Pr\left(P_0 \left| B\right.\right)\right] \\ &\quad + \frac{1}{2}\left[\pi \Pr\left(P_A \left| A\right.\right) - (1-\pi)\Pr\left(P_A \left| B\right.\right)\right] \end{aligned} \tag{1}$$

where

$$\begin{aligned} & \pi \Pr\left(P_0 \left| A\right.\right) - (1-\pi)\Pr\left(P_0 \left| B\right.\right) \\ = \; & \pi\left((1-p)(1-\sigma_A)\right)^{n-1} \\ & -(1-\pi)\sum_{j=0}^{\frac{n-1}{2}}\left(\frac{(n-1)!}{\left(\frac{n-1-2j}{2}\right)!\left(\frac{n-1-2j}{2}\right)!(2j)!}\right)\left((1-p)(1-\sigma_A)\right)^{2j} p^{\frac{n-1-2j}{2}}\left((1-p)\sigma_A\right)^{\frac{n-1-2j}{2}}, \end{aligned}$$

and

$$\begin{aligned} & \pi \Pr\left(P_A \left| A\right.\right) - (1-\pi)\Pr\left(P_A \left| B\right.\right) \\ = \; & -(1-\pi)\sum_{j=0}^{\frac{n-3}{2}}\left(\frac{(n-1)!}{\left(\frac{n-(2j+1)}{2}\right)!\left(\frac{n-2-(2j+1)}{2}\right)!\,(2j+1)!}\right) \\ & \cdot\left((1-p)(1-\sigma_A)\right)^{(2j+1)} p^{\frac{n-(2j+1)}{2}}\left((1-p)\sigma_A\right)^{\frac{n-2-(2j+1)}{2}}. \end{aligned}$$

since in this case $\Pr\left(P_A \left| A\right.\right) = 0$ (in state A no voter ever votes for B). If uninformed voter mix between voting for A and abstaning in equilibrium, then the equation that gives us σ_A is: $u_A - u_\phi = 0$. From Proposition 1 we know that $\sigma_A = 0$ when $\pi = \frac{1}{2}$, so we only need to compute the equation for the case in which $\pi > \frac{1}{2}$. Equation (1) can be easily computed for specific parameters.

Partisan Bias

Let us now consider an environment in which A has a partisan advantage: $m > 0$ Assume first that $\pi = \frac{1}{2}$. In this case the swing voter's curse is confounded by the bias introduced by the partisans. Conditioning on the event in which the two alternatives receive the same number of votes, the voter realizes that it is more likely that B has received some votes from informative voters because he knows for sure that some of the votes cast in favor of A, coming from partisans, are uninformative. Indeed, the voter may be willing to vote for B, because doing so offsets a partisan vote. As in the previous case with $m = 0$, the voters' problem is more complicated when $\pi > \frac{1}{2}$. In this case the prior probability favors A, so the incentives to vote for B are weaker, and a voter will find it optimal to do so only if there are enough informed voters in the population. This is summarized in the following result:

Lemma 2 *Let $m > 0$. If $\pi = \frac{1}{2}$,then $\sigma_A \leq \sigma_B$; if $\pi > \frac{1}{2}$, then there is a $\overline{p}$ such that $p > \overline{p}$ implies $\sigma_A \leq \sigma_B$.*

In this case too this result can be made more precise by showing that no voter would ever vote for A:

Proposition 2 *Let $m > 0$. If $\pi = \frac{1}{2}$, or if $\pi > \frac{1}{2}$ and p is large enough, then $\sigma_B > \sigma_A = 0$.*

Comparative Statics

The probability with which the uninformed voters vote for B depends on the parameters of the model, m, p, n, π. For example, the higher is the bias in favor of A, the higher is the incentive for uninformed voters to offset it by voting for B. The exact probability σ_B can be easily computed for specific parameter values when $m > 0$.[6] From Proposition 1 we know that we only have one variable to determine, σ_B; and one equation to respect: in a mixed strategy equilibrium the agent must be indifferent between abstaining and voting for B. This indifference condition requires that the net expected utility of voting to be zero. We can write the equilibrium condition as:

$$u_B - u_\phi = \frac{1}{2}\left[(1-\pi)\Pr(P_0\,|B) - \pi\Pr(P_0\,|A)\right] + \frac{1}{2}\left[(1-\pi)\Pr(P_B\,|B) - \pi\Pr(P_B\,|A)\right] = 0$$

where u_B is the expected utility of voting for B for an uninformed voter; $(1-\pi)\Pr(P_0\,|B) - \pi\Pr(P_0\,|A)$ is equal to:

$$\begin{aligned}
&(1-\pi)\left(\frac{(n-1)!}{(n-1-m)!m!}\right)\left((1-p)(1-\sigma_B)\right)^{n-1-m}\left(p+(1-p)\sigma_B\right)^m \\
&-\pi\sum_{j=0}^{\frac{n-1-m}{2}}\left(\frac{(n-1)!}{\left(\frac{n-1-2j-m}{2}\right)!\left(\frac{n-1-2j+m}{2}\right)!(2j)!}\right)\left((1-p)(1-\sigma_B)\right)^{2j}\cdot \\
&\cdot p^{\frac{n-1-2j-m}{2}}\left((1-p)\sigma_B\right)^{\frac{n-1-2j+m}{2}},
\end{aligned}$$

and $(1-\pi)\Pr(P_B\,|B) - \pi\Pr(P_B\,|A)$ is equal to:

$$\begin{aligned}
&(1-\pi)\left(\frac{(n-1)!}{(n-m)!\,(m-1)!}\right)\left((1-p)(1-\sigma_B)\right)^{n-m}\left(p+(1-p)\sigma_B\right)^{m-1} \\
&-\pi\sum_{j=0}^{\frac{n-3-m}{2}}\left(\frac{(n-1)!}{\left(\frac{n-(2j+1)-m}{2}\right)!\left(\frac{n-2-(2j+1)+m}{2}\right)!\,(2j+1)!}\right) \\
&\cdot\left((1-p)(1-\sigma_B)\right)^{(2j+1)} p^{\frac{n-(2j+1)-m}{2}}\left((1-p)\sigma_B\right)^{\frac{n-2-(2j+1)+m}{2}}.
\end{aligned}$$

Consider the expected utility of voting for B for an uninformed voter when $p = \frac{1}{4}$, $n = 7$, $\pi = 0.5, m = 2$. We have a unique symmetric equilibrium since the expected utility of voting for B equals zero only once in the $[0, 1]$ interval. When $m = 2$, the equilibrium strategy is $\sigma_B = 0.36$. Correspondingly, when $m = 4$, we have $\sigma_B = 0.76$.[7]

In a similar way we can find the equilibrium in the case in which $\pi > 0.5$. We have explicitly computed the equilibrium when $\pi = \frac{5}{9}$, and the other parameters are as above. In this case

[6] The case with $m = 0$ is not necessary since from Proposition 2 we know that the uninformed voters always abstain.

[7] Unless otherwise noted in the paper, we round off to two decimal places.

too we have a unique equilibrium in correspondence of which with $m = 2$, $\sigma_B = 0.33$, and with $m = 4$, $\sigma_B = 0.73$. Not surprisingly, a small increase in π has a small effect on the equilibrium strategies and tends to reduce the probability of voting for B.

Our results then provide testable predictions about voter behavior as a function of π and m. Later we compare our results to alternative, decision-theoretic, models of turnout as well. That is, if information increases turnout increases simply because voters are more certain about their choices as posited by Matsusaka [1995], then we would not expect uninformed voters to vote for B more often when there is a partisan bias as compared to no bias. In voters vote on the basis of their prior, the change in π from .5 to .55 should induce them to vote for A, regardless of the partisan bias.[8]

EXPERIMENTAL DESIGN

We use controlled laboratory experiments to evaluate the theoretical predictions. Once a specific parametrization for n, m, and p is chosen, the model described and solved in the previous section can be directly tested in the lab without changes. All the laboratory experiments used $n = 7$ and $p = 0.25$. We used two different treatments for the state of the world: $\pi = 1/2$ and $\pi = 5/9$ and three different treatments for partisan bias: $m = 0, 2$, and 4. Table 1 summarizes the equilibrium strategies for each treatment as derived in the previous section.

In the last row of Table 1 we contrast our theoretical predictions with those of the decision theoretic approach of Matsusaka [1995]. Matsusaka assumes that voters participate for consumption benefits that are independent of whether they are pivotal. These consumption benefits are positively related to voters' certainty over which choices yield them the highest utility which depends on their information about the choices. When voters' are uninformed and perceived all options as equally likely, the decision-theoretic model predicts that they will abstain, but that more precise information increases the probability that they will vote. Thus, in our experimental design, uninformed decision-theoretic voters should abstain when $\pi = 0.5$, regardless of the size of the partisan bias. When $\pi = 5/9$, uninformed decision-theoretic voters should have a positive probability of voting for A and a zero probability of voting for B, regardless of the size of the partisan bias.

Table 1: Equilibrium Strategies for Uninformed Voters

	Probability of State A	
Partisan Bias	$\pi = 1/2$	$\pi = 5/9$
$m = 0$	$\sigma_B = \sigma_A = 0$	$\sigma_A = \sigma_B = 0$
$m = 2$	$\sigma_B = 0.36 > \sigma_A = 0$	$\sigma_B = 0.33 > \sigma_A = 0$
$m = 4$	$\sigma_B = 0.76 > \sigma_A = 0$	$\sigma_B = 0.73 > \sigma_A = 0$
Decision-Theoretic Voters	$\sigma_B = \sigma_A = 0$	$\sigma_A > \sigma_B = 0$

The experiments were all conducted at the Princeton Laboratory for Experimental Social Science and used registered students from Princeton University. Four sessions were conducted, each with 14 subjects.[9] Each subject participated in exactly one session. Each session was divided into three subsession, each of which lasted for 10 periods. All three subsessions used the same value of π, but used different values of $m = 0, 2$, and 4. We varied the sequence of m in

[8] This is also consistent with models of expressive voting. See, for example, Coate, et al. [2006].

[9] Each session included one additional subject who was paid \$20 to serve as a monitor.

the different sessions in order to provide some control for learning effects. Table 2 summarizes the experimental design.

Subjects were randomly divided into groups of seven for each period. Instructions were read aloud and subjects were required to correctly answer all questions on a short comprehension quiz before the experiment was conducted. Subjects were also provided a summary sheet about the rules of the experiment which they could consult. A copy of the experimental instructions is available online at http://www.hss.caltech.edu/~trp/svc-instruction-appendix.pdf. The experiments were conducted via computers.[10] Subjects were told there were two possible jars, Jar 1 and Jar 2. Jar 1 contained six white balls and two red; jar 2 contained six white balls and two yellow. The monitor from the experiment randomly chose a jar for each group in each period by tossing a fair die according to the value of π in the treatment where jar 1 was equivalent to state A in the model and jar 2 was equivalent to state B in the model.[11] The balls were then shuffled in random order on each subject's computer screen, with the ball colors hidden. Each subject then privately selected one ball by clicking on it with the mouse revealing the color of the ball to that subject only. The subject then chose whether to vote for jar 1, vote for jar 2, or abstain. In the treatments without partisan bias, i.e. $m = 0$, if the majority of the votes cast by the group were for the correct jar, each group member, regardless of whether he or she voted, received a payoff of 80 cents. If the majority of the votes cast by the group were incorrect guesses, each group member, regardless of whether he or she voted, received a payoff of 5 cents. Ties were broken randomly. In the treatment with partisan bias, subjects were told that the computer would cast m votes for jar 1 in each election. This was repeated for 30 periods, with the variations described in Table 2 above, and with the group membership shuffled randomly after each round. Each subject was paid the sum of his or her earnings over all 40 rounds in cash at the end of the experiment. Average earnings were approximately \$20, plus a \$10 show-up payment, with each session lasting about 60 minutes.

EXPERIMENTAL RESULTS

Aggregate Voter Choices

Informed Voters

Of the 1680 voting decisions we observed, in 422 cases (25.1%) subjects were informed, that is, revealed a red or yellow ball. Across all treatments and sessions, these informed voters chose 100% as predicted, 100% of the time if a voter revealed a red ball, he or she voted for jar 1 (state A) and 100% of the time if a voter revealed a yellow ball, he or she voted for jar 2 (state B). We interpret this as indicating that all subjects had a least a basic comprehension of the task.

Uninformed Voters

Case 1: $\pi = 0.5$

[10] The computer program used was similar to Battaglini, et al. [2005] as an extension to the open source Multistage game software. See http://multistage.ssel.caltech.edu.

[11] We used a 10 sided die with numbers 0-9 when $\pi = 5/9$, where numbers 1-5 resulted in state A, numbers 6-9 resulted in state B, and if a number 0 was thrown, the die was thrown until 1-9 appeared.

Effects of Treatments on Voter Choices Table 2 summarizes the choices of uninformed voters when $\pi = 0.5$. In all treatments we find that uninformed voters abstain in large percentages compared to informed voters and these differences are significant.

We find highly significant evidence that the majority of uninformed voters alter their voting choices as predicted by the swing voter's curse theory and contrary to the decision-theoretic theory. When $m = 0$, uninformed voters abstain 91% of the time, vote for A less than one percent of the time, and vote for B 8% of the time. However, with partisan bias, uninformed voters reduce abstention and increase their probability of voting for B. The changes are all statistically significant. In the case of $m = 4$ the observed voting choices almost perfectly match the equilibium values; in the $m = 2$ treatment there is significantly less abstention than predicted by the theory (51% versus 64%).

Table 2: Uninformed Voter Choices, $\pi = 1/2$

Partisan Bias	# obs	A Votes	B Votes	Abstain
$m = 0$	217	0.00	0.08	0.91
$m = 2$	221	0.05	0.43	0.51
$m = 4$	206	0.04	0.77	0.19

Session, Ordering, and Learning Effects Figure 1 presents the average choices of uninformed voters over time for the two sessions when $\pi = 0.5$. First observe that there are sharp changes in behavior immediately following a change in partisan bias. Second, there appear to be some differences between the two sessions, in Session 2 the probability of voting for B in the $m = 2$ treatment (periods 11-20) appears higher than the corresponding periods (1-10) in Session 1 (a difference which is statistically significant at the 10% level, t-statistic = 1.4, one-tailed test) and the opposite appears to be true in the $m = 4$ rounds (a difference which is not significant at acceptable levels, t-statistic = 0.86).

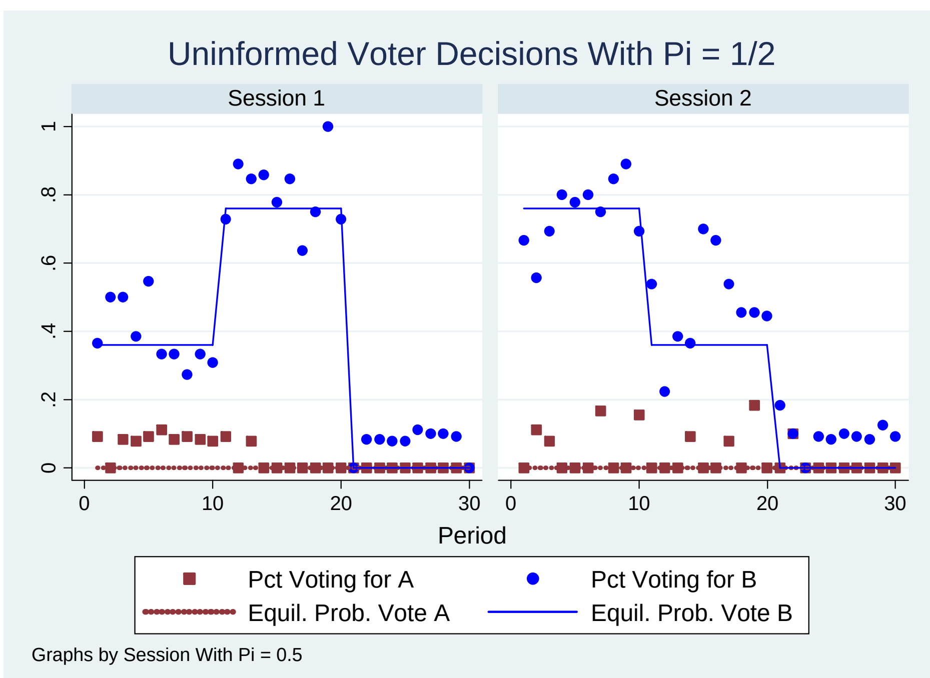

Figure 1: Uninformed Voter Decisions with $\pi = 0.5$

Third, we also tested whether there were significant changes in behavior within a subsession that reflects possible learning. To do this, we estimated separate multinomial probits of voter choices for each subsession as nonlinear functions of the variable period in the subsession (results from these estimations are presented in Appendix, note that the standard errors in the estimations were adjusted for clustering by subject).[12] We find that subjects' voting behavior appears to demonstrate learning in early periods in all the subsessions (with some slight increase in nonrational choices towards the end of a subsession) except for the case where $m = 2$ when subjects not only vote more for B than the equilibrium level, but increase their voting for B during the early periods in the subsessions with some evidence of learning in later periods in the subsession.

Case 2: $\pi = 5/9$

Effects of Treatments on Voter Choices Table 3 summarizes uninformed voter choises when the probability of state $A = 5/9$. Again, we find that in all treatments uninformed voters abstain large percentages compared to informed voters and these differences are significant, as predicted by the swing voter's curse theory.

We find some support, however, for the decision-theoretic model of voting when $m = 0$ as voting for A is significantly higher than when $\pi = 0.5$ (19.7% compared to 0.46%). But the decision-theoretic model falters as partisan bias increases and we again find highly significant evidence that uninformed voters alter their voting choices as predicted by the swing voter's curse theory and contrary to the decision-theoretic theory. With partisan bias, voting for A when $\pi = 5/9$ is not significantly different from voting for A when $\pi = 0.5$, as predicted by the swing voter's curse theory and contrary to the decision-theoretic approach. With partisan bias, the percent of uninformed voters voting for B increases with m, from 7% to 30% to 58% for $m = 0, 2, 4$, respectively. All of these differences are highly significant.

Table 3: Uninformed Voter Choice Frequencies, $\pi = 5/9$

Partisan Bias	# obs	A Votes	B Votes	Abstain
$m = 0$		0.20	0.07	0.73
$m = 2$		0.06	0.30	0.63
$m = 4$		0.04	0.58	0.38

Session, Ordering, and Learning Effects Figure 2 presents the average choices of uninformed voters over time for the two sessions when $\pi = 5/9$. First, as in the case where $\pi = 0.5$, there are sharp changes in behavior immediately following a change in partisan bias. Second, we also find differences between the two sessions, in Session 3 the probability of voting for B in the treatments with positive partisan bias appear higher than in the same treatments in Session 4. The difference when $m = 2$ (periods 21-30 in Session 3 and periods 11-20 in Session 4) is significant at the 10% level, t-statistic = 1.32 (one-tailed test) and the difference when

[12] Multinomial probit or logit is appropriate since the dependent variable is an unordered multinomial response, multinomial logit yielded the same qualitative results. The model was fitted via maximum likelihood in Stata 9. As an alternative to clustering observations by subject, we estimated a fixed effects version of multinomial logit (multinomial probit failed to converge in most subsessions) with largely the same qualitative predictions although in some cases the data was insufficient for accurate predictions. See Wooldridge [2002], pages 496-504 for a discussion of multinomial response models and cluster sampling procedures for their estimation.

$m = 4$ (periods 11-20 in Session 3 and periods 21-30 in Session 4) is significant at the 2% level, t-statistic = 2.07 (one-tailed test). These differences appear to reflect differences in ordering of the treatments.

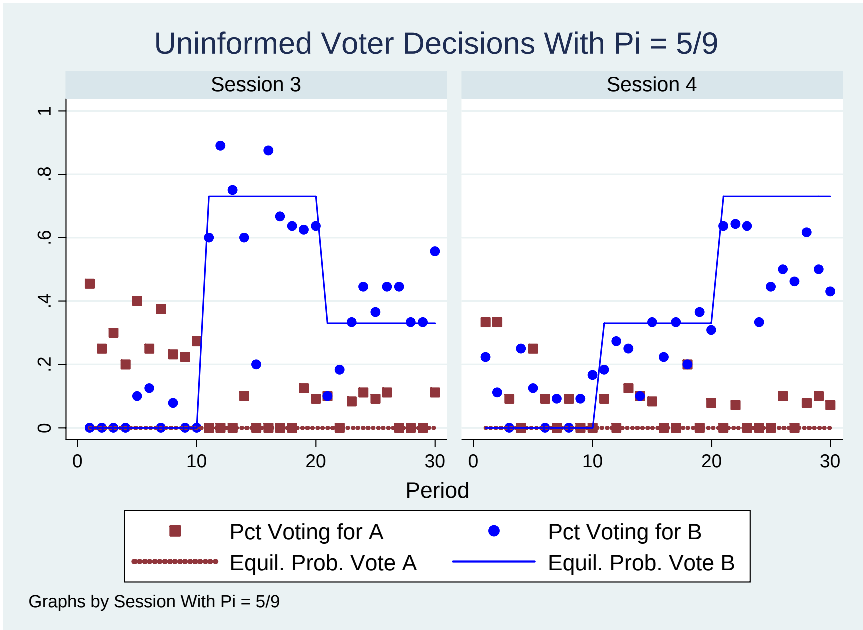

Figure 2: Uninformed Voter Decisions with $\pi = 5/9$

Our analysis suggests that Session 3 voters were primarily responsible for the ability of the decision-theoretic model to explain voting when there is no partisan bias. When $m = 0$, (periods 1-10 in both Sessions) uninformed voters in Session 3 cast their ballots for A 30% of the time and for B only 3% of the time, while in Session 4 uninformed voters cast ballots for A exactly same percentage of the time that they cast them for B (10% of the time). A statistical comparison of voting for A when $m = 0$ in Session 3 compared to Session 4 is significant at less than 1% with a t-statistic = 3.46.

Third, as for Sessions 1 and 2 we tested whether there were significant changes in behavior within a subsession that reflects possible learning estimating separate multinomial probits for voter choices for each subsession as nonlinear functions of the variable period in the subsession as above (see Appendix for detailed results). As in the analysis above, we find that learning tends to occur early in subsessions. We find evidence that voter learning trends towards the swing voter's curse theory as compared to the decision-theoretic model; uninformed voters decrease their probability of voting for A as the number of periods in a subsession increases, even in the one case where the decision-theoretic model outperforms the swing-voter's curse (Session 3 when $m = 0$).

Alternative Models with Bounded Rationality

So far we have adopted Nash equilibrium behavior as the leading benchmark to explain the data. As discussed above, in our voting environment the predictions of the Nash equilibrium provide a good fit. Can alternative behavioral models provide a similar or better fit? As we said, the data unequivocally reject decision theoretic models that postulate no strategic sophistication. The literature, however, provides a wide range of alternative models of bounded strategic sophistication. It would be impossible to discuss all of them here, so we focus on three approaches that have received particular attention in recent work. First, the so called *Level k* theories, second the *Cursed Equilibrium*, finally the *Quantal Response Equilibrium*.

Bounded rationality I: Strategic Sophistication One recent approach to bounded rationality in games is to relax the assumption that players have perfectly accurate beliefs about how the other players in the game are making their choices. The models proposed by Nagel [1995], Stahl and Wilson [1995], and Camerer, Ho, and Chong [2004] posit diversity in the population with respect to levels of strategic sophistication. These "Level-k" models are anchored by the lowest level types, or "Level-0 players", who are completely naive. In the specific context of the swing voter's curse, the obvious way to define level 0 players is that they do not condition on being pivotal, and simply vote their posterior belief of the state, as in the decision theoretic model. Higher types are more sophisticated, but have imperfect beliefs about how others will be playing the game. Level-1 players optimize assuming they face a world of level-0 players; level-2 players act as if they face a world of level-1 players; and so forth. In general then, Level-k players optimize assuming they face a world of level-$(k-1)$ players. The number of levels is in principle unbounded. This model was introduced by Stahl and Wilson [1995] and applied by Crawford and Irriberri [2006] to study the winners' curse in experimental auctions.

It is easy to characterize the predictions of this model in our specific voting environment. Informed voters have a dominant strategy: so, as in the Nash equilibrium and in the data, they always vote for their signal, regardless of their degree of sophistication. The behavior of the uniformed voters would depend on the treatment. Assume first that $m = 0$ and $\pi = 1/2$. A level 0 voter would either abstain or choose A or B with the same probabilities. Given this, it can be shown that for all k, level k uniformed voters would always abstain.[13] In this case too, therefore, the prediction is in line with the Nash equilibrium and with the empirical findings. In all the other treatments, however, the predictions of the Level k model sharply diverges from the Nash equilibrium and the data. Assume $m = 0$ and $\pi > 1/2$. In this case uninformed level-0 types would vote for A, while level k would vote for A if k is even and B if k is odd. The intuition is the following: given that all level $k-1$ are voting for the same policy, say A, the level k's would realize that event B is more likely in the pivotal event, since it can occur only if all the informed voters voted B, so they would choose to vote for B. Independently of the choice of distribution of types, therefore the model would predict zero abstention. The remaining cases are similar. When $m > 0$ and $\pi = 1/2$, level 0 would randomly vote for A, B or abstain with equal probability. Level 2 would vote for A for the same reason as above: in the pivotal event the bias introduced by the partisans would make B more likely. Level 3 would then react by always voting A: this because the vote of the uninformed voters overcompensates the bias of the partisans. Level 4 would then vote for B with probability one.[14] So, in conclusion: even types would vote B and odd types would vote A. Finally consider the case $m > 0$ and $\pi > 1/2$. Level 1 votes A, since the prior favors this option. Level 2 then reacts by all voting B. As above, level 3 would then vote A. Again: odd types always vote A and even types vote B. These predictions can not be reconciled with the data. First it can not explain abstention in

[13] Since the informed voters vote their signal sincerely, conditional on being pivotal, it would be more likely that a level 1 voter votes against the vote of an informed voter than in favor, so he would prefer to abstain. Similarly, if level k-1 voters abstain, then the same reasoning is true for level k voters.

[14] Given our parametrization the equilibrium is in mixed strategies, when all voters vote B, then B is a suboptimal choice.

the treatment $m > 0$, $\pi > 1/2$. Second, it can not explain the comparative statics in treatment $m > 0$, $\pi = 1/2$. In the data we observe that abstention is decreasing in m. However the model predicts that abstention is constant, since it may depend only on the fraction of level 0 voters. In the light of this evidence, we conclude that the level k model is not good in predicting voter's behavior and it is dominated by Nash equilibrium.

Cursed Equilibrium The idea of the cursed equilibrium was introduced by Eyster and Rabin [2005]. It postulates that players correctly anticipate the marginal distribution of the choices (i.e., votes for A, votes for B, and abstentions) of the other players in the game, but make mistakes in updating their beliefs in the pivotal event: specifically, by failing to account for the correlation between the other players' information and their decisions. In our voting environment, the equilibrium logic requires players to understand that informed voters will vote their information, i.e., there is a strong correlation, while in the "cursed" equilibrium, voters would not take this correlation into account when deciding how to vote. This would lead all voters, both informed and uninformed to simply vote their prior (or posterior) belief, and hence the predictions correspond exactly with the decision theoretic model.

There is also a "partially cursed" equilibrium, which makes more subtle predictions about behavior, and is a realistic hybrid of fully cursed and fully rational behavior. In a partially cursed equilibrium, players form beliefs that partially partially takes account of the correlation, so for our game the predictions would generally lie somewhere between the fully rational Nash equilibrium and decision theoretic model. Formally, in an X-cursed equilibrium, the equilibrium strategy is derived based on beliefs that voter vote naively with probability X and vote according to the equilibrium strategy with probability $1 - X$. When $X = 1$ ("fully cursed") voters follow the decision theoretic model; when $X = 0$, they play Nash equilibrium model. This is therefore an extension of the Nash equilibrium, and as such can not do worse than it: by adding an additional free parameter (X) this model can therefore fine tune the prediction of the Nash equilibrium.

The predictions of the cursed equilibrium are easy to characterize for the case $m = 0$, $\pi = 1/2$. In this case the informed voters would vote their signal. The uniformed voters would always abstain, regardless of the level of X. So voters would behave in a cursed equilibrium exactly as in a Nash equilibrium. The cases of the remaining treatments are more complicated and depend on the choice of parameters. Consider the case $m = 0$, $\pi > 1/2$. If X is high, than the posterior probability that the state is A for an uninformed voter would be larger than $1/2$, and the voter would vote for A. So if we want to explain abstention, we need to assume X sufficiently small, which implies a behavior close to a Nash equilibrium. In this particular treatment, however, we observe in the data a significant fraction of votes cast for A. The cursed equilibrium may contribute in explaining this phenomenon if we assume that the population is composed by agents with different degrees of cursedness. This indeed may be supported by the individual behavior analysis discussed in the next to last section of the paper, where we show that a significant fraction of agents is composed of agents who vote A with probability one when $m = 0$ and $\pi > 1/2$. The cases with $m > 0$ and $\pi > 1/2$ are similar: here too the cursed equilibrium may explain why agents vote for A, though this is a much less frequent phenomenon than with $m = 0$. Finally consider the case with $m > 0$ and $\pi = 1/2$, here the cursedness of the equilibrium would tend to reduce the incentives to vote for B, so it would skew downward the fraction of votes for B. We do not observe this phenomenon in the data: in fact the fraction of votes for B is almost exactly equal to the Nash prediction.

In summary the cursed equilibrium can explain the data with sufficiently low level of cursedness. The bias introduced by X, however, sometimes pushes the model in the wrong direction and performs worse than a simple Nash equilibrium (if we assume that X is positive). By adding an additional degree of discretionality in fitting the data, however, it may contribute in explaining the votes cast for A in treatments with $\pi > 1/2$ that can not be explained by the Nash equilibrium.

Quantal Response Equilibrium Quantal response equilibrium applies stochastic choice theory to strategic games, and is motivated by the idea that a decision maker may take a suboptimal action, and the probability of doing so is increasing in the expected payoff of the action. Hence, in contrast to both of the models above, it does not assume that players can perfectly optimize, and therefore is not a pure rational choice model. One way to think about quantal response equilibrium is that players try to "estimate" the expected payoff from each strategy and then choose what appears to be the best strategy. The randomness in choice arises because the players make mistakes in the estimation of their payoffs. However it is an equilibrium model, in the sense that one assumes the estimation of payoffs, although subject to error disturbances, is unbiased. That is, *on average* players have correct beliefs about payoffs. Thus it is a rational expectations equilibrium model, but with stochastic choice rather than deterministic rational choice (see McKelvey and Palfrey [1995, 1998]). The probability of choosing a strategy is a continuous increasing function of the expected payoff of using that strategy, and strategies with higher payoffs are used with higher probability than strategies with lower payoffs. A quantal response equilibrium is then a fixed point of the quantal response stochastic choice function. In a logit equilibrium, for any two strategies, the stochastic choice function is given by logit function, described below, with free parameter λ that indexes responsiveness of choices to payoffs (or the slope of the logit curve).[15] That is:

$$\sigma_{ij} = \frac{e^{\lambda U_{ij}}}{\sum_{k \in S_i} e^{\lambda U_{ik}}} \quad \text{for all } i,\, j \in S_i$$

where σ_{ij} is the probability i chooses strategy j and U_{ij} is the *equilibrium* expected payoff to i if they choose decision j. These expected payoffs are of course also conditioned on any information that i might have. Note that a higher λ reflects a "more precise" response to the payoffs. The extreme cases $\lambda = 0$ and $\lambda \to +\infty$ correspond to the pure noise (completely random behavior) and Nash equilibrium, respectively.

It is straightforward to apply this to the swing voters curse game. The strategies that voters choose stochastically are A, B, and ϕ, and the quantal response equilibrium choice probabilities of uninformed voters for a given value of λ, $\{\sigma_A^\lambda, \sigma_B^\lambda, \sigma_\phi^\lambda\}$ depend on the utility differences $u_A - u_B$, $u_A - u_\phi$, and $u_B - u_\phi$, expressions for which are derived in the appendix.[16]

We use standard maximum likelihood estimation techniques to estimate a single value of λ for the pooled dataset consisting of all observations of uninformed voter decisions in all 6 treatments. The results are given in table 4.

[15] The free parameter can also be interpreted as the inverse of the variance of the players' estimates of the expected payoffs of different strategies.

[16] With our experimental parameters, the logit equilibria are unique. To simplify the computational problem of numerically finding solutions for the logit equilbrium, we do not model the choices of informed voters as stochastic, and simply assume they always vote their signal (as, in fact, they did).

Table 4: Quantal Response Analysis									
		QRE Frequencies			Observed Frequencies				
π	m	A	B	Abstain	A	B	Abstain	Log. Like.	F
0.5	0	0.09	0.09	0.83	0.00	0.08	0.91	-84.24	0.91
5/9	0	0.11	0.08	0.82	0.20	0.07	0.73	-155.59	0.90
0.5	2	0.03	0.39	0.58	0.06	0.43	0.51	-197.15	0.91
5/9	2	0.04	0.37	0.60	0.06	0.30	0.63	-171.83	0.95
0.5	4	0.00	0.71	0.29	0.04	0.77	0.19	-149.70	0.81
5/9	4	0.01	0.68	0.31	0.04	0.58	0.38	-178.84	0.79

Columns 3-5 of the table present the QRE-predicted values of choice frequencies, evaluated at the estimated $\widehat{\lambda} = 42$. The next three columns give the observed choice frequencies in our data. Column 9 reports the value of the likelihood function restricted to the observations in the specific treatment. (There are slightly more than 200 observations for each treatment.) The final column displays a measure of fit that is constructed from the likehood function. Because we are fitting aggregate choice frequencies in this model, the best possible fit we could get would be a "perfect" model that predicted precisely the observed choice frequencies. Call $\overline{L}$ the value of the log likelihood function at this perfect model, and it is given by $\overline{L} = N_A \ln f_A + N_B \ln f_B + N_\phi \ln f_\phi$ where N_j is the number of observations of choice j and f_j is the relative frequency of choice j in the data. For the opposite benchmark, $\underline{L}$, we use the value of the log likelihood function for the random ($\lambda = 0$) model, so $\underline{L} = (N_A + N_B + N_\phi)\ln(\frac{1}{3})$. Denoting by $L(\widehat{\lambda})$ the value of the likelihood function at $\widehat{\lambda} = 42$, we define our measure of fit as $\frac{L(\widehat{\lambda})-\underline{L}}{\overline{L}-\underline{L}}$. This measure of fit equals 1 for the "perfect" model and equals 0 at the random model, so it measure the improvement over the random model, relative to a perfect model. The fit by this measure is .90 or higher in 4 of 6 treatments, and is lowest in the two m=4 treatments. Another way to understand how well the data is being fitted by the QRE model is to see that the model does not systematically over- or under- predict the choices of different strategies. A scatter diagram of the QRE-predicted frequencies and the observed choice frequencies is shown in Figure 3. The observed and predicted values are very close: the regression line through this collection of points has a slope equal to 0.97, an intercept of 0.01, and $R^2 > 0.95$.

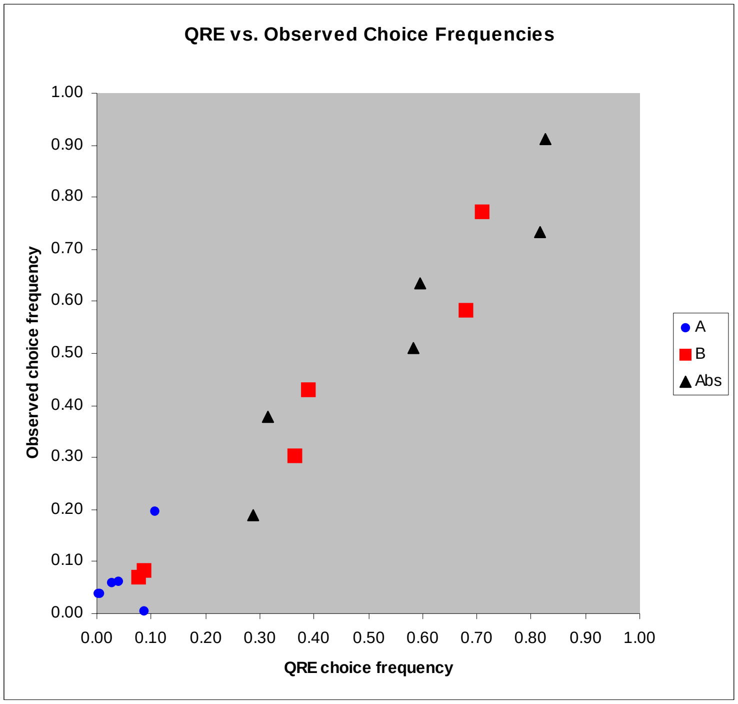

Figure 3: QRE versus Observed Choice Frequencies

An interesting feature of the data, which is captured in the QRE model is that the probability an uninformed voter chooses A is higher when $\pi = 5/9$ than when $\pi = .50$, and this relationship holds for all values of λ. This is quite intuitive, because the naive strategy of voting with your prior is obviously not as bad if the prior is further from $1/2$, since, a priori, by doing so you will vote correctly more often than not. Of course it is still not optimal because of the pivot calculations and the swing voter's curse, but a π becomes further from .5, the swing voter's curse diminshes. However, this effect is predicted to be very small when $m > 0$. In our data, we do find a significant difference in the expected direction for $m = 0$, and there is no significant difference for $m > 0$.

The QRE probability an uninformed voter votes for A is also a decreasing function of m for all values of λ. In other words, regardless of the exact value of the QRE noise parameter, the model predicts that f_A should be highest when $m = 0$ and lowest when $m = 4$, which is borne out by our data. The logic behind this is quite intuitive. If $m > 0$ then voting for A is a bad strategy not only because it increases the probability that the uninformed voter himself is pivotal (the swing voter's curse), but also because it increases the probability a partisan is pivotal. When $m = 0$, there is only the first effect.

Committee Decisions

Information and Turnout

In the previous subsection we averaged across all committees within a treatment. We now turn to an analysis of committee decisions. First we examine therelationship between turnout and the number of informed voters. Theoretically, we expect that as the number of informed voters increases, the turnout level will increase from σ_B to 1. That is, in equilibrium informed voters vote 100% of the time, while uninformed voters cast votes with probability σ_B. When a voter becomes informed then total turnout increases by 1 and decreases by only σ_B.

To evaluate this prediction we estimate the effect of increasing the number of informed voters in a group on the number of voters in the group who chose to vote (including both informed and uninformed voters but excluding of course computer voters). We take our individual voter predictions from the multinomial probit estimations described above and summarized in the Appendix for each voter in each committee in each period in each session to construct a mean committee turnout level by number of informed voters for each subsession. This allows us to estimate the relationship between the number of informed voters and committee turnout levels incorporating individual subject and learning effects that might affect committee turnout levels.[17]

Figure 4 presents a comparison of the estimated turnout levels with the actual mean turnout levels of the committees and the swing voter's curse theoretically predicted turnout levels as a function of the number of informed voters. These relationships are only shown for the range of informed voters realized in the subsession–in some subsessions there were no committees with more than 3 informed voters. First notice that although the estimated relationships are nonlinear, reflecting the effects of learning and subject cohorts, the estimated relationships' slopes closely track the theoretical slopes. Thus, even with such effects, our comparative static prediction of the relationship between number of informed voters and committee turnout receives support. Furthermore, as partisan bias increases, the relationship between turnout and number of informed voters becomes flatter as expected.

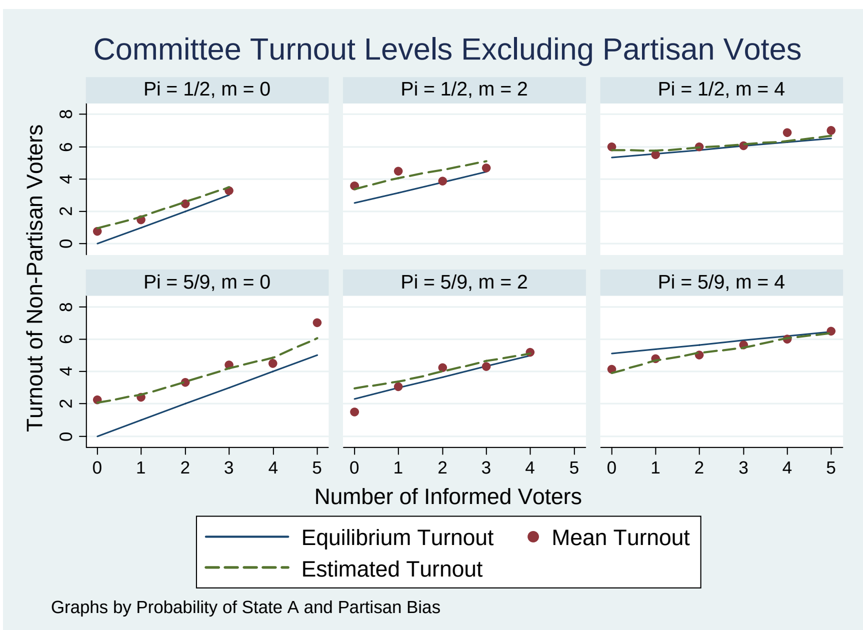

Figure 4: Committee Turnout Levels Excluding Partisan Votes

[17] We also estimated separate binomial regressions, as described in Wooldridge [2002] pages 659-660, to estimate votes for A and for B, which we then used to construct estimated turnout levels by number of informed voters for each subsession. These levels were similar to the ones reported here, but assume an independence between the votes for A and B. We also estimated a binomial regression where the dependent variable was aggregate turnout with similar results. Using the multinomial probit estimations allow us to consider subject specific effects and learning that might affect committee turnout choices.

Second, except for the case when $m = 4$ and $\pi = 5/9$, estimated actual turnout exceeds equilibrium turnout, reflecting the tendency of uninformed voters to vote more than predicted when there is zero partisan bias or low levels of partisan bias. When $m = 4$ and $\pi = 0.5$ the estimated turnout relationships almost perfectly coincide with the equilibrium relationship. These results are consistent with the aggregate individual behavior results reported above; when partisan bias is low, uninformed voters tend to vote more than predicted, but when partisan bias is high, uninformed voters vote either less or very close to the equilibrium predicted levels.

Margin of Victory and Information

As the number of informed voters in a committee is expected to affect turnout, it is also expected to affect the margin of victory for the winning outcome. We also evaluate this comparative static prediction by comparing estimated committee margins of victory calculated using the estimated individual probabilities of voting by subject, period, and subsession with the equilibrium probabilties. However, the theoretically predicted margin of victory depends on the signals received by informed voters and thus the true state. For example, if the true state is A and the number of informed voters are 4, $m = 4$, and $\pi = 0.5$, theoretically we expect a victory margin of $|8 - 3(0.78)| = 5.66$ while if the true state is B theoretically we expect a victory margin of $|4 - 3(0.78) - 4| = 2.34$. Thus we make two comparisons, we compare the estimated plurality for A with the equilibrium plurality for A when the true state is A and we compare the estimated plurality for B with the equilibrium plurality for B when the true state is B. Figures 5a and 5b present these comparisons.

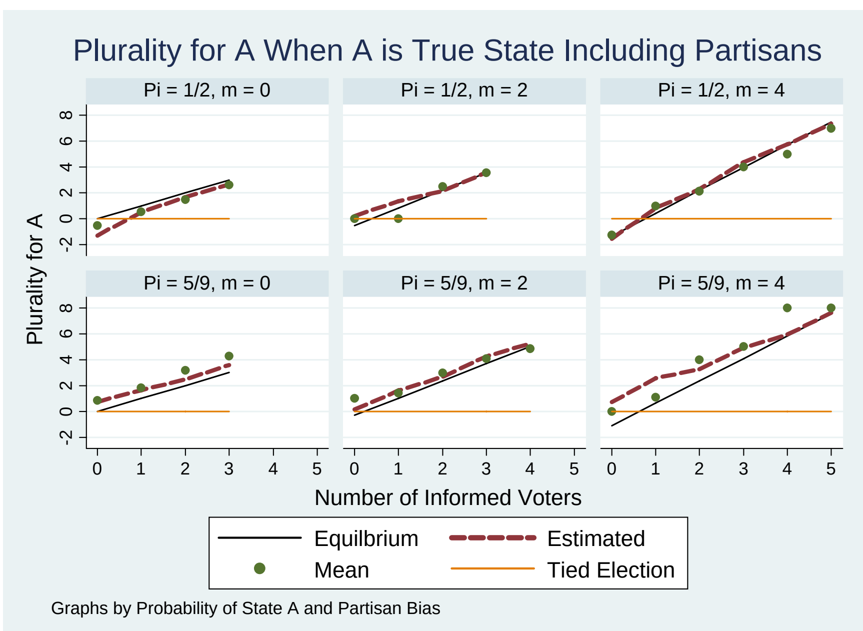

Figure 5a: Plurality for A When A is the True State Including Partisans

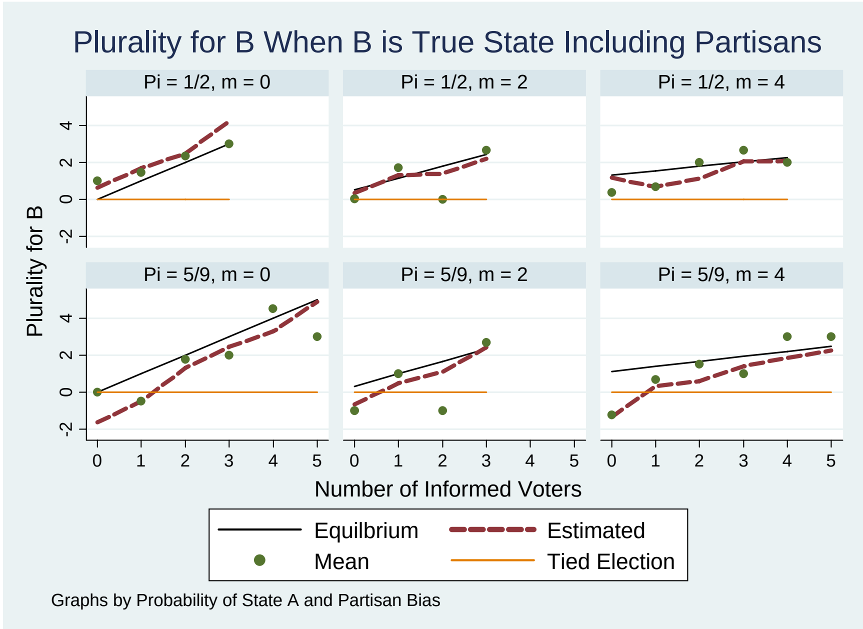

Figure 5b: Plurality for B When B is the True State Including Partisans

In the figures, the light solid line represents when an election was tied. Observations below this line represent wins by state B and above the line represent wins by state A in Figure 5a and vice-versa in Figure 5b. Thus, observations below this line represent cases where committees chose incorrectly, while observations above this line represent cases where committees chose correctly.

First notice that as with the turnout levels, the slope of the equilibrium plurality relationships depend on the degree of partisan bias and the estimated relationships demonstrate similar dependence. Second, we find that generally the margins of victory for A are greater than equilibrium when A is the true state and the margins of victory for B are less than equilibrium when B is the true state, which follows from the excess voting for A. Third we find that it takes very few informed voters for the true state to have a positive margin of victory–in most cases with just one informed voter, the plurality of votes in favor of the true state is positive, even when $m = 4$. Thus, uninformed voters sufficiently balance out the partisan bias such that the true state receives a positive plurality.

Closeness and Turnout

A common perceived prediction of the rational model of voting is that turnout should be positively related to the expected closeness of an election since when elections are expected to be close, votes are more likely to be pivotal, and thus the investment benefits from voting are greater (see for example Filer, et al. [1993]). However, in our analysis closeness and turnout may be negatively related since increasing the number of informed voters increases the margin of victory (decreasing closeness) while it increases turnout. These results imply that simple tests of the effect of closeness on turnout decisions or aggregate turnout are not nuanced enough to determine if voters are making participation decisions rationally.

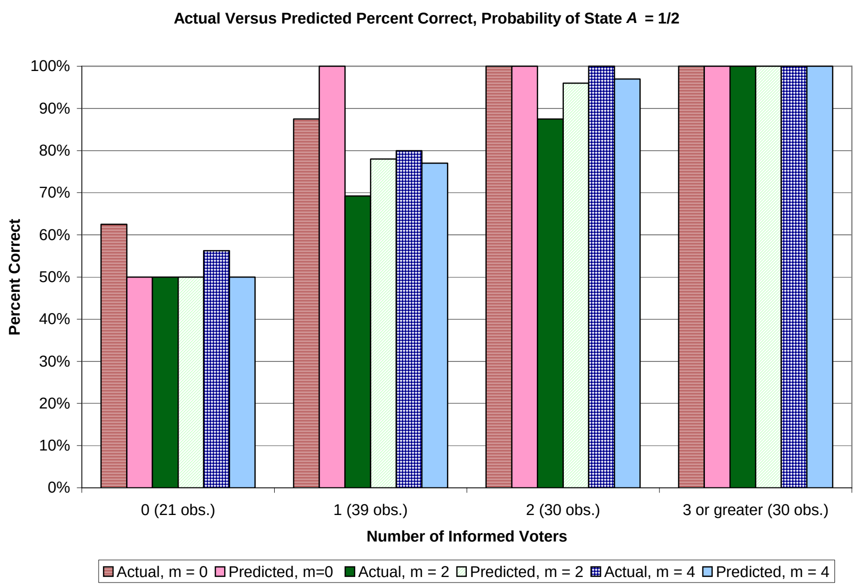

Figure 1: Figure 6a: Actual Versus Predicted Percent Correct, $\pi = 0.5$

Efficiency of Committee Choices

Figure 6a below shows the percentage of correct committee choices as a function of the number of informed voters when $\pi = 0.5$ (Note that we omit cases where we have no observations, for example, we have no observations when $m < 4$ and the number of informed voters is greater than 3). We compare these percentages to the percentages theoretically predicted to be correct which are calculated by estimating the binomial probabilities that a group is correct given the assumed number of informed voters. We find that group decisions are generally either more likely to be correct than theoretically predicted or close to the theoretical prediction. The largest and only statistically significant shortfall occurs when only one voter is informed and $m = 0$, theory predicts that the group decision will be correct 100% of the time, we find that the group decisions are correct only 87.5% of the time, which is significant at a 2% confidence level. In some cases, due to fortunate draws, the group decisions are correct a greater percentage of time than theoretically predicted. For example, when $m = 0$ and no voter is informed, we predict that the group will be correct 50% of the time, we find in the experiment that the group is correct 62.5% of the time. None of these differences are statistically significant, however.

Figure 6b shows the same efficiency comparisons for the case when $\pi = 5/9$. We find that when zero voters are informed the efficiencies are lower but the difference between the theoretically predicted percent correct and the actual percent correct is significantly different only for the case where $m = 4$ (8% confidence level). We also find a significant shortfall in percent correct when only one voter is informed and there is zero partisan bias; only 75% of the group decisions are correct, although theory predicts that 100% will be, which is significant at the 2% confidence level. This reflects the tendency of voters to vote for A when there is zero partisan bias and $\pi > 0.5$. However, for the cases where two or more voters are informed, the group is correct 100% of the time when there is zero partisan bias. There are no other significant differences between the percent of time the group is correct and the theoretical predictions.

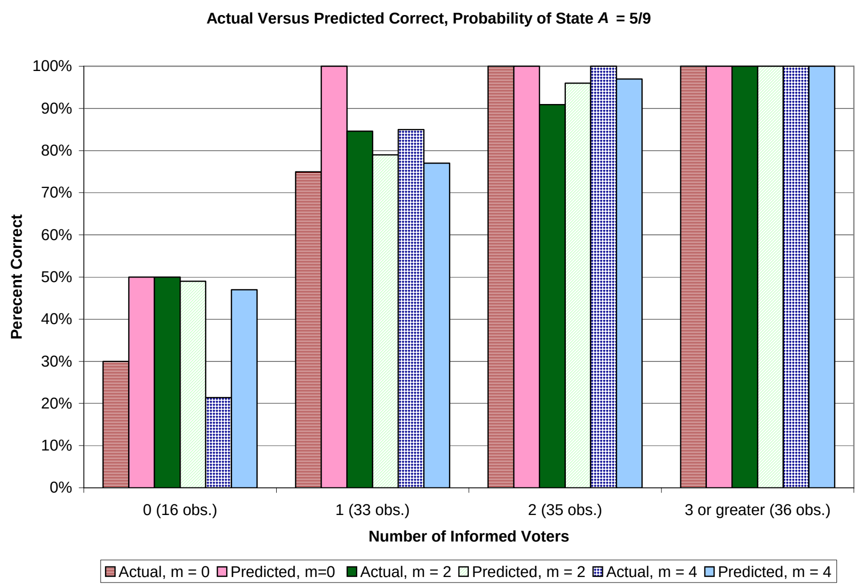

Figure 2: Figure 6b: Actual versus Predicted Percent Correct, $\pi = 5/9$

In order to evaluate the efficiency of committee decisions we compared the equilibrium probabilities that a committee will make a correct decision for each treatment with the estimated probabilities calculated using the probabilities of voting for A, B, or abstaining as estimated by period, group, and treatment in the multinomial probits discussed above. This is shown in Figures 7a,b.

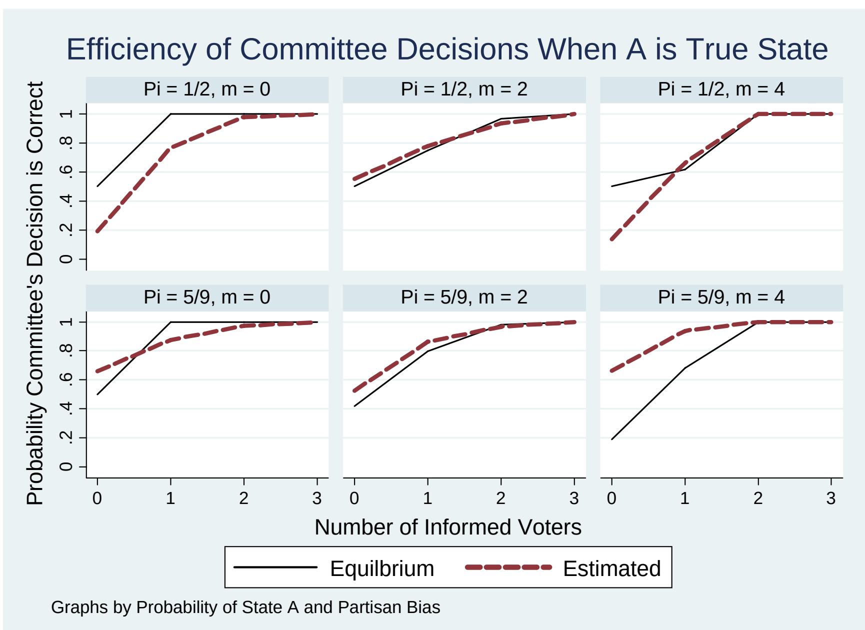

Figure 7a: Efficiency of Committee Decisions When A is True State

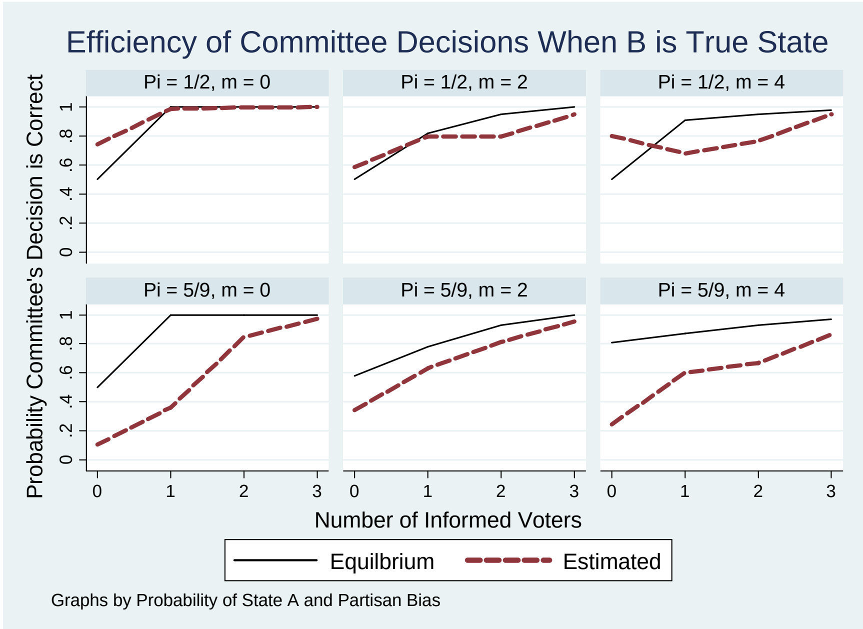

Figure 7b: Efficiency of Committee Decisions \When B is True State

We control for the true state and the number of informed voters since informed voters voted their signals 100% of the time. For example, consider a committee where $m = 0$, A is the true state, $\pi = 0.5$, and there are seven uninformed voters. In this case, we only need to compute the probability that the number of votes received by A is greater than the number of votes received by B. We do so by calculating the probability of this event given the estimated individual probabilities of voting for A, B, or abstaining from the multinomial probits for this committee which depended on the session and the period of the experiment. Similarly, in a committee where $m = 4$, B is the true state, $\pi = 0.5$, and there are five uninformed voters, we need to compute the probability that the number of uninformed voters for B exceeds the number of uninformed voters for A by more than 2 (since A will get 4 computer votes and the 2 informed voters will vote for B). We performed these calculations for each committee and the particular configuration of computer votes, true state, and number of informed voters.

We find that the committees tend to be less efficient in decision making when $\pi = 5/9$ and/or the true state is B. However, the committee decisions, like the equilibrium decisions, are approximately 100% correct if there are 3 or more informed voters, even when there are four computer voters and the true state is B. Thus, balancing by uninformed voters does help the committees reach more informed decisions than would be reached if uninformed voters voted naively as predicted by the decision-theoretic model.

Individual Behavior

In this subsection we analyze patterns of individual behavior. The within subject design enables us to compare how an individual behaves across different treatments; that is, as a function of the number of partisans. For each value of m we classify the subject's behavior as either always abstaining (Abs.), always voting for B, or mixing (Abs/B), by observing their choices when uninformed. Individual subject choices are classified by profile in Table 5 below. We classify a subject as following a profile if 90% or more of his or her choices are predicted choices. Some subjects could not be classified primarily because they frequently either voted when $m = 0$ or for A when $m > 0$.

Table 5: Uninformed Voter Individual Profiles

Partisan Bias			Session			
$m = 0$	$m = 2$	$m = 3$	1	2	3	4
Abs.	*Abs.*	*Abs.*	0.07	0.07	0.07	0.14
Abs.	*Abs.*	*Abs/B*				0.14
Abs.	*Abs.*	*B*	0.29	0.14		0.07
Abs.	*B*	*B*	0.29	0.14		
Abs.	*Abs/B*	*B*	0.07	0.29	0.29	0.07
Abs.	*Abs/B*	*Abs/B*	0.21	0.14	0.14	0.21
Total			0.93	0.79	0.50	0.65

Turning to the subjects who are not classified in Table 5, when $\pi = 5/9$ we observed several voters choosing to vote A when $m = 0$, particularly in Session 3. We find that a number of voters chose a profile where they voted for A when $m = 0$ but either abstained or voted for B when $m > 0$. These percentages of subjects choosing these profiles are summarized in Table 6 below with 36% choosing this type of profile in Session 3 and 14% in Session 4.

Table 6: Additional Profiles

Partisan Bias			Session	
$m = 0$	$m = 2$	$m = 4$	3	4
A	*Abs.*	*B*	0.07	
A	*Abs.*	*Abs.*	0.14	
Abs/A	*B*	*B*	0.07	
Abs/A	*Abs/B*	*B*	0.07	
Abs/A	*Abs.*	*Abs.*		0.14
Total			0.36	0.14

CONCLUDING REMARKS

Significant evidence exists that voters often choose to abstain when voting is apparently costless and the standard rational model of voting would predict participation. Empirical analysis suggests that such abstention may be related to differences in voter information. The Swing Voter's Curse theory provides a complicated game theoretic explanation for why uninformed voters would be willing to abstain and delegate decision making to more informed voters. Hence, it is a candidate explanation for the empirical evidence that lower information elections have lower turnout. In this paper we have provided the first experimental test of the theory, where we control for key parameters of the model, which are difficult to measure precisely or control for in naturally occuring data. We find strong support for the theory. Uninformed voters behave strategically: they strategically abstain when uninformed and both outcomes are equally likely, delegating their votes to more informed voters. With partisan bias, they vote strategically to balance out the votes of partisans, at probabilities close to equilibrium, increasing the probability of voting as partisan bias increases. Even when the partisan-favored outcome is the *more* likely outcome we find most voters balancing in this way. These results are supported at both the aggregate and individual level and across sessions and treatment configurations.

We also find that turnout and margin of victory both increase with the number of informed voters and that there is a positive relationship between these two variables, contrary to the common view that rational models of turnout predict that closeness and turnout should be positively related. These results suggest that tests using field data of whether turnout is related to closeness, which are unable to control for information asymmetries, are inadequate or at best very weak tests of rational voting models.

APPENDIX

Proof of Lemma 1

Let u_θ for $\theta = A, B$ be the expected utility of an uninformed swing voter of voting for policy θ. To evaluate $u_A - u_B$ there are only three relevant events: P_0, the event when there is a tie among the other voters between A and B; and P_θ for $\theta = A, B$, which is the event in which policy θ is losing by one vote. The expected net utility of voting for A rather than B conditional on event P_i is

$$E\left(u_A - u_B \left| P_i \right.\right) = \begin{cases} \Pr(A \left| P_i \right.) - 0.5 & i = A, B \\ 2\Pr(A \left| P_i \right.) - 1 & i = 0 \end{cases}$$

We can therefore write:

$$\begin{aligned} u_A - u_B &= \left[\pi \Pr\left(P_0 \left| A \right.\right) - (1-\pi)\Pr\left(P_0 \left| B \right.\right)\right] + \frac{1}{2}\sum_{i=A,B} \Pr(P_i)\left(2\Pr(A \left| P_i \right.) - 1\right) & (2) \\ &= \left[\pi \Pr\left(P_0 \left| A \right.\right) - (1-\pi)\Pr\left(P_0 \left| B \right.\right)\right] + \frac{1}{2}\left[\begin{array}{c} \pi \Pr\left(P_B \left| A \right.\right) - (1-\pi)\Pr\left(P_B \left| B \right.\right) \\ +\pi \Pr\left(P_A \left| A \right.\right) - (1-\pi)\Pr\left(P_A \left| B \right.\right) \end{array}\right] & (3) \\ &= \left(\Lambda_0 + \frac{1}{2}\Lambda_1\right) & (4) \end{aligned}$$

where $\Lambda_0 = \left[\pi \Pr\left(P_0 \left| A \right.\right) - (1-\pi)\Pr\left(P_0 \left| B \right.\right)\right]$ and

$$\Lambda_1 = \pi \Pr\left(P_B \left| A \right.\right) - (1-\pi)\Pr\left(P_B \left| B \right.\right) + \pi \Pr\left(P_A \left| A \right.\right) - (1-\pi)\Pr\left(P_A \left| B \right.\right)$$

Consider Λ_1 first. Since n is odd, we can write:

$$\begin{aligned} \Lambda_1 &= \sum_{j=0}^{\frac{n-3}{2}} \left(\frac{(n-1)!}{\left(\frac{n-(2j+1)}{2}\right)!\left(\frac{n-2-(2j+1)}{2}\right)!\,(2j+1)!}\right)\left[(1-p)\,\sigma_\phi\right]^{(2j+1)} \\ &\quad \cdot \left[p + (1-p)(1-\sigma_\phi)\right] \cdot \left\{\begin{array}{c} \pi\left[\begin{array}{c} p(1-p)\,\sigma_B \\ +(1-p)^2\,\sigma_A\sigma_B \end{array}\right]^{\frac{n-(2j+1)-2}{2}} \\ -(1-\pi)\left[\begin{array}{c} p(1-p)\,\sigma_A \\ +(1-p)^2\,\sigma_A\sigma_B \end{array}\right]^{\frac{n-(2j+1)-2}{2}} \end{array}\right\} \end{aligned}$$

Consider now Λ_0. We can write:

$$\begin{aligned}\Lambda_0 &= \sum_{j=0}^{\frac{n-1}{2}} \left(\frac{(n-1)!}{\left(\frac{n-1-2j}{2}\right)! \left(\frac{n-1-2j}{2}\right)! (2j)!} \right) \left[(1-p)\,\sigma_\phi\right]^{2j} \\ &\quad \cdot \left\{ \begin{array}{c} \pi \left[p\,(1-p)\,\sigma_B + (1-p)^2\,\sigma_A\sigma_B\right]^{\frac{n-1-2j}{2}} \\ -\,(1-\pi)\left[p\,(1-p)\,\sigma_A + (1-p)^2\,\sigma_A\sigma_B\right]^{\frac{n-1-2j}{2}} \end{array} \right\} > 0\end{aligned}$$

Assume by contradiction that $\sigma_B > \sigma_A$. Since $\pi \geq \frac{1}{2}$, we conclude that $\Lambda_1 > 0$ and $\Lambda_0 > 0$. So $u_A - u_B > 0$, which implies that $\sigma_B \leq \sigma_A$, a contradiction. We conclude that $\sigma_A \geq \sigma_B$. When $\pi = \frac{1}{2}$ we can make the symmetric argument and prove $\sigma_B \geq \sigma_A$. Hence $\pi = \frac{1}{2} \Rightarrow \sigma_B = \sigma_A$. ■

Proof of Proposition 1

If $\sigma_B > 0$, then the voter must be indifferent between the two alternatives since $\sigma_A \geq \sigma_B$ $\forall \pi \geq \frac{1}{2}$. Assume this is the case, then:

$$\begin{aligned}0 &= u_A - u_B = \Pr[P_0] \cdot [2\Pr(A\,|P_0\,) - 1] \\ &\quad + \frac{1}{2}\Pr[P_A] \cdot [2\Pr(A\,|P_A\,) - 1]\,v + \frac{1}{2}\Pr[P_B] \cdot [2\Pr(A\,|P_B\,) - 1]\end{aligned}$$

This equation implies:

$$\begin{aligned}&[\pi \Pr(P_0\,|A\,) - (1-\pi)\Pr(P_0\,|B\,)] \\ =\ & \frac{1}{2}\left[(1-\pi)\Pr(P_B\,|B\,) - \pi\Pr(P_B\,|A)\right] + \frac{1}{2}\left[(1-\pi)\Pr(P_A\,|B\,) + \pi\Pr(P_A\,|A)\right]\end{aligned} \tag{5}$$

Moreover, we have:

$$u_A - u_\phi = \frac{1}{2}\left[\pi\Pr(P_0\,|A\,) - (1-\pi)\Pr(P_0\,|B\,)\right] + \frac{1}{2}\left[\pi\Pr(P_A\,|A\,) - (1-\pi)\Pr(P_A\,|B\,)\right] \tag{6}$$

Substituting (5) in (6), we obtain:

$$u_A - u_\phi = \frac{1}{4}\pi\left[\Pr(P_A\,|A\,) - \Pr(P_B\,|A\,)\right] + \frac{1}{4}(1-\pi)\left[\Pr(P_B\,|B\,) - \Pr(P_A\,|B\,)\right]$$

We can compute:

$$\Pr(P_B\,|B\,) = \sum_{j=0}^{\frac{n-3}{2}} \Phi(j) \frac{\left[p(1-p)\sigma_A + (1-p)^2\,\sigma_A\sigma_B\right]^{\frac{n-(2j+1)}{2}}}{p + (1-p)\sigma_B}$$

$$\Pr(P_B\,|A\,) = \sum_{j=0}^{\frac{n-3}{2}} \Phi(j) \frac{\left[p(1-p)\sigma_B + (1-p)^2\,\sigma_A\sigma_B\right]^{\frac{n-(2j+1)}{2}}}{(1-p)\sigma_B}$$

and

$$\Pr(P_A\,|A\,) = \sum_{j=0}^{\frac{n-3}{2}} \Phi(j) \frac{\left[p(1-p)\sigma_B + (1-p)^2\,\sigma_A\sigma_B\right]^{\frac{n-(2j+1)}{2}}}{p + (1-p)\sigma_A}$$

$$\Pr(P_A|B) = \sum_{j=0}^{\frac{n-3}{2}} \Phi(j) \frac{\left[p(1-p)\sigma_A + (1-p)^2 \sigma_A \sigma_B\right]^{\frac{n-(2j+1)}{2}}}{(1-p)\sigma_A}$$

where: $\Phi(j) = \left(\frac{(n-1)!}{\left(\frac{n-(2j+1)}{2}\right)! \left(\frac{n-2-(2j+1)}{2}\right)! (2j+1)!} \right) \left[(1-p)\sigma_\phi\right]^{(2j+1)}$. From these expressions is evident that $[\Pr(P_A|A) - \Pr(P_B|A)] < 0$ and $[\Pr(P_B|B) - \Pr(P_A|B)] < 0$, which implies that $u_A - u_\phi < 0$, and therefore $\sigma_A = 0$. So $\sigma_B \leq \sigma_A = 0$, a contradiction. Using Lemma 1, we conclude that $\pi = \frac{1}{2}$ implies $\sigma_A = \sigma_B = 0$; and $\pi > \frac{1}{2}$implies $\sigma_A \geq \sigma_B = 0$, as stated in the proposition. ■

Proof of Lemma 2

Assume by contradiction that $m > 0$ and $\sigma_A \geq \sigma_B$. The expected utility of voting for A net of the utility of voting for B can be expressed as in (2) and 3. In this case:

$$\begin{aligned} \Lambda_1 &= \sum_{j=0}^{\frac{n-3-m}{2}} \left(\frac{(n-1)!}{\left(\frac{n-(2j+1)-m}{2}\right)! \left(\frac{n-2-(2j+1)+m}{2}\right)! (2j+1)!} \right) \left[(1-p)\sigma_\phi\right]^{(2j+1)} \\ &\cdot \left[p + (1-p)(1-\sigma_\phi)\right] \\ &\cdot \left\{ \begin{array}{c} \pi \left[\frac{(1-p)\sigma_B}{p+(1-p)\sigma_A}\right]^{\frac{m}{2}} \left[p(1-p)\sigma_B + (1-p)^2 \sigma_A \sigma_B\right]^{\frac{n-(2j+1)-2}{2}} \\ -(1-\pi) \left[\frac{p+(1-p)\sigma_B}{(1-p)\sigma_A}\right]^{\frac{m}{2}} \left[p(1-p)\sigma_A + (1-p)^2 \sigma_A \sigma_B\right]^{\frac{n-(2j+1)-2}{2}} \end{array} \right\} \end{aligned}$$

Consider now Λ_0. We can write:

$$\begin{aligned} \Lambda_0 &= \sum_{j=0}^{\frac{n-1-m}{2}} \left(\frac{(n-1)!}{\left(\frac{n-1-2j-m}{2}\right)! \left(\frac{n-1-2j+m}{2}\right) (2j)!} \right) \left[(1-p)\sigma_\phi\right]^{2j} \\ &\cdot \left\{ \begin{array}{c} \pi \left[\frac{(1-p)\sigma_B}{p+(1-p)\sigma_A}\right]^{\frac{m}{2}} \left[p(1-p)\sigma_B + (1-p)^2 \sigma_A \sigma_B\right]^{\frac{n-2j-1}{2}} \\ -(1-\pi) \left[\frac{p+(1-p)\sigma_B}{(1-p)\sigma_A}\right]^{\frac{m}{2}} \left[p(1-p)\sigma_A + (1-p)^2 \sigma_A \sigma_B\right]^{\frac{n-2j-1}{2}} \end{array} \right\} < 0 \end{aligned}$$

Consider first the case in which $\pi = \frac{1}{2}$, and assume by contradiction that $\sigma_A > \sigma_B$. Since $\frac{(1-p)\sigma(B)}{p+(1-p)\sigma(A)} < \frac{p+(1-p)\sigma(B)}{(1-p)\sigma(A)}$ we have $\Lambda_0 < 0$ and $\Lambda_1 < 0$: so < 0, which implies that $\sigma_B \geq \sigma_A$, a contradiction. Consider now the case in which $\pi > \frac{1}{2}$. There is a $\overline{p}$ such that $\pi \left[\frac{(1-p)\sigma_B}{p+(1-p)\sigma_A}\right]^{\frac{m}{2}} < (1-\pi)\left[\frac{p+(1-p)\sigma_B}{(1-p)\sigma_A}\right]^{\frac{m}{2}}$ for any $p > \overline{p}$. Assume by contradiction that $\sigma_A > \sigma_B$ and $p \geq \overline{p}$. In this case too $\Lambda_0 < 0$ and $\Lambda_1 < 0$: so again $u_A - u_\phi < 0$, which implies that $\sigma_B \geq \sigma_A$, a contradiction. ■

Proof of Proposition 2

Assume that $\sigma_A > 0$, then since $\sigma_B \geq \sigma_A$, it must be that $u_A - u_B = 0$. Proceeding as in Proposition 1 we can obtain:

$$u_A - u_\phi = \frac{1}{4}\pi\left[\Pr(P_A|A) - \Pr(P_B|A)\right] + \frac{1}{4}(1-\pi)\left[\Pr(P_B|B) - \Pr(P_A|B)\right]$$

We can compute:

$$\Pr(P_B|B) = \sum_{j=0}^{\frac{n-3}{2}} \Phi(j) \frac{\left[p(1-p)\sigma_A + (1-p)^2 \sigma_A \sigma_B\right]^{\frac{n-(2j+1)-m}{2}}}{p + (1-p)\sigma_B}$$

$$\Pr(P_B|A) = \sum_{j=0}^{\frac{n-3}{2}} \Phi(j) \frac{\left[p(1-p)\sigma_B + (1-p)^2 \sigma_A \sigma_B\right]^{\frac{n-(2j+1)-m}{2}}}{(1-p)\sigma_B}$$

and

$$\Pr(P_A|A) = \sum_{j=0}^{\frac{n-3}{2}} \Phi(j) \frac{\left[p(1-p)\sigma_B + (1-p)^2 \sigma_A \sigma_B\right]^{\frac{n-(2j+1)-m}{2}}}{p + (1-p)\sigma_A}$$

$$\Pr(P_A|B) = \sum_{j=0}^{\frac{n-3}{2}} \Phi(j) \frac{\left[p(1-p)\sigma_A + (1-p)^2 \sigma_A \sigma_B\right]^{\frac{n-(2j+1)-m}{2}}}{(1-p)\sigma_A}$$

where: $\Phi(j) = \left(\frac{(n-1)!}{\left(\frac{n-(2j+1)-m}{2}\right)! \left(\frac{n-2-(2j+1)+m}{2}\right)! (2j+1)!} \right) ((1-p)(1-\sigma))^{(2j+1)}$. From these expressions is evident that $[\Pr(P_A|A) - \Pr(P_B|A)] < 0$ and $[\Pr(P_A|B) - \Pr(P_B|B)] < 0$, which implies that $u_A - u_\phi < 0$: and therefore $\sigma_A = 0$, a contradiction.

We now prove that $\sigma_B > 0$. If this is not the case, the only other possibility is that $\sigma_B = \sigma_A = 0$: we now show that this is impossible. We can write:

$$u_B - u_\phi = \frac{1}{2}(1-\pi)\Pr(P_0|B) - \pi \Pr(P_0|A) + \frac{1}{2}[(1-\pi)\Pr(P_B|B) - \pi \Pr(P_B|A)]$$

Since when $\sigma_B = \sigma_A = 0$ we have $\Pr(P_0|A) = \Pr(P_B|A) = 0$, and $\Pr(P_0|B) > 0$, $\Pr(P_B|B)$, we have $u_B - u_\phi > 0$, which implies $\sigma_B > 0$. $\blacksquare$

Multinomial Probit Estimations of Learning Effects by Session

Table A summarizes the results of the multinomial logit estimations discussed in sections V.2.1. Each subsession was estimated separately and the standard error was adjusted for clustering by subject in the subsession.

Table A: Session 1 Multinomial Probits of Uninformed Voter Choices				
Abs. is Base Choice, Std. Err. Adj. for Clustering by Subj., Constant Sup.				
$m = 0$	Coefficient (Robust Standard Error)			
Ind. Var.	Session 1	Session 2	Session 3	Session 4
	Effect on Prob. Vote for A			
Period	NA*	-1.36 (0.49)	-0.23 (0.19)	-0.41 (0.24)
Period^2	NA*	0.09 (0.06)	0.01 (0.02)	0.01 (0.02)
	Effect on Prob. Vote for B			
Period	-0.75 (0.34)	-0.76 (0.30)	-0.72 (0.30)	-0.62 (0.14)
Period^2	0.06 (0.03)	0.06 (0.02)	0.05 (0.03)	0.05 (0.01)
Log Pseudolikelihood	-33.70	-39.29	-75.50	-63.13
Observations	111	106	98	105
$m = 2$	Effect on Vote for A			
Period	-0.47 (0.23)	-0.81 (0.18)	-0.65 (0.30)	-0.69 (0.20)
Period^2	0.03 (0.02)	0.07 (0.02)	0.05 (0.03)	0.06 (0.02)
	Effect on Vote for B			
Period	0.00 (0.17)	-0.00 (0.14)	-0.24 (0.14)	-0.37 (0.18)
Period^2	-0.01 (0.02)	0.00 (0.01)	0.03 (0.02)	0.03 (0.02)
Log Pseudolikelihood	-102.23	-92.50	-84.80	-87.29
Observations	112	109	98	107
$m = 4$	Effect on Vote for A			
Period	-0.48 (0.33)	-0.49 (0.27)	-0.79 (0.25)	-0.78 (0.25)
Period^2	0.01 (0.04)	0.05 (0.02)	0.07 (0.02)	0.07 (0.02)
	Effect on Vote for B			
Period	0.52 (0.19)	0.36 (0.21)	0.25 (0.20)	0.06 (0.16)
Period^2	-0.05 (0.02)	-0.02 (0.02)	-0.02 (0.02)	-0.01 (0.01)
Log Pseudolikelihood	-56.85	-73.76	-68.23	-99.39
Observations	99	107	89	117
*There were 0 votes for A in Session 1, $m = 0$				

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