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. 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.

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

[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.

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.

To overcome the problems with field data, this paper reports the first laboratory study of the swing voter's curse. 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. We find strong support for the theory. In a common value environment where all voters have the same preferences but are asymmetrically informed, poorly informed voters always strategically abstain when both outcomes are equally likely, delegating their votes to more informed voters. When a partisan bias is introduced -i.e., some voters' preferences favor a given candidate independently from private information- uninformed voters vote strategically to balance out the partisans' votes, thus increasing the probability of voting as partisan bias increases. The main comparative static predictions of the model are tested: as key parameters of the environment change, the fraction of voters who vote against the partisan bias tracks very closely the equilibrium predictions. Even when the partisan-favored outcome is the more *ex ante* likely outcome, we find most voters balancing in this way by voting against their prior beliefs. These results are supported at both the aggregate and individual level and across sessions and treatment configurations.

[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, and argue that it explains turnout in local Texas referenda better than the standard pivotal voting model.

Our results, however, provide insights on the larger "pivotal-voter" literature.[4] Among other things, we 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 should predict that closeness and turnout are 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.

Although there is a growing literature testing predictions of voting models, 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.[5] 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 [2007] 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],

[4]This literature includes the earlier 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).

[5]See Schram and Sonnemans [1996], Cason and Mui [2005], Grosser, et al. [2005], and Duffy and Tavits [2008] 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).

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 concedes that there are alternative possible explanations for the relationship between information and turnout, and field data may not be accurate enough to identify the correct theory: "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 accommodate in even random social experiments.." (p. 116). Our controlled laboratory experiment precisely allows us to put under scrutiny these subtle differences between the swing voter's curse and other alternative theories.

I 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 $\varnothing$ with probabilities:

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

The agent, therefore, is perfectly informed on the state of the world with probability p (i.e., observes a or b) and has no information with probability $1-p$ (i.e., observes $\varnothing$). 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 $m \leq n - 3$.[6]

After swing voters have seen their private signal, all voters vote or abstain simultaneously. Each voter can vote for A, vote for B, or abstain. The policy choice with the majority of votes cast wins and ties are broken randomly. In any equilibrium, the independent voters who receive an informative signal always strictly prefer the state that matches their signal; and the partisans 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

[6] 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.

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.

II THE VOTING EQUILIBRIUM

In this section we characterize the equilibria of the voting game, and the equilibrium is unique for the experimental parameters. Contrary 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.

II.1 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 the probabilities of pivotal events, which in turn depend on σ. Let P_0 denote the event when there is a tie among the other voters between A and B; and let P_A denote the event in which policy A is losing to B by one vote. The difference between the expected utility of voting for A and the expected utility of abstaining is:

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

where

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

and

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

since in this case $\Pr(P_A \,|A) = 0$ (in state A no voter ever votes for B). If uninformed voters 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. In the following analysis we chose parameters such that $\sigma_A = \sigma_B = 0$ when $m = 0$ even when $\pi > \frac{1}{2}$.

II.2 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* $\sigma_B > \sigma_A = 0$*.*

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 $m > 0$.[7] From Proposition 2 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:

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

[7] The case with $m = 0$ is not necessary since from Proposition 1 we know that the uninformed voters never vote for B.

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

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

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 difference between the expected utility of voting for B the the expected utility of abstaining 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 $\sigma_B=0.76$.[8]

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 too we have a unique equilibrium in correspondence of which with $m=2$, $\sigma_B=0.33$, and with $m=4$, $\sigma_B=0.73$. Hence, a small increase in π has a small effect on the equilibrium strategies and tends to reduce the probability of voting for B.

II.3 Alternative benchmarks

To evaluate the performance of the Swing Voters' Curse theory, it is useful to test its predictions about voter behavior as a function of π and m against alternative models of turnout. A natural benchmark is the non-strategic decision theoretic model (e.g., Matsusaka's [1995]). This is the model chosen by Fedderesen and Pesendorfer [1996] and the leading alternative explanation of the phenomena motivating their theory. The decision theoretic model assumes that agents are not strategic and do not form expectations conditioning on being pivotal, but choose actions rationally on the basis of their available information, as in a "decision theoretic" environment, as if there were no other voters. In Matsusaka's model, therefore, we would not expect uninformed

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

voters to vote for B more often when there is a partisan bias as compared to no bias. If 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. This is also consistent with models of expressive voting used as a benchmark in Coate, et al. [2006].

The decision theoretic model is appealing because it is simple and intuitive: it postulates that voters vote sincerely, that is according to their individual preferences (as determined by their information), without consideration of how other voters may be voting, and therefore requires no strategic sophistication on the part of the voters. This makes it a polar opposite to the Bayesian Nash equilbirium model proposed by Feddersen and Pesendorfer (1998). Although the political science literature has not articulated many other models of behavior to explain the swing voter's curse phenonenon, recent work in game theory provides a range of intermediate theories between these extremes: models of partially bounded rationality that modulate the players' strategic sophistication from the extreme of complete naivete to fully rational equilibrium behavior. In Section IV.2, we focus on four approaches that have received particular attention in recent work: the Level k theories, the Analogy-Based Expectations and Cursed Equilibria, and finally the Quantal Response Equilibrium. That section describes in detail the predictions of these models and compares them with the data and the predictions of the swing voter's curse model.

III 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 a simple decision theoretic model with sincere (non strategic voting) similar to Matsusaka [1995]. Matsusaka assumes that voters participate for consumption benefits that are independent of whether they are pivotal, they vote sincerely for the option they most prefer regardless of strategic considerations. These consumption benefits then are positively related to voters' certainty over which choices yield them the highest utility which depends on their information about the choices, but not about the strategic consequences of their choices. When voters are uninformed and therefore perceive all options as equally good, a sincere voting, decision-theoretic model predicts that they will abstain, but that more precise information about the value of an option to the individual increases the probability that they will vote. Thus, in our experimental design, uninformed sincere, decision-theoretic voters should abstain when $\pi = 0.5$, regardless of the size of the partisan bias since they do not care about pivotality and they believe all options are equally good. When $\pi = 5/9$, uninformed sincere, decision-theoretic voters should have a positive probability of voting for a since their belief is that a has a higher probability than b of yielding them a higher utility and a zero probability of voting for b, regardless of the size of the partisan bias (since they do not vote strategically based on whether their votes are pivotal).

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, Sincere Voters	$\sigma_B = \sigma_A = 0$	$\sigma_A > \sigma_B = 0$

We acknowledge, however, that most research that assumes sincere, decision-theoretic voting implicitly also assumes that voters have little information about the strategic consequences of their votes such as the precise number of partisans in the electorate and that sincere, decision-theoretic voting is a consequence of that lack of information rather than a response in the face of information on strategic consequences of a vote. Thus, our analysis cannot reject sincere, decision-theoretic voting due to a lack of information on strategic consequences in the electorate at large and can only speak to the predictive power of the decision-theoretic model when such information is available to voters.

The experiments were all conducted at the Princeton Laboratory for Experimental Social Science and used registered students from Princeton University. Each experiment was divided into three parts, each of which lasted for 10 periods. All three parts used the same value of π, but used different values of $m = 0, 2$, and 4. We varied the sequence of m in the different parts in order to provide some control for learning effects, using a within subjects design. Five different sequences were conducted. Each subject participated in exactly one sequence.

The experiment was conducted in seven sessions. In five sessions 14 subjects participated; in two sessions 7 subjects participated for a total of 84 distinct subjects.[9] In sessions with 14 participants, subjects were randomly divided into groups of seven for each period. In sessions with 7 participants, subjects comprised a single voting group for all periods. Table 2 summarizes the sequences and values of π by session.

Table 2: Sequences and π by Session

Session	Sequence	π	Number
1	$m = (2, 4, 0)$	1/2	14
2	$m = (4, 2, 0)$	1/2	14
3	$m = (0, 4, 2)$	5/9	14
4	$m = (0, 2, 4)$	5/9	14
5	$m = (4, 0, 2)$	5/9	14
6	$m = (4, 2, 0)$	5/9	7
7	$m = (4, 2, 0)$	5/9	7

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

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

[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.

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 in sequence, and with the group membership shuffled randomly after each round for sessions with 14 subjects. Each subject was paid the sum of his or her earnings over all 30 periods 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.

IV EXPERIMENTAL RESULTS

IV.1 Voter Choices

IV.1.1 Informed Voters

Of the 2,520 voting decisions we observed, in 646 cases (25.63%) subjects were informed, that is, revealed a red or yellow ball. Across all treatments and sequences, only one of these informed voters chose incorrectly (voting for the wrong option). The remaining 645 informed subjects, if revealed a red ball, voted for jar 1 (policy a) and if revealed a yellow ball, voted for jar 2 (policy b). We interpret this as indicating that all subjects had a least a basic comprehension of the

[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.

task.

IV.1.2 Uninformed Voters

Aggregate Choices Table 3 summarizes the aggregate choices of uninformed voters. The equilibrium frequencies of voting for b are shown in parenthesis. In all treatments we find that uninformed voters abstain in large percentages compared to informed voters and these differences are significant.

When $\pi = 1/2$ 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 sincere voting theory. When $\pi = 1/2$ and $m = 0$, 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 3: Uninformed Voter Choices

Partisan Bias	Observations	a	b	ϕ
$\pi = 1/2$				
$m = 0$	217	0.00	0.08 (0.00)	0.91
$m = 2$	221	0.06	0.43 (0.36)	0.51
$m = 4$	206	0.04	0.77 (0.76)	0.19
$\pi = 5/9$				
$m = 0$	404	0.20	0.07 (0.00)	0.73
$m = 2$	410	0.12	0.35 (0.33)	0.53
$m = 4$	416	0.16	0.56 (0.73)	0.28

We find some support, however, for the sincere, decision-theoretic model of voting when $\pi = 5/9$ as voting for a by uninformed voters is significantly higher than when $\pi = 0.5$ for all values of m. We find also that when we compare $\pi = 5/9$ with $\pi = 1/2$, uninformed voters vote b significantly less when $m = 2$ and $m = 4$. The direction of this effect is as predicted, but the size of the effect is larger than predicted. Furthermore, subjects in the $\pi = 5/9$ treatments abstain significantly less than in the $\pi = 1/2$ case when $m = 0$ and $m = 4$ (which is contrary to the prediction). The difference is explained by the significantly positive voting for a (also unpredicted). These differences as we vary π may also reflect sequence ordering effects and learning by subjects. We explore these other explanations for these differences in the next section.

Nevertheless, when $\pi = 5/9$ we again find highly significant evidence that uninformed voters alter their voting choices with higher values of m as predicted by the swing voter's curse theory and contrary to the decision-theoretic theory. With partisan bias, the percent of uninformed voters choosing b increases with m, from 7% to 35% to 56% for $m = 0, 2, 4$, respectively. All of these differences are highly significant.

Individual Profiles Our within subject design enables us to compare how each individual behaves across different treatments of m; that is, as a function of the number of partisans, and thus we can control for individual specific effects. In Table 4 below we classify the choices of individuals by their profiles of behavior across values of m. Specifically, we classify individuals as to which choices they choose a majority of the time given a particular value of m and the value of π in their session. That is, a subject represented in the first column of percentages of subjects abstained more than any other choice for all values of m, while a subject represented in the second column abstained more than any other choice when $m = 0$ and $m = 2$, but voted for b mostly when $m = 4$.[12] Omitted profiles were not observed. The columns highlighted in bold represent uninformed voter profiles that are overall consistent with the theoretical comparative static predictions. As we see, the majority of voter profiles can be classified as overall consistent (76 percent), although more so when $\pi = 1/2$ (89 percent) than when $\pi = 5/9$ (70 percent). Thus, we find that the voting patterns broken down at the individual level are consistent with the observed aggregate voting behavior. These patterns are generally also consistent with the

[12] If a subject tied in a classification, we classified him or her as abstaining mostly.

theory although somewhat less systematically when $\pi = 5/9$.

Table 4: Percentages of Uninformed Voter Profiles														
(Omitted Profiles Not Observed, Bold Consistent)														
$\emptyset$ = Mostly Abstain, a = Mostly Vote a, b = Mostly Vote b														
$m = 0$	$\emptyset$								a or b					
$m = 2$	$\emptyset$			b			a		$\emptyset$		b		a	
$m = 4$	$\emptyset$	b	a	$\emptyset$	b	a	$\emptyset$	b	$\emptyset$	b	b	a	b	a
$\pi = 1/2$	**21**	**32**	0	**0**	**36**	4	0	0	0	0	4	0	4	0
$\pi = 5/9$	**18**	**25**	4	**2**	**25**	0	4	2	5	2	4	4	0	7
Total	**19**	**27**	2	**1**	**29**	1	2	1	4	1	4	2	1	5

IV.2 Learning Effects

Each subject participated in exactly one session with three different m-treatments, each in a sequence of 10 different committees. Our within subjects design allows us to better measure the effects of varying m while holding subject specific factors constant, as illustrated in the individual analysis of the previous section. We also varied the sequences in which subjects experienced different values of m in order to balance out any learning effects that may arise from experience with the committee voting task across all 30 committees a subject experienced. These features of the experimental design enable us to examine three kinds of learning effects. First, we can examine whether subjects learn *within a treatment*. That is, are there any systematic trends toward or away from the equilibrium predictions? Second, we can see whether there is any significant learning by a subject *over the course of the entire set* of 30 committees in which they participated. Third, we can ask whether there are any important *cross-treatment effects*. That is, are the findings reported in the previous section robust to the sequencing of treatments in a session? We address the robustness question first because it is especially relevant given that different sequences were used for different sessions.[13]

[13] We are grateful to an anonymous referee of an earlier version for suggesting that that the findings of the study would be more convincing if they did not depend on the treatment sequence, and if we obtained more data from different sequences. Two additional sequences for the $\pi = .55$ committees ((4,0,2) and (4,2,0)) were added to the design in response to this concern about robustness.

IV.2.1 Sequencing effects

Are the findings reported in the previous section robust to the sequencing of treatments in a session? Table 5 displays choice behavior of uninformed voters, broken down by session and treatment.

Table 5: Percentage Uninformed Choices by Sequence

Voting for a is the Omitted Category

		$m = 0$			$m = 2$			$m = 4$		
Sequence	π	$\emptyset$	b	Obs.	$\emptyset$	b	Obs.	$\emptyset$	b	Obs.
$(2, 4, 0)$	1/2	92	7	111	54	38	112	18	80	99
$(4, 2, 0)$	1/2	90	9	106	49	48	109	20	75	107
$(0, 4, 2)$	5/9	67	3	98	59	35	98	30	66	89
$(0, 2, 4)$	5/9	79	10	105	67	26	107	44	52	117
$(4, 0, 2)$	5/9	63	16	101	43	39	109	18	47	107
$(4, 2, 0)$	5/9	81	0	100	43	41	96	19	61	103

Figure **??** displays the relative vote choice frequencies for the 6 different treatments broken down by session for $\pi = .5$ and $\pi = .55$. Several features of these data are striking. First, *all* of the comparative static observations noted in the aggregate analysis of the previous section are also observed in *every single session regardless of sequence*. In every session, there are sharp changes in behavior following a change in partisan bias. Second *all* these comparative static observations are consistent with swing voter's curse theory. If partisanship goes up between two treatments in a session, then voting for b goes up and abstention goes down. Thus, the obvious conclusion is that the results are robust to whatever sequencing effects may or may not exist. Any learning of this sort is minor and has no effect on the conclusions of this study.

Figure 1 about here. Caption: Voting Behavior by session pi=.50 and pi=.55

We can also ask about the statistical significance of the comparative statics, session by session. Although this vastly reduces the sample size for each test, we nonetheless still find that most of these comparative statics tests are still significant.

First, in all sequences there is significantly more voting for b when $m = 2$ or $m = 4$ compared to $m = 0$.[14] Furthermore, there is significantly more voting for b when $m = 4$ compared to

[14] All of the comparisons are significant at a p value of less than 1%.

$m = 2$ in all but one sequence.[15] The one exception is in the sequence when $m = (4, 0, 2)$ and $\pi = 5/9$ where the difference, although positive, is not statistically significant.[16] These findings of significance for nearly all sequences, even with rather small samples, as further support of the robustness of this phenomenon.[17]

Second, by disaggregating by sequence we can compare uninformed voter behavior across values of π controlling for sequence since we use sequence $(4, 2, 0)$ for both values. As we found in the aggregate data, uninformed voters in this sequence vote significantly more for a across all values of m when $\pi = 5/9$. We also find that when $\pi = 5/9$, voters vote significantly less for b compared to $\pi = 5/9$ when $m = 0$ and when $m = 4$ (as theoretically predicted for the case when $m = 4$). Thus, the results in the disaggregated data are largely similar to those found in the aggregate data. Furthermore, we find the pattern of choices by uninformed voters to support the swing voter's curse theory for both values of π.

Third, by examining voter behavior by sequence, we find no statistically significant sequence effects between pairs of sequences. There is a minor difference when we compare the two sequences used when $\pi = 1/2$: we find that uninformed voters in the sequence $(4, 2, 0)$ vote more for b when $m = 2$ and less for b when $m = 4$ than uninformed voters in the sequence $(2, 4, 0)$. However, these differences in choices are not significant, and in any case may simply reflect relatively inexperienced behavior in the first 10 periods in both cases.

Finally, we check for robustness of individual voter profiles with respect to treatment sequencing. In Table 6 we disaggregate the voter classification analysis of Table 5 above by sequence. Note that we again find that disaggregated by sequence, the majority of uninformed subjects make choices that are overall consistent with the comparative static predictions of the theory. We do find some variation in the choices of profiles that are inconsistent when $\pi = 5/9$; in particular subjects who experience the $m = 4$ treatment first are more likely to err by voting

[15] All of the comparisons are significant at a p value of less than 1%.

[16] The p value for the conparison is 14%.

[17] Battaglini, Morton, and Palfrey (2008) demonstrate robustness with respect to group size as well, considering committees two or three times the size of the committees studied in this article.

instead of abstaining when $m = 0$ or to vote specifically for a when $m = 2$ or $m = 4$, than subjects who experience the $m = 0$ treatment first. However, our results above show that even accounting for these sequencing effects, the comparative static predictions of the theory hold.

Table 6: Percentages of Uninformed Voter Profiles

(Omitted Profiles Not Observed, Bold Consistent with Pred.)

$\emptyset$ = Mostly Abstain, a = Mostly Vote a, b = Mostly Vote b

$m=0$		$\emptyset$								a or b					
$m=2$		$\emptyset$			b			a		$\emptyset$		b		a	
$m=4$		$\emptyset$	b	a	$\emptyset$	b	a	$\emptyset$	b	$\emptyset$	b	b	a	b	a
Seq.	π														
$(2,4,0)$	$1/2$	**21**	**36**	0	**0**	**36**	0	0	0	0	0	0	0	7	0
$(4,2,0)$	$1/2$	**21**	**29**	0	**0**	**36**	7	0	0	0	0	7	0	0	0
$(0,4,2)$	$5/9$	**7**	**21**	0	**0**	**43**	0	7	0	14	7	0	0	0	0
$(0,2,4)$	$5/9$	**36**	**29**	0	**0**	**21**	0	0	0	7	0	0	0	0	7
$(4,0,2)$	$5/9$	**14**	**21**	14	**0**	**14**	0	0	0	0	0	14	7	0	14
$(4,2,0)$	$5/9$	**14**	**29**	0	**7.14**	**21**	0	7	7	0	0	0	7	0	7

IV.2.2 Learning effects within a treatment

Given that we have established that our comparative static predictions are robust to sequencing effects, we now examine whether the data demonstrates learning effects. We first examine learning within a treatment (in this subsection) and then learning within a session (in the next subsection). If learning is occurring within a treatment we expect that observed voter choices would converge in the direction of the equilibrium choice frequencies. We measure whether this convergence is occurring by examining the effect of time on the Euclidean distance between aggregate observed voters choices in a period with the predicted voter choice frequencies in that period given π and m. We estimate an exponential learning model of the following form. We assume that this Euclidean Distance, labeled ED, declines as a exponential function of the period in a given treatment, t. Let Obs_{jt} denote the observed frequency of choice j in t, and let σ_{jt} denote the Bayesian Nash equilibrium predicted probability of choice j in t, and ε is a disturbance term with mean zero and a constant variance:

$$ED_t = \sqrt{(\text{Obs}_{\emptyset t} - \sigma_{\emptyset t})^2 + (\text{Obs}_{at} - \sigma_{at})^2 + (\text{Obs}_{bt} - \sigma_{bt})^2} = \alpha t^{\beta} + \varepsilon$$

If $\alpha > 0$ and $\beta < 0$ then, initially, $ED_0 > 0$, but over time we would have $\lim_{t\to\infty} E(ED_t) = 0$.

We estimate this equation by nonlinear LS using the data pooled across treatments. The coefficient estimates for the data pooled across treatments is reported in Table 7a. Table 7b reports the results of the estimation disaggregated by our treatment variables, π and m. Figure **??** graphs the predicted estimate values of Euclidean Distance versus the observed values, broken down by π and m.

Table 7a: Regression Estimations of Euclidean Distance As Flexible Inverse Function of Period in Treatment

Independent Variable	Coefficient	Robust Std. Err.	t	Pr $> \lvert t\rvert$
All Data Pooled, Adj. $R^2 = 0.70$, Obs. $= 180$				
α	0.33	0.03	10.25	0.00
β	-0.18	0.06	-2.85	0.01

Table 7b: Regression Estimations of Euclidean Distance As Flexible Inverse Function of Period in Treatment

Independent Variable	Coefficient	Robust Std. Err.	t	Pr $> \lvert t\rvert$
$\pi = 1/2, m = 0$, Adj. $R^2 = 0.76$, Obs. $= 20$				
α	0.14	0.04	3.62	0.00
β	-0.07	0.17	-0.38	0.71
$\pi = 1/2, m = 2$, Adj. $R^2 = 0.72$, Obs. $= 20$				
α	0.21	0.07	3.04	0.01
β	-0.002	0.20	-0.01	0.99
$\pi = 1/2, m = 4$, Adj. $R^2 = 0.70$, Obs. $= 20$				
α	0.14	0.05	2.93	0.01
β	-0.02	0.21	-0.08	0.94
$\pi = 5/9, m = 0$, Adj. $R^2 = 0.85$, Obs. $= 40$				
α	0.53	0.07	8.14	0.00
β	-0.25	0.08	-3.01	0.01
$\pi = 5/9, m = 2$, Adj. $R^2 = 0.76$, Obs. $= 40$				
α	0.30	0.05	5.43	0.00
β	-0.14	0.12	-1.17	0.25
$\pi = 5/9, m = 4$, Adj. $R^2 = 0.70$, Obs. $= 40$				
α	0.44	0.08	5.26	0.00
β	-0.25	0.13	-1.91	0.06

Figure 2 about here. Caption: Predicted vs. actual Euclidean distance from equilibrium

All of the signs on the power coeffiecient are negative in all cases, which is consistent with learning in the sense of convergence toward equilibrium choice behavior. Results from the pooled regression indicate that this is statistically significant overall at the $p < 1\%$ level, but when the estimation is broken down by treatment, it is significant at conventional levels only for $\pi = 5/9$ $m = 0$ ($p < 1\%$) and $\pi = 5/9$ $m = 4$ ($0 < 10\%$). It is also the case that the magnitude of the estimated learning parameter is higher for all three treatments in the $\pi = 5/9$ environment than the $\pi = 1/2$ environment. While subjects' initial choices were further away from the equilibrium frequencies in the $\pi = 5/9$ environment compared to the $\pi = 1/2$ environment, behavior was gravitating toward equilibrium.

IV.2.3 Experience effects within a session

We also estimate possible learning across all three treatments of an entire 30 period session, which would be reflect general task learning. The simplest way to determine if there is overall task learning is to look at how the frequency of voting for a changes over time. In the Bayesian Nash equilibrium, voting for b to vary with m, theoretically subjects should not vote for a regardless of the value of m. Evidence that subjects decrease their voting for a over time would demonstrate learning, in the sense of convergence to the Bayesian Nash equilibrium.

In order to determine whether such learning occurs, we estimated two pooled probit equations for each value of π for voting for a as a function of the period in a sequence, clustered by subject. The results of these estimations is summarized in Table 7 below.[18] We find that voting for a declines with the number of periods in all the sequences, however, it is insignificant for sequences $(0, 4, 2)$ and $(4, 2, 0)$ when $\pi = 5/9$ and significant only at the 10% level for sequence $(4, 2, 0)$ when $\pi = 1/2$. Although more "learning" occurs in some sequences than others, there does not appear to be a clear pattern. Moreover, significant learning requires that subjects make poorer choices at the begining of the sequence than at the end, so significant effects may simple reflect sequences where subjects made poorer choices in the first treatments. Finally, we test whether the marginal effects were significantly different by sequence. We can not reject the null hypothesis that the marginal effects were equal across sequences. See Table 8.

[18] We also estimated equations where the period variables enter nonlinearly with comparable results.

Table 8: Probit Estimations of Uninformed a Votes As Functions of Period in Sequence (Clustered by Subject)				
Ind. Var.	Marg. Eff.	Robust Std. Err.	z	Pr $> \|z\|$
$\pi = 1/2$				
Period in $(2,4,0)$	-0.003	0.002	-4.11	0.00
Period in $(4,2,0)$	-0.002	0.002	-1.81	0.07
Log Pseudolikelihood = -89.08, Pseudo $R^2 = 0.07$, Obs. = 644				
$\pi = 5/9$				
Period in $(0,4,2)$	-0.004	0.004	-1.14	0.25
Period in $(0,2,4)$	-0.01	0.003	-3.29	0.00
Period in $(4,0,2)$	-0.01	0.005	-2.16	0.03
Period in $(4,2,0)$	-0.003	.003	-0.93	0.35
Log Pseudolikelihood = -501.83, Pseudo $R^2 = 0.06$, Obs. = 1230				

In summary, we find that there are some differences in uninformed voter behavior related to the different sequences used. Nevertheless, despite these differences we find, as noted above, that the comparative static predictions of the swing voter's curse theory hold within each sequence. We interpret this as strong support for the theory.

IV.3 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 *Analogy-Based Expectations* and *Cursed Equilibria*; finally the *Quantal Response Equilibrium*.

IV.3.1 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. In the model by Stahl and Wilson [1995] and Crawford and Irriberri [2007], that we adopt here as a benchmark, Level-k players are assumed to optimize relative to beliefs that they face a world of only level-$(k-1)$ players. The model is anchored by nonstrategic level-0 types, usually assuming that level 0 types randome uniformaly across all strategies. The number of levels is in principle unbounded.

It is easy to characterize the predictions of this model in our specific voting environment. Informed voters have a trivial dominant strategy: so, as in the Nash equilibrium and in the data, all strategic types will always vote for their signal, regardless of their degree of sophistication. The behavior of the uniformed voters would depend on the treatment. Consider first the case where $m = 0$ 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 level $k > 0$, uniformed voters would always abstain,which is in line with the Nash equilibrium and with the empirical findings.[19] In all the other treatments, however, the predictions of the Level k model sharply diverges from the Nash equilibrium and the data. Consider $m = 0$ and $\pi > 1/2$. In this case uninformed level-0 types would vote for A, while level $k > 0$ uninformed voters 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.[20] The

[19] 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.

[20] The distribution of types is irrelevant because a type k believes that all other types are of type $k-1$. It is easy to see that assuming that beliefs on other types follow a Poisson distribution with mean τ as in Camerer,

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 1 would vote for B for the same reason as above: in the pivotal event the bias introduced by the partisans would make B more likely. Level 2 would then react by always voting A (given the experimental parameters): this because the vote of the uninformed voters overcompensates the bias of the partisans. Level 3 would then vote for B with probability one, and so forth: even types $k > 0$ vote B and odd types vote A. Finally, consider the case $m > 0$ and $\pi > 1/2$. Level 0 votes A, since the prior favors this option. Level 1 then reacts by all voting B. As above, level 2 would then vote A, etc.: odd types vote A; even types vote B. Such behavior is completely inconsistent with our data. First it fails to explain abstention in the treatment $m > 0$, $\pi > 1/2$. Second, it misses the key comparative statics in treatment $m > 0$, $\pi = 1/2$: abstention is decreasing in m. However, the level k model implies abstention rates that are constant in m, since it would depend only on the fraction of level 0 voters. In the light of this evidence, we conclude that the level k model does not provide a good explanation of the data, and it is dominated by Nash equilibrium.

IV.3.2 The Cursed and Analogy-Based Expectation Equilibria

We now discuss two equilibrium concepts that give similar predictions for the swing voter's curse: Eyster and Rabin's [2005] Cursed equilibrium and Jehiel and Koessler's [2006] Analogy-Based Expectation 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

Ho and Chong [2004] would not solve the problems of the $k-$level models. Regardless of assumption on beliefs, types 0 and 1 would always vote, and always vote for either a or b. As it can be easily seen from Table 7, the fraction of voters that vote in this way is 0 in our experiment. Given that we have 84 distinct subjects, assuming (for example) a Poisson distribution of types, the event in which there are no type 0 or 1 in our experiment would have a significant probability only if τ is very large. Camerer et al. [2003], however estimate a value between 0 and 2.

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 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 cursed equilibrium can be seen as a special case of a more general equilibrium concept introduced by Jehiel and Koessler [2006]: the Analogy-Based Expectation equilibrium (henceforth ABEE). According to this equilibrium concept players are boundedly rational because they bundle states of nature in which opponents may be in "analogy classes" and play best response to the opponents' *average* strategies in these analogy classes.[21]

What are the predictions of the cursed equilibrium in the voting model described above? Consider the cursed equilibrium first. The case with $m = 0$, $\pi = 1/2$ is relatively straightforward. Informed voters would vote their signal. The uniformed voters would always abstain,

[21] To see the relationship with the cursed equilibrium, assume that agent i believes that a subset n_i of the set of players N will use the same strategy no matter what their signal is, but they anticipate their strategy consistently with their correct average equilibrium strategies. If $n_i = N - i$ the agent would not update beliefs conditioning on the pivotal event, and so he would behave naively according to his private information as in a fully cursed equilibrium. On the contrary, when $\forall i \; n_i = \varnothing$ voters would fully condition their expectations on the pivotal event, and we have a Nash equilibrium. For intermediate cases, we can have different forms of partially cursed equilibria.

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 if we assume, respectively, sufficiently low level of cursedness. The bias introduced by the degree of cursedness, however, sometimes pushes the model in the wrong direction and performs worse than a simple Nash equilibrium (if we assume that the degree of cursedness is positive). On the other hand, by adding an additional degree of freedom in fitting the data 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.

IV.3.3 Quantal Response Equilibrium

Quantal response equilibrium (henceforth QRE) applies stochastic choice theory to strategic games, and is motivated by the idea that a decision maker may take a suboptimal action. In a

QRE, 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. Since expected utilities depend on players' strategies, this defines a quantal response stochastic choice function that maps the strategy space to itself. A quantal response equilibrium is then a fixed point of the quantal response stochastic choice function (see McKelvey and Palfrey [1995, 1998]). 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).[22] That is:

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

where σ_{ij} is the probability i chooses strategy j and $U_{ij}(\sigma)$ is the *equilibrium* expected payoff to i if i chooses decision j and the players' strategy profile is σ. 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. Therefore, as with the Cursed equilibrium, by adding a free paramether (λ), logit QRE has more flexibility than the Nash equilibrium to fit the data.

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.[23]

We use maximum likelihood 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 in Table 8.

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

[23] 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 8: **Quantal Response Analysis**									
		QRE Frequencies			Obs. Frequencies				
π	m	A	B	ϕ	A	B	ϕ	lnL	$\#obs$
0.5	0	0.21	0.21	0.58	0.00	0.08	0.91	−138.96	217
5/9	0	0.24	0.19	0.57	0.20	0.07	0.73	−329.62	404
0.5	2	0.07	0.42	0.51	0.06	0.43	0.51	−193.08	221
5/9	2	0.09	0.40	0.51	0.12	0.35	0.53	−393.67	410
0.5	4	0.01	0.70	0.29	0.04	0.77	0.19	−143.60	206
5/9	4	0.02	0.67	0.32	0.16	0.56	0.28	−504.12	416

Columns 3-5 of the table present the QRE-predicted values of choice frequencies, evaluated at the estimated $\widehat{\lambda} = 31$. The next three columns give the observed choice frequencies in the data. Column 9 reports the value of the log likelihood function restricted to the observations in the specific treatment, and the last column gives the number of observations in that treatment. A scatter diagram of the QRE-predicted frequencies and the observed choice frequencies is shown in Figure **??**. The observed and predicted values are highly correlated: the regression line through this collection of points has a slope equal to 0.71, an intercept of 0.09, and $R^2 > 0.80$. There is no obvious pattern of overprediction or under prediction.

Figure 3 about here. Caption: QRE-predicted frequencies vs. observed choice frequencies.

It is useful to compare this with cursed equilibrium. As explained above, both cursed equilibrium and QRE, cannot do worse at fitting data than Nash equilibrium, because both subsume the Nash equilibrium as a special case and each has a free parameter that regulates how far away the model is from Nash equilibrium. The free parameters, however, play different roles in the two models. In the cursed equilibrium, a higher X leads to a distinct monotonic bias on the outcome in favor of "naive behavior". When $\pi > 1/2$, this helps to fit the data, which is indeed characterized by the same type of bias; but when $m > 0$ and $\pi = 1/2$, this bias against strategic behavior makes the Cursed equilibrium underestimate the probability that uninformed independents vote against the partisans. The QRE does not add a systematic bias for naive behavior because it does not require an ex ante assumption on how beliefs are updated: λ regulates the intensity of the noise that is added in a player's decision, but it does not affect the Bayesian process by which beliefs are updated given the other players' strategies.

An additional 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 $\pi = 1/2$, and this relationship holds for *every* value 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 as π becomes further from .5, the swing voter's curse diminshes. In our data, we do find significantly more voting for A when $\pi = 5/9$ than $\pi = 1/2$, for all three values of m. Another prediction of QRE is that the frequency of voting for A should be decreasing in m. The data show no systematic relationship between m and the frequency of voting for A.

IV.4 Committee Decisions

Efficiency of Committee Choices

In the previous subsection we averaged across all committees within a treatment or focused on individual voter choices. We now turn to an analysis of committee decisions. First we examine the efficiency of committee choices as defined by the percentage of times committees make the correct choice. We find not surprisingly that committees make correct decisions is highest when there were zero computer voters (97% when $\pi = 1/2$ and 94% when $\pi = 5/9$).[24] Efficiency declines when there were two computer voters (77% when $\pi = 1/2$ and 91% when $\pi = 5/9$) which is significantly lower than the case with zero computer voters at the 2% level when $\pi = 1/2$ and insignificantly different when $\pi = 5/9$.[25] Efficiency is lowest when there were four computer voters (66% when $\pi = 1/2$ and 71% when $\pi = 5/9$) which is insignificantly different with two computer voters when $\pi = 1/2$ but significantly different when $\pi = 5/9$.[26] Although when computer voters are introduced efficiency is lower when $\pi = 1/2$ compared to

[24]We code tie elections which were randomly decided as a 50% correct decision.
[25]The t statistics are 2.5 and 0.74 for $\pi = 1/2$ and $\pi = 5/9$, respectively.
[26]The t statistics are 1.03 and 2.38 for $\pi = 1/2$ and $\pi = 5/9$, respectively.

the case when $\pi = 5/9$, these differences are not significant at conventional levels.[27]

In Table 9 below we summarize the mean efficiency results by the state of the world and treatment (with ties coded as 0.5) compared to the mean predicted efficiencies given the number of informed voters in each period and predicted voting behavior.

Table 9: Mean Efficiency By Treatment

Treatment		True State	Cases	Actual	Predicted
π	m				
0.5	0	State A	9	0.94	1
		State B	8	1	1
5/9	0	State A	28	1	1
		State B	19	0.87	1
0.5	2	State A	15	0.53	0.98
		State B	16	1	0.99
5/9	2	State A	20	0.83	0.99
		State B	17	1	0.98
0.5	4	State A	15	0.30	0.93
		State B	16	1	0.98
5/9	4	State A	25	0.46	0.84
		State B	22	1	0.98

Information, Turnout, and Closeness

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. We find that this is indeed in our data. Since informed voters participated 100% of the time, while uninformed voters participate much less, as the number of informed voters increases, turnout in the committees mechanically increases.

Furthermore, as the number of informed voters in a committee increases, turnout increases, it also increases the margin of victory for the winning outcome. This follows because informed voters, 99% of the time, voted for the same policy (the correct jar) while uninformed voters abstained more and also sometimes voted for the incorrect option. Hence, as the number of informed voters increases, the margin of victory increases mechanically as well.

These two relationships have an interesting implication. A common perceived prediction of

[27] The t statistics of the comparison of $\pi = 1/2$ and $\pi = 5/9$ are 0.55, 1.52, and 0.49 for $m = 0, 2, 4$, respectively.

the rational model of voting based on voting costs 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 are 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.

The cost of voting may be a factor affecting the exact relationship between participation and the margin of victory, but one could easily have a positive correlation between turnout and participation even if the cost of voting is positive.[28] The key determinant in the relationship between closeness and turnout with small voting costs is whether there is sufficient heterogeneity in preferences and information. The informed nonpartisan voters always vote with higher probability than the uninformed voters, and always vote for the candidate most preferred by nonpartisans. If the cost of voting is not too high, uninformed voters vote only to offset the bias introduced by the partisans. If therefore participation of the uninformed voters is high enough to offset the partisans, an increase in informed voters implies an increase in participation and of the margin of victory as well. This positive relationship may be weakened if the cost of voting is high enough to prevent the uninformed nonpartisans from voting with sufficiently high probability, and therefore one can have situations in which participation and the margin of victory are not positively related. The sign of the relationship, however, depends more on the details of the environment (heterogeneity in information, cost of voting, number of partisans)

[28]To see this, consider the case in which the cost of voting is small enough that both uninformed and informed voters find it optimal to vote. Since uninformed nonpartisan voters have a strictly dominant strategy to vote informatively when the cost of voting c is 0, by continuity they would still continue to vote in the same way when c is sufficiently small. In addition to this, from the equilibrium conditions discussed in Section II.1 and II.2, it is easy to see that the behavior of uninformed non partisans is continuous in the cost of voting (conditions $u_A - u_\phi = 0$ and $u_B - u_\phi = 0$ would become $u_A - u_\phi = c$ and $u_B - u_\phi = c$). So having a small positive cost of voting would reduce the equilibrium value of participation, but it would not change the comparative statics and it would have only a small effect on behavior.

rather than on the rationality or strategic savvy of the players. The key point is that, when confronting field data, there is no reason a priori to expect one effect to dominate another, and therefore the relationship between turnout and margin of victory could go in either direction and still be consistent with a rational choice theory of voting.

V 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 may be seen as an unlikely 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.

VI APPENDIX

VI.1 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:

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

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 $\pi = \frac{1}{2} \Rightarrow \sigma_B = \sigma_A$. ■

VI.2 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:

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

This equation implies:

$$[\pi \Pr(P_0|A) - (1-\pi)\Pr(P_0|B)] \quad (5)$$
$$= \frac{1}{2}[(1-\pi)\Pr(P_B|B) - \pi\Pr(P_B|A)] + \frac{1}{2}[(1-\pi)\Pr(P_A|B) + \pi\Pr(P_A|A)]$$

Moreover, we have:

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

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

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

We can compute:

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

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

and

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

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

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 $\left[\Pr\left(P_A\left|A\right.\right)-\Pr\left(P_B\left|A\right.\right)\right]<0$ and $\left[\Pr\left(P_B\left|B\right.\right)-\Pr\left(P_A\left|B\right.\right)\right]<0$, 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:

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

Consider now Λ_0. We can write:

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

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.

■

VI.3 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 $\left[\Pr(P_A|A) - \Pr(P_B|A)\right] < 0$ and $\left[\Pr(P_A|B) - \Pr(P_B|B)\right] < 0$, 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:

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

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 $\sigma_B > 0$. ■

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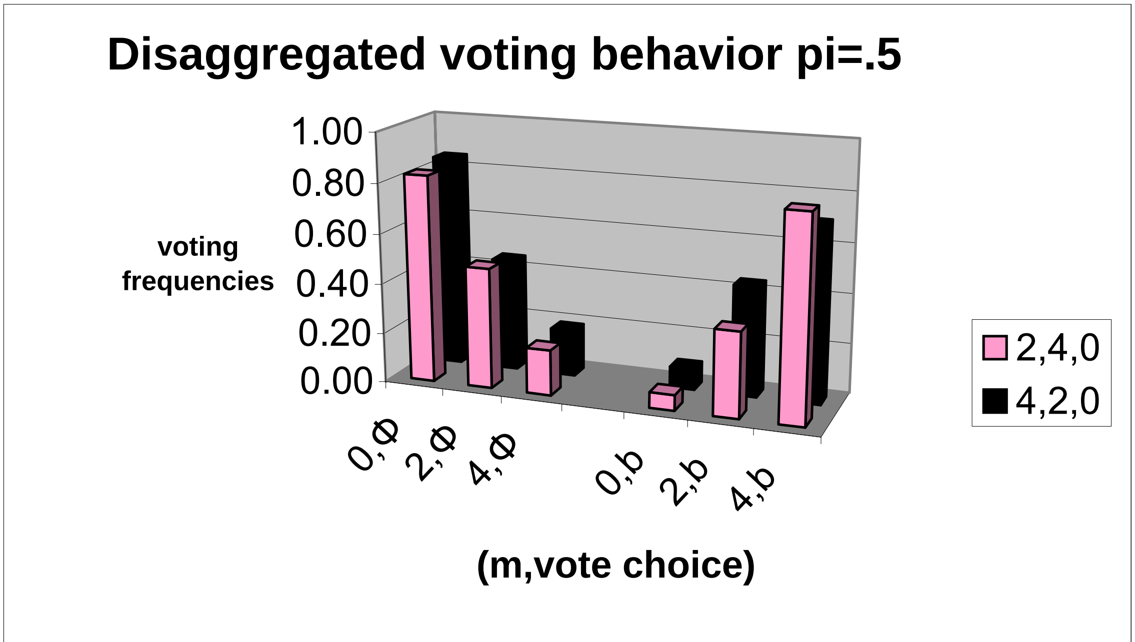
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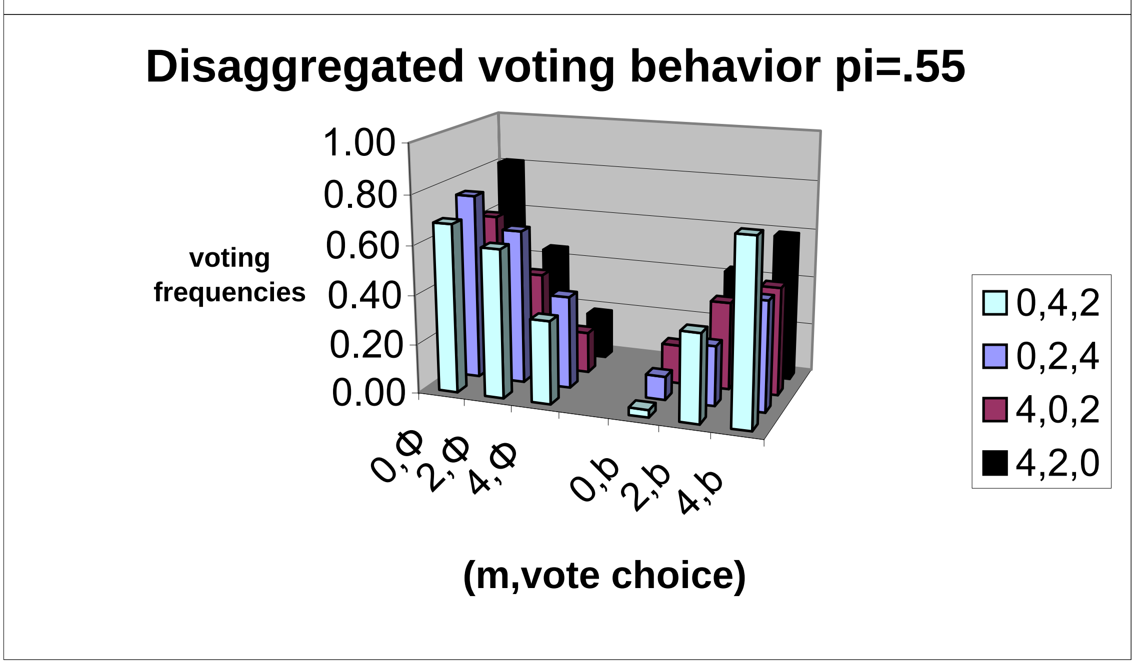
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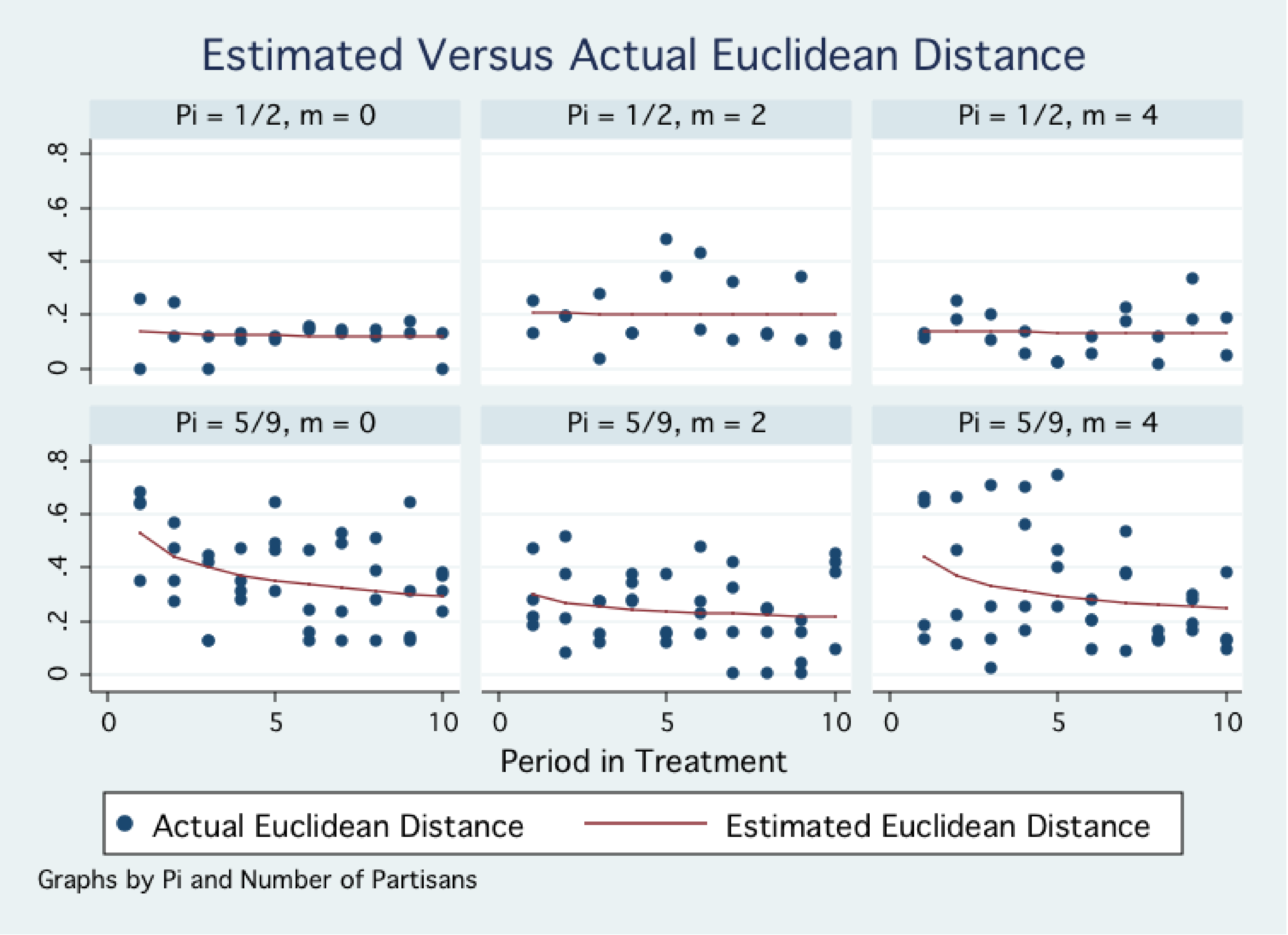
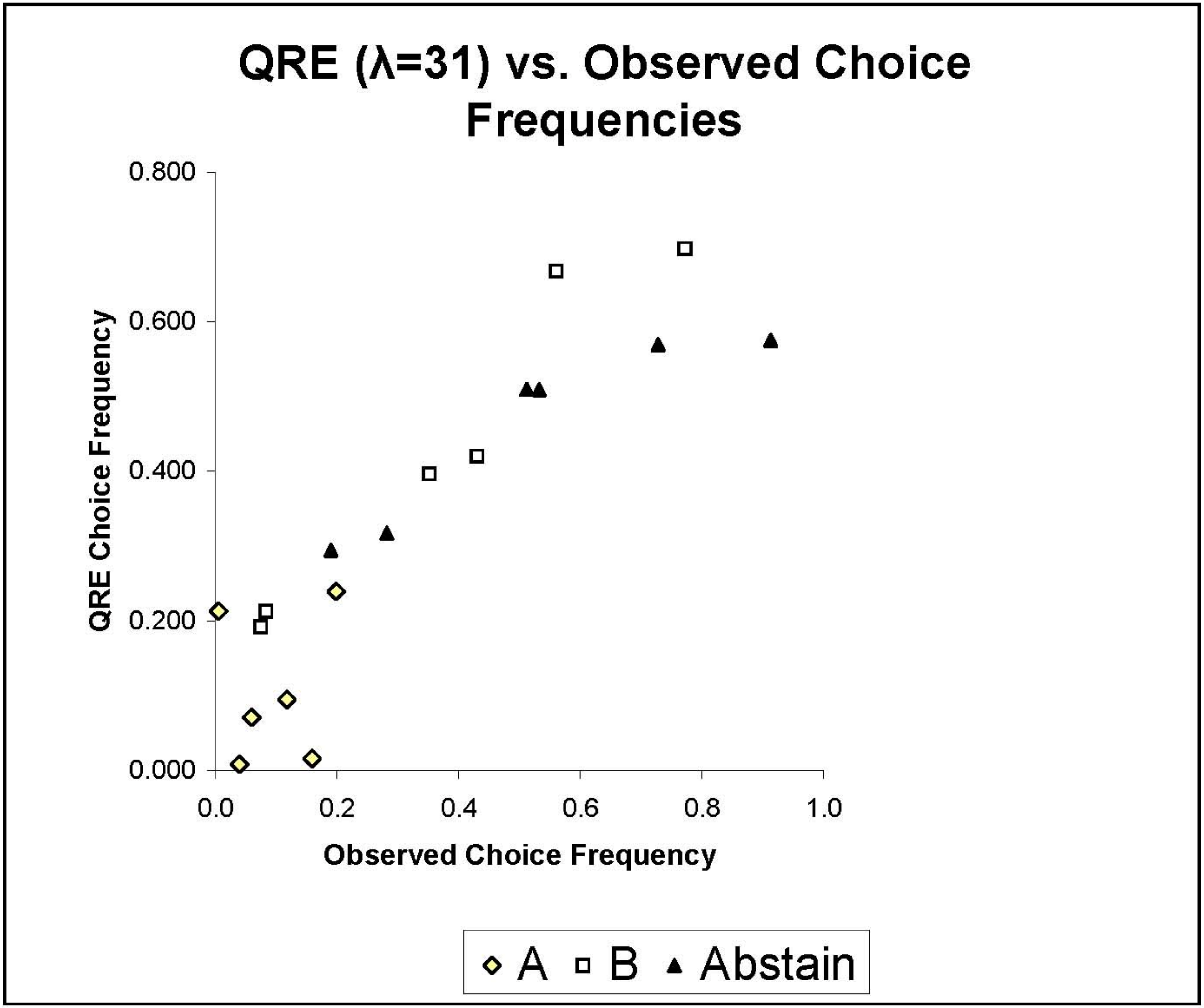


Estimated Versus Actual Euclidean Distance
Pi = 1/2, m = 0
Pi = 1/2, m = 2
Pi = 1/2, m = 4
Pi = 5/9, m = 0
Pi = 5/9, m = 2
Pi = 5/9, m = 4
0
.2
.4
.6
.8
0
5
10
Period in Treatment
Actual Euclidean Distance
Estimated Euclidean Distance
Graphs by Pi and Number of Partisans


QRE (λ=31) vs. Observed Choice Frequencies
0.800
0.600
0.400
0.200
0.000
QRE Choice Frequency
0.0
0.2
0.4
0.6
0.8
1.0
Observed Choice Frequency
A
B
Abstain