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Getting Out the Vote: Information and Voting Behavior

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This paper experimentally examines the effects of information on voter turnout in the Palfrey-Rosenthal pivotal voter (PR) model. In particular, I compare two different degrees of information revelation: one is that voters know each party's support base (complete information scenario), and the other is that voters know one party's support base but are limited to knowing the probability of the support base of the other party (partial information scenario). There are two main findings. First, in the partial information scenario with a revelation of a weak support base, subjects tend to have a higher belief in being pivotal than theory predicts, which causes their turnout rate to be not lower than those in the corresponding complete information scenario. Second, in the complete information scenario, turnout of the subjects of the frontrunner party is significantly higher than the subjects' best response to their pivotal belief, which can be explained by a PR model incorporating the generalized disappointment aversion effect.

Keywords: information revelation, polls, campaigns, strategic voting, collective choice
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1 Introduction

Although voter turnout is a core issue in political economy, there is little consensus on how best to understand it. Arguably the most controversial theory in studying voter turnout is Downs (1957)'s rational choice theory, which was initially formulated as a decision theoretic model, and was modified in order to serve as a pivotal voter model. Pivotal voter models claim that voters decide whether or not to vote based on their chances of being pivotal. Although the real-world probability of a single vote being pivotal in a mass election is very low, pivotal voter models still provide useful guidance. For example, the results from Levine and Palfrey (2007)'s experimental examination of the Palfrey and Rosenthal (1985) pivotal voter model clearly identify and support the three main equilibrium static effects of size, competition, and the underdog in voter participation games.

Furthermore, and perhaps more importantly, pivotal voter models provide useful guidance regarding how information about outcomes affects voting behavior (Agranov et al., 2018). Researchers using pivotal voter models to study the impacts of information revealed by polls have reported higher overall turnout rates when pollsters are free to inform electorates of information about support levels for individual candidates (especially compared to scenarios where polls are prohibited), and have found evidence indicating that polls exert different effects in close versus widely-divided elections (Klor and Winter, 2007; Groβer and Schram, 2010; see Agranov et al., 2018 for an overview).

The present paper studies the effects of different degrees of information revelation about outcomes on voter turnout in the Palfrey-Rosenthal pivotal voter (PR) model. Specifically, this paper considers a two-party election, with each party consisting of two types of voters: base partisans (those who always vote for their preferred party and therefore can represent the base of support for the party) and passive partisans (those who either vote for their preferred party or abstain). Since base partisans always turn out to vote, in the following, "turnout" refers to turnout of passive partisans. It is assumed that there is a π_i probability that an i party has a large number of base partisans (represented by R_{iL}) and a $1 - \pi_i$ probability that this i party has a small number of base partisans (represented by R_{iS}). According to the PR model, a strategic voter (i.e., the passive partisan in this paper) decides whether or not to vote depending on her voting cost and her probability of casting a pivotal vote in an election. A passive partisan's belief regarding her probability of being pivotal depends on what she has learned about the base partisans, or support bases, of the two parties. Hence, by comparing voter turnout under different scenarios of information revelation about support bases, we can study how different degrees of information revelation affect voter turnout.

In particular, two types of scenarios are considered. One is the partial information scenario, defined as the scenario where passive partisans learn R_{iL} or R_{iS} of the i party but only learn π_j of the j party. The other is the complete information scenario, defined as the scenario where passive partisans learn R_{iL} or R_{iS} of the i party as well as R_{jL} or R_{jS} of the j party. In other words, in the partial information scenario, one party reveals complete information about its support base to voters but the other party only reveals partial information (i.e., the probability). By contrast, in the complete information scenario, two parties both reveal complete information about their respective support bases to voters.

This paper uses laboratory experiments to study the effects of information revelation on voter turnout and has two main findings. First, theory predicts that subjects' voting propensity would be higher in the complete information scenario than in the partial information scenario, given the revelation of close support bases of two parties. The experimental data, however, show that revealing a party's weak support base in the partial information scenario still made subjects believe that they had a high chance to cast a pivotal vote, and hence still encouraged them to vote. Second, when subjects were informed of being in an advantageous position in the complete information scenario, their turnout became significantly higher than the best response to their pivotal belief. This behavior can be explained by the PR model incorporating the generalized disappointment aversion effect. That is, the effect of disappointment aversion encouraged the subjects of the frontrunner party to vote, leading to a high turnout rate, even if the subjects knew that their probability of being pivotal was low.

In practice, there are a number of methods that a party can use to inform its passive partisans of information about the support base and hence encourage them to vote. One is to conduct polls and announce poll results before elections. Since polls usually reveal distributions of electorate preferences, this method corresponds to partial information revelation in our model. Compared with polls, conducting campaigns such as rallies provides more certainty in the form of the actual base of support for a party, and hence more corresponds to complete information revelation to voters in our model. This is because supporters have to pay time or money to participate in rallies, while through polls a party's supporters show their support without paying costs (which can be viewed as cheap talk).

There are several real-world examples about complete information revelation. Ralph Nader organized a series of campaign rallies in an attempt to get his supporters to the polls so as to achieve the minimum 5% vote to secure public campaign financing for his Green Party in 2004. The purpose of the rallies was to convince voters that he was capable of achieving that percentage (Morton, 2006). Another example is the 2004 presidential campaign in Taiwan, which Mattlin (2004) describes as a "virtual arms race of mass rallies" (p. 167). To support the Chen Shui-bian campaign, the Democratic Progressive Party and Taiwan Solidarity Union organized a human chain around a theme of "protecting Taiwan." An estimated 2 million people took part in forming the chain, which ran 486 kilometers from the island's northernmost point to its southern tip. According to Clark (2004), "The huge turnout certainly proved the rally to be a tremendous success in igniting Pan-Green [multiple parties with similar platforms] supporters" (p. 32).

Previous experimental studies on similar topics, such as Klor and Winter (2007) and Groβer and Schram (2010), always compare the cases with and without polls (i.e., no information and partial information scenarios). Agranov et al. (2018) compare different kinds of polls: regular polls that reveal the correct distribution of electorate preferences, and lab polls reported by subjects themselves. The former provides more accurate information about the electorate preferences than the latter does, but still, both of them provide partial information of each party. Levine and Palfrey (2007) examine the effect of party size on voter turnout, which is similar to the complete information scenario considered in the present paper, but that paper does not consider the partial information scenario. Compared with them, the present paper compares the partial and complete information scenarios, and hence can provide more comprehensive advice for parties' election strategies (Section 5).

The rest of this paper is organized as follows. In Section 2, I describe a model, based on the PR model, that shows how partial or complete information revelation affects voter turnout. The experimental design and hypotheses for the study are introduced in Section 3, and experimental results are presented in Section 4. The last section concludes and provides suggestions.

2 The model

2.1 The two-party race

The model used in this study is based on the turnout model developed and refined by Palfrey and Rosenthal (1985) and Levine and Palfrey (2007), in which voters are described as having and reacting to privately known voting costs, which more accurately reflect real world characteristics. There are two parties, T_1 and T_2, with N_1 supporters of T_1 and N_2 supporters of T_2; that is, supporters belonging to T_i choose either to vote for T_i or to abstain, where $i \in \{1, 2\}$. Supporters are categorized as either base partisans or passive partisans. It is assumed that base partisans have zero voting costs, and therefore voting can be considered to be a dominant strategy. Accordingly, a party's base partisans can be viewed as this party's support base. Voting costs for passive partisan j are denoted as c_j and are set at a value greater than zero for any j. Furthermore, c_j is independently drawn from a common density function $f(c)$ and is privately known by j before j decides whether or not to vote. The sizes of N_1 and N_2 and the density function of the cost distribution $f(c)$ are common knowledge; $f(c)$ is assumed to be positive everywhere on its support.

There is a probability π_1 that T_1 has a large number of base partisans (represented by R_{1L}) and a probability $1 - \pi_1$ that T_1 has a small number of base partisans (represented by R_{1S}). The respective large and small numbers of base partisans for T_2 are represented by R_{2L} (probability π_2) and R_{2S} (probability $1 - \pi_2$). The π_1 and π_2 probabilities are independent. Each party knows its actual number of base partisans (i.e., support base), but if a party T_i only reveals its π_i to voters, T_i's support base will be a random variable to voters; that is, voters only have partial information of T_i. By contrast, if T_i reveals its actual support base to voters, each voter will know the actual number of T_i's base partisans (i.e., either R_{iL} or R_{iS}); that is, voters have complete information of T_i. A passive partisan decides whether or not to vote for her party based on what she knows about the support bases of the two parties, which will be discussed in detail later.

Passive partisan j must incur voting cost c_j in order to cast her vote. If T_1 wins, all T_1 partisans receive reward H and all T_2 partisans receive reward $L < H$; the opposite occurs if T_2 wins. These rewards are common knowledge. In this study it is assumed that all passive partisans in the same party use the same decision rule in equilibrium. According to Palfrey and

Rosenthal (1985), a quasi-symmetric voting equilibrium consists of a pair of critical points $(\hat{c}_1, \hat{c}_2)$ such that any passive partisan j in T_1 votes if and only if $c_j < \hat{c}_1$, and any passive partisan j in T_2 votes if and only if $c_j < \hat{c}_2$. A quasi-symmetric equilibrium implies a $(\hat{p}_1, \hat{p}_2)$ aggregate voting probability for passive partisans in each party given by

$$\hat{p}_1 = \int_0^{\hat{c}_1} f(c)dc = F(\hat{c}_1), \quad (1)$$

$$\hat{p}_2 = \int_0^{\hat{c}_2} f(c)dc = F(\hat{c}_2). \quad (2)$$

Since $(\hat{c}_1, \hat{c}_2)$ is an equilibrium, for any interior solution a passive partisan with a voting cost equal to $(\hat{c}_1, \hat{c}_2)$ must feel indifferent about voting or abstaining. As a result,

$$\hat{c}_1 = \frac{H - L}{2}\hat{q}_1, \quad (3)$$

$$\hat{c}_2 = \frac{H - L}{2}\hat{q}_2, \quad (4)$$

where $\hat{q}_1 (\hat{q}_2)$ is the probability that a vote cast by a passive partisan in $T_1 (T_2)$ will be pivotal in making or breaking a tie given the equilibrium voting strategies of all other voters in both parties.

The proposed model considers three types of scenarios: (1) the complete information scenario, defined as the scenario where voters have complete information of each party, (2) the scenario where voters only have partial information of each party, and (3) the partial information scenario, defined as the scenario where voters have complete information of one party and partial information of the other party. The primary study parameter is how much information passive partisans have about the numbers of base partisans in the two parties. Let R_1 and R_2 represent the realized numbers of T_1 and T_2 base partisans, respectively. In the complete information scenario, $R_i \in \{R_{iL}, R_{iS}\}$ where $i \in \{1, 2\}$; in the second scenario described above, $R_1 = R_2 = \emptyset$; in the partial information scenario, if one party, say T_1, only reveals its π_1, R_1 is defined as an empty set (i.e., $R_1 = \emptyset$) and $R_2 \in \{R_{2L}, R_{2S}\}$. The equilibrium values of $(\hat{c}_1, \hat{c}_2)$, $(\hat{p}_1, \hat{p}_2)$, and $(\hat{q}_1, \hat{q}_2)$ depend on the actions of the two parties, (π_1, π_2), (R_{1L}, R_{1S}), and (R_{2L}, R_{2S}). In the following section, I will characterize voter turnout equilibria under different scenarios.

2.2 Voter turnout equilibria

Complete information scenario. The probability that k passive partisans turn out to vote when there are n passive partisans and each passive partisan has a probability p of voting is denoted as $P_p(k|p,n)$. Note that p is not well-defined when $n = 0$ because there are no passive partisans. In such cases, $P_p(k|p,n) = 1$ and $\sum_k P_p(k|p,n) = 1$, which ensures that the formulas in Section 2 are well-defined. Let (c_1^*, c_2^*), (p_1^*, p_2^*), and (q_1^*, q_2^*) denote the equilibrium values of $(\hat{c}_1, \hat{c}_2)$, $(\hat{p}_1, \hat{p}_2)$, and $(\hat{q}_1, \hat{q}_2)$, respectively. In the complete information scenario, voters have precise knowledge of the numbers of base partisans in the two parties (R_1 and R_2). Hence, the probability that a passive partisan in party T_1 or T_2 will be pivotal in making or breaking a tie is expressed as

$$
\begin{aligned}
q_1^* = & \sum_{k=\max\{R_1,R_2\}}^{\min\{N_1-1,N_2\}} \left\{ P_p\left(k - R_1 | p_1^*, N_1 - R_1 - 1\right) \right. \\
& \left. \times P_p\left(k - R_2 | p_2^*, N_2 - R_2\right) \right\} \\
& + \sum_{k=r_1}^{\min\{N_1-1,N_2-1\}} \left\{ P_p\left(k - R_1 | p_1^*, N_1 - R_1 - 1\right) \right. \\
& \left. \times P_p\left(k + 1 - R_2 | p_2^*, N_2 - R_2\right) \right\}, \qquad (5) \\
q_2^* = & \sum_{k=\max\{R_1,R_2\}}^{\min\{N_1,N_2-1\}} \left\{ P_p\left(k - R_2 | p_2^*, N_2 - R_2 - 1\right) \right. \\
& \left. \times P_p\left(k - R_1 | p_1^*, N_1 - R_1\right) \right\} \\
& + \sum_{k=r_2}^{\min\{N_1-1,N_2-1\}} \left\{ P_p\left(k - R_2 | p_2^*, N_2 - R_2 - 1\right) \right. \\
& \left. \times P_p\left(k + 1 - R_1 | p_1^*, N_1 - R_1\right) \right\}, \qquad (6)
\end{aligned}
$$

where $r_i = \max\{R_1, R_2\} - 1$ if $R_i < R_j$, otherwise $r_i = \max\{R_1, R_2\}$. Equations (1)-(6) can be used to solve (c_1^*, c_2^*), (p_1^*, p_2^*) and (q_1^*, q_2^*).

Scenario where voters have partial information of each party. In this scenario, voters are limited in their knowledge to the probabilities of large numbers of base partisans in their own and the other party (π_1 and π_2). Assume that there are n voters, with r_L base partisans with probability π

and r_S base partisans with probability $1-\pi$, and with each passive partisan having a probability p of voting in an election. The probability of a precise k number of voters casting their ballots can be expressed as

$$P_N(k|p,\pi,n,r_L,r_S) = \pi \times P_p(k-r_L|p,n-r_L) + (1-\pi) \times P_p(k-r_S|p,n-r_S).$$

Given that T_1 has R_{1L} base partisans with probability π_1 and R_{1S} base partisans with probability $1-\pi_1$, and that T_2 has R_{2L} base partisans with probability π_2 and R_{2S} base partisans with probability $1-\pi_2$, equations (5) and (6) become

$$\begin{aligned}\tilde{q}_1 = &\sum_{k=0}^{\min\{N_1-1,N_2\}} \{P_N(k|\tilde{p}_1,\pi_1,N_1-1,R_{1L},R_{1S}) \\ &\times P_N(k|\tilde{p}_2,\pi_2,N_2,R_{2L},R_{2S})\} \\ &+ \sum_{k=0}^{\min\{N_1-1,N_2-1\}} \{P_N(k|\tilde{p}_1,\pi_1,N_1-1,R_{1L},R_{1S}) \\ &\times P_N(k+1|\tilde{p}_2,\pi_2,N_2,R_{2L},R_{2S})\}, \qquad (7)\end{aligned}$$

$$\begin{aligned}\tilde{q}_2 = &\sum_{k=0}^{\min\{N_1,N_2-1\}} \{P_N(k|\tilde{p}_2,\pi_2,N_2-1,R_{2L},R_{2S}) \\ &\times P_N(k|\tilde{p}_1,\pi_1,N_1,R_{1L},R_{1S})\} \\ &+ \sum_{k=0}^{\min\{N_1-1,N_2-1\}} \{P_N(k|\tilde{p}_2,\pi_2,N_2-1,R_{2L},R_{2S}) \\ &\times P_N(k+1|\tilde{p}_1,\pi_1,N_1,R_{1L},R_{1S})\}, \qquad (8)\end{aligned}$$

where $(\tilde{p}_1, \tilde{p}_2)$ and $(\tilde{q}_1, \tilde{q}_2)$ are the equilibrium values of $(\hat{p}_1, \hat{p}_2)$ and $(\hat{q}_1, \hat{q}_2)$, respectively.

Partial information scenario. In this scenario, voters know the precise number of base partisans in one party, and are limited to knowing the probability of the other party's support base. With no loss of generality, assume that voters know the actual value of R_1 (i.e., $R_1 = R_{1L}$ or $R_1 = R_{1S}$) but they do not know the actual value of R_2; they only know that there is a probability π_2 that $R_2 = R_{2L}$ and a probability $1-\pi_2$ that $R_2 = R_{2S}$.

Given π_2 and R_1, equations (5) and (6) become

$$q_1^{**} = \sum_{k=R_1}^{\min\{N_1-1,N_2\}} \left\{ P_p\left(k - R_1 | p_1^{**}, N_1 - R_1 - 1\right) \times P_N\left(k | p_2^{**}, \pi_2, N_2, R_{2L}, R_{2S}\right)\right\} + \sum_{k=R_1}^{\min\{N_1-1,N_2-1\}} \left\{ P_p\left(k - R_1 | p_1^{**}, N_1 - R_1 - 1\right) \times P_N\left(k+1 | p_2^{**}, \pi_2, N_2, R_{2L}, R_{2S}\right)\right\}, \quad (9)$$

$$q_2^{**} = \sum_{k=R_1}^{\min\{N_1,N_2-1\}} \left\{ P_N\left(k | p_2^{**}, \pi_2, N_2 - 1, R_{2L}, R_{2S}\right) \times P_p\left(k - R_1 | p_1^{**}, N_1 - R_1\right)\right\} + \sum_{k=\max\{R_1-1,0\}}^{\min\{N_1-1,N_2-1\}} \left\{ P_N\left(k | p_2^{**}, \pi_2, N_2 - 1, R_{2L}, R_{2S}\right) \times P_p\left(k + 1 - R_1 | p_1^{**}, N_1 - R_1\right)\right\}, \quad (10)$$

where (p_1^{**}, p_2^{**}) and (q_1^{**}, q_2^{**}) respectively represent the ($\hat{p}_1$, $\hat{p}_2$) and ($\hat{q}_1$, $\hat{q}_2$) equilibrium values.

3 Experimental design and hypotheses

3.1 Experimental design

In the experiment, all parameters described in the preceding section are controlled for. Following the lead of Levine and Palfrey (2007), payoffs are established at $L = 1$ and $H = 21$, and the voting cost distribution f is uniform, ranging from 0 to 11. Experimental parameters are set as $N_1 = N_2 = 4$, $\pi_1 = 0.6$, $\pi_2 = 0.4$, $R_{1L} = R_{2L} = 3$, and $R_{1S} = R_{2S} = 1$. The reasons for choosing these parameter values are as follows. The purpose of this paper is to investigate the impacts of information using a pivotal model in which turnout is affected by voters' beliefs of being pivotal. Therefore, there are advantages to using an environment in which voters have correct beliefs. such an environment is easier to achieve when the voter pool is small (i.e., $N_1 = N_2 = 4$). In addition, a large variance of the actual numbers of base partisans (i.e., $R_{iL} = 3$, $R_{iS} = 1$) is more helpful for identifying the impacts of different degrees of information revelation.

The experiment consists of four treatments designed to examine voter response to different information-revelation scenarios. The two primary roles are base and passive partisan. Human subjects play the role of passive partisans deciding whether or not to vote, while client computers play the role of base partisans who always vote. Furthermore, in the experiment there are two types of groups, an A group representing the T_1 party and a B group representing the T_2 party, leading to $N_A = N_B = 4$, $\pi_A = 0.6$, $\pi_B = 0.4$, $R_{AL} = R_{BL} = 3$, and $R_{AS} = R_{BS} = 1$. The timing for each period of an experimental session is established as follows:

States and Partisanship. There are equal numbers of A and B groups. At the start of each period, all A and B groups are randomly paired, with each subject randomly assigned to an A or B group; in addition, the server computer randomly determines the numbers of base partisans of the A and B groups. Note that, given a period of a session, each A group has the same number of base partisans, and so does each B group. For example, if in one period the server computer determines that an A group has 1 base partisan and a B group has 3 base partisans, then in that period, each A group has 1 base partisan (and 3 passive partisans) and each B group has 3 base partisans (and 1 passive partisan). If subject i is assigned to an A group in that period, then subject i and 2 other subjects serve as that A group's passive partisans in that period. As mentioned earlier, client computers play the role of base partisans.

Complete or Partial Information Revelation. Depending on the treatment, subjects are provided with different information on the numbers of base partisans in the A and B groups. The four treatments are as follows:

- *The CC treatment.* Subjects are informed of the actual numbers of base partisans in the A and B groups. This treatment represents the complete information scenario.
- *The CP treatment.* Subjects are told the actual number of base partisans in the A groups but not told that number in the B groups, even though it has been determined. Subject knowledge is limited to a 0.4 probability of the B groups having 3 base partisans and a 0.6 probability of the B groups having 1 base partisan.
- *The PC treatment.* This is similar to the CP treatment; subjects are informed of a 0.6 probability of the A groups having 3 base partisans

and a 0.4 probability of the A groups having 1 base partisan, while learning the actual number of base partisans of the B groups. Both the PC and CP treatments represent the partial information scenario.

- *The PP treatment.* Subjects are only informed of the probabilities of support bases for the A and B groups. This treatment represents the scenario where voters have partial information of each party.

Voting Decisions and Beliefs. After receiving information regarding base partisans, subjects decide whether or not to vote for their respective parties. Voting entails a cost that is independently drawn from the uniform distribution and is known by each subject individually. Neutral language is used in the experiment instructions (see Appendix A). Following Levine and Palfrey (2007), the experiment lets subjects choose between "X" (casting a vote) and "Y" (abstaining). In terms of voting costs, a subject who chooses Y is given a "Y bonus" that is added to that subject's earning, while a subject choosing X does not receive a "Y bonus", thereby treating voting costs as opportunity costs. Y bonuses are randomly drawn (independently for each subject) from the uniform distribution between 0 and 11, in integer increments, for each period; subjects are only informed of their own Y bonuses. After making voting decisions, subjects are asked to report their beliefs about the numbers of the votes for their group and the competing group. The data are used to examine subjects' beliefs regarding whether or not their voting decisions are pivotal.[1]

Payoffs. Each group's votes are counted once all decision and belief data are gathered. Recall that there are several pairs of A and B groups. In each pair, the group receiving the majority of votes wins, and each subject in that

[1] In order to elicit subjects' beliefs regarding whether or not their voting decisions are pivotal, I also followed the method proposed by Duffy and Tavits (2008) to ask subjects to make guesses as to the probabilities of their votes being pivotal, and paid the subjects based on the method proposed by Karni (2009). However, the experimental data show that lots of subjects were confused with the meaning of the pivotal probability. Some of them were unable to distinguish between the pivotal probability and the winning probability. In addition, subjects' belief about the numbers of the votes for their group and the competing group and subjects' belief about the probability of their votes being pivotal were found to be statistically uncorrelated, which does not make sense. Hence, data about subjects' pivotal probability beliefs are not considered in this paper.

group receives 21 points; subjects in the other group receive 1 point each. In cases of ties, each subject receives 11 points. Subjects are paid based on the accuracy of their beliefs — a bonus of 1 point for correctly guessing the numbers of the votes for their group and the competing group.

Notice that from subjects' points of view, each of the CC, CP, and PC treatments has four cases and the PP treatment has two cases, as shown in Table 2. The description of each case of each treatment is shown in Table 6 in Appendix B. Take the PP treatment as an example. If subject i is assigned to the PP treatment, in each period he will face one of the two cases as follows: (1) the case where $\pi_A = 0.6$, $\pi_B = 0.4$, and subject i is in an A group (denoted as Case $(0.6, 0.4; A)$ in Table 2); (2) the case where $\pi_A = 0.6$, $\pi_B = 0.4$, and subject i is in a B group (denoted as Case $(0.6, 0.4; B)$ in Table 2). Therefore, to make turnout rates of different cases comparable, each of the CC, CP, and PC treatments is designed to have 40 periods and the PP treatment is designed to have 20 periods, with each case occurring with equal probability. By doing so, given a treatment, each case of the treatment will appear around 10 periods in the experiment.

3.2 Hypotheses

Denote $p_S^*(R_A, R_B)$, $p_S^*(R_A, \pi_B)$, $p_S^*(\pi_A, R_B)$, and $p_S^*(\pi_A, \pi_B)$ as the equilibrium turnout probabilities for the S group in the CC, CP, PC, and PP treatments, respectively, where $S \in \{A, B\}$. With the parameter values chosen for the experiment, Table 1 shows the Nash equilibrium turnout probabilities (denoted as p^*) for the A and B groups in each treatment, calculated by Section 2. The equilibrium is unique for all the treatments.[2]

To study the effects of information revelation on voting decisions, I focus on the following four hypotheses, all derived from Table 1. Hypothesis 1 is about the underdog effect, which is one of the important controversies in the literature on voting behavior. Pivotal voter models predict the underdog effect that turnout of the minority group is higher than that of the majority one, which is supported by the experimental data in Levine and Palfrey (2007); however, Duffy and Tavits (2008), Groβer and Schram (2010), Kartal (2015), and Agranov et al. (2018) all find the opposite result. To test the underdog effect, I analyze voting behavior in the CC treatment, where support base of each group is revealed to voters.

[2]The numerical grid searches are used to show that only one equilibrium exists for each treatment.

Table 1: Parameter values for the experiment and predictions

Treatment	R_A	R_B	π_A	π_B	p_A^*	p_B^*
CC	1	1	–	–	0.573	0.573
	3	1	–	–	0.407	0.465
	1	3	–	–	0.465	0.407
	3	3	–	–	0.909	0.909
CP	1	–	–	0.4	0.525	0.537
	3	–	–	0.4	0.762	0.659
PC	–	1	0.6	–	0.500	0.500
	–	3	0.6	–	0.787	0.867
PP	–	–	0.6	0.4	0.694	0.661

Note: The group size is four in each treatment, i.e., $N_A = N_B = 4$. Let $S \in \{A, B\}$. R_S: the number of base partisans of group S. $\pi_S(1 - \pi_S)$: the probability that $R_S = 3(R_S = 1)$. p_S^*: the equilibrium turnout probability for group S.

Hypothesis 1 (H1). In each pair of A and B groups in the CC treatment, turnout of the group with a weak support base is greater than turnout of the group with a strong support base. That is, $p_A^*(1, 3) > p_B^*(1, 3)$ and $p_B^*(3, 1) > p_A^*(3, 1)$.

Hypotheses 2 to 4 focus on how different degrees of information revelation affect voter turnout. Compared with partial information revelation, complete information revelation provides complete certainty of the support base, thus providing greater certainty of an election outcome, resulting in a higher or lower propensity to cast a vote, depending on the closeness of competition between A and B groups. Hypotheses 2 and 3 are about the comparisons between the CC treatment and the CP or PC treatment. Specifically, Hypothesis 2 is for the situation where the actual numbers of base partisans of the two groups are close; Hypothesis 3 is for the situation where the actual number of base partisans of one group is large and that of the other group is small. Hypothesis 4 is about the comparisons between the PP and CP treatments and between the PP and PC treatments.

Hypothesis 2 (H2). In any A and B group pair, given that the two groups have close support bases, passive partisans in both groups will have a greater propensity to vote in the CC treatment than in the CP or PC treatment. This is because revealing the closeness of the election makes each passive partisan of each group to perceive a high probability of holding a pivotal vote. That is, $p_S^*(r, r) > p_S^*(0.6, r)$, $p_S^*(r, r) > p_S^*(r, 0.4)$, where $S \in \{A, B\}$ and $r \in \{1, 3\}$.

Hypothesis 3 (H3). In any pair of A and B groups, given that the two groups have landslide support bases, passive partisans in both groups will have a greater propensity to vote in the CP or PC treatment than in the CC treatment. This is because revealing a landslide race makes each passive partisan of each group to perceive a low probability of holding a pivotal vote. That is, $p_S^*(r, \hat{r}) < p_S^*(0.6, \hat{r})$, and $p_S^*(r, \hat{r}) < p_S^*(r, 0.4)$, where $S \in \{A, B\}$, $r \in \{1, 3\}$, $\hat{r} \in \{1, 3\}$, and $r \neq \hat{r}$.

Hypothesis 4 (H4). In any pair of A and B groups, given that the competing group, say group B, reveals partial information about its support base, if group A chooses to reveal partial information as well, turnout of group A will be between the following two turnout rates. One is the turnout rate of group A revealing complete information and showing a weak support base; the other is the turnout rate of group A revealing complete information and showing a strong support base. That is, $p_A^*(0.6, 0.4)$ is between $p_A^*(1, 0.4)$ and $p_A^*(3, 0.4)$; $p_B^*(0.6, 0.4)$ is between $p_B^*(0.6, 1)$ and $p_B^*(0.6, 3)$.

3.3 Procedures

A total of 15 experimental sessions were held in the Missouri Social Science Experimental Laboratory (MISSEL) of Washington University in St. Louis, 8 in the winter of 2012 and 7 in the spring of 2013. Each session lasted approximately 2.5 hours. A total of 110 study subjects were recruited through the MISSEL subject pool. Of these, 26 were randomly assigned to the CC treatment, 28 were randomly assigned to the CP treatment, 30 were randomly assigned to the PC treatment, and 26 were randomly assigned to the PP treatment. Each subject only took part in one session. The instructions varied for each treatment.

In each period of a session of a treatment, there were four possible elections. Election 1: 1 client computer and 3 subjects in each A and B group; Election 2: 1 client computer and 3 subjects in each A group, and 3 client computers and 1 subject in each B group; Election 3: 1 client computer and 3 subjects in each B group, and 3 client computers and 1 subject in each A group; Election 4: 3 client computers and 1 subject in each A and B group. The instructions told subjects that given a period, one of the four elections would occur. Hence, every subject sitting in the lab faced the same election in the period (but subjects did not know which election would occur before making voting decisions unless they were in the CC treatment).

To make each subject face the same election in a period of a session, I used a round-table method to group subjects. Suppose that there were $2N$ subjects in a session, where $2N$ was even and not less than 6. In each period, the server computer randomly assigned N subjects to be A group members and N subjects to be B group members, and then gave each S group member a number, from 1_S to N_S, where $S \in \{A, B\}$. Then, for a subject with the number i_S, when Election 1 occurred, or Election 2 occurred and subject i_S was an A group member, or Election 3 occurred and subject i_S was a B group member, subject i_S would be grouped with a client computer and other two subjects with the numbers $(i + 1)_S$ and $(i + 2)_S$. If $(i + 1)_S$ and $(i + 2)_S$ were larger than N_S, they were replaced by the numbers 1_S and 2_S. By contrast, subject i_S would be grouped with three client computers when the other elections occurred.[3] Let's call it the i_S^{th} group. Then, if subject i_S was assigned to be an A group member (i.e., $S = A$), the i_A^{th} group would be randomly paired with a competing B group, and vice versa. After making voting decisions, if the i_A^{th} group had fewer, equal, or more votes than its competing group, subject i_S earned 1, 11, or 21 points, respectively. With the assumption in Section 2 that all passive partisans in the same party use the same decision rule in equilibrium, the round-table method made the experiment and the theory entirely consistent.[4]

Subjects were paid US$5 for showing up on time and listening to the instructions, after which they were requested to respond to control questions. The experiment began after the experimenter answered subjects' questions. Subjects interacted via a computer network in the laboratory, with work station partitions ensuring anonymity. Experiments were conducted using the

[3] That is, when Election 2 occurred and subject i_S was a B group member, or Election 3 occurred and subject i_S was an A group member, or Election 4 occurred, subject i_S would be grouped with three client computers.

[4] For simplicity, the instructions did not show the round-table method to subjects. But with the assumption of the theory used in the present study, this should not cause a problem.

z-Tree program developed by Fischbacher (2007). Subjects earned an average of US$35, including the show-up fee. The exchange rate was 25 points to US$1.

4 Results

4.1 Hypotheses testing

The analysis of results is carried out using subjects' turnout rates observed in the experiments. Table 2 displays for each case the Nash equilibrium turnout rate (denoted as p^*) and the observed turnout rate (denoted as $\hat{p}$). Note that for the CC treatment, the experimental data from the A and B groups are combined for each case since the A and B groups are identical in each case of the CC treatment. That is, $\hat{p}_A(1,1) = \hat{p}_B(1,1)$, $\hat{p}_A(3,3) = \hat{p}_B(3,3)$, $\hat{p}_A(1,3) = \hat{p}_B(3,1)$ and $\hat{p}_A(3,1) = \hat{p}_B(1,3)$. To test the relationship between $\hat{p}$ and p^* for each case, I use each subject's average turnout rate as an observation to conduct Wilcoxon signed-rank tests. Since each subject only participated in one case of one treatment for around 10 periods, the sample size is not that large. I, therefore, perform my tests at the 0.05 critical level. The test results show that $\hat{p}$ is significantly different from p^*, with a p-value below 0.05, in one third of the cases. Specifically, they are $\hat{p}_B(1,0.4)$, $\hat{p}_B(3,0.4)$, $\hat{p}_A(0.6,1)$, $\hat{p}_B(0.6,1)$, $\hat{p}_A(0.6,3)$, and $\hat{p}_A(3,1)$ (and so does $\hat{p}_B(1,3)$).

To see if the hypotheses are supported by the experimental data, the observed turnout rate shown in Table 2 is compared with each other for each hypothesis. Specifically, H1 predicts that, in the CC treatment, or the complete information scenario, turnout of the group with a weak support base is greater than turnout of the group with a strong support base. However, instead of being supported, the data show the opposite: $\hat{p}_B(3,1) < \hat{p}_A(3,1)$ (and so does $\hat{p}_A(1,3) < \hat{p}_B(1,3)$), implying that the under dog effect did not occur in my experiment. This result is consistent with Duffy and Tavits (2008), Groβer and Schram (2010), Kartal (2015), and Agranov et al. (2018).

H2 predicts that when competition is close, both A and B groups revealing complete information about their support bases will lead to higher turnout than only one of them revealing it; that is, turnout in the complete information scenario is higher than that in the partial information scenario. However, the predictions that $p^*_B(1,0.4) < p^*_B(1,1)$, $p^*_A(0.6,1) <$

Table 2: Turnout rates — comparison of theory and data

Treatment	Case	R_A	R_B	π_A	π_B	p_A^*	$\hat{p}_A$	p_B^*	$\hat{p}_B$
$CC(n = 26)$	$(1, 1; A)$	1	1	–	–	0.573	0.635	–	–
	or $(1, 1; B)$	1	1	–	–	–	–	0.573	0.635
	$(3, 1; A)$	3	1	–	–	0.407	0.659	–	–
	or $(1, 3; B)$	1	3	–	–	–	–	0.407	0.659
	$(1, 3; A)$	1	3	–	–	0.465	0.402	–	–
	or $(3, 1; B)$	3	1	–	–	–	–	0.465	0.402
	$(3, 3; A)$	3	3	–	–	0.909	0.870	–	–
	or $(3, 3; B)$	3	3	–	–	–	–	0.909	0.870
$CP(n = 28)$	$(1, 0.4; A)$	1	–	–	0.4	0.525	0.554	–	–
	$(1, 0.4; B)$	1	–	–	0.4	–	–	0.537	0.677
	$(3, 0.4; A)$	3	–	–	0.4	0.762	0.794	–	–
	$(3, 0.4; B)$	3	–	–	0.4	–	–	0.659	0.533
$PC(n = 30)$	$(0.6, 1; A)$	–	1	0.6	–	0.500	0.661	–	–
	$(0.6, 1; B)$	–	1	0.6	–	–	–	0.500	0.634
	$(0.6, 3; A)$	–	3	0.6	–	0.787	0.609	–	–
	$(0.6, 3; B)$	–	3	0.6	–	–	–	0.867	0.746
$PP(n = 26)$	$(0.6, 0.4; A)$	–	–	0.6	0.4	0.694	0.735	–	–
	$(0.6, 0.4; B)$	–	–	0.6	0.4	–	–	0.661	0.692

Note: Let $S \in \{A, B\}$. R_S: the number of base partisans of group S. π_S $(1 - \pi_S)$: the probability that $R_S = 3(R_S = 1)$. p_S^*: the equilibrium turnout probability for group S. $\hat{p}_S$: the observed turnout rate for group S. In addition, $N_A = N_B = 4$, meaning the group size of four in each treatment.
From subjects' points of view, each of the CC, CP, and PC treatments has four cases and the PP treatment has two cases. For example, if subject i is assigned to the PP treatment, in each period he will face one of the following two cases: (1) Case $(0.6, 0.4; A)$: the case where $\pi_A = 0.6$, $\pi_B = 0.4$, and subject i is in an A group; (2) Case $(0.6, 0.4; B)$: the case where $\pi_A = 0.6$, $\pi_B = 0.4$, and subject i is in a B group. The description of each case of each treatment is shown in Table 6 in Appendix B.

$p_A^*(1, 1)$, and $p_B^*(0.6, 1) < p_B^*(1, 1)$ are not supported by the data. This is because $\hat{p}_B(1, 0.4)$, $\hat{p}_A(0.6, 1)$, and $\hat{p}_B(0.6, 1)$ are significantly higher than the corresponding theoretical predictions.

Table 3: Failure of support for the hypotheses

Hypothesis	Theoretical Prediction	Experimental Data	Cause
H1	$p_A^*(3,1) < p_B^*(3,1)$ and $p_B^*(1,3) < p_A^*(1,3)$	$\hat{p}_A(3,1) > \hat{p}_B(3,1)$ and $\hat{p}_B(1,3) > \hat{p}_A(1,3)$	$\hat{p}_A(3,1)$ and $\hat{p}_B(1,3)$ are respectively significantly higher than $p_A^*(3,1)$ and $p_B^*(1,3)$
H2	$p_B^*(1,0.4) < p_B^*(1,1)$	$\hat{p}_B(1,0.4) > \hat{p}_B(1,1)$	$\hat{p}_B(1,0.4)$ is significantly higher than $p_B^*(1,0.4)$
	$p_A^*(0.6,1) < p_A^*(1,1)$	$\hat{p}_A(0.6,1) > \hat{p}_A(1,1)$	$\hat{p}_A(0.6,1)$ is significantly higher than $p_A^*(0.6,1)$
	$p_B^*(0.6,1) < p_B^*(1,1)$	$\hat{p}_B(0.6,1) \approx \hat{p}_B(1,1)$	$\hat{p}_B(0.6,1)$ is significantly higher than $p_B^*(0.6,1)$
H3	$p_A^*(3,1) < p_A^*(0.6,1)$	$\hat{p}_A(3,1) \approx \hat{p}_A(0.6,1)$	$\hat{p}_A(3,1)$ is significantly higher than $p_A^*(3,1)$

H3 predicts that for a landslide election where one group has a weak support base and the other has a strong support base, both A and B groups revealing complete information about their support bases will lead to lower turnout than only one of them revealing it; i.e., turnout in the complete information scenario is lower than that in the partial information scenario. But the prediction that $p_A^*(3,1) < p_A^*(0.6,1)$ is not supported by the data, and this is because $\hat{p}_A(3,1)$ is significantly higher than the theoretical prediction $p_A^*(3,1)$.

Table 3 summarizes the comparisons of the turnout rates for H1 to H3 that are not supported by the experimental data. In sum, the differences between the observed and theoretical turnout rates cause the failure of support for hypotheses H1 to H3, especially the unexpectedly high values of $\hat{p}_A(3,1)$, $\hat{p}_B(1,3)$, $\hat{p}_B(1,0.4)$, $\hat{p}_A(0.6,1)$, and $\hat{p}_B(0.6,1)$. By contrast, comparisons of turnout rates for H4 are supported by the experimental data. Result 1 summarizes section 4.1.

Result 1. *In the complete information scenario, subjects in the group with a strong support base had a unexpectedly high turnout, causing the failure of support for the underdog effect hypothesis (H1) and the hypothesis about the* *information-revelation effect for a landslide election (H3). In the partial information scenario with a revelation of a weak support base, subjects' turnout was unexpectedly high and not lower than that in the corresponding complete information scenario, causing the failure of support for the hypothesis about the information-revelation effect for a close election (H2).*

4.2 Response to information

In order to explore the unexpectedly high turnout in the experiment, I investigate subjects' beliefs of being pivotal in each case, since it is assumed that the propensity to vote increases with voters' beliefs of being pivotal. Recall that in the experiment, subjects were asked to report their beliefs about the numbers of the votes for their own group and the competing group. The data can be used to calculate subjects' guesses regarding the lead of their own group, and subjects' guess leads equal to 0 or -1 can be viewed as subjects' beliefs of being pivotal. Figures 1–4 compare the frequency distribution of subjects' guess leads with the theoretical distribution for each case defined in Table 2. In Figures 1–4, the dots corresponding to "Guess Lead of Own Group $= -1$" and "Guess Lead of Own Group $= 0$" represent the theoretical probability for a vote of being pivotal (denoted as b^*), and the corresponding bars represent the observed percentage of subjects who believed that their votes would be pivotal (denoted as $\hat{b}$).

A comparison between Table 2 with Figures 1–4 shows that for any case where the observed turnout rate $\hat{p}$ is higher than the theoretical prediction p^* (shown in Table 2), the $\hat{b}$ is higher than b^* in that case (shown in Figures 1–4), and the opposite holds as well.[5] In particular, Figures 2 and 3 both show that in the partial information scenario (CP and PC treatments), $\hat{b}$ was much higher than b^* when subjects observed a weak support base (i.e., $R_A = 1$ or $R_B = 1$), while $\hat{b}$ was a little lower but close to b^* when subjects observed a strong support base (i.e., $R_A = 3$ or $R_B = 3$).

To further explore the relationship between subjects' beliefs of being pivotal and their voting strategies, I conduct a regression analysis. The regression results, presented in Appendix C, show that both higher beliefs of being pivotal and lower voting costs both significantly increased subjects'

[5]There are only two exceptions: one is $\hat{p}_A(3, 0.4) > p^*_A(3, 0.4)$ but $\hat{b}_A(3, 0.4) < b^*_A(3, 0.4)$, and the other is $\hat{p}_B(0.6, 0.4) > p^*_B(0.6, 0.4)$ but $\hat{b}_B(0.6, 0.4) < b^*_B(0.6, 0.4)$. The differences, however, are very small — they are only 0.032 and 0.031, respectively.

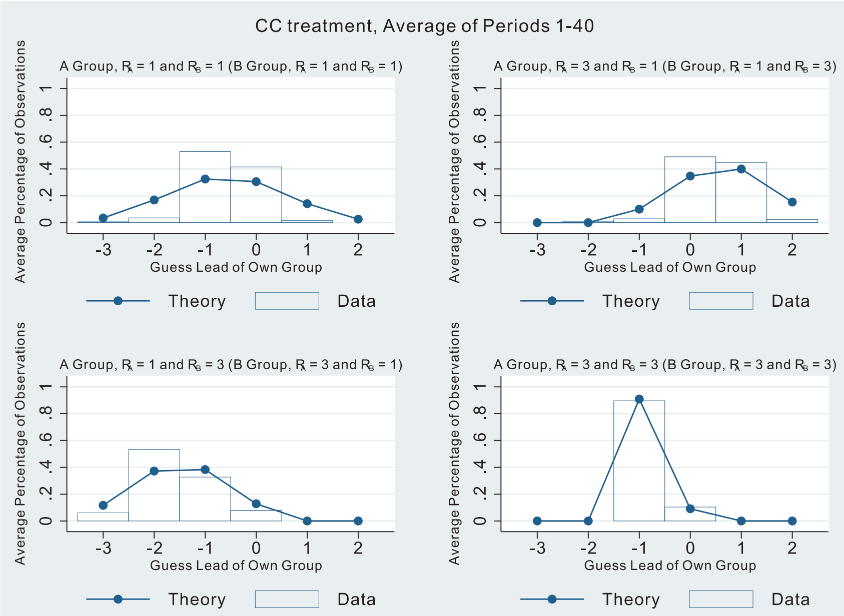

Figure 1: Distributions of subjects' guess leads of their own group in the CC treatment

propensity to vote.[6] These results are consistent with the literature, implying that subjects followed the main ideas of the Palfrey-Rosenthal pivotal voter model.[7] More importantly, the significantly positive effect of the pivotal belief on turnout helps explain the failure of support for H2. That is, large $\hat{b}_S(0.6, 1)$ and $\hat{b}_S(1, 0.4)$, $S \in \{A, B\}$, imply that when subjects observed a weak support base of a group in the partial information scenario, they tended to have higher beliefs of being pivotal and thus became more willing to vote, leading to high $\hat{p}_S(0.6, 1)$ and $\hat{p}_S(1, 0.4)$, $S \in \{A, B\}$.[8]

[6]Another interesting finding from the regression analysis is that subjects' beliefs did not become more accurate over time, implying no learning during the course of the experiment. Details for this finding are presented in Table 8 in Appendix C.

[7]In addition to the regression results, an examination of subjects' cutpoint rules also shows that subjects followed consistent cutpoint rules to make voting decisions as the pivotal voter model predicts. The result is presented in Appendix D.

[8]It is interesting to see that the reason for high $\hat{b}_A(1, 0.4)$ and $\hat{b}_B(0.6, 1)$ is different from that for high $\hat{b}_A(0.6, 1)$ and $\hat{b}_B(1, 0.4)$. In the former cases, where subjects' own group had

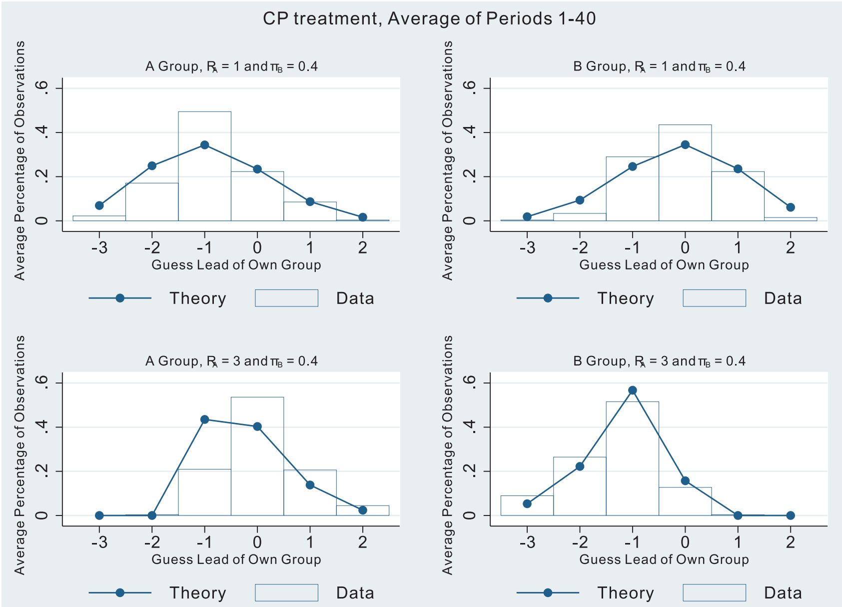

Figure 2: Distributions of subjects' guess leads of their own group in the CP treatment

This behavior, however, did not occur when a strong support base was revealed in the partial information scenario.

Finally, for H1 and H3, the effect of the high pivotal belief on turnout is not enough to explain the failure of support. This is because the difference between $\hat{p}_A(3, 1)$ and $p^*_A(3, 1)$ ($\hat{p}_B(1, 3)$ and $p^*_B(1, 3)$) is the largest among all the cases, while the difference between $\hat{b}_A(3, 1)$ and $b^*_A(3, 1)$ ($\hat{b}_B(1, 3)$ and $b^*_B(1, 3)$) is small, as shown in the right top panel in Figure 1. Hence, in

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a weak support base, the subjects tended to underestimate the probability of losing the game, shown by the bars lower than the dots at "Guess Lead of Own Group $= -2$" and "Guess Lead of Own Group $= -3$" in the top left subfigure in Figure 2 and top right subfigure in Figure 3. By contrast, in the latter cases, where subjects' competing group had a weak support base, the subjects tended to underestimate the probability of winning the game, shown by the bars lower than the dots at "Guess Lead of Own Group $= 1$" and "Guess Lead of Own Group $= 2$" in the top left subfigure in Figure 3 and top right subfigure in Figure 2. In sum, subjects in the partial information scenario with a revelation of a weak support base of a group tended to be moderate in beliefs with different reasons.

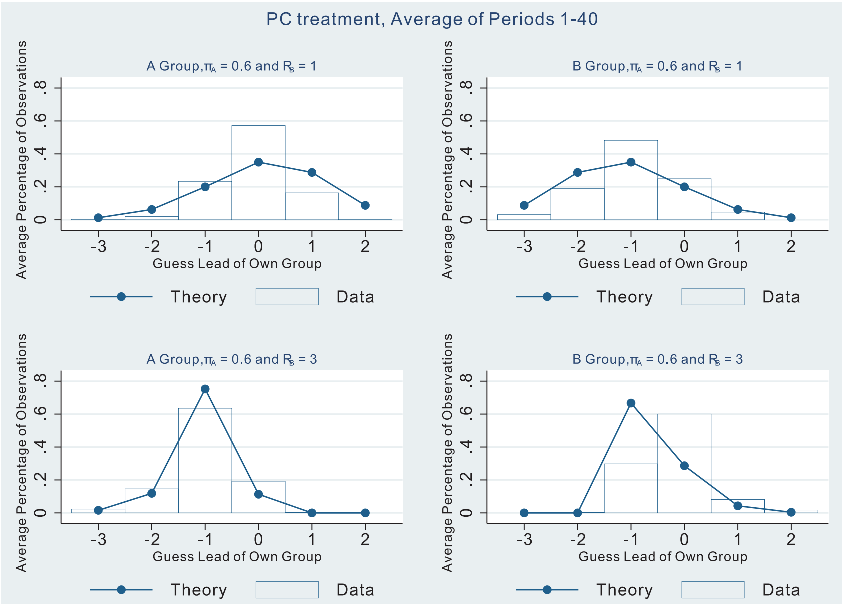

Figure 3: Distributions of subjects' guess leads of their own group in the PC treatment

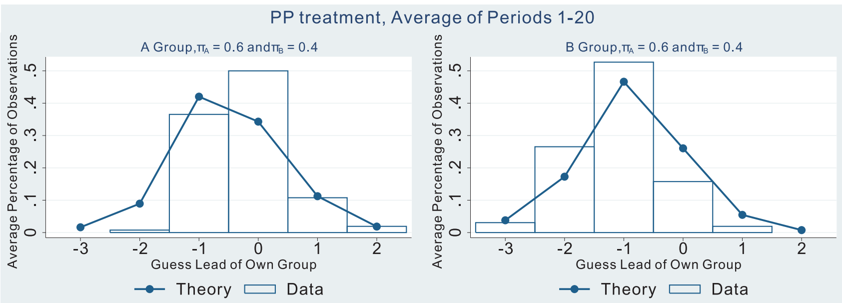

Figure 4: Distributions of subjects' guess leads of their own group in the PP treatment

addition to the pivotal effect, there were likely to be other important factors affecting turnout of the subjects who had complete certainty that their group was the frontrunner in the election. This will be discussed in Section 4.3.

Result 2 summarizes Section 4.2 and explains the failure to support H2.

Result 2. *On average, subjects' beliefs of being pivotal were much higher than theory predicts when they observed a weak support base in the partial information scenario. Combined with the finding that subjects' voting propensity increased with their pivotal beliefs, the high pivotal beliefs help explain the unexpectedly high turnout in the cases with a revelation of a weak support base in the partial information scenario, causing it to be not lower than the turnout in the corresponding complete information scenario.*

4.3 Generalized disappointment aversion

In this section, I study the unexpectedly high value of $\hat{p}_A(3, 1)$ or $\hat{p}_B(1, 3)$; that is, the unexpectedly high turnout of the subjects who were in the $(3, 1; A)$ or $(1, 3; B)$ case of the CC treatment. Without loss of generality, in the following I consider the $(3, 1; A)$ case, and refer to the A group revealing a strong support base ($R_A = 3$) as the frontrunner party and its competing B group revealing a weak support base ($R_B = 1$) as the underdog party. The $\hat{p}_A(3, 1)$ is 0.659, yielding the observed critical voting cost of 7.25 for passive partisans of the frontrunner party.[9] This value is much higher than the theoretical critical voting cost of 4.48, obtained from $p^*_A(3, 1) = 0.407$. The difference between the theoretical and observed critical voting costs is 2.77, implying that when a subject learned that her party was the frontrunner party,she would be willing to pay an additional 2.77 costs to vote in order to increase her party's probability of not losing from 0.9 to 1.[10]

The literature has discussed various factors, such as the pivotal beliefs, bounded rationality, bandwagon effects, and risk aversion, that may account for high voter turnout. In addition to the pivotal beliefs that has been discussed in Section 4.2, the effects of bounded rationality, bandwagon, and

[9]According to equation (1) or (2), $\hat{p} = F(\hat{c})$, where $\hat{p}$ refers to the voting probability, and $\hat{c}$ refers to the critical voting cost. Since the voting cost distribution is uniform ranging from 0 to 11, $\hat{p} = \hat{c}/11$. That is, $\hat{c} = 11\hat{p}$.

[10]If subject i of the frontrunner party decides not to vote, her party's probability of not losing the election will be $1 - (p^*_B)^3 = 1 - 0.465^3 = 0.9$, where $p^*_B = 0.465$ is the voting probability of each member of the competing underdog party. By contrast, if subject i decides to vote, her party's probability of not losing the election will be 1 since all of her members will vote.

risk aversion have also been examined. The results are presented in Appendices E, F, and G, showing that all of them are unsuccessful in explaining the unexpectedly high turnout of the frontrunner party in the experiment.

In addition to the factors mentioned above, a possible explanation for the high turnout of the frontrunner party is expectation-based loss aversion (Kőszegi and Rabin, 2006, 2007) or disappointment aversion (Gul, 1991). They both belong to the concept of reference-dependent preferences. The idea is as follows: when passive partisans are in a situation where their party is very likely to succeed, their expectation of winning the election will be high; therefore, if their party loses the election in the end, they will suffer a lot of disappointment. To prevent this from happening, those passive partisans are willing to vote even if their party is considered to be very likely to win the election without their votes. As a result, a pivotal voter model considering disappointment aversion (DA) predicts a higher turnout for the frontrunner party than the model without considering it.

Although the DA effect may explain the high turnout of the frontrunner party, it cannot explain the turnout of the underdog party observed in my experiment. This is because it predicts a lower turnout for the underdog party than the model without considering the DA effect.[11] However, the turnout rate of the underdog party observed in my experiment is close to the prediction of the benchmark model, or the model presented in Section 2. That is, the DA effect may account for $\hat{p}_A(3, 1)$ being much higher than $p_A^*(3, 1)$, whereas it cannot explain that $\hat{p}_B(3, 1)$ is close to $p_B^*(3, 1)$.

To solve the asymmetric observed turnout rates in my experiment, we may consider Routledge and Zin (2010), which extends Gul (1991)'s idea to build a generalized disappointment aversion model in which only the outcomes that lie below the disappointment threshold are considered. Specifically, they provide a preference specification capturing DA as follows

$$u(\mu(p)) = \sum_{x_j \in X} p\left(x_j\right) u\left(x_j\right) - \theta \sum_{x_j \leqslant \delta\mu(p)} p\left(x_j\right)\left(u(\delta\mu(p)) - u\left(x_j\right)\right), \tag{11}$$

where x_j is an outcome of lottery p with probability $p(x_j)$, $\mu(p)$ is the

[11] If the DA effect is considered, then when passive partisans are in a situation where their party is very likely to lose but they still turn out to vote, it will raise their expectation of winning, leading to more disappointment once their party loses the election in the end, when compared with abstaining from voting. To avoid this, the passive partisans are less willing to vote when the chance of winning the election is small.

certainty equivalent for lottery p, and θ and δ are preference parameters. The δ parameter is assumed to be less than one, indicating that outcomes are disappointing only if they lie below the certainty equivalent. The θ parameter measures the utility loss once the disappointing outcomes occur. For convenience, in the following, I call the benchmark model incorporating the GDA effect presented in equation (11) the GDA model.

I first apply the GDA model to the frontrunner party. For simplicity, I assume $u(x) = x$. Both voting and abstaining can be viewed as lotteries with three possible outcomes: WIN, LOSE, or TIE. The differences between the *voting* lottery (lottery V) and the *abstaining* lottery (lottery A) are as follows. First, lottery A does not cost anything, whereas lottery V costs each subject a privately drawn voting cost. Second, compared with lottery A, lottery V has a higher probability for WIN, the reward of which is higher than those of LOSE and TIE. For a subject of the frontrunner party, whether her party wins the election depends on the turnout rates of the frontrunner and underdog parties. Hence, given that group A is the frontrunner party, I use $p_A^*(3, 1)$ and $p_B^*(3, 1)$ to calculate the probabilities for outcomes of lottery V and lottery A for group A. Then, according to equation (11), each (θ, δ) pair provides $\mu(V)$ and $\mu(A)$ for lottery V and lottery A, respectively, representing the expected payoffs from voting and abstaining.

To estimate the parameters θ and δ, I follow individual choice behavior research (Luce, 1959; McFadden, 1974; McKelvey and Palfrey, 1995) to consider a probabilistic choice function with a logit response parameter λ, which can be interpreted as the level of rationality. Then, with the expected payoffs presented above as well as the decision and voting cost data of the frontrunner party, I obtain maximum-likelihood parameter estimates (and standard errors): $\hat{\theta} = 50$ (0.07), $\hat{\delta} = 0.138$ (0.07), and $\hat{\lambda} = 17.02$ (0.12). The results suggest that only the outcomes that were very far below the certainty equivalent disappointed the subjects ($\hat{\delta} = 0.138$), but when the disappointing outcome occurred, it caused a lot of disutility ($\hat{\theta} = 50$).[12] Details for the maximum likelihood estimation are given in Appendix H.

Substituting $\theta = 50$ and $\delta = 0.138$ into equation (11) yields $\mu(V) = 19.95$ and $\mu(A) = 12.1$, which respectively represents the expected payoffs

[12] So far the model proposed by Routledge and Zin (2010) has been used by only a few studies (Bonomo et al., 2011; Chapman and Polkovnichenko, 2009; Liu and Miao, 2015; Routledge and Zin, 2010), and the values of the θ and δ parameters are very different in different studies. As a result, the range of the value of θ and that of δ are undetermined.

Table 4: Comparison between with and without GDA

	Frontrunner Case (3, 1; A)	*Underdog* Case (3, 1; B)
Observed critical voting cost	7.25	4.42
Theoretical critical voting cost (w/GDA)	7.82	5.00
Theoretical critical voting cost (w/o GDA)	4.48	5.12

Note: Case (3, 1; A) and Case (3, 1; B) are defined in Table 2. Theoretical critical voting cost (w/GDA) refers to the predicted critical voting cost of the GDA model. Theoretical critical voting cost (w/o GDA) refers to the predicted critical voting cost of the benchmark model presented in Section 2.

from voting and abstaining after considering the GDA effect for subjects of the frontrunner party. The difference between $\mu(V)$ and $\mu(A)$ is 7.82, representing the critical voting cost after considering the GDA effect. This number is close to the observed critical voting cost of 7.25, implying that taking the GDA effect into account seems to be able to explain the voting behavior of subjects of the frontrunner party. By contrast, without the GDA effect, the theoretical critical voting cost derived from the benchmark model is 4.48, which is very different from the observed critical voting cost.

Then, I turn to see if the GDA model can explain the voting behavior in the underdog party. With the same method presented above, I obtain the critical voting cost of 5 for the underdog party after considering the GDA effect.[13] This number is close to the observed critical voting cost of 4.42 (obtained from $\hat{p}_B(3, 1)$) and therefore implies that taking the GDA effect into consideration seems to be able to explain the voting behavior of the underdog party as well. Table 4 summarizes the discussions above.

Although the LOSE outcome leads to disappointment in both the frontrunner and underdog parties, the levels of disappointment in the two parties are very different. When subjects of the frontrunner party choose to abstain, the disutility from disappointment is 3.34 if it causes their party to lose the election, while when subjects of the underdog party choose to vote but

[13] Specifically, given that group B is the underdog party, I use $p_A^*(3, 1)$ and $p_B^*(3, 1)$ to calculate the probabilities for the WIN, LOSE, and TIE outcomes of lottery V and lottery A for the underdog party. Substituting $\theta = 50$ and $\delta = 0.138$ into equation (11) yields $\mu(V) = 7.28$ and $\mu(A) = 2.28$ for the underdog party; the difference between them is 5.

their party eventually loses the election, the disutility from disappointment is only 0.12.[14] This is because the LOSE outcome lies far below the expectation of the subjects of the frontrunner party but not the underdog party. The GDA model captures this asymmetric phenomenon, and hence fits the observed turnout rates of the frontrunner and underdog parties better than other models.

Finally, I examine whether the GDA model fits the observed turnout rates in other cases. The results presented in Table 10 of Appendix H show that the GDA model fits the data better than the benchmark model in the cases with a revelation of a strong support base in the partial information scenario. This finding helps explain the unexpectedly low turnout of the subjects who had partial information that they were likely to fall behind in the election (i.e., $\hat{p}_A(0.6, 3)$ and $\hat{p}_B(3, 0.4)$). In addition, it is worth noting that the disutility from disappointment is small in the cases of the partial information scenario. This is because partisans do not have certain information about each party's support base, which lowers their expectation for the election outcome and hence the disappointment level.

By contrast, the GDA model does not perform well in the cases with a revelation of a weak support base in the the partial information scenario (Appendix H, Table 10). However, this does not mean that disappointment aversion did not occur in those cases. Recall that Result 2 shows that in the CP and PC treatments, when a weak support base was revealed, subjects' beliefs of being pivotal became higher than theory predicts, which affects $p(x_j)$ in equation (11). The same finding is shown in Case (1, 1; A) or (1, 1; B) and Case (0.6, 0.4; A).[15] If the effect of high pivotal beliefs can be appropriately incorporated into the GDA model, a good fit between the GDA model and the data in those cases may be found. I leave it to the future work. Result 3 summarizes Section 4.3, which provides an explanation for the failure to support H1 and H3.

[14]The disappointment level is calculated by the absolute difference between the the predicted critical voting cost of the GDA model and that of the benchmark model presented in Table 4.

[15]That is, subjects had unexpectedly high pivotal beliefs in these cases, affecting $p(x_j)$ in equation (11) and hence the performance of the GDA model. The only exception is Case (0.6, 0.4; B), where subjects' pivotal belief was similar to the theoretical prediction but the GDA model does not perform well.

Result 3. *The pivotal voter model incorporating the generalized disappointment aversion effect provides an explanation for the observed unexpectedly high turnout of the frontrunner party in the complete information scenario. The idea is that to avoid a great disappointment from losing the election, subjects of the frontrunner party were willing to vote, even if they knew their votes would not be pivotal.*

5 Conclusion and policy implications

This paper examines how different degrees of information revelation affect voting behavior. In particular, it compares two types of scenarios: one is that voters know each party's support base (complete information scenario), and the other is that voters know one party's support base but are limited to knowing the probability of the support base of the other party (partial information scenario).

There are two main findings. First, in the partial information scenario with a revelation of a weak support base, subjects tended to have higher beliefs of being pivotal than theory predicts, which caused their turnout rates to be not lower than those in the corresponding complete information scenario. Second, in the complete information scenario, turnout of the subjects of the frontrunner party was significantly higher than the subjects' best response to their pivotal belief, which can be explained by the pivotal voter model incorporating the generalized disappointment aversion effect (hereafter the GDA model). The caveat for this finding is that the GDA model does not fit the cases where subjects had unexpectedly high pivotal beliefs. Since disappointment aversion is a possible important factor affecting voting behavior, one of the future research directions would be designing experiments aimed to study such effect, including studying how to appropriately incorporate the effect of high pivotal beliefs into the GDA model.

The experimental results provide useful advice for parties or candidates in elections. If a candidate is a frontrunner in the election, showing this information to her passive supporters would encourage them to vote, rather than decreasing their voting propensity. This is because those supporters would like to avoid a great disappointment caused by their preferred candidate from leading to losing the election due to their abstention from voting. But how to convince voters that a candidate is a frontrunner is important since it would affect the disappointment level. For example, both polls and campaign rallies can reveal parties' support levels; which one is better? Polls usually reveal distributions of electorate preferences, and more importantly, support levels shown by polls may be viewed as cheap talk since people show their support through polls without paying any costs. By contrast, if a candidate conducts campaign rallies, her base supporters will pay (money or time) to participate and show their support for the candidate, thus providing more certainty regarding the actual level of support for the candidate.

Appendices

Appendix A Experimental instructions

There were four treatments in the experiment: CC, CP, PC, and PP treatments. The CC treatment was easy for subjects to understand since the information regarding the actual number of the base partisans of each party was revealed to subjects. However, the CP, PC, and PP treatments were not that easy to understand since only the probabilities, not the actual numbers, of the base partisans of the parties were revealed.

To help subjects understand the experiment more easily, I set two stages for the experiment. In the first stage all subjects had to make their voting decisions in a situation where the actual number of the base partisans of each party was revealed. After participating in the first stage, the subjects became familiar with the experiment. Then, I conducted the second stage, which was similar to the first stage, except that in the second stage the information regarding the base partisans of each party varied for each treatment. By doing so, we can make sure that the subjects fully understood the experiment, and I collected the experimental data for the second stage to investigate the effects of information on voting behavior.

The instructions provided below are for the PC treatment. The instructions for the other treatments coincide with this one except for the information regarding the base partisans of each party.

A.1 Experimental instructions and screenshots for the PC treatment

[Each subject received instructions on his or her computer screen. In addition to the computerized instructions, Powerpoint slides with the same content were projected in front of the room. Instructions were read aloud to make sure every subject understood them. After reading the instructions, several control questions were asked. This allows us to check whether subjects understood how to make decisions and how to calculate their earnings. The experiment started after all subjects had answered all control questions correctly.]

General information

Welcome! You are now going to participate in a decision-making session. In this session you can earn money. How much money you will actually earn depends on your decisions, chance, and on others' decisions. You are under no obligation to reveal your winnings to other participants. During the session your earnings are counted in points. At the end of the session your earnings in points will be exchanged into dollars according to the following exchange rate: 25 points = 1 dollar. At the end of the session you will be paid the $5 show up fee plus your earnings confidentially in cash. This total will be rounded up to the nearest quarter or dollar. It is important that you understand these instructions correctly. So we ask you to listen to these instructions carefully. During the session you may not communicate with other participants. During the session, if you have a question please raise your hand. One of us will then come to your table and answer your question personally.

The session you are participating in is broken down into 2 stages. The two stages are independent, and each stage consists of 2 parts: 1 practice and 1 paid part. In the first stage, the practice part consists of 2 periods and the paid part consists of 10 periods. In the second stage, the practice part consists of 4 periods and the paid part consists of 40 periods. In each period you will be randomly assigned to a group with other participants. And you will be randomly reassigned to a new group with different participants after each period. All interaction is anonymous during the session.

Instructions for the First Stage

There are two types of groups: ALPHA groups and BETA groups. Each ALPHA group will be randomly paired with a BETA group in each period. In the beginning of each period, you will be randomly assigned to an ALPHA group or a BETA group. You will not necessarily be in the same group during this experiment.

Each ALPHA group has 4 members and each BETA group has 4 members. For each group, these 4 group members include human members and computer members. Human members are participants who are sitting in the lab and are participating in this experiment. Computer members are computers.

There are four possible cases:

1. Each ALPHA group has 1 computer member; each BETA group has 1 computer member.
2. Each ALPHA group has 1 computer member; each BETA group has 3 computer members.
3. Each ALPHA group has 3 computer members; each BETA group has 1 computer member.
4. Each ALPHA group has 3 computer members; each BETA group has 3 computer members.

In each period, one of the four cases will randomly occur.

Your Decision

Each participant (i.e., human member) will have to choose between the following two options: X or Y. Computer members will always choose X. Before you make your choice, the screen will inform you which group you are in and how many computer and human members there are in each group.

[Show SCREEN 1.]

On the top of the screen, you can see the numbers of computer members in each ALPHA group and in each BETA group. It should be 1 or 3. Since each group has 4 members, the number of human members is equal to 4 minus the number of computer members. Note that every participant will see the same information. On the middle of the screen you can see which group you belong to in this period. And you can see the two options, X and Y.

Your Payoffs

After each participant has made the choice, your earnings are computed according to two rules: Rule 1 and Rule 2. Recall that an ALPHA group is randomly paired with a BETA group. For convenience, we call the group paired with your group "your paired group."

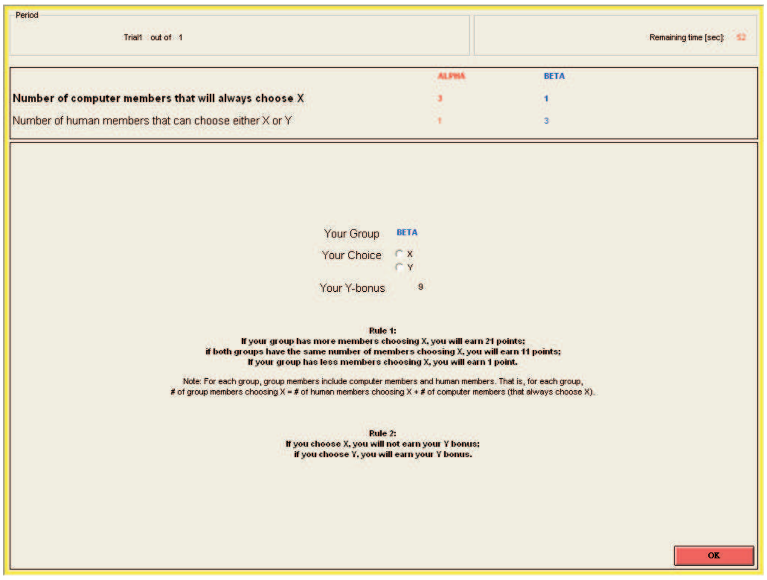

Figure 5: SCREEN 1

Your Payoffs - Rule 1. If your group has more members choosing X than your paired group, you will earn 21 points. If both groups have the same number of members choosing X, then you will earn 11 points. If your group has less members choosing X than your paired group, you will earn 1 point. Note that for each group, group members include human members and computer members.

Your Payoffs - Rule 2. In addition to the earnings described above, you may earn your Y bonus. The amount of your Y-bonus is assigned randomly by the computer and is shown on your screen. In any given period you have an equal chance of being assigned any Y-bonus between 0 and 11 points. Different participants will typically have different Y-bonuses. If you choose Y, you will earn your Y bonus. If you choose X, you will NOT earn your Y bonus.

[Show SCREEN 1.]

On the middle of the screen, you can see your Y-bonus. On the bottom of the screen, you can see Rule 1 and Rule 2. They show you how your

Table 5: Examples for decisive/non-decisive cases

	case 1	case 2	case 3
# of other members in you group choosing X	2	2	2
# of your paired group members choosing X	2	3	4
Your choice	X	X	X
Your payoff from Rule 1	21	11	1
Your choice	Y	Y	Y
Your payoff from Rule 1	11	1	1
Are you decisive?	Yes	Yes	No

earnings will be calculated according to your choice. Now you can make your choice there by clicking with your mouse.

Guess: Probability that your choice is decisive

After making your actual choice, you will be asked to guess: "What is the probability that your choice is decisive for this period's outcome?" Your choice is decisive if your choice determines your payoff from Rule 1 holding constant the choices of all other participants. In other words, your choice is decisive if the number of other members in your group choosing X is equal to or one less than the number of your paired group members choosing X. Below are examples. [Show Table 5.]

[Show SCREEN 2.]

On the middle of the screen, you can see the question, "Your guess as to the probability that your choice is decisive," and an input box. In this box, please indicate your probability by entering any real number between 0 and 1 inclusive. A "0" means "I definitely will not be decisive" and "1" means "I definitely will be decisive." For example, if you think there is a 23 percent chance that your choice will be decisive, enter 0.23 in the input box. If you think there is a 89 percent chance that your choice will be decisive, enter 0.89. This number can go up to two decimal points.

For each of you, after entering a probability $u \in [0, 1]$, your computer will select a random number $r \in [0, 1]$ for you. If $u \geqslant r$, you will earn the guess bonus by Scheme U. If $u < r$, you will earn the guess bonus by Scheme R.

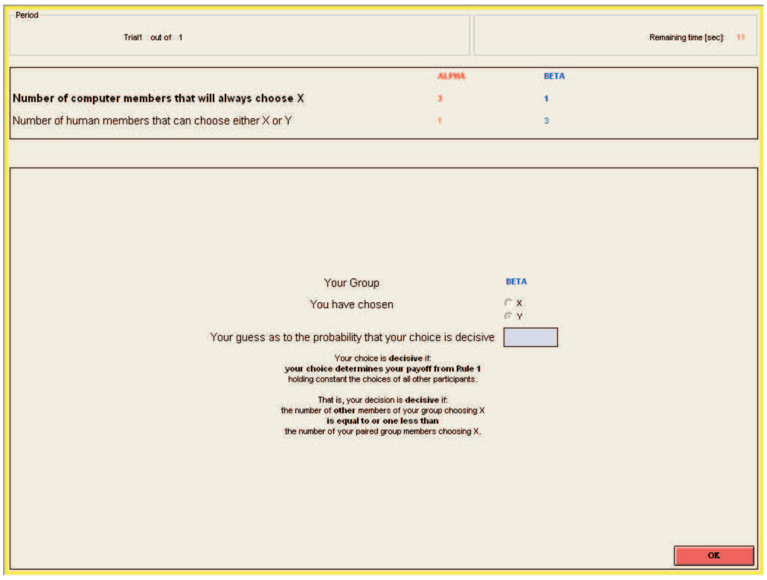

Figure 6: SCREEN 2

- Scheme U: You will earn 0.5 points if your choice is decisive and 0 points otherwise.
- Scheme R: You will earn 0.5 points with probability r and 0 points with probability $1 - r$.

According to Schemes U and R, you will maximize your decisive-guess bonus by reporting your true belief about what you think the probability is that you will be decisive.

Suppose that you think your choice will be very likely to be decisive. For example, suppose that you think there is a 92 percent chance that your choice will be decisive, and therefore you enter a probability of 0.92. Then your computer will select a random number for you. Suppose that the randomly selected number is 0.77. Since the selected number is smaller than your guess, you will earn 0.5 points if your choice is decisive and 0 points if it is not. Suppose that the randomly selected number is 0.98. Since the selected number is larger than your guess, you will earn 0.5 points with a probability of 0.98 and 0 points with a probability of 0.02.

Guess: Final outcome

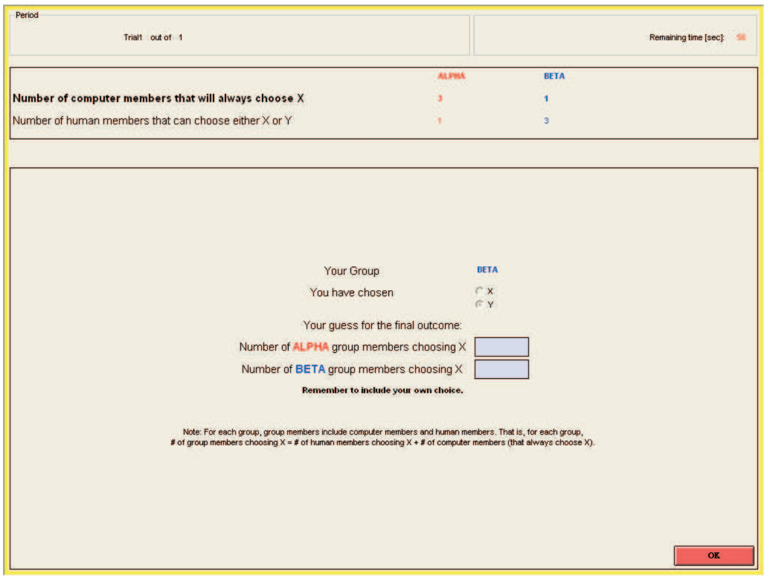

Figure 7: SCREEN 3

In addition to reporting your decisiveness prediction, you will be also asked to guess "the number of your group members (including you) choosing X." The number of your paired group members choosing X. You will earn 0.5 points if one of your guesses is correct and earn 1 point if both are correct.

[Show SCREEN 3.]

On the middle of the screen, you can see two input boxes. In these boxes, please enter your guesses for the final outcome. Note that for each group, group members include human members and computer members. Don't forget to include your own choice when entering your guess about the number of your group members choosing X.

Feedback

After you and other participants have all made your choices of X or Y and made your guesses, the screen will show you the results of this period. First, you can see which group you are in and the choice you have made for

Figure 8: SCREEN 4

the current period. Second, you can see the number of your group members (including you) choosing X and the number of your paired group members choosing X. And you can also see your payoffs from Rules 1 and 2. Third, you can see your guesses about your group and your paired group and your outcome-guess bonus. Fourth, you can see whether you were decisive for the current period, your guess about the probability that your choice is decisive, the number which was randomly selected by your computer, and your decisive-guess bonus. In sum, your net payoff is equal to your payoff from Rule 1 plus your payoff from Rule 2 plus your guess bonus. And you can also see your cumulative payoff.

[Show SCREEN 4.]

History Table and Record Sheet

After you have made your choice and clicked the OK button, you need to wait for other participants. When you are waiting, the screen shows you the history table. It reminds you of your recent history of all past periods. When all participants have made their choices, you will automatically move on to the next screen. So you may not have enough time to read the history. If you want to record the history, you can write it down on the record sheet we gave you.

Control Questions

[QUIZ] You are now going to see a few questions on the screen. These questions apply to the first stage. Please answer the questions by clicking the mouse on the radio button you think is correct. The questions are only meant to indicate whether you have understood the instructions correctly. All questions are based on arbitrary examples. If you have questions, please raise your hand. [END QUIZ]

If you have any questions, please raise your hand. If you don't have questions, we now get started! You'll first have 2 periods for practice and then 10 periods for paid. [Play periods 1–10.]

Instructions for the second stage

The second stage is the same as the first stage EXCEPT that

1. The screen will inform you how many computer members there are in a BETA group but will NOT inform you the number of the computer members in an ALPHA group.
2. For ALPHA groups, the screen will only inform you the probabilities that the numbers of computer members are selected.

The probabilities are as follows. The probability that each ALPHA group has 1 computer member is 0.4. The probability that each ALPHA group has 3 computer members is 0.6. The realization of the numbers of computer members each period is independent of the realization in all other periods.

[Show SCREEN 5.]

On the top of the screen, you can see the number of computer members in each BETA group. It should be 1 or 3. For each ALPHA group, you only see the probabilities. The probability that each ALPHA group has 1 computer member is 0.4. The probability that each ALPHA group has 3 computer members is 0.6. Since each group has 4 members, the number of human members equals 4 minus the number of computer members. Note that every participant sees the same information.

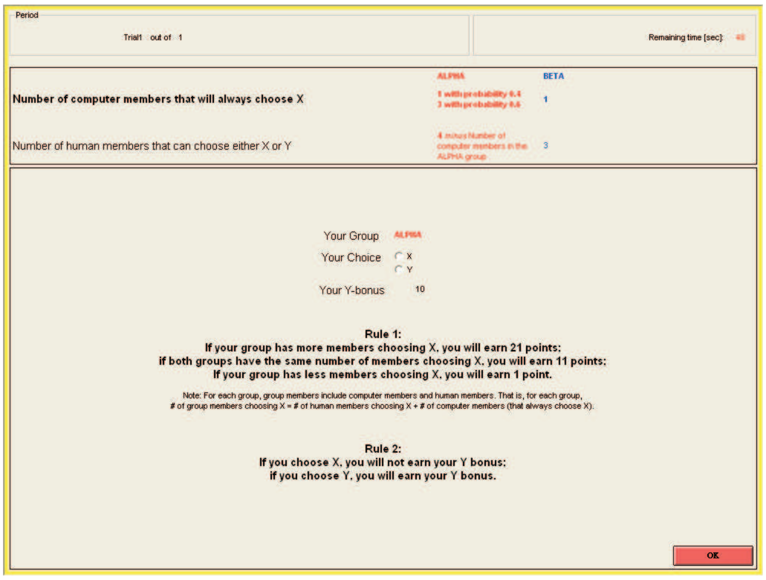

Figure 9: SCREEN 5

[Show SCREEN 6, SCREEN 7, and SCREEN 8.]

History Table and Record Sheet

The history table will show you the realized numbers of the computer members in each ALPHA group in previous periods. That is, when you make your choice for the current period, you don't know the number of the computer members in each ALPHA group; you only know the probabilities. But when this period has finished, you can see the realized number from the history table.

Control Questions

[QUIZ] You are now going to see a few questions on the screen. These questions apply to the first stage. Please answer the questions by clicking the mouse on the radio button you think is correct. The questions are only meant to indicate whether you have understood the instructions correctly. All questions are based on arbitrary examples. If you have questions, please raise your hand. [END QUIZ]

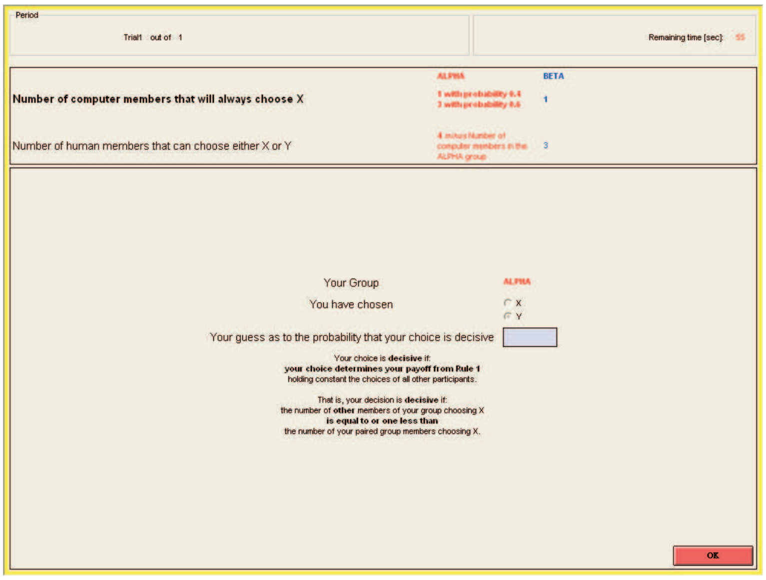

Figure 10: SCREEN 6

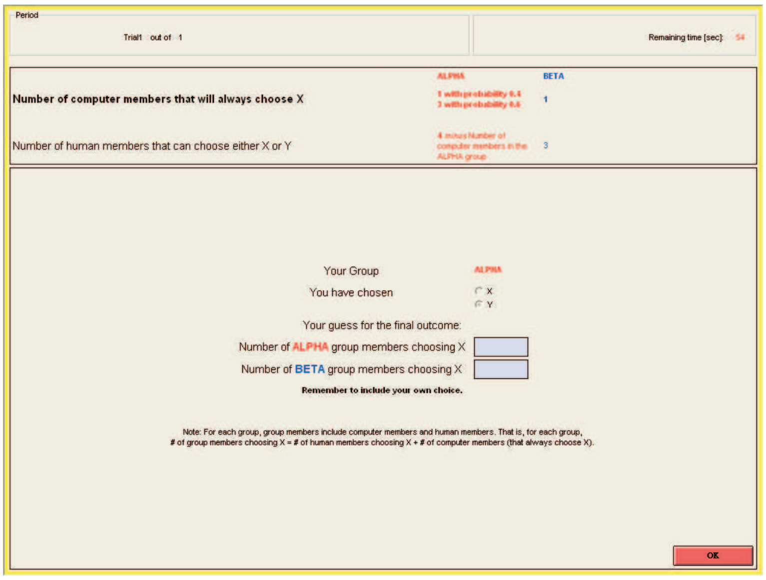

Figure 11: SCREEN 7

Figure 12: SCREEN 8

If you have any questions, please raise your hand. If you don't have questions, we now get started! You'll first have 4 periods for practice and then 40 periods for paid. [Play periods 1–40.] The experiment has finished.

Appendix B Descriptions of cases of treatments

Table 6: Description of each case of each ttreatment

Treatment	Case	Description
CC	(1, 1; A) or (1, 1; B)	There are 1 base and 3 passive partisans in each of A and B groups. Subject i is in either an A or B group.
	(3, 1; A) or (1, 3; B)	There are 3 base and 1 passive partisans in each A group; there are 1 base and 3 passive partisans in each B group; subject i is in an A group. Or there are 3 base and 1 passive partisans in each B group; there are 1 base and 3 passive partisans in each A group; subject i is in a B group.
	(1, 3; A) or (3, 1; B)	There are 3 base and 1 passive partisans in each A group; there are 1 base and 3 passive partisans in each B group; subject i is in a B group. Or there are 3 base and 1 passive partisans in each B group; there are 1 base and 3 passive partisans in each A group; subject i is in an A group.
	(3, 3; A) or (3, 3; B)	There are 3 base and 1 passive partisans in each of A and B groups. Subject i is in either an A or B group.
CP	(1, 0.4; A)	There are 1 base and 3 passive partisans in each A group. There is a probability of 0.4 that each B group has 3 base and 1 passive partisans, and a probability of 0.6 that each B group has 1 base and 3 passive partisans. Subject i is in an A group.
	(1, 0.4; B)	There are 1 base and 3 passive partisans in each A group. There is a probability of 0.4 that each B group has 3 base and 1 passive partisans, and a probability of 0.6 that each B group has 1 base and 3 passive partisans. Subject i is in a B group.

Table 6: Description of each case of each ttreatment (Cont.)

Treatment	Case	Description
	$(3, 0.4; A)$	There are 3 base and 1 passive partisans in each A group. There is a probability of 0.4 that each B group has 3 base and 1 passive partisans, and a probability of 0.6 that each B group has 1 base and 3 passive partisans. Subject i is in an A group.
	$(3, 0.4; B)$	There are 3 base and 1 passive partisans in each A group. There is a probability of 0.4 that each B group has 3 base and 1 passive partisans, and a probability of 0.6 that each B group has 1 base and 3 passive partisans. Subject i is in a B group.
PC	$(0.6, 1; A)$	There are 1 base and 3 passive partisans in each B group. There is a probability of 0.6 that each A group has 3 base and 1 passive partisans, and a probability of 0.4 that each A group has 1 base and 3 passive partisans. Subject i is in an A group.
	$(0.6, 1; B)$	There are 1 base and 3 passive partisans in each B group. There is a probability of 0.6 that each A group has 3 base and 1 passive partisans, and a probability of 0.4 that each A group has 1 base and 3 passive partisans. Subject i is in a B group.
	$(0.6, 3; A)$	There are 3 base and 1 passive partisans in each B group. There is a probability of 0.6 that each A group has 3 base and 1 passive partisans, and a probability of 0.4 that each A group has 1 base and 3 passive partisans. Subject i is in an A group.
	$(0.6, 3; B)$	There are 3 base and 1 passive partisans in each B group. There is a probability of 0.6 that each A group has 3 base and 1 passive partisans, and a probability of 0.4 that each A group has 1 base and 3 passive partisans. Subject i is in a B group.

Table 6: Description of each case of each ttreatment (Cont.)

Treatment	Case	Description
PP	(0.6, 0.4; A)	There is a probability of 0.6 that each A group has 3 base and 1 passive partisans, and a probability of 0.4 that each A group has 1 base and 3 passive partisans. There is a probability of 0.4 that each B group has 3 base and 1 passive partisans, and a probability of 0.6 that each B group has 1 base and 3 passive partisans. Subject i is in an A group.
	(0.6, 0.4; A)	There is a probability of 0.6 that each A group has 3 base and 1 passive partisans, and a probability of 0.4 that each A group has 1 base and 3 passive partisans. There is a probability of 0.4 that each B group has 3 base and 1 passive partisans, and a probability of 0.6 that each B group has 1 base and 3 passive partisans. Subject i is in a B group.

Note: Although I use subject i in the table as an example, each subject only participated in one session of a treatment. That is, a subject only faced 4 cases in the experiment if she was assigned to either the CC, CP, or PC treatment, or faced 2 cases if being assigned to the PP treatment.

Appendix C Regression analysis

This section consists of two parts. Part 1 is about examining the effect of pivotal beliefs on voting behavior. Part 2 is about testing whether learning occurred during the course of the experiment.

Part 1. To explore the relationship between subjects' beliefs of being pivotal and their voting strategies, I run a probit regression for each treatment, clustering standard errors at the individual level. Regression models involve the following variables. The *Vote* dummy dependent variable equals 1 when a subject decided to vote. Two independent variables are used to test the predictions of the pivotal voter model: (1) *Lead* $= 0$ *or* -1: a dummy variable equal to 1 if a subject's stated belief about the lead of her group (not including this subject's own vote) equaled 0 or -1. This dummy variable equal to 1 implies that a subject believed her vote would change the election outcome; (2) *Voting Cost*: a subject's Y bonus which was randomly drawn in each period. In addition to these two variables, I follow Duffy and Tavits (2008) and Agranov et al. (2018) to consider other relevant independent variables: *Voted at t-1*, *Won at t-1*, *Voted and Won at t-1*, and *Period*; the first three are dummy variables. To control for the effect of different information revelation about the base partisans of the two groups in each case, the *Case* variables (as defined in Table 2) are added.

Table 7 shows the regression results. *Period* is insignificant (or significant but very small), implying that there were barely any time effects.[16] *Voted at* $t-1$ is insignificant in every treatment, implying that every election in the experiment was viewed as a one shot game as assumed. The coefficients of *Voted and Won at* $t-1$ are positive and those of *Won at* $t-1$ are negative, implying that subjects tended to choose a strategy that had led to a good outcome in the past period of the game, but this effect did not occur to the subjects who had not chosen that strategy in the past. These results are consistent with those in Duffy and Tavits (2008) and Agranov et al. (2018).

The results for $Lead = 0$ *or* -1 and *Voting Cost* are consistent with the predictions of the pivotal voter model. Specifically, $Lead = 0$ *or* -1 is significantly positive and *Voting Cost* is significantly negative in every treatment, implying that subjects' propensity to vote increased with their beliefs of being pivotal but decreased with their voting costs. In addition, the similarity of the coefficients for $Lead = 0$ *or* -1 in the four treatments implies that the pivotal effect was similar across different treatments.

Part 2. To examine whether learning occurred during the course of the experiment, I performed a probit regression for each treatment with the accuracy of a subject's belief about the lead of her group as the dependent variable and *Period* as the independent variable, clustering standard errors at the individual level. More specifically, the *Accuracy* dummy dependent variable equaled 1 when a subject's stated belief about the lead of her group (*Guess Lead*) equaled the actual lead (*Actual Lead*). In addition to *Accuracy*, I used the absolute difference between *Guess Lead* and *Actual Lead* as another dependent variable for robustness check. Other independent variables included *Voting Cost* and *Case* variables, as defined in Tables 7 and 2.

Table 8 shows the regression results for the *Accuracy* dummy dependent variable. As shown, *Period* is insignificant in every treatment, implying that

[16]The coefficient of *Period* is insignificant in every treatment except the CC treatment. This may be due to the clear information regarding base partisans in the CC treatment.

Table 7: Probit regressions explaining turnout (marginal effects reported)

	Treatment			
Dep = Vote	CC	CP	PC	PP
Voting Cost	−0.126***	−0.129***	−0.119***	−0.093***
	(0.015)	(0.013)	(0.011)	(0.012)
Period	−0.004**	−0.002	0.0004	0.001
	(0.002)	(0.002)	(0.001)	(0.003)
Voted at t-1	−0.015	−0.003	0.071	0.055
	(0.056)	(0.060)	(0.062)	(0.100)
Won at t-1	−0.003	−0.012***	−0.008***	−0.009
	(0.002)	(0.003)	(0.003)	(0.006)
Voted and Won at t-1	0.009***	0.012***	0.006	0.008
	(0.003)	(0.004)	(0.004)	(0.007)
Lead = 0 or -1	0.149**	0.121**	0.116*	0.135*
(pivotal, dummy)	(0.063)	(0.049)	(0.066)	(0.081)
Case (1, 1; A) or (1, 1; B)	−0.299***			
	(0.110)			
Case (3, 1; A) or (1, 3; B)	−0.374***			
	(0.075)			
Case (1 ,3; A) or (3, 1; B)	−0.665***			
	(0.086)			
Case (1, 0.4; A)		0.035		
		(0.054)		
Case (1, 0.4; B)		0.170***		
		(0.040)		
Case (3, 0.4; A)		0.293***		
		(0.052)		
Case (0.6, 1; A)			0.067	
			(0.047)	
Case (0.6 1; B)			0.018	
			(0.046)	
Case (0.6, 3; B)			0.149***	
			(0.050)	
Case (0.6, 0.4; B)				−0.041
				(0.082)
# of obs.	1,014	1,092	1,170	494

Note: The variables in the first column are defined in the text of Appendix 5 and Table 2. *Case (3, 3; A) or (3, 3, B)* is the baseline in the CC treatment, *Case (3, 0.4, B)* is the baseline in the CP treatment, *Case (0.6, 3; A)* is the baseline in the PC treatment, and *Case (0.6, 0.4; A)* is the baseline in the PP treatment. Standard errors clustered on individuals in parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 8: Probit regressions examining learning (marginal effects reported)

	Treatment			
Dep = Accuracy	CC	CP	PC	PP
Voting Cost	0.003 (0.004)	0.003 (0.005)	0.004 (0.005)	−0.008 (0.008)
Period	−0.001 (0.002)	0.001 (0.001)	0.001 (0.002)	0.004 (0.004)
Case (1, 1; A) or (1, 1; B)	−0.363*** (0.045)			
Case (3, 1; A) or (1, 3; B)	−0.290*** (0.044)			
Case (1, 3; A) or (3, 1; B)	−0.365*** (0.036)			
Case (1, 0.4; A)		−0.085** (0.034)		
Case (1, 0.4; B)		0.017 (0.042)		
Case (3, 0.4; A)		0.082* (0.044)		
Case (0.6, 1; A)			−0.051 (0.049)	
Case (0.6, 1; B)			−0.097** (0.043)	
Case (0.6, 3; B)			−0.002 (0.042)	
Case (0.6, 0.4; B)				−0.051 (0.035)
# of obs.	1,040	1,120	1,200	520

Note: The variables in the first column are defined in the text of Appendix 5 and Table 2. $Case(3,\ 3;\ A)$ or $(3,\ 3,\ B)$ is the baseline in the CC treatment, $Case(3,\ 0.4,\ B)$ is the baseline in the CP treatment, $Case(0.6,\ 3;\ A)$ is the baseline in the PC treatment, and $Case(0.6,\ 0.4;\ A)$ is the baseline in the PP treatment. Standard errors clustered on individuals in parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Results for the $|GuessLead - ActualLead|$ dependent variable are available on request.

learning did not occur during the course of the experiment. This may be because each of the CC, CP, and PC treatments consisted of 4 different cases, and each case randomly occurred in 40 periods of the experiment; similarly, the PP treatment had 2 cases and 20 periods in total, with each case randomly occurring in the 20 periods of the experiment. In other words, subjects were not in a specific case for 10 periods and then entered the next case for another 10 periods. Instead, subjects might face one case in the $t-1^{th}$ period and then another case in the t^{th} period, and on average they faced each case for around 10 periods. Therefore, it is not surprising that subjects' beliefs about others' behavior did not get improved as time went by since they were unable to directly learn from the last period. The same result was found for the $|GuessLead - ActualLead|$ dependent variable.

Appendix D Subjects' cutpoints

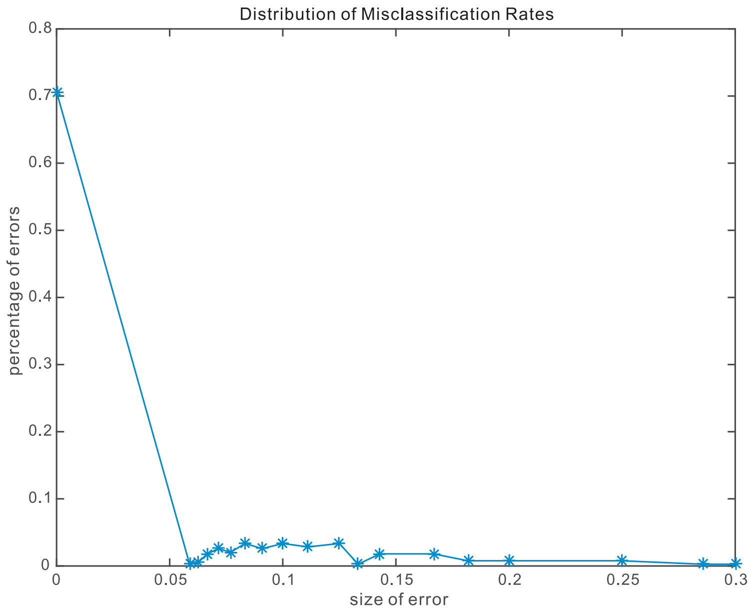

Figure 13: Distribution of misclassification rates

In addition to the regression analysis, I further investigate subjects' behavior by examining whether subjects followed their cutpoint rules as the pivotal voter model assumes. I first estimate each subject's cutpoint rule based on the method in Levine and Palfrey (2007); then, for each subject, I use the estimated cutpoint for her to calculate the size of the error with respect to that cutpoint.[17] Figure 13 displays the density for error rates. As

[17] See Levine and Palfrey (2007) pp. 150–152 for more details.

shown, around 70 percent of the subjects perfectly classified the decisions based on their cutpoint rules, and for all subjects the percentage of decisions correctly classified is greater than 70. This shows that subjects followed consistent cutpoint rules.

Appendix E Bounded rationality

To explain the difference between theory and experimental data, researchers may first consider the effect of bounded rationality and try the Quantal Response Equilibrium (QRE) method. That is, human beings are not fully rational, resulting in deviations from the equilibrium. However, the pivotal voter model incorporating only the effect of bounded rationality (yielding a QRE prediction) is not enough to explain the difference between $p_A^*(3, 1) = 0.407$ and $\hat{p}_A(3, 1) = 0.659$ in my experiment. This is because a QRE value will approach to the theoretical prediction as subjects are more rational, and it will approach to 0.5, meaning behaving randomly, as subjects are more irrational. In other words, given that the predicted $p_A^*(3, 1) = 0.407$ is below 0.5, the highest QRE value will not be greater than 0.5 and hence cannot explain the observed $\hat{p}_A(3, 1) = 0.659$.

Appendix F Bandwagon effect

An unexpectedly high turnout of majority voters has been found in several voting studies such as Duffy and Tavits (2008), Groβer and Schram (2010), and Agranov et al. (2018). These studies provide a possible explanation: the bandwagon effect, according to which voters are more likely to vote if they believe that their preferred candidates are likely to succeed. To see if the bandwagon effect occurred in my experiment, I run a probit regression for the frontrunner party by considering, in addition to the variables presented in Table 7, an additional independent variable *Lead of the majority if in majority*: a subject's stated belief about the lead of her group (not including this subject's own vote) if that number is positive; otherwise, the variable equals zero.[18] If the bandwagon effect existed in the frontrunner party in my experiment, the coefficient of *Lead of the majority if in majority* is expected to be significantly positive, meaning that the subjects' propensity to vote increased with the number of votes for their party.

[18] The independent variable *Lead of the majority if in majority* has been discussed in Agranov et al. (2018). I follow Agranov et al. (2018) to consider this independent variable.

Table 9: Probit regressions for the frontrunner party (marginal effects reported)

Dep = *Vote*	*Frontrunner* Case (3, 1; *A*) or (1, 3; *B*)	*Frontrunner* Case (3, 1; *A*) or (1, 3; *B*)
Voting Cost	-0.099^{***}	-0.097^{***}
	(0.024)	(0.024)
Period	-0.007^{***}	-0.007^{***}
	(0.002)	(0.002)
Voted at t-1	0.676^{*}	0.661
	(0.403)	(0.418)
Won at t-1	−0.004	−0.003
	(0.008)	(0.008)
Voted and Won at t-1	−0.008	−0.007
	(0.017)	(0.017)
Lead =0 or -1 (pivotal, dummy)	0.150^{**}	
	(0.059)	
Lead of the majority if in majority		-0.125^{**}
		(0.059)
# of obs.	188	188

Note: Case (3, 1; *A*) or (1, 3; *B*) is defined in Table 2. The variables in the first column are defined in the text of Appendix F. Standard errors clustered on individuals in parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

The regression results are presented in Table 9. First, let us see the variables that have been examined in Table 7. The coefficients of *Voted at* $t-1$, *Won at* $t-1$, and *Voted and Won at* $t-1$ are not consistent with those in Table 7. This is because these three variables in Table 9 do not represent subjects' choices and the election outcome in the last period, but represent those in the last time that subjects were in the frontrunner party. The coefficient of *Lead* $=$ *0 or* -1 is significantly positive, consistent with that in Table 7, implying that subjects' propensity to vote increased with their beliefs of being pivotal. Next, we see *Lead of the majority if in majority*, which is used to test the bandwagon effect. The coefficient of *Lead of the majority if in majority* is significantly negative, implying that when subjects believed that their party was the frontrunner in the election, their propensity to vote decreased with the number of the votes for their party. In other words, this result shows that the bandwagon effect did not occur in my experiment.

Appendix G Risk aversion

I also examine whether the high turnout of subjects of the frontrunner party was due to risk aversion. Recall that my experimental data show that a subject of the frontrunner party was willing to pay an additional 2.77 points to increase her party's probability of not losing from 0.9 to 1. This implies that if only the effect of risk aversion is considered to explain the turnout rate, the curvature of the utility function has to be smaller than 0.1.

More specifically, in the CC treatment, theoretically, the turnout rate of subjects of the frontrunner party is 0.407 and that of its competing party, or the underdog party, is 0.465. Hence, if a subject i of the frontrunner party chooses to vote, there is a probability of 0.465^3 for a tie outcome (i.e., all 3 passive partisans of the underdog party choose to vote), and there is a probability of $1 - 0.465^3$ that the frontrunner party wins the election. If the tie outcome occurs, subject i obtains 11 points minus i's voting cost; if the frontrunner party wins the election, subject i obtains 21 points minus i's voting cost.

According to Tversky and Kahneman (1992), a subject's utility function can be represented as a two-part power function of the form

$$v(x) = \begin{cases} x^{\alpha} & \text{if } x \geqslant 0, \\ -\lambda(-x)^{\beta} & \text{if } x < 0, \end{cases}$$

with the weighting functions $w^{+}(p) = [(p^{\gamma})/((p^{\gamma} + (1-p)^{\gamma})^{1/\gamma})]$ and $w^{-}(p) = [(p^{\delta})/((p^{\delta} + (1-p)^{\delta})^{1/\delta})]$, where $\gamma = 0.61$ and $\delta = 0.69$. Substituting the payoff and the corresponding probability for each outcome into the model proposed by Tversky and Kahneman (1992) gives subject i's expected utility from voting, which is a function of α (i.e., the curvature of the utility function). Similarly, subject i's expected utility from abstaining can be calculated, which is also a function of α. By definition, the critical voting cost makes i's expected utility from voting equal to i's expected utility from abstaining. That is, with a critical voting cost, the corresponding α can be obtained. With the observed critical voting cost of 7.25, α must be smaller than 0.1.

However, $\alpha < 0.1$ is not consistent with the values found in the literature on risk aversion. For example, according to Tversky and Kahneman (1992), at the aggregate level, the curvature of the utility function measuring the risk attitude is 0.88. Similar values ranging from 0.84 to 0.97 have been found in many other studies (Fennema and van Assen, 1998; Abdellaoui, 2000; Etchart-Vincent, 2004; Schunk and Betsch, 2006; see Abdellaoui, Bleichrodt, and Paraschiv, 2007 for an overview). As a result, the pivotal voter model combined with only the risk aversion effect cannot successfully explain the observed high turnout of subjects of the frontrunner party in my experiment.

Appendix H Estimation

From a voter's point of view, voting and abstaining can be viewed as two lotteries, lottery V and lottery A. To consider the effect of disappointment aversion, I use the GDA model proposed by Routledge and Zin (2010) to calculate the certainty equivalent $\mu(V)$ for lottery V and the certainty equivalent $\mu(A)$ for lottery A. Specifically, a certainty equivalent $\mu(p)$ for lottery p can be obtained by the following equation, or equation (11):

$$u(\mu(p)) = \sum_{x_j \in X} p\left(x_j\right) u\left(x_j\right) - \theta \sum_{x_j \leqslant \delta\mu(p)} p\left(x_j\right)\left(u(\delta\mu(p)) - u\left(x_j\right)\right),$$

where x_j is an outcome with probability $p(x_j)$, and θ and δ are preference parameters that I want to estimate. For simplicity, I assume that $u(x_i) = x_i$.

The following shows how to apply the GDA model to the frontrunner party. For a subject of the frontrunner party, there are two outcomes for lottery V, TIE and WIN, where TIE means 11 points and WIN means 21 points. The probability for the TIE outcome is the probability that 3 subjects of the competing party turn out to vote, which is 0.465^3 since the theoretical turnout probability of a subject in of the underdog party is $p_B^*(3, 1) = 0.465$. The probability for the WIN outcome is the probability that there are fewer than 3 subjects of the competing party turning out to vote, which is $1 - 0.465^3$.

For lottery A, there are three outcomes: WIN, TIE, and LOSE (which means 1 point). In addition, if a subject chooses lottery A, she does not need to pay her voting cost, which is privately drawn in the experiment. The probabilities for LOSE, TIE, and WIN are respectively p_3, p_2, and $(1 - p_3 - p_2)$, where p_n indicates that there are n subjects of the underdog party turning out to vote. I use $p_B^*(3, 1) = 0.465$ to calculate p_3, p_2, and $(1 - p_3 - p_2)$.

With the information about the outcomes and the probabilities, each (θ, δ) pair gives a certainty equivalent $\mu(V)$ for lottery V and a certainty equivalent $\mu(A)$ for lottery A, respectively representing the expected payoffs from voting and abstaining. Then, to allow bounded rationality, I follow individual choice behavior research to consider a probabilistic choice function with a noise parameter λ to capture the sensitivity of choices to expected payoffs. Hence, the probability that subject i chooses to vote is expressed as

$$\Pr(\text{choose to vote}) = \sigma_{i1} = \frac{e^{\lambda\mu(V;\theta,\delta,c_i)}}{e^{\lambda\mu(V;\theta,\delta,c_i)} + e^{\lambda\mu(A;\theta,\delta)}}, \tag{12}$$

where c_i is subject i's voting cost.

From the experiment I have each subject's decision–d_{ia}, $i = 1, \cdots, n$, $a \in \{1, 0\}$. Then, the maximum likelihood estimates of θ and δ can be obtained by the following log-likelihood function:

$$\begin{aligned}
\max_{\theta,\delta,\lambda} \quad \ln L(\theta, \delta, \lambda | d_{i1}) &= \sum_{i=1}^{N_F} d_{i1} \ln[\sigma_{i1}(\theta, \delta, \lambda)] \\
&\quad + (1 - d_{i1}) \ln[(1 - \sigma_{i1}(\theta, \delta, \lambda))], \\
\text{s.t.} \quad \mu(V, c_i) &= \sum_{x_j \in X} p(x_j) x_j - \theta \sum_{x_j \leqslant \delta\mu(V)} p(x_j) (\delta\mu(V, c_i) - x_j), \\
\mu(A) &= \sum_{x_j \in X} p(x_j) x_j - \theta \sum_{x_j \leqslant \delta\mu(A)} p(x_j) (\delta\mu(A) - x_j),
\end{aligned}$$

where N_F represents the number of observations for the frontrunner party. With the voting decision data from subjects of the frontrunner party, the maximum-likelihood parameter estimates (and standard errors) are: $\hat{\theta} = 50$ (0.07), $\hat{\delta} = 0.138$ (0.07), and $\hat{\lambda} = 17.02$ (0.12).

Substituting $\theta = 50$ and $\delta = 0.138$ into equation (11) yields $\mu(V) = 19.95$ and $\mu(A) = 12.1$. The difference between $\mu(V)$ and $\mu(A)$ is 7.82, which represents the critical voting cost after considering the GDA effect for subjects of the frontrunner party. With the same method presented above, I can obtain the critical voting cost with the GDA effect for each case. The results are presented in Table 10.

Table 10: Comparison between with and without GDA for all cases

	Observed critical voting cost	Theoretical critical voting cost (w/GDA)	Theoretical critical voting cost (w/o GDA)
Treatment CC			
Case (1, 1; A) or (1, 1; B)	6.99	2.81	6.30
Case (3, 1; A) or (1, 3; B)	7.25	7.82	4.48
Case (1, 3; A) or (3, 1; B)	4.42	5.00	5.12
Case (3, 3; A) or (3, 3; B)	9.57	10.00	10.00
Treatment CP			
Case (1, 0.4; A)	6.09	4.09	5.78
Case (1, 0.4; B)	7.45	4.19	5.91
Case (3, 0.4; A)	8.73	9.14	8.38
Case (3, 0.4; B)	5.86	5.57	7.25
Treatment PC			
Case (0.6, 1; A)	7.27	5.12	5.50
Case (0.6, 1; B)	6.97	3.52	5.50
Case (0.6, 3; A)	6.70	6.96	8.66
Case (0.6, 3; B)	8.21	9.53	9.54
Treatment PP			
Case (0.6, 0.4; A)	8.09	4.50	7.63
Case (0.6, 0.4; B)	7.61	4.39	7.27

Note: The variables in the first column are defined in Table 2. Theoretical critical voting cost (w/ GDA) refers to the predicted critical voting cost of the GDA model. Theoretical critical voting cost (w/o GDA) refers to the predicted critical voting cost of the benchmark model presented in Section 2. The absolute difference between the the predicted critical voting cost of the GDA model and that of the benchmark model shows the disappointment level.

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資訊對投票行為的影響

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本文以實驗方法, 探究資訊對 Palfrey-Rosenthal 關鍵投票者模型 (簡稱 PR 模型) 中的投票行爲的影響。作者比較完全資訊情境和部分資訊情境: 前者爲受試者知道每一政黨的基本盤大小, 後者爲受試者知道某一政黨基本盤大小, 而另一政黨基本盤大小, 受試者僅知其機率。兩發現如下: 第一, 部分資訊情境下, 當知悉某政黨爲小基本盤時, 受試者相信自己是關鍵投票者的機率會高於理論值, 使其投票率增加, 不低於其在完全資訊情境的投票率。第二, 完全資訊情境下, 當受試者支持的政黨爲大基本盤時, 受試者投票率會增加, 顯著高於其相信自己爲關鍵投票者的機率下的最適反應; PR 模型結合厭惡失望效果可解釋此行爲。

關鍵詞: 資訊揭露, 民調, 造勢, 策略性投票, 集體選擇
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