WASHINGTON UNIVERSITY IN ST. LOUIS
Department of Economics

Dissertation Examination Committee:
David K. Levine, Chair
Brian W. Rogers
Joseph Tao-yi Wang
Juan Pantano
Calvert Randall

Essays in Experimental and Public Economics

by

Yi-Yi Chen

Graduate School of Arts and Sciences
of Washington University in
fulfillment of the requirements
for the degree of Doctor of Philosophy

April 2014

St. Louis, Missouri

Contents

Chapter 1

Introduction

This dissertation focuses on two issues in Public Economics: public goods provision and voting theory. It consists of three independent papers, with two using experimental methodology and one using empirical data to examine the effectiveness of the models. In the following I briefly summarize each of the papers.

Economists have long understood the challenges of providing proper incentives to groups, such as divisions or teams of a firm, that produce a joint product. The first paper (chapter 1) proposes a mechanism in which a firm creates a competitive environment for its two teams by awarding prizes based on aggregate outputs produced by these two teams, and uses laboratory experiments to examine how effectively it induces team members to contribute. The experimental results verify the prediction that the proposed mechanism encourages a greater number of participants to make contributions, compared to a simple profit-sharing scheme. I also find that participants contributed significantly more when they believed that their team had lower output, which can be well explained by a model that incorporates the effect of envy at the group level.

The second paper (chapter 2) is an experimental examination of information revelation in a voting model. Typically parties can conduct public events, such as rallies or demonstrations that reveal their level of support in hopes this might influence voter turnout and the outcome of the election. How effective is this? I compare two information-revealing mechanisms in the Palfrey-Rosenthal pivotal voter model: one through which active supporters show their support without paying costs ("polls"), which can be viewed as cheap talk; the other where active supporters have to pay their time (active participation in "campaigns") or money (e.g., contributing to super PACs) to support their preferred candidates, thus providing more certainty about the actual level of support. To capture the difference between the two mechanisms, I assume that polls reveal the distribution of active supporters of a party, while the campaigns provide the actual numbers of the active supporters of that party. There are two main experimental findings. (a) In most of the situations, subjects followed the main ideas of the Palfrey-Rosenthal pivotal voter model, with appropriately responding to the cost of voting and the belief of being pivotal. (b) However, when subjects are informed of being in an advantageous position by campaigns, their turnout becomes significantly higher than the best response to their pivotality belief. This can be attributed to that leading in an interim stage has a positive psychological impact on performance in tournaments.

The third paper (chapter 3) investigates candidates' rallying strategies in two-party races. Like chapter 2, it views campaign rallies as an information-revealing mechanism that allows candidates to project images of strong current support among voters. By incorporating this mechanism into the Palfrey-Rosenthal pivotal voter model, this study can explain under what circumstances a candidate should hold a rally and how that rally affects voters' decisions regarding whether or not to vote. The investigation hypothesizes that (a) when two parties are different in size but have the same chances of strong base support, the larger party is more likely to hold a rally, while (b) when the sizes of the two parties are equal but base support is unequal, the party with a smaller probability of strong base support is more likely to hold a rally. These two hypotheses are supported by the empirical analysis of the 1988, 1992, and 1996 U.S. Presidential elections.

To summarize, this thesis contributes to the literature on group incentive mechanisms, with chapter 1 being the first experimental study on inter-team competition with an endogenously determined prize level in a stage game. This thesis also contributes to the literature on voting behavior and campaign strategy. Chapter 2 is the first experimental study on the effect of information revealed through campaigns on voting behavior in the Palfrey-Rosenthal model. Chapter 3 supplements political science literature on campaigns by using pivotal-voter theory to analyze the effect of holding rallies and how that effect influences candidates' rallying strategy.

Chapter 2

Promoting Group Productivity: A Tournament-Based Mechanism

2.1 Introduction

Organizations are becoming increasingly reliant on team-based structures to improve employee productivity (Manz and Sims, 1993; Brian, 1994; Mueller et al., 2000; Che and Yoo, 2001; Thompson and Choi, 2006). However, economists have long understood the challenges of providing proper incentives to groups, such as divisions or teams of a firm, that produce a joint product—for example, if team outputs are observable while individual outputs are unobservable, a free-rider problem may emerge and provide insufficient incentives for efficient production.

In this paper, I propose an inter-team competition mechanism in which a firm creates a competitive environment by awarding prizes based on aggregate outputs of the entire firm. This mechanism captures the idea that in real-world organizations individual employee earnings depend on aggregate outputs produced by all employees, and a firm can transfer resources from its team with inferior performance to its team with superior performance. For example, employees at DuPont receive bonuses and company stock rewards based on individual and company performance (DuPont, 2002). Fuji Xerox developed two technologies in parallel for its color copier project and then transferred resources of the non-selected technology team to the selected one (Birkinshaw, 2001).

In addition to the theoretical study, I conduct laboratory experiments to examine how effectively the proposed mechanism induces team members to contribute their efforts. There are two main experimental findings. First, contributions were inefficient when only team outputs were observable. More importantly, the experimental results confirm the prediction that the proposed competition mechanism encourages a greater number of participants to make contributions and mitigates the free rider problems, compared to a simple profit-sharing scheme. Second, experimental data show that participants contributed significantly more when they believed that their team had lower output. This kind of behavior has been discussed in literature such as Adams (1963), Homans (1974), and Mui (1995), and has been found in the laboratory by Halevy et al. (2010). The main idea is that people compare their economic status, and those with relatively low status suffer utility losses and may take actions to improve their relative status. People suffering utility losses from the relatively low status is characterized as *envy* (Mui, 1995). I therefore incorporate the effect of envy produced by the members of the team with lower output into the benchmark model that considers only monetary payoffs. After taking into account the envy effect at the group level, the model fits my experimental data very well.

To provide proper incentives to groups, a number of devices have been tested and reviewed in the literature, with inter-team competition increasingly used as an incentive scheme. There are two main reasons for considering inter-team competition mechanisms. First, inter-team competition is commonly used in real-world companies. Empirically, companies that use inter-team competition approaches include 3M, GM, P&G, IBM, and HP (Peters and Waterman, 1988); Motorola (Carroll and Tomas, 1995); Rubbermaid, DuPont, and Fidelity (Kanter et al., 1997); Ericsson, HP, Spirent, Fuji Xerox, SEB, Skandia, Volvo, and Telstar (Birkinshaw, 2001); and Apple (Purcher, 2011). Second, theoretical studies such as Rapoport and Bornstein (1987) and experimental studies such as Erev, Bornstein, and Galili (1993), Bornstein and Erev (1994), Nalbantian and Schotter (1997), and Gunnthorsdottir and Rapoport (2006) have shown that inter-team competition can effectively increase individual effort and mitigate free-rider problems. More importantly, they find that inter-team competition mechanisms outperform other incentive schemes such as intra-team profit sharing and target-based schemes (Nalbantian and Schotter, 1997).[1]

In all theoretical and experimental studies mentioned above, prize levels are exogenously fixed, whereas in practice, when teams within a firm such as Fuji Xerox (Birkinshaw, 2001) or DuPont (DuPont, 2002) compete, the size of the prize is itself endogenous and depends upon aggregate output. To my best knowledge, my paper is the first experimental study on inter-team competition with an endogenously determined prize level in a stage game.[2] Marino and Zábojník (2004) also propose a tournament-based model in which compensation contracts for individual employees are based on the aggregate output of the entire firm rather than on a fixed amount. The primary differences between my paper and Marino and Zábojník's work are as follows. First, Marino and Zábojník (2004) work only on a theoretical application, while my main interest is to test the proposed mechanism and study worker behavior in the laboratory, and my experimental results show that the

[1] In an intra-team profit sharing scheme, all revenue generated by the team is shared equally by all team members of this team. In a target-based scheme, there is a revenue target set exogenously for a team. If the target is achieved, all team members share in all of the revenue generated, while if the target is not attained, a penalty is paid by each team member—that is, each team member is paid a relatively low penalty payoff.

[2] Guillen and Merrett (2010) also propose an inter-group competition scheme (ICS) with endogenously determined prize levels. In their experiments, subjects played 10 rounds of the ICS; however, the subjects remained in the same group for the entire 10 rounds. According to their experimental design, subjects played repeated games, where the issues are different.

model that considers only monetary payoffs fails to explain the findings in the laboratory. Second, to support more accurate examinations of worker behavior, my model entails a binary choice, while Marino and Zábojník's model considers a strictly convex cost function.[3] In Marino and Zábojník's model, the individual teams serve as each other's budget breakers that help solve free-rider problems, as shown in Holmstrom (1982). But Holmstrom's theory does not apply to my model due to my non-strictly convex cost function. In contrast, in my model, individual teams serve to increase each other's marginal benefit from contributing efforts, thus helping to achieve Pareto optimality under Nash equilibrium.

The rest of this paper is structured as follows: in Section 2 I present a benchmark model and discuss various mechanism hypotheses, and in Section 3 I introduce the experimental design. Experimental results are reviewed in Section 4.1, and in Section 4.2 I examine the effect of group envy. A conclusion is offered in Section 5.

2.2 The Benchmark Model

Consider a firm that consists of two teams, A and B, each with n members indexed $i = 1, 2, ..., n$. Each member can choose one of two effort levels $x_i^h \in \{0, 1\}, h = A, B$. That is, each worker can choose between contributing (i.e., $x_i = 1$) or not contributing (i.e., $x_i = 0$). The output of team h is $y^h = \sum_{i=1}^{n} x_i^h + \epsilon^h$, where ϵ^h are i.i.d. random variables across the two teams, according to a distribution function $F(\cdot)$ that has a density $f(\cdot)$ and mean zero. Effort cost is defined as $c(x_i^h) = x_i^h$. The firm is assumed as selling its output for price g with $1 < g < n$, so firm revenue is $g(y^A + y^B)$.

The aggregate output produced by the two teams can be viewed as the firm's total resources. Each worker's payoff is based on the resources allocated to her team by the

[3]That is, in my model workers can choose to contribute or not contribute their efforts, but they cannot determine the sizes or amounts of their contributions.

firm. For simplicity, I assume that the payoff of a team equals the resources allocated to that team times the price g. Assume that y^A and y^B are observable by the firm, but the individual effort levels x_i^A and x_j^B and the noise terms ϵ^h are not. Firms generally use a simple profit-sharing scheme in which a firm allocates to a team, say team A, the resources generated by team A, and equally splits the payoff of team A among the members of team A; however, this will result in a free-rider problem.

Here I will follow Marino and Zábojník (2004) to propose a **team-tournament mechanism** in which a firm creates competition between its teams for the firm's internal resources. The team with higher y is viewed as the winning team, and the team with lower y is viewed as the losing team. Regarding the internal reallocation of resources, the firm transfers a μ share of resources generated by the losing team to the winning team, meaning the total resources of the winning team (in this case, team h) can be expressed as $y^h + \mu y^m$, and the total resources of the losing team (m) can be expressed as $(1-\mu)y^m$. Since the firm is limited to awarding all of the resources of the losing team to the winning team, $0 \leqslant \mu \leqslant 1$. Here I will use $\mu = 1$ to represent a pure tournament.[4]

Pareto-optimal effort levels

Pareto-optimal effort level is first examined for each worker, with efficient effort levels found by maximizing the expected total surplus over a choice of x_i^h, $i = 1, ..., n$, $h \in \{A, B\}$. Therefore,

$$\max_{x_i^A \in \{0,1\}, x_i^B \in \{0,1\}} gE\left(y^A + y^B\right) - \sum_{i=1}^{n} x_i^A - \sum_{i=1}^{n} x_i^B$$

Solving the maximization problem gives a unique profit-maximizing effort level as

$$x_i^h = 1, \ i = 1, 2, ..., n, \ h = A, B. \tag{2.1}$$

[4]See Marino and Zábojník (2004) pp. 713-714

Simple profit-sharing equilibrium

Before proving the ability of the proposed team-tournament mechanism to solve the free-rider problem, it is instructive to show that the free-rider problem exists under a simple profit-sharing scheme. For firms that use the simple profit-sharing scheme, the lack of a tournament environment means that $\mu = 0$. From worker i's point of view, the following maximization problem must be solved:

$$\max_{x_i^h \in \{0,1\}} \frac{g}{n} E\left(x_i^h + \sum_{j \neq i}^{n} x_j^h + \epsilon^h\right) - x_i^h$$

where $0 < \frac{g}{n} < 1 < g$. Parameter $\frac{g}{n}$ is the marginal per capita return (MPCR) from contributing effort to produce output. Since $\frac{g}{n} < 1$, each worker's unique effort level is

$$x_i^h = 0, \ i = 1, 2, ..., n, \ h = A, B. \tag{2.2}$$

Comparing (2.2) with (2.1) yields the result that under simple profit sharing, workers contribute less than the efficient level of effort. Intuitively, since i's payoff depends on team output rather than personal output, i has an incentive to free-ride. For the sake of convenience, I will call any player whose $x_i^h = 0$ a *free rider*, and any player whose $x_i^h = 1$ a *contributor*.

The team tournament

We now examine the efficiency characteristics of the team tournament scheme. Let N_A denote the number of contributors on team A, and N_B the number of contributors on team

B. The probability team A wins against team B is assumed to be

$$\begin{aligned} Pr(y^A > y^B) &= Pr(\epsilon^B - \epsilon^A < N_A - N_B) \\ &= \frac{1}{2} + \frac{N_A - N_B}{2n} \end{aligned} \tag{2.3}$$

which increases for N_A and decreases for N_B. It is easy to find a distribution function $F(\cdot)$ that satisfies (2.3). For example, given that $n = 2$, then

$$f(\epsilon^h) = \begin{cases} 1 & \text{if } \epsilon^h \in (-1, -\frac{1}{2}) \bigcup (\frac{1}{2}, 1), \;\; h = A, B, \\ 0 & \text{otherwise.} \end{cases}$$

This looks like the pdf of the bimodal distribution and satisfies (2.3). To examine the tournament effect, μ is set as 1, therefore, from the point of view of i as a member of team A, the maximization problem to be solved is expressed as:

$$\max_{x_i^A \in \{0,1\}} \;\; \pi_i^A = \left(\frac{1}{2} + \frac{x_i^A + \sum_{j \neq i}^n x_j^A - \sum_k^n x_k^B}{2n} \right) \frac{g}{n} E \left(x_i^A + \sum_{j \neq i}^n x_j^A + \sum_k^n x_k^B + \epsilon^A + \epsilon^B \right) - x_i^A \tag{2.4}$$

Following the main focus of team tournament literature, I will concentrate on a symmetric equilibrium, in which all workers contribute the same effort level (a pure symmetric equilibrium), or all workers contribute with the same probability (a symmetric mixed equilibrium). Symmetric equilibria are summarized as follows:

Proposition 1 *Let N_h denote the number of contributors on team h, $h \in \{A, B\}$.*

(a) The necessary and sufficient condition for the existence of the equilibrium $N_A^* = N_B^* = 0$ is that $\frac{g}{n} \leqslant \frac{2n}{n+1}$. That is, $x_i^h = 0, \;\; i = 1, 2, ..., n, \;\; h = A, B$, which is the same as the result in the simple profit-sharing equilibrium. For convenience, I will call this equilibrium a

free-rider equilibrium. Note that this condition is always satisfied given that $g < n$.

(b) *The necessary and sufficient condition for the existence of the equilibrium* $N_A^* = N_B^* = n$ *is* $\frac{g}{n} \geqslant \frac{2n}{3n-1}$. *That is,* $x_i^h = 1$, $i = 1, 2, ..., n$, $h = A, B$, *which is the same as the Pareto-optimal effort levels. For convenience, I will call this equilibrium a Pareto-optimal equilibrium.*

(c) *Suppose that* i *is a member of team* A. *In the symmetric mixed Nash equilibrium, all workers contribute with a probability* $p \in (0,1)$ *given by:*

$$\sum_{N_B=0}^{n} \sum_{N_A=0}^{n-1} p^{N_A+N_B}(1-p)^{2n-1-N_A-N_B} \binom{n-1}{N_A} \binom{n}{N_B} \left[\left(\frac{1}{2} + \frac{1+N_A-N_B}{2n} \right) \frac{g}{n} (1+N_A+N_B) \right]$$
$$= 1 + \sum_{N_B=0}^{n} \sum_{N_A=0}^{n-1} p^{N_A+N_B}(1-p)^{2n-1-N_A-N_B} \binom{n-1}{N_A} \binom{n}{N_B} \left[\left(\frac{1}{2} + \frac{N_A-N_B}{2n} \right) \frac{g}{n} (N_A+N_B) \right].$$

Proof: See Appendix A.1.

A comparison of Proposition 1(b) with (2.1) shows that the efficient effort level can be achieved by a tournament between two teams. From this section we have two hypotheses. To examine the proposed tournament mechanism and the two hypotheses, I performed experiments, which will be described in the next section.

Hypothesis 1 *Given that team output is observable but individual effort level is not, each worker contributes less than the efficient level of effort.*

Hypothesis 2 *A two-team tournament mechanism with a payoff structure such as that shown in* (2.4) *weakly increases workers to contribute greater effort.*

2.3 Experimental Design

The experiment consisted of two treatments: an experimental treatment (TT) representing the tournament scheme, and a control treatment (SPS) representing the profit-sharing scheme. To test static game theory predictions, I followed the tendency among economists to randomly rematch participants for each period since unchanged team composition (fixed matching) might give incomplete information about the motivation of other participants, thereby altering the nature of the equilibrium via reputation effects (Kreps et al. (1982)).[5]

The condition for Hypothesis 1 is that $\frac{g}{n} < 1$, so that players have incentives to become free-riders in the SPS treatment (Equation (2.2)). Note that under the condition $\frac{g}{n} < 1$, the necessary and sufficient condition for Proposition $1(a)$ is automatically satisfied, leading to the existence of the free-rider equilibrium in the TT treatment. Also, according to Proposition $1(b)$, the condition for Hypothesis 2 is that $\frac{g}{n} \geqslant \frac{2n}{3n-1}$ in support of the Pareto-optimal equilibrium in the TT treatment. To satisfy the conditions for Hypothesis 1 and Hypothesis 2, I therefore set $n = 4$ and $g = 3$, resulting in the MPCR $= \frac{g}{n} = 0.75$. According to this setting, the free-rider equilibrium is predicted to occur in the SPS treatment. For the TT treatment, if we focus on symmetric equilibria, this setting leads to the existence of the free-rider equilibrium, the existence of the Pareto-optimal equilibrium, and the existence of one symmetric mixed equilibrium where all players contribute with a probability of 0.944 (Proposition $1(c)$).[6]

2.3.1 SPS treatment

Each session of the SPS treatment consisted of 10 periods. At the beginning of every period, each participant received a token worth 20 points as an initial endowment. In every period, each of the 4 team members contributed 20 points of the initial endowment to either a common team account or private individual account. Participants made decisions simultaneously and without communication. They earned points in their private

[5] See Nikiforakis (2008) p. 93.

[6] I use numerical grid searches to show that there is only one symmetric mixed equilibrium for my parameters.

accounts plus the total amount of common points multiplied by the MPCR. Earnings for any participant i in a given period is expressed as

$$\pi_i = 20 - x_i + 0.75\left(x_i + \sum_{h=1}^{3} x_h\right)$$

where $x_i \in \{0, 20\}$ represents the points contributed by i, and $x_h \in \{0, 20\}$ represents the points contributed by i's team member h, $h \in \{1, 2, 3\}$.

It is noteworthy that in the model the payoff for a team member is the equally shared payoff of her team. The payoff of a team is the price times its output, and the output of a team is its common points plus a random variable. In the experiment, however, the payoff of a team was the price times its common points. This is because the theory does not change when using the price times a team's common points as that team's payoff. More importantly, when compared to using the price times a team's output as that team's payoff, it was easier to conduct experiments by using the price times a team's common points as that team's payoff since the common points did not consist of the random variable.

After making contribution decisions, participants could estimate the total number of points in their common team accounts. If the estimate was the same as the actual value, each participant earned an extra 2 points; they did not lose anything for incorrect estimates. Participants were reminded of their contributions at the end of each period and informed of total team points, personal earnings, and bonuses for the current period. Participants were randomly rematched with others after each period.

2.3.2 *TT* treatment

In this treatment scheme, each session also had 10 periods, and participants were randomly matched with others in each period. In the *TT* treatment, participants made contribution decisions similar to those made by the *SPS* treatment participants, but with a different payoff structure. The two teams competed after all participants made their contribution decisions, each with a winning probability expressed as

$$\frac{1}{2}+\frac{1}{20}\frac{\sum_{i=1}^{4}x_i^A-\sum_{j=1}^{4}x_j^B}{2n}$$

as defined in Section 2. The number $\sum_{i=1}^{4}x_i^l \in \{0,20,40,60,80\}$ represents the total number of points in the common account of team l, $l \in \{A,B\}$.

Participants on the winning team earned all points in their private accounts, plus points in the commonly held account multiplied by the MPCR, plus points in the competing team's commonly held account multiplied by the MPCR. Members of the losing team earned private account points only. Earnings for participant i on team A in a given period are expressed as

$$\pi_i^A = 20 - x_i^A + \left(\frac{1}{2}+\frac{1}{20}\frac{x_i^A+\sum_{h=1}^{3}x_h^A-\sum_{j=1}^{4}x_j^B}{2n}\right)0.75\left(x_i^A+\sum_{h=1}^{3}x_h^A+\sum_{j=1}^{4}x_j^B\right)$$

where $x_i^A \in \{0,20\}$. Note that I used two teams' common points, which did not consist of random variables, as the reward for the members of the winning team. The reason for using teams' common points rather than teams' output is the same as that given in the 3.1 subsection.

After contribution decisions were made, participants estimated the total number of points in commonly held accounts for both teams. Participants earned 2 bonus points for correct estimates, but did not lose anything for incorrect estimates. At the end of each period, participants were reminded of their contributions and informed of their team's total common points, the competing team's total common points, their personal earnings, and their bonus points.

2.3.3 Procedures

Ten experimental sessions took place in 2011 and three experimental sessions took place in 2012, in the Missouri Social Science Experimental Laboratory of Washington University in St. Louis. Each session lasted approximately one hour. One hundred and four participants were recruited through the Missouri Social Science Experimental Laboratory subject pool. Of these, 80 were randomly assigned to the TT treatment, and 24 to the SPS treatment. Each participant only took part in one session. Participants were paid \$5 for showing up on time and listening to the instructions which varied for each treatment. Neutral language was used to write instructions for the two treatments. After listening to the instructions, participants were asked to respond to control questions. The experiment began after responding to participant questions. The students interacted via a computer network in the laboratory. Workstation partitions ensured anonymity between individuals. Experiments were conducted using Fischbacher's (2007) z-Tree. Participants earned an average of \$22.86, including the show-up fee. The point-to-dollar exchange rate was 25:1.

2.4 Results

I organize the discussion of my results as follows. In Section 2.4.1, I first compare the aggregate contribution decisions in the TT and SPS treatments and investigate Hypothesis 1 and Hypothesis 2. Then, I examine experimental data at the individual level by regression analysis. In Section 2.4.2, I first examine the emergence of different outcomes in the TT treatments to see if the experimental data are consistent with the predictions of the team tournament model. Next, I introduce the effect of group envy to the team tournament model and examine its performance by comparing the data with the quantal response equilibrium prediction.

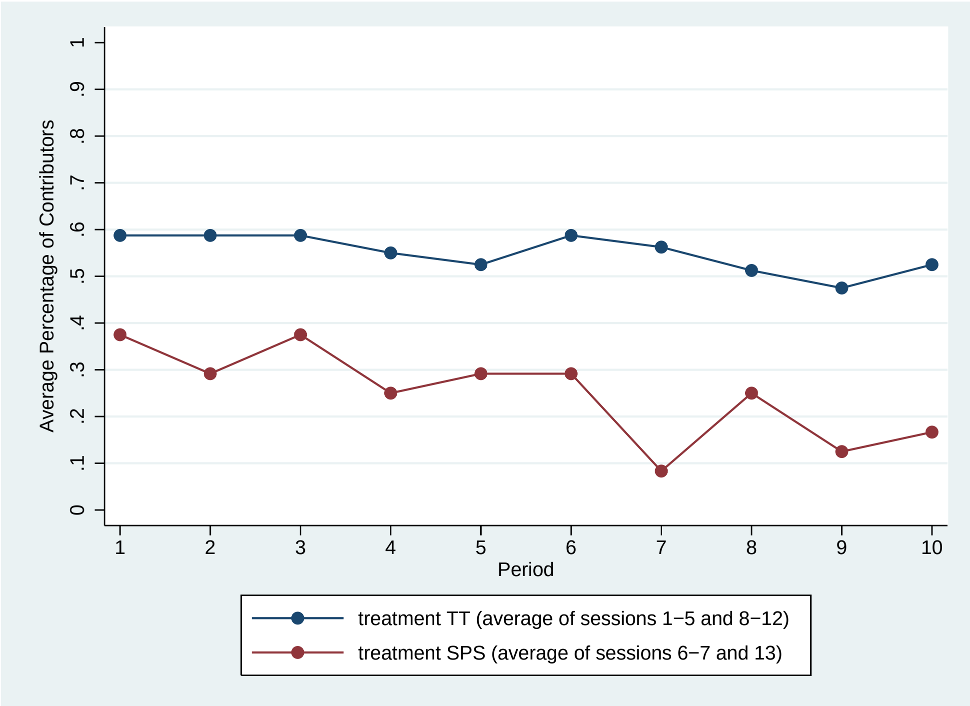

Figure 2.1: Evolution of average percentage of contributors for TT and SPS treatments.

2.4.1 Effort Decisions

Overall Contribution Decisions. The two treatments were compared in terms of average percentage of contributors per period across 10 periods, and this pooled treatment data are presented in Figure 4.6. As shown, initially approximately half of the participants contributed effort under SPS treatment, and sixty percent of the participants contributed effort under TT treatment. But during the experiment, the percentage decreased in the SPS treatment, while the percentage remained constant in the TT treatment. Next, I compared the average percentage of contributors during each session. As shown in Table 2.1, the mean percentage during the TT sessions was 0.55 and during the SPS sessions

Table 2.1: Experimental participant and contributor data.

Session	Number of participants	Treatment	Average Percentage of Contributors of 10 Periods
1	8	TT	0.3375
2	8	TT	0.575
3	8	TT	0.3875
4	8	TT	0.725
5	8	TT	0.7125
6	8	SPS	0.5
7	8	SPS	0.1375
8	8	TT	0.625
9	8	TT	0.6875
10	8	TT	0.575
11	8	TT	0.4625
12	8	TT	0.4125
13	8	SPS	0.1125

0.25.[7] The Mann-Whitney test result indicates a statistically significant difference between the two treatments ($|z| = 3.197$, $p = 0.0014$).

Individual Regression Analysis. I now turn from examining the data at the aggregate level to investigating the data at the individual level by using regression analysis. The estimation method is the probit method with heteroskedasticity-robust standard errors clustered on individuals. This permits both error heteroskedasticity and error serial correlation within cluster. Regression models involve the following variables. The *Contribution* dummy dependent variable equaled 1 when a participant contributed 20 points to a common team account. Independent variables are as follows: TT, a dummy variable equal to 1 for observations from treatment TT and 0 from treatment SPS; *Period*, a variable for controlling time effects; SPS**Period* and TT**Period*, interaction terms between *Period*,

[7] $(0.3375 + 0.575 + 0.3875 + 0.725 + 0.7125 + 0.625 + 0.6875 + 0.575 + 0.4625 + 0.4125)/10 = 0.55$; $(0.5 + 0.1375 + 0.1125)/3 = 0.25$.

SPS and TT for testing whether the trends observed in Figure 4.6 are significant.

Table 2.2 presents the regression results for the effect of competition on contribution behavior. Regressions 1, 2, and 4 show the positive significance of TT, implying that TT treatment participants were significantly more likely to contribute than SPS participants, which is consistent with the aggregate results. Further, the negative significance of *Period* indicates that team member contributions declined significantly over time. However, when *Period* is separated into SPS**Period* and TT**Period*, the former is still significantly negative, while the latter becomes insignificant (regressions 3 and 4). The combined negative significance of *Period*, negative significance of SPS**Period*, and insignificance of TT**Period* indicate that declining contributions over time were limited to the SPS treatment sessions—that is, the presence of competition prevented a decrease in contributor percentage over time, thus confirming the data shown in Figure 4.6. These findings for aggregate contribution decisions plus regression analysis data support both H1 (contributions were inefficient when only team output is observable) and H2 (creating competition mitigates the potential of a free-rider problem). This result is summarized as follows:

Table 2.2: Contribution Behavior (Marginal Effects Reported)

	(1) *Contribution*	(2) *Contribution*	(3) *Contribution*	(4) *Contribution*
TT	0.300***	0.302***		0.197*
	(0.072)	(0.073)		(0.091)
Period		-0.014**		
		(0.005)		
*SPS*Period*			-0.056***	-0.032**
			(0.013)	(0.010)
*TT*Period*			-0.004	-0.010
			(0.005)	(0.005)
N	1040	1040	1040	1040

Standard errors clustered on individuals in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Result 1. *On average, the percentage of contributors in the TT treatment group was significantly higher than that in the SPS treatment group. This percentage remained constant in the TT group and decreased over time in the SPS. These findings support the hypothesis that creating competition mitigates the potential for a free-rider problem.*

2.4.2 Inter-Team Competition and Group Envy

Table 2.3: Frequency (and percentage) of each (x, y) outcome in the TT treatment

$(x,\, y)$	0	1	2	3	4
0	1 (0.01)	0 (0.00)	2 (0.02)	5 (0.05)	1 (0.01)
1	-	5 (0.05)	17 (0.17)	11 (0.11)	3 (0.03)
2	-	-	9 (0.09)	23 (0.23)	6 (0.06)
3	-	-	-	10 (0.10)	6 (0.06)
4	-	-	-	-	1 (0.01)

Note: (x, y) represent the numbers of contributors on two teams such that $x \leqslant y$, where $x, y \in \{0, 1, 2, 3, 4\}$.

The Puzzle. After comparing the TT and SPS treatment group contribution decisions, I examined the fit between the team tournament model and the TT treatment experimental data. Theoretically, a symmetric equilibrium for the team tournament benchmark model presented in Section 2.2 predicts that each team will have either zero or four contributors (pure symmetric equilibria), or each team member will contribute at a probability of 0.944 (a symmetric mixed equilibrium). The TT treatment had 10 experimental sessions, with each session consisting of 10 periods, thus yielding 100 outcome observations. Let (x, y) denote the numbers of contributors on two teams such that $x \leqslant y$, where $x, y \in \{0, 1, 2, 3, 4\}$; (x, y) outcome frequencies are shown in Table 2.3. As shown, $(0, 0)$ and $(4, 4)$—predicted as the most likely to occur when considering pure symmetric equilibria—each occurred only once in the experiment. In terms of the symmetric mixed equilibrium, the contribution probability of 0.944 predicts that $(4, 4)$ is the most likely to occur (probability of 63%); the actual data indicates a 1 percentage.

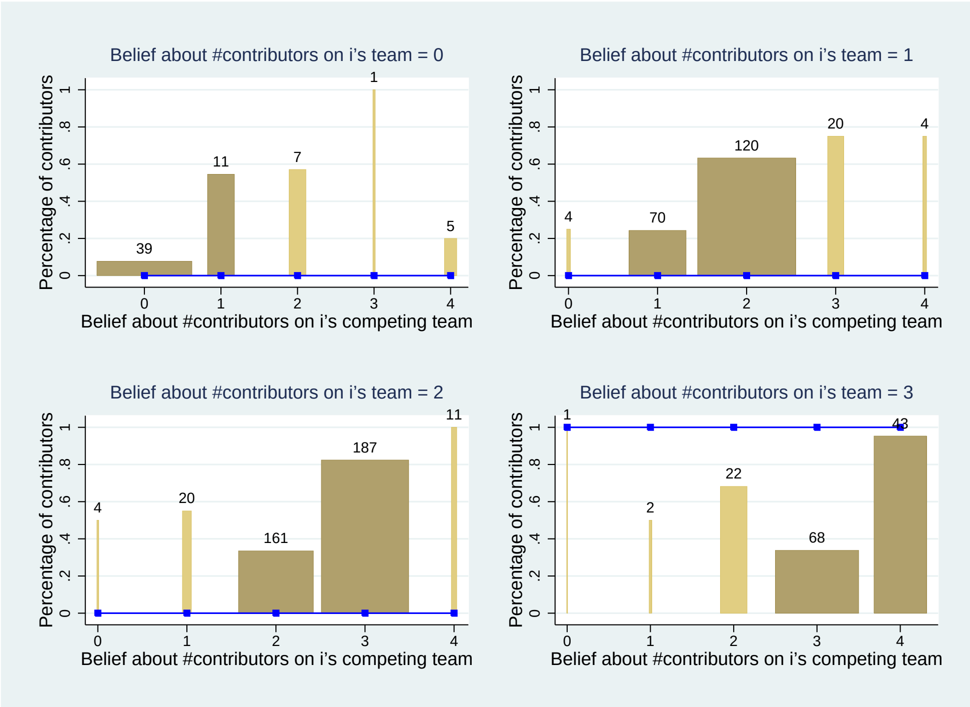

Figure 2.2: Percentage of contributors in each case: data versus predictions
Note: Data [bars] and predictions [blue lines] of the benchmark model proposed in Section 2.2.

To clarify this inconsistency, I considered the beliefs of participants, not including themselves, concerning the numbers of contributors on their own (denoted as J) and competing teams (denoted as K), and investigated how these beliefs affected their contribution decisions. Note that $J \in \{0, 1, 2, 3\}$ and $K \in \{0, 1, 2, 3, 4\}$. Theoretically, according to the benchmark model setting, for a participant i, given any K, i will contribute only when $J > 2$, and given any J, i won't change her contribution behavior as K increases or decreases. This reason is that an increase in K decreases the probability of winning a tournament of i's team, but increases the monetary payoff i would win if i's team does win. These two effects of K offset each other.

During the experiment, participants were asked to state J and K in each period, generating 800 (J, K) pair observations.[8] Figure 2.2 presents the contributor percentages given J and K: the top left panel displays the $J = 0$ case, top right the $J = 1$ case, bottom left the $J = 2$ case, and bottom right the $J = 3$ case. Each $J = j$ panel consists of 5 bars, with each bar representing one (J, K) case in which $J = j$ and $K \in \{0, 1, 2, 3, 4\}$. I will use the first bar in the $J = 0$ panel (top left) as an example. The number above the bar, 39, indicates 39 observations for the $(0, 0)$ case.[9] The 0.077 bar height value indicates contributions from 3 of 39 observations for the $(0, 0)$ case.[10] That is, the 0.077 bar height represents that the percentage of contributors in the $(0, 0)$ case was 0.077. The bar width represents the relative frequency of $(0, 0)$ for the $J = 0$ case[11]; since there are 63 observations[12] for this case, the bar width is $\frac{39}{63}$. According to Figure 2.2, for any fixed J, the frequencies of the $K = J + 1$ and $K = J$ cases (marked in dark brown) were significantly larger than those of the other cases. More importantly, each panel displays a substantial decrease in contributor percentage from the $K = J + 1$ case to the $K = J$ case. According to these findings, most of the participants were substantially more willing to contribute when $J < K$ than when $J \geqslant K$, and this contribution behavior did not change when J and K changed—a finding that is inconsistent with the benchmark model predictions (Figure 2.2, blue line). Individual level data showing the same results are presented in Appendix A.3.

Models that Fail to Explain the Puzzle. To explain the puzzle presented above, I tested several relevant theories such as (1) bounded rationality (McKelvey and Palfrey, 1995), (2) probability distortion (Tversky and Kahneman, 1992), (3) risk aversion (Holt and Larury, 2002), and (4) other-regarding preferences. Theories (1) to (3) have failed to

[8] Recall that there were 10 sessions for the TT treatment, with each session consisting of 8 participants and 10 periods.

[9] The number over each bar represents the number of observations for each (J, K) case.

[10] The height of each bar represents the percentage of contributors for each (J, K) case.

[11] The width of each bar represents the relative frequency of each (J, K) case given a fixed J.

[12] $39 + 11 + 7 + 1 + 5 = 63$

explain the puzzle because they did not describe a dramatic increase in contribution when participants moved from the situation where $J \geqslant K$ to the situation where $J < K$.[13] For other-regarding preferences, the literature had yielded a number of models with different specifications, and most of them follow the main idea of Fehr and Schmidt (1999) that people are **self-centered inequity averse**. That is, people only care about their own monetary payoff relative to the payoff of others (e.g., Charness and Rabin, 2002; Cappelen et al., 2007; Cox et al., 2007; Mago et al., 2013; see Cooper and Kagel 2013 for an overview). I tested two types of models in this category: the fairness model and the relative payoff maximization model.

For the fairness model, I considered the strict egalitarian model, the libertarian model, and the liberal egalitarian model in Cappelen et al. (2007). The predictions of these model are not consistent with the experimental data. The reason is the following: if people care about fairness, they should contribute when more of their group and competing group members contribute because they dislike taking advantage of others, and they should not contribute when less of their group and competing group members contribute because they dislike that other people take advantage of them as well. For the relative payoff maximization model, I considered the pro-social model and the status-seeking model in Mago, Samak, and Sheremeta (2013). The predictions of these model are still not consistent with the experimental data because: if people (pro-social individuals) strive to increase the payoff of the entire organization (i.e., their own group and the competing group), they should always contribute, and if people (status-seeking individuals) strive to obtain a higher relative payoff within the entire organization, they should never contribute. As discussed above, these self-centered inequity aversion models did not capture the dramatic increase in contribution from $J \geqslant K$ cases to $J < K$ cases.

[13]For each of the theories, I used the maximum likelihood method to estimate its parameters with the experimental data, but the estimates could not be identified.

Model Incorporating the Effect of Group Envy. Although the self-centered inequity aversion models seem to fail to explain the puzzle, the idea that people are inequity averse may still work to explain my experimental data if we consider a **group-centered inequity aversion model**. According to the theory of equity in psychology proposed by Adams (1963), inequity exists not only at the individual level but also at the group level as well.[14] Further, evidence for people caring about inequity at the group level has been found in the laboratory-based studies. For example, Halevy, Bornstein, and Sagiv (2008), Halevy et al. (2010), and Halevy, Weisel, and Bornstein (2012) (hereafter referred to as *HHH*) perform a series of experiments to investigate inter-team competition. They find that participants did not contribute to their team when their team was in the lead, but participants sacrificed their own benefits and contributed to their team when their team was falling behind, implying that people are group-centered inequity averse in inter-team competition.

Mui (1995) applies Adams (1963)'s theory to the standard economic choice framework. The main idea is that people compare their economic status and suffer utility losses when they are in an unfavorable position. For two agents (groups) engaging in independent productivities, Mui (1995) proposes a model in which the relative status of an agent (group) is determined by this agent's (group's) output, and the agent (group) with lower output suffers utility losses due to the relatively low status, causing this agent to take actions either to increase her (its) output or to decrease the output of the other agent (group). People suffering utility losses from the relatively low status is characterized as *envy*.

Based on the theoretical model of Mui (1995) and the experimental findings from *HHH*, I therefore consider the effect of envy at the inter-group level by assuming that participants who believed their team had lower output experienced envy. Further, I incorporate this

[14]Adams (1963) has proposed a theory of equity in psychology: "Inequity exists for Person whenever his perceived job inputs and/or outcomes stand psychologically in an obverse relation to what he perceives are the inputs and/or outcomes of Other" and "Person and Other may also refer to groups rather than to individuals" (p.424).

envy effect into the benchmark model described in Section 2.2; from this point forward I will refer to this as the "group envy model". This group envy model can be viewed as an application of Mui (1995)'s model at the group level. Assume n participants in team h, $h = A, B$ and their contributions are given by $(x_1^h, ..., x_n^h)$. Therefore, the expected output of team h is $E\left(y^h\right) = \sum_{i=1}^n x_i^h$. The utility of participant i on team A is thus defined as

$$U_i^A = \pi_i^A - \gamma_i \max\left\{\sum_{k\in B} x_k^B - \left(x_i^A + \sum_{j\in A, j\neq i} x_j^A\right), 0\right\}, \tag{2.5}$$

where π_i^A denotes i's material payoff (presented in equation (2.4)). The γ_i parameter measures i's utility loss when the expected output of i's team is less than that of i's competing team; this indicates i's utility loss from relatively low status. Also following Mui (1995), I assumed that $\gamma_i \geqslant 0$ for all i. For simplicity, I assumed that $\gamma_i = \gamma$ for all i, and thus was able to derive symmetric equilibria from equation (2.5).

Proposition 2 *Let N_h denote the number of contributors on team h, $h \in \{A, B\}$.*

(a) *The necessary and sufficient condition for the existence of the equilibrium $N_A^* = N_B^* = 0$ is $\frac{g}{n} \leqslant \frac{2n}{n+1}$, which is the same as in Proposition 1(a).*

(b) *The necessary and sufficient condition for the existence of the equilibrium $N_A^* = N_B^* = n$ is $\frac{g}{n} \geqslant \frac{2n(1-\gamma)}{3n-1}$. Given that $\gamma \geqslant 0$, for any $n > 0$, a smaller g can achieve this equilibrium when compared with that described in Proposition 1(b).*

(c) *For i as a member of team A, in the symmetric mixed Nash equilibrium, all workers contribute with probability $p \in (0, 1)$ given by:*

$$\sum_{N_B=0}^{n} \sum_{N_A=0}^{n-1} p^{N_A+N_B}(1-p)^{2n-1-N_A-N_B}\binom{n-1}{N_A}\binom{n}{N_B}\left[\left(\frac{1}{2}+\frac{1+N_A-N_B}{2n}\right)\frac{g}{n}(1+N_A+N_B) - \gamma\max\{N_B-N_A-1, 0\}\right]$$
$$= 1 + \sum_{N_B=0}^{n} \sum_{N_A=0}^{n-1} p^{N_A+N_B}(1-p)^{2n-1-N_A-N_B}\binom{n-1}{N_A}\binom{n}{N_B}\left[\left(\frac{1}{2}+\frac{N_A-N_B}{2n}\right)\frac{g}{n}(N_A+N_B) - \gamma\max\{N_B-N_A, 0\}\right].$$

Proof: See Appendix A.2.

Estimation. According to proposition 2, the equilibrium contribution level or probability depends on the value of the γ parameter. Since the data regarding participants contribution decisions and their beliefs about the number of contributors on their own team (denoted as J) and that on the competing team (denoted as K) were collected in the experiment, the γ parameter can be estimated using a maximum likelihood method. To allow a small amount of bounded rationality, I followed individual choice behavior research (Luce, 1959; McFadden, 1973; McKelvey and Palfrey, 1995) to consider a probabilistic choice function with a noise parameter λ to capture the sensitivity of choices to expected payoffs. This is expressed as

$$\Pr\left(\text{choose to contribute}\right) = \frac{e^{\lambda EU_C^A(\gamma)}}{e^{\lambda EU_C^A(\gamma)} + e^{\lambda EU_F^A(\gamma)}}, \tag{2.6}$$

where $EU_C^A(\gamma)$ and $EU_F^A(\gamma)$ are calculated by equation (2.5), respectively representing a team A member i's expected payoff of contributing and not contributing (i.e., free-riding). Details for equation (2.6) are given in Appendix A.4.

Using the participants' contribution decision and belief data, I obtained maximum-likelihood parameter estimates (and standard errors) for this group envy utility function: $\gamma = 0.43$ (0.0012), and $\lambda = 4.99$ (0.0201), with a log-likelihood of -447.306.[15] These parameter values were used to plot the predicted contribution probabilities for different (J, K) cases shown in Figure 2.3. As shown, there were good fits between the theoretical predictions (red lines) and most of the actual data (brown bars). It is noteworthy that γ captures the increase of the pattern in each panel. If only the noise parameter λ was taken

[15] In Appendix A.3, I have shown that there were some participants who did not show a significant difference in contribution between when $J < K$ and when $J \geqslant K$. If we remove the data from those participants, the estimates (and standard errors) are $\gamma = 0.4414$ (0.0014), and $\lambda = 5.764$ (0.0261), with a log-likelihood of -338.088.

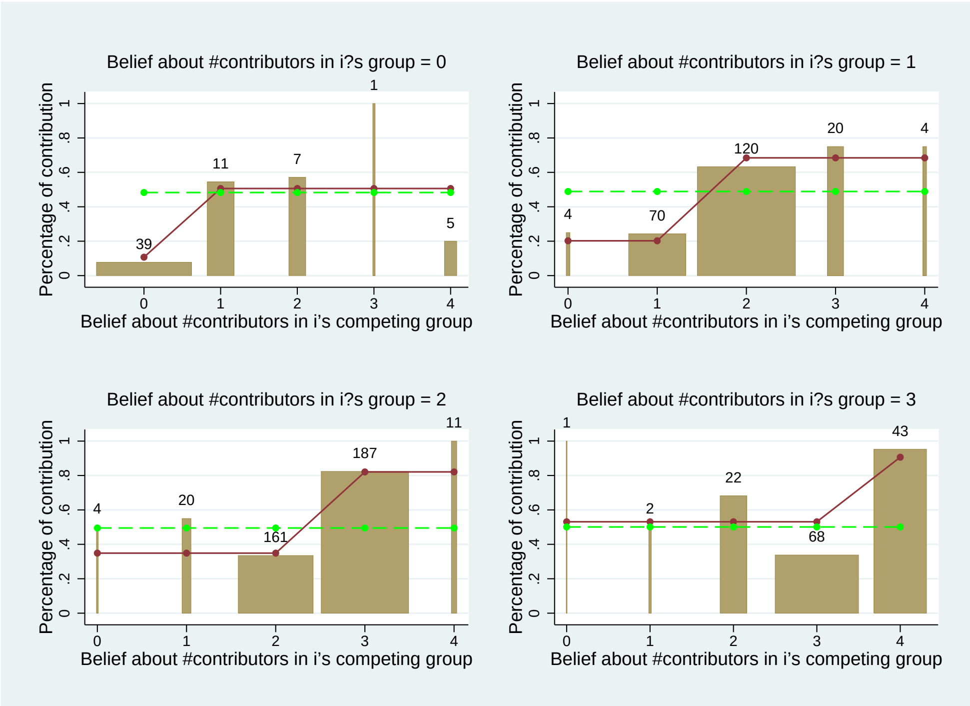

Figure 2.3: Percentage of contributors in each case: data versus predictions
Note: Data [bars], predictions [green lines] with noise, for the standard utility function with noise = 0.16, and predictions [red lines] with noise, for the "group-envy" utility function with $\gamma = 0.43$ and noise = 4.99.

into account, the predictions (green lines) and the data (brown bars) are still inconsistent. Furthermore, substituting $\gamma = 0.43$ into Proposition 2.(c) yields a contribution probability of 0.474, which is much closer to the average data percentage of 0.55 than the benchmark model prediction. Details for the likelihood function are given in Appendix A.4.

Quantal Response Equilibrium. The logit quantal response equilibrium (QRE) of this group envy model can also be calculated using the same parameter values as given in the preceding section. Given $\gamma = 0.43$ and $\lambda = 4.99$, the QRE contribution probability is 0.5405 (see Appendix A.4 for details). The QRE prediction and experimental data are displayed as Figure 2.4; shown are the average contribution percentages, average belief

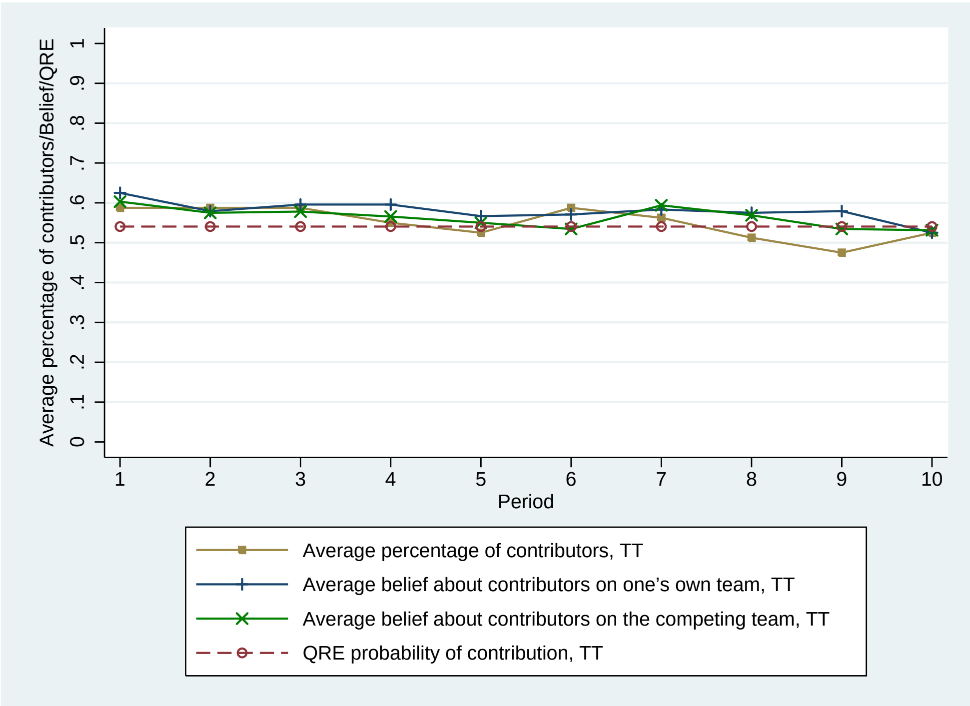

Figure 2.4: Percentage of contributors and beliefs (solid lines), compared to the QRE prediction (dash line)

Figure 2.5: Data frequencies (brown bars) versus QRE frequencies (red bars)
Note: (x, y) represent the numbers of contributors on two teams such that $x \leqslant y$, where $x, y \in \{0, 1, 2, 3, 4\}$.

about contributions from one's own team, and average belief about contributions from a competing team per period across 10 periods. As indicated, the belief and contribution percentages are very close, with a good fit with the QRE prediction. To further examine the group envy model performance, I compared the QRE predictions with the frequencies of different contribution outcomes. Let (x, y) denote the numbers of contributors from two teams, such that $x \leqslant y$ and $x, y \in \{0, 1, 2, 3, 4\}$. Recall that Table 2.3 presents frequency data for each (x, y) outcome in the experiment. The theoretical frequency of each (x, y) outcome was calculated at a QRE contribution probability of 0.5405. As shown in Figure 2.5, the theoretical frequencies (red bars) fit well with most of the data frequencies (brown bars) that have been presented in Table 2.3. Result 2 summarizes the findings.

Result 2. *Participants significantly contributed more when they believed that their team had lower ouput, and this behavior was consistent with the prediction of the model after taking into consideration the effect of group envy produced by participants who believed their team had lower output.*

2.5 Conclusion

This paper presents an experimental examination of how incentives can be provided to groups that produce joint products (e.g., divisions in a firm). Previous researchers have focused on profit-sharing schemes or tournaments schemes with exogenously determined prizes. In practice, for example when teams within a firm compete, the size of the prize is itself endogenous and depends upon aggregate output of the entire firm, so I focus on that case. For the present study I proposed a tournament-based scheme in which a firm creates an environment for team competition, while awarding prizes that depend on the firm's aggregate output: workers on the winning team receive payoffs depending on tokens contributed by its members to a common account plus similarly contributed tokens in an account held by the losing team, while workers on the losing team receive nothing from their own team account.

There are two main findings from my experiment. First, compared to a simple profit-sharing scheme, the proposed team tournament mechanism encouraged participants to make a larger number of contributions, and contribution percentages remained constant when the team tournament mechanism was used, while the percentage of contributions decreased over time when the simple profit-sharing scheme was used. These findings support the hypothesis that creating competition mitigates the potential for a free-rider problem.

However, even though the results support the hypothesis, data for the team tournament mechanism are not consistent with the benchmark model predictions (which only considers monetary payoffs) presented in Section 2—for example, average percentage of contributions (Figure 4.6), tournament outcome frequencies (Table 2.3), and contribution responses to beliefs about other individuals' contribution decisions (Figure 2.2). To resolve these inconsistencies, I applied Mui (1995)'s envy model from individual levels to group levels by incorporating the effect of envy produced by participants who believed their team had lower output into the benchmark model. After taking this effect into consideration, a good fit was found between the model and the experimental data (Figures 2.3-2.5), which is the second main finding from my experiment.

Discussion and Future Work. An obvious question from my second main finding is whether this effect also emerges from inter-team competitions with other kinds of prize structures. To discuss this question, it is very important to note that **relative deprivation** is the fundamental "aggravating condition" underlying group envy (Halevy et al. (2010), p. 695)[16]. According to relative deprivation theory, feelings of anger and resentment arise

[16]Note that it is called out-group hate rather than group envy in Halevy et al. (2010), but the meanings of these two terms are exactly the same.

when individuals want something they feel entitled to and when they perceive another person having that thing (Halevy et al. (2010)). The key phrase here is "think they are entitled to." Recall that individuals on the winning team in the TT treatment group received tokens from commonly held team account plus tokens from the commonly held account of the losing team. It is reasonable to assume that losing team members felt entitled to the tokens they contributed to their own team's account, thus creating a situation of perceived deprivation when those tokens were taken away and given to members of the winning team. However, most studies on inter-team competition use exogenous prizes in which amounts are independent of the contributions made by the winning and losing teams. In such settings, members of both teams get to keep the proceed of their respective accounts, with members of the winning team receiving bonuses. Therefore, these scenarios should not be considered examples of deprivation leading to high levels of group envy. The relationship between emergence of group envy and competition structures could be tested in future experiments.

Chapter 3

Getting Out the Vote: Information and Voting Behavior

3.1 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) 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; however, the real-world probability of a single vote being pivotal in a mass election is very low: According to Gelman, Silver, and Edlin (2012), an American voter had a 1 in 60 million chance of being pivotal in the 2008 presidential election. In other words, pivotal voter models underpredict turnout rates in mass elections. Nonetheless, pivotal voter models still provide useful guidance. For example, results from Levine and Palfrey (2007) 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.

Further, and perhaps more importantly, pivotal voter models provide useful guidance regarding how information affects voting behavior (Agranov et al. (2012)). The present paper studies effects of information on voter turnout in the Palfrey-Rosenthal pivotal voter model and compares two information-revealing mechanisms: one through which active supporters show their support without paying costs, which can be viewed as cheap talk; the other where active supporters have to pay to support their preferred candidates, therefore providing more certainty in the form of actual levels of support for a party than the first mechanism.

Examples for the first mechanism are political polls. Researchers using pivotal voter models to study the impacts of information have reported higher overall turnout rates when pollsters are free to inform electorates on 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 (2006); Grober and Schram (2010); Agranov et al. (2012)). For convenience, I will call the first mechanism *polls* in the rest of the paper.

Examples for the second mechanism are political endorsement, Super PACs, and party campaigns, where supporters need to pay their money (e.g., contributing to Super PACs) or time (participating in campaign activities) to show their support. 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 (DPP) and Taiwan Solidarity Union (TSU) organized a human chain around a theme of "protecting Taiwan." An estimated 2 million people took part in 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). These kinds of activities are based on the core belief that a political party can mobilize its supporters by proving to them that there is strong support for their candidate or referendum, thereby convincing them that victory is likely if they make the effort to vote. For convenience, I will call the second mechanism *campaigns* in the rest of the paper.

From the examples of the two mechanisms, we see that while both campaigns and polls can indicate support for parties, the campaigns provide more certainty in the form of actual levels of support; the polls are more likely to reveal distributions of electorate preferences. There are some papers studying the effects of information revealed through polls (Klor and Winter (2006); Grober and Schram (2010); Agranov et al. (2012)); however, from my review of the literature it appears that economists and political scientists pay little attention to the campaigns in terms of its information effects described above. Therefore, the current paper focuses on (1) the impacts of information revealed through campaigns on voter turnout and (2) the comparison of turnout in a campaign environment with a poll environment.

In this paper I will consider a two-party election, with each party consisting of two types of voters: active partisans (those who always vote for their preferred party) and passive partisans (those who either vote for their preferred party or abstain). Since active 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 active partisans and a $1 - \pi_i$ probability that this i party has a small number of active partisans. The probability π_i is prior information, and the actual number of the active partisans can be revealed only by campaigns. To capture differences in effects of revealing information between campaigns and polls, the model used in this study was based on the Palfrey-Rosenthal pivotal voter model and was designed so that in the absence of campaigns, voters know the probability of a large number of active partisans for each party (π_1 and π_2), but do not know the actual active partisan number, which represents poll effects. According to pivotal voter models, a strategic voter decides whether or not to vote based on voting costs and the probability of casting a pivotal vote in an election. Similar to the pivotal voter models, each passive partisan (i.e., strategic voter) in the proposed model decides whether or not to vote based on voting costs and what is learned from either campaigns or polls.

To analyze the impacts of campaigns on voter turnout, three comparative static effects based on Levine and Palfrey (2007) are considered: (a) *size*: holding the relative numbers of base partisans for two parties constant, turnout decreases as the number of passive partisans increases; (b) *competition*: given the equal sizes of two parties, turnout for each party is higher in situations where they have similar numbers of active partisans; (c) *underdog*: given the equal sizes of two parties, the turnout for the party with a smaller bloc of active partisans will be exceed the turnout of the party with a larger bloc of active partisans. Further, differences between campaigns and polls are analyzed according to the prediction that if two parties have similar numbers of active partisans, passive partisans in each party will be more likely to vote when both parties organize and execute campaign activities than when only one party does so. If the two parties have very different numbers of active partisans, the opposite result is likely to occur. In this study this is referred to as the *information-revealing effect* of campaigns.

I performed an array of experiments to examine the hypotheses presented above. There are two main findings. First, in most of the situations, subjects followed the main ideas of the Palfrey-Rosenthal pivotal voter model, with appropriately responding to the cost of voting and the belief of being pivotal. Second, however, when subjects were informed of being in an advantageous position by campaigns, their turnout became significantly higher than the best response to their belief of being pivotal. This can be attributed to that leading in an *interim* stage has a positive psychological impact on performance in tournaments. On the other hand, compared with campaigns, it is more difficult for polls to cause the same effect. In addition to these two findings, subjects incorrectly estimated their beliefs of being pivotal when being in the treatment where the parties used different information-revealing mechanisms, while they seemed to not have this problem when being in the treatment where the parties used the same information-revealing mechanisms.

The rest of this paper is organized as follows. In Section 2, I will describe a model, based on the Palfrey-Rosenthal pivotal voter model, that shows how the information regarding active partisans revealed through campaigns and polls 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.

3.2 The Model

3.2.1 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 voters in T_1 and N_2 voters in T_2. Since real-world parties always aim their mobilization efforts at partisan voters Holbrook and McClurg (2005), the proposed model does not consider independent voters—in other words, voters belong to T_1 choose either to vote for T_1 or to abstain and voters belong to T_2 choose either to vote for T_2 or to abstain. Voters are categorized as either active partisans or passive partisans. It is assumed that active partisans have zero voting costs, therefore voting can be considered a dominant strategy. Accordingly, a party's active partisans can be viewed as this party's support base. Voting costs for passive partisan j are denoted as c_j and set at a value greater than zero for any j. Further, 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 active partisans (represented by R_{1L}) and a probability $1-\pi_1$ that T_1 has a small number of active partisans (represented by R_{1S}). The respective large and small numbers of active 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 and commonly known by all, representing information revealed by polls. According to this setting, the active partisan numbers for the two parties are random variables. If T_i organizes campaign activities, each voter will learn the actual number of that party's active partisans (i.e., either R_{iL} or R_{iS}); otherwise, each voter must rely on poll data (i.e., π_i).

Passive partisan j decides whether or not to vote for her party based on what she learns from campaign activities or polls. Recall that she 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 $c_A < \hat{c}_2$. A quasi-symmetric equilibrium implies a $(\hat{p}_1, \hat{p}_2)$ aggregate voting probability for passive partisans in each party given by

$$\hat{p}_1 = \int_0^{\hat{c}_1} f(c)dc = F(\hat{c}_1) \tag{3.1}$$

$$\hat{p}_2 = \int_0^{\hat{c}_2} f(c)dc = F(\hat{c}_2). \tag{3.2}$$

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,

$$\hat{c}_1 = \frac{H-L}{2}\hat{q}_1 \tag{3.3}$$

$$\hat{c}_2 = \frac{H-L}{2}\hat{q}_2 \tag{3.4}$$

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 situations: both parties conduct campaign activities, only one party does, and neither party does. The primary study parameter is how much information passive partisans have about the numbers of active partisans in the two parties. Let R_1 and R_2 represent the realized numbers of T_1 and T_2 active partisans, respectively. In the first situation described above, $R_i \in \{R_{iL}, R_{iS}\}$ where $i \in \{1, 2\}$; in the second, if one party (T_1) refrains from campaign activities, R_1 is defined as an empty set (i.e., $R_1 = \emptyset$) and $R_2 \in \{R_{2L}, R_{2S}\}$; in the third, $R_1 = R_2 = \emptyset$. 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 sections, I will characterize voter turnout equilibria under different situations.

Voter Turnout Equilibria

Both parties conduct campaign activities. 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. If both parties conduct campaign activities, all individuals will have precise knowledge of the numbers of active partisans in each of the two parties (R_1 and R_2). Given R_1 and R_2, the probability of a passive partisan in party T_1 or T_2 making or breaking an election is expressed as

$$\begin{aligned} q_1^* = & \sum_{k=\max\{R_1,R_2\}}^{\min\{N_1-1,N_2\}} \left\{ P_p(k-R_1|p_1^*, N_1-R_1-1) \cdot P_p(k-R_2|p_2^*, N_2-R_2) \right\} \\ & + \sum_{k=r_1}^{\min\{N_1-1,N_2-1\}} \left\{ P_p(k-R_1|p_1^*, N_1-R_1-1) \cdot P_p(k+1-R_2|p_2^*, N_2-R_2) \right\} \end{aligned} \tag{3.5}$$

$$\begin{aligned} q_2^* = & \sum_{k=\max\{R_1,R_2\}}^{\min\{N_1,N_2-1\}} \left\{ P_p(k-R_2|p_2^*, N_2-R_2-1) \cdot P_p(k-R_1|p_1^*, N_1-R_1) \right\} \\ & + \sum_{k=r_2}^{\min\{N_1-1,N_2-1\}} \left\{ P_p(k-R_2|p_2^*, N_2-R_2-1) \cdot P_p(k+1-R_1|p_1^*, N_1-R_1) \right\} \end{aligned} \tag{3.6}$$

where $r_i = \max\{R_1, R_2\} - 1$ if $R_i < R_j$, otherwise $r_i = \max\{R_1, R_2\}$. Equations (4.1)-(4.4), (C.1) and (C.2), can be used to solve (c_1^*, c_2^*), (p_1^*, p_2^*) and (q_1^*, q_2^*).

Neither party conducts campaign activities. In this scenario, individuals in the two parties are limited in their knowledge to the probabilities of large numbers of active partisans in their own and the other party (π_1 and π_2). Assume n voters, with r_L active partisans with probability π and r_S active partisans with probability $1-\pi$, and with each passive partisan having probability p of voting in an election. The probability of a precise k number of voters casting their ballots can be expressed as

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

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

$$\begin{aligned} \tilde{q}_1 = & \sum_{k=0}^{\min\{N_1-1,N_2\}} \left\{ P_N(k|\tilde{p}_1, \pi_1, N_1 - 1, R_{1L}, R_{1S}) \cdot P_N(k|\tilde{p}_2, \pi_2, N_2, R_{2L}, R_{2S}) \right\} \\ & + \sum_{k=0}^{\min\{N_1-1,N_2-1\}} \left\{ P_N(k|\tilde{p}_1, \pi_1, N_1 - 1, R_{1L}, R_{1S}) \cdot P_N(k + 1|\tilde{p}_2, \pi_2, N_2, R_{2L}, R_{2S}) \right\} \end{aligned} \tag{3.7}$$

$$\begin{aligned} \tilde{q}_2 = & \sum_{k=0}^{\min\{N_1,N_2-1\}} \left\{ P_N(k|\tilde{p}_2, \pi_2, N_2 - 1, R_{2L}, R_{2S}) \cdot P_N(k|\tilde{p}_1, \pi_1, N_1, R_{1L}, R_{1S}) \right\} \\ & + \sum_{k=0}^{\min\{N_1-1,N_2-1\}} \left\{ P_N(k|\tilde{p}_2, \pi_2, N_2 - 1, R_{2L}, R_{2S}) \cdot P_N(k + 1|\tilde{p}_1, \pi_1, N_1, R_{1L}, R_{1S}) \right\} \end{aligned} \tag{3.8}$$

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.

Only one party conducts campaign activities. In this scenario, individuals know the precise number of active partisans in the party that conducts campaign activities. For the party that doesn't conduct campaign activities, individuals are limited to knowing the probability of this party's support base. With no loss of generality, assume that T_1 conducts campaign activities and T_2 does not. Then, individuals know the actual value of R_1 (i.e., $R_1 = R_{1L}$ or $R_1 = R_{1S}$) but they don't 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 (C.1) and (C.2) become

$$\begin{aligned} q_1^{**} = & \sum_{k=R_1}^{\min\{N_1-1,N_2\}} \left\{ P_p(k-R_1|p_1^{**}, N_1-R_1-1) \cdot P_N(k|p_2^{**}, \pi_2, N_2, R_{2L}, R_{2S}) \right\} \\ & + \sum_{k=R_1}^{\min\{N_1-1,N_2-1\}} \left\{ P_p(k-R_1|p_1^{**}, N_1-R_1-1) \cdot P_N(k+1|p_2^{**}, \pi_2, N_2, R_{2L}, R_{2S}) \right\} \end{aligned} \tag{3.9}$$

$$\begin{aligned} q_2^{**} = & \sum_{k=R_1}^{\min\{N_1,N_2-1\}} \left\{ P_N(k|p_2^{**}, \pi_2, N_2-1, R_{2L}, R_{2S}) \cdot P_p(k-R_1|p_1^{**}, N_1-R_1) \right\} \\ & + \sum_{k=\max\{R_1-1,0\}}^{\min\{N_1-1,N_2-1\}} \left\{ P_N(k|p_2^{**}, \pi_2, N_2-1, R_{2L}, R_{2S}) \cdot P_p(k+1-R_1|p_1^{**}, N_1-R_1) \right\} \end{aligned} \tag{3.10}$$

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.

3.3 Experimental Design and Hypotheses

3.3.1 Experimental Design

All parameters described in the preceding section were controlled for. Following the lead of Levine and Palfrey (2007), payoffs were established at $L = 1$ and $H = 21$, and voting cost distribution f was uniform, ranging from 0 to 11. Experiment parameters were set as $N_1 = N_2 = 4$, $\pi_1 = 0.6$, $\pi_2 = 0.4$, $R_{1L} = R_{2L} = 3$, and $R_{1S} = R_{2S} = 1$. I offer two reasons for these parameters. First, the purpose of this paper is to investigate the impacts of information using a pivotal model in which turnout is affected by voter belief in being/not being pivotal, and therefore there are advantages to using an environment in which voters have correct beliefs, and such an environment is easier to achieve when the voter pool is small. Second, one goal of this study is to compare differences between campaigns and polls. Since campaigns identify actual levels of support while polls only identify the probabilities of support bases, a large variance of the actual sizes of support bases (i.e., $R_{iL} = 3$, $R_{iS} = 1$) is more helpful for identifying the different impacts of campaign activities and polls.

The experiment consisted of four treatments designed to examine voter response to information revealed by campaign activities and polls. The two primary roles were active and passive partisan. Human subjects played the role of passive partisans deciding whether or not to vote, while client computers played the role of active partisans who always voted. Further, the experiment was divided into 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 $R_{AS} = R_{BS} = 1$. More specifically, each group had 4 members: for the A groups, there was a 0.6 probability of having 3 active partisans and a 0.4 probability of having 1 active partisan; for the B group, there was a 0.4 probability of having

3 active partisans and a 0.6 probability of having 1 active partisan. Each experimental session consisted of 40 periods, with the timing for each period established as follows:

States and Partisanship. Here there were equal numbers of A and B groups. At the start of each period, all A and B groups were randomly paired, with each subject randomly assigned to an A or B group; in addition, the server computer randomly determined the numbers of active partisans of the A and B groups. Note that in each period, all A groups had the same number of active partisans, and all B groups had the same number of active partisans. If in one period the server computer determined that each A group had 1 active partisan, then each A group had 1 active partisan and 3 passive partisans in this period. If subject i is assigned to an A group in this period, than subject i and 2 other subjects served as the A group passive partisans in this period. As mentioned earlier, client computers played the role of active partisans.

Campaigns or Polls. Depending on the treatment, subjects were provided with different information on the numbers of active partisans in the A and B groups. The four treatments were:

The CC treatment: Subjects were informed of the actual numbers of active partisans in the A and B groups. This treatment represents the situation in which both parties conduct campaign activities.

The CP treatment: Subjects were told the actual number of active partisans in the A groups but not told that number in the B groups, even though it had been determined. Subject knowledge was limited to a 0.4 probability of the B groups having 3 active partisans and a 0.6 probability of the B groups having 1 active partisan.

The PC treatment: This was similar to the CP treatment, except that subjects were only informed of the probabilities of support bases for the A groups while learning the actual number of active partisans of the B groups. Combined, PC and CP treatments represent the situation where one party conducts campaigns but the other does not.

The PP treatment: Subjects were only informed of the probabilities of support bases for the A and B groups. This treatment represents the situation where neither party conducts campaign activities.

Voting Decisions and Beliefs. After receiving information regarding active partisans, subjects decided whether or not to vote for their respective parties. Voting entailed a cost that was independently drawn from the uniform distribution and was known by each subject individually. Every attempt was made to use neutral language in the experiment instructions. Accordingly, I followed Levine and Palfrey (2007) to let subjects choose between "X" (casting a vote) and "Y" (abstaining). In terms of voting costs, a subject who chose Y was given a "Y bonus" that was added to that subject's earning, while a subject choosing X did not receive a "Y bonus," thereby treating voting costs as opportunity costs. Y bonuses were randomly redrawn (independently for each subject) from the uniform distribution between 0 and 11, in integer increments, for each period; subjects were only informed of their own Y bonuses. After making their voting decisions, subjects was asked to make guesses as to the probabilities of their votes being pivotal and about other subjects' decisions. The data on the other subjects' decisions were used to examine beliefs regarding whether or not their voting decisions were pivotal.

Payoffs. Each group's votes were counted once all decision and guess data were gathered. Recall that there were several pairs of A and B groups. In each pair, the group receiving the majority of votes won, and each subject in that group received 21 points; subjects in the other group received 1 point each. In cases of ties, each subject received 11 points. Subjects were paid based on the accuracy of their guesses—a bonus of 1 point for guessing the pivotal probability according to Karni (2009) method, and an additional bonus of 1 point for correctly guessing decisions made by their subject counterparts.

Table 3.1: Experimental Design and Predictions

Treatment	N_A	N_B	R_A or π_A	R_B or π_B	p_A^*	p_B^*
CC	4	4	1	1	0.573	0.573
	4	4	3	1	0.407	0.465
	4	4	1	3	0.465	0.407
	4	4	3	3	0.909	0.909
CP	4	4	1	0.4	0.525	0.537
	4	4	3	0.4	0.762	0.659
PC	4	4	0.6	1	0.500	0.500
	4	4	0.6	3	0.787	0.867
PP	4	4	0.6	0.4	0.694	0.661

3.3.2 Hypotheses

For the study hypotheses, recall that all A groups were identical, as were all B groups, and that each A group was randomly paired with a B group. In each pair, the actual numbers of the active partisans in the A and B groups are denoted by R_A and R_B, respectively; the probabilities of large numbers of active partisans in the A and B groups are denoted by π_A and π_B, respectively. In each pair, the turnout rate for the A group as a function of the information on the actual numbers of active partisans of the A and B groups is denoted as $p_A^*(R_A, R_B)$ for the CC, $p_A^*(R_A, \pi_B)$ for the CP, $p_A^*(\pi_A, R_B)$ for the PC, and $p_A^*(\pi_A, \pi_B)$ for the PP treatment; similarly, the turnout rate for the B group is denoted as p_B^*. The Nash equilibrium turnout probabilities for the A and B groups according to each treatment are shown in Table 3.1. Equilibrium is unique for all my treatments.[1]

I initially focused on the CC treatment group to study the impacts of campaign-revealed information on voting behavior. Following the lead of Levine and Palfrey (2007), three

[1] I used numerical grid searches to show that only one equilibrium existed for each treatment.

hypotheses were established for this treatment. The predictions for these hypotheses are consistent with those of Levine and Palfrey's (2007) first three hypotheses.

H1: Size Effect. For each pair of A and B groups, holding the relative numbers of their active partisans constant, turnout in each group decreases as the number of passive (active) partisans increases (decreases). That is, $p^*_A(1,1) < p^*_A(3,3)$ and $p^*_B(1,1) < p^*_B(3,3)$.

H2: Competition Effect. For each pair of A and B groups, turnout is higher when the two groups have close support bases. That is, $p^*_s(r,r) > p^*_s(r,\hat{r})$ and $p^*_s(r,r) > p^*_s(\hat{r},r)$, where $s \in \{A,B\}$, $r \in \{1,3\}$, $\hat{r} \in \{1,3\}$, and $r \neq \hat{r}$.

H3: Underdog Effect. In each pair of A and B groups, , 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 $p^*_B(3,1) > p^*_A(3,1)$.

Next, I investigated differences in the information-revealing effects of polls and campaigns on voter turnout by comparing CC and PC treatments for A groups and comparing CC and CP treatments for B groups.

H4: Information-Revealing Effect. Both campaigns and polls are capable of revealing the information on a party's support base, but campaign activities provide greater certainty of its level than polls, thus providing greater certainty of an election outcome than polls, resulting in a higher or lower propensity to cast a vote.

Specifically, in any A and B group pair, given that one group (for this example, the B group) conducts campaign activities, passive partisans in both groups will have a greater propensity to vote if the A group also conducts campaign activities and reveals the same number of active partisans as the B group than if the A group does not conduct campaign activities and limits the information about its active partisans to polls. In brief, $p^*_s(r,r) > p^*_s(\pi_A,r)$, $p^*_s(r,r) > p^*_s(r,\pi_B)$, where $s \in \{A,B\}$ and $r \in \{1,3\}$. The reason is that in this case campaign activities are much more likely to reveal the closeness of an election, causing each passive partisan to perceive a high probability of holding a pivotal vote.

On the other hand, in any pair of A and B groups, given that one group (again I will use the B group here) conducts campaign activities, if the A group also conducts campaign activities but reveals a larger or smaller number of active partisans, there will be lower propensities for either A or B group passive partisans to vote than if the A group does not conduct campaign activities. That is, $p_s^*(r, \hat{r}) < p_s^*(\pi_A, \hat{r})$, and $p_s^*(r, \hat{r}) < p_s^*(r, \pi_B)$, where $s \in \{A, B\}$, $r \in \{1, 3\}$, $\hat{r} \in \{1, 3\}$, and $r \neq \hat{r}$.

3.3.3 Experimental Protocol

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 112 study subjects were recruited through the MISSEL subject pool. Of these, 28 were randomly assigned to one of the four treatment groups, with each participating in only one session. Subjects were paid \$5 for showing up on time and listening to the instructions, which varied for each treatment, after which they were requested to respond to control questions. Students interacted via a computer network in the laboratory, with work station partitions ensuring anonymity. Experiments were conducted using Fischbacher (2007) the z-Tree program. Subjects earned an average of \$35, including the show-up fee. The point-to-dollar exchange rate was 25:1.

Table 3.2: Abbreviation of Each Case of Each Treatment

	Case		Situation		Position	
	$R_A;\pi_A$	$R_B;\pi_B$	*Alpha*	*Beta*	*Alpha*	*Beta*
CC	1	1	*CCTie1*	*CCTie1*	-	-
	3	1	*CCMajority*	*CCMinority*	*advantageous*	*disadvantageous*
	1	3	*CCMinority*	*CCMajority*	*disadvantageous*	*advantageous*
	3	3	*CCTie3*	*CCTie3*	-	-
CP	1	0.4	*CPMinority*	*CPFaceMinority*	*disadvantageous*	*advantageous*
	3	0.4	*CPMajority*	*CPFaceMajority*	*advantageous*	*disadvantageous*
PC	0.6	1	*PCFaceMinority*	*PCMinority*	*advantageous*	*disadvantageous*
	0.6	3	*PCFaceMajority*	*PCMajority*	*disadvantageous*	*advantageous*
PP	0.6	0.4	*PPMajority*	*PPMinority*	*advantageous*	*disadvantageous*

3.4 Results

3.4.1 Aggregate Results

I first analyze the experimental results at the aggregate level. Before the analysis, two things need to be mentioned. First, for each treatment, subjects were randomly assigned to one of two or one of four situations of that treatment. For convenience, in the following, I will use an abbreviation to represent each of these situations (Table 3.2). Second, for the CC treatment, experimental data from A and B groups were combined for each situation since the A and B groups were identical in each situation of the CC treatment.[2]

Table 3.3 displays for each group and each treatment the Nash equilibrium turnout rates (denoted p^*) and the observed turnout rates (denoted $\hat{p}$).[3] To test the relationship between $\hat{p}$ and p^*, I used subjects' average turnout rates for each situation of each treat-

[2]In other words, $\hat{p}_A(1,1) = \hat{p}_B(1,1)$ and $\hat{p}_A(1,1) = \hat{p}_B(1,1)$ in *CCTie1*; $\hat{p}_A(3,3) = \hat{p}_B(3,3)$ and $\hat{p}_A(3,3) = \hat{p}_B(3,3)$ in *CCTie3*; $\hat{p}_A(1,3) = \hat{p}_B(3,1)$ and $\hat{p}_A(1,3) = \hat{p}_B(3,1)$ in *CCMinority*; $\hat{p}_A(3,1) = \hat{p}_B(1,3)$ and $\hat{p}_A(3,1) = \hat{p}_B(1,3)$ in *CCMajority*.

[3]Columns 5 and 8 for $\hat{\hat{p}}$ will be discussed later.

Table 3.3: Turnout Rates–Comparison of Theory and Data

	No. of Subjects	R_A;π_A	R_B;π_B	p_A^*	$\hat{p}_A$	$\hat{\hat{p}}_A$	p_B^*	$\hat{p}_B$	$\hat{\hat{p}}_B$
CC	26	1	1	0.573	0.635	0.647	-	-	-
		3	1	0.407	0.659	0.473	0.465	0.402	0.420
		1	3	0.465	0.402	0.420	0.407	0.659	0.473
		3	3	0.909	0.870	0.802	-	-	-
CP	28	1	0.4	0.525	0.554	0.569	0.537	0.677	0.618
		3	0.4	0.762	0.794	0.606	0.659	0.533	0.529
PC	30	0.6	1	0.500	0.661	0.625	0.500	0.634	0.612
		0.6	3	0.787	0.609	0.662	0.867	0.746	0.716
PP	28	0.6	0.4	0.694	0.735	0.680	0.661	0.692	0.665

ment as an observation to conduct Wilcoxon rank sum tests. Since each subject only participated in one situation for around 10 periods, the sample size is not that large; I, therefore, performed my tests at the 0.01 critical level. According to the tests, I found that $\hat{p}$ is significantly different from p^*, with p-value below 0.01, in the following situations: *CCMajority*, *CPFaceMinority*, *CPFaceMajority*, *PCMinority*, *PCFaceMinority*, and *PCFaceMajority* (Finding 1).

Then, I used the same observations[4] to conduct Wilcoxon signed-rank tests for the hypotheses of the size (H1), the competition (H2), and the underdog effects (H3) and to conduct Wilcoxon rank sum tests for the hypothesis of the information-revealing effect (H4). H1 is supported by the data. H2 is supported with the exception of the comparison of turnout in *CCTie1* and *CCMajority* since turnout in *CCMajority* is significantly higher than the Nash equilibrium prediction.[5] For H3, instead of being supported, the data show the opposite: the turnout in *CCMajority* is significantly greater than that in *CCMinority*,

[4]That is, I used subjects' average turnout rates for each situation in each treatment as an observation.

[5]In that comparison, the null hypothesis $\hat{p}_A(1,1) = \hat{p}_A(3,1)$ ($\hat{p}_B(1,1) = \hat{p}_B(1,3)$) was not rejected by the Wilcoxon signed-rank test.

implying that subjects were more likely to vote when they were frontrunners than when they were underdogs. This result is consistent with Duffy and Tavits (2008), Grober and Schram (2010), and Agranov et al. (2012). For H4, about half of the comparison of turnout is not supported by the data.[6] This is because turnout in each of the *CCMajority*, *CPFaceMinority* or *PCFaceMinority* is higher than the corresponding Nash equilibrium prediction. Result 1 summarizes the discussions above.

Result 1. *The observed turnout rates were significantly different from the Nash equilibrium turnout rates in about half of the situations. Among them, the unpredictably high turnout in CCMajority causes the failure of support for the hypotheses about the competition effect and the underdog effect, and the unpredictably high turnout in CCMajority, CPFaceMinority, and PCFaceMinority causes the failure of support for the hypothesis of the information-revealing effect.*

There are three possible explanations for Result 1: (1) subjects' beliefs of being pivotal were consistent with the Nash equilibrium predictions, but they did not behave as predicted by the pivotal voter model; (2) subjects' beliefs of being pivotal were not consistent with the Nash equilibrium predictions, but they appropriately conditioned their behavior on those beliefs; (3) subjects neither formed correct pivotality beliefs nor behaved appropriately.

To test if subjects appropriately responded to the probability of being pivotal, I substituted subjects' stated pivotality probabilities for equilibrium pivotality probabilities into the proposed model (i.e., equations (4.1) to (4.4)) to obtain the best-response-to-subjective-belief turnout rates (denoted $\hat{\hat{p}}$). By using the same test method and the same critical level, I found that $\hat{p}$ is close to $\hat{\hat{p}}$ in every situation except in *CCMajority* and *CPMajority*, where $\hat{p}$ is significantly higher than $\hat{\hat{p}}$ (Finding 2).

[6] Specifically, $p^*_A(0.6, 3) < p^*_A(3, 3)$, $p^*_A(1, 3) < p^*_A(0.6, 3)$, $p^*_B(3, 0.4) < p^*_B(3, 3)$, and $p^*_B(3, 1) < p^*_B(3, 0.4)$ are supported by the data, but $p^*_A(0.6, 1) < p^*_A(1, 1)$, $p^*_A(3, 1) < p^*_A(0.6, 1)$, $p^*_B(1, 0.4) < p^*_B(1, 1)$, and $p^*_B(1, 3) < p^*_B(1, 0.4)$ are not supported by the data.

Table 3.4: Test of Appropriate Behavior ($\hat{p}$, $\hat{\hat{p}}$) and Test of Pivotality Belief ($\hat{\hat{p}}$, p^*)

	CCMajority	*CCMinority*	*CCTie1*	*CCTie3*
Finding 1: Observed turnout & NE	$\hat{p} > p^*$	-	-	-
Finding 2: Test of appropriate behavior	$\hat{p} > \hat{\hat{p}}$	-	-	$\hat{p} > \hat{\hat{p}}$
Finding 3: Test of pivotality belief	-	-	-	-
	CPMajority	*CPMinority*	*CPFaceMajority*	*CPFaceMinority*
Finding 1: Observed turnout & NE	-	-	$\hat{p} < p^*$	$\hat{p} > p^*$
Finding 2: Test of appropriate behavior	$\hat{p} > \hat{\hat{p}}$	-	-	-
Finding 3: Test of pivotality belief	$\hat{\hat{p}} < p^*$	-	$\hat{\hat{p}} < p^*$	$\hat{\hat{p}} > p^*$
	PCMajority	*PCMinority*	*PCFaceMajority*	*PCFaceMinority*
Finding 1: Observed turnout & NE	-	$\hat{p} > p^*$	$\hat{p} < p^*$	$\hat{p} > p^*$
Finding 2: Test of appropriate behavior	-	-	-	-
Finding 3: Test of pivotality belief	$\hat{\hat{p}} < p^*$	$\hat{\hat{p}} > p^*$	$\hat{\hat{p}} < p^*$	$\hat{\hat{p}} > p^*$
	PPMajority	*PPMinority*		
Finding 1: Observed turnout & NE	-	-		
Finding 2: Test of appropriate behavior	-	-		
Finding 3: Test of pivotality belief	-	-		

"-" represents that the two values are not significantly different at the 0.01 critical level.

To test if subjects' beliefs of being pivotal were consistent with the Nash equilibrium predictions, I tested the relationship between $\hat{\hat{p}}$ and p^*. By using the average subjects' stated pivotality probabilities for each situation of each treatment as an observation to conduct Wilcoxon rank sum tests, I found that $\hat{\hat{p}}$ is significantly different from p^*, with p-value below 0.01, in *CCTie3*, *CPMajority*, *CPFaceMinority*, *CPFaceMajority*, *PCMajority*, *PCMinority*, *PCFaceMinority*, and *PCFaceMajority* (Finding 3).

Table 3.4 summarizes and reports the details for Finding 1, Finding 2, and Finding 3. As can be seen, the *CCMajority* subjects and the *CPMajority* subjects did not behave as predicted by the pivotal voter model—they were more willing to vote, when compared with the best responses to their subjective pivotality beliefs (Puzzle 1) On the other hand, except for being in *CCMajority* or *CPMajority*, subjects were appropriately conditioning

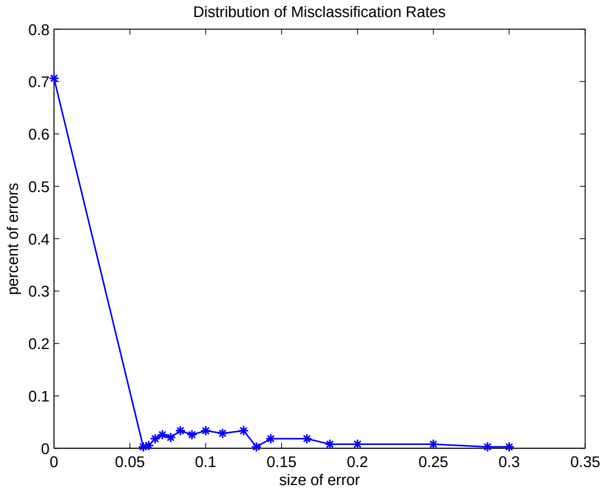

Figure 3.1: Distribution of Misclassification Rates

their behavior on their subjective pivotality beliefs, but they incorrectly estimated those beliefs when being in the treatments where two parties used different information-revealing mechanisms (Puzzle 2)

3.4.2 Individual Results

After examining the data at the aggregate level, I turn to analyze the experimental data at the individual level. By assuming that each subject was following a cutpoint rule for each situation, I estimated each subject's cutpoint rule according to the method in Levine and Palfrey (2007). With the estimated cutpoints, for each subject, I used his/her estimated cutpoint to calculate the size of error with respect to that cutpoint.[7] Figure 3.1 displays the density for error rates. As can be seen, around seventy percent of the subjects perfectly classified the decisions based on their cutpoint rules, and for all subjects the percent of decisions correctly classified is greater than 70%. This shows that subjects followed consis-

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

tent cutpoint rules. Then, I tested H1-H4 hypotheses at the individual level by reproducing Figure 6 and Table 6 of Levine and Palfrey (2007) (See Figure B.1, Figure B.3, and Table B.1 in the Appendix B.1). Not surprisingly, H2, H3, and H4 are not supported by the data at the individual level for the same reasons presented in the last section. Result 2 summarizes the discussion above and the discussion in the last section.

Result 2. *Table 3.4 and Figure 3.1 demonstrate that (1) in most of the situations, that the hypotheses are not supported by the experimental data is because subjects' beliefs of being pivotal were not consistent with the Nash equilibrium predictions, and is not because subjects' voting behavior was inconsistent with the Nash equilibrium prediction; (2) in general, subjects followed the main ideas of the Palfrey-Rosenthal pivotal voter model, with appropriately responding to the cost of voting and the belief of being pivotal.*

Explanation for Puzzle 1

To study Puzzle 1 and Puzzle 2, I used regression analysis to investigate individual behavior. First, I investigated Puzzle 1 by separating the data of *CCMajority* and the data of *CPMajority* from the data of other situations and ran a probit regression for each treatment, predicting the relationship between voting decisions and various variables related to the pivotal voter model, clustering standard errors at the individual level.

Regression models involve the following variables. The *Vote* dummy dependent variable equaled 1 when a subject decided to vote. Four independent variables were used to test the predictions of the pivotal voter model. (1) *Belief of being Pivotal*: a subject's stated belief about the probability that her vote would be pivotal. (2) *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 -1 or zero. This dummy variable equal to 1 implied that she believed her vote would change the election outcome. (3) *lead of the majority*

Table 3.5: Probit Regressions: *CCMajority* and *CPMajority*

Dependent variable: *Vote*	*CCMajority*	*CCMajority*	*CPMajority*	*CP Majority*
Voting Cost	-0.084***	-0.087***	-0.050***	-0.051***
	(0.027)	(0.028)	(0.015)	(0.014)
Period	-0.0049*	-0.0054**	-0.0018	0.0019
	(0.0028)	(0.0027)	(0.0014)	(0.0014)
Voted at t-1	0.71**	0.73***	0.45**	0.45**
	(0.304)	(0.279)	(0.228)	(0.221)
Won at t-1	-0.0065	-0.0066	-0.0021	-0.0016
	(0.0077)	(0.0075)	(0.0043)	(0.0043)
Voted and Won at t-1	-0.0057	-0.0069	-0.00047	-0.00073
	(0.010)	(0.010)	(0.0050)	(0.0050)
lead of the majority if in majority	-0.13**		-0.078**	
	(0.062)		(0.035)	
Belief of being Pivotal	-0.33***	-0.34***	-0.17*	-0.16*
	(0.13)	(0.13)	(0.095)	(0.093)
lead = 0 or -1 (dummy)		0.16**		0.11*
		(0.066)		(0.064)
# of obs.	188	188	263	263

if in majority: a subject's stated belief about the lead of her group (not including this subject's own vote) if that number was positive; otherwise, the variable equaled zero. (4) *Voting Cost*: a subject's Y bonus which was randomly drawn in each period. In addition to these four variables, I followed Duffy and Tavits (2008) and Agranov et al. (2012) to create other relevant independent variables: *Voted at t-1*, *Won at t-1*, *Voted and Won at t-1*, and *Period*.[8]

Findings. Regression results for *CCMajority* and *CPMajority* are presented here (Table 3.5) and regression results for other situations are presented in the Appendix B.1 (Table

[8]The coefficients of these variables are consistent with those in Duffy and Tavits (2008) and Agranov et al. (2012).

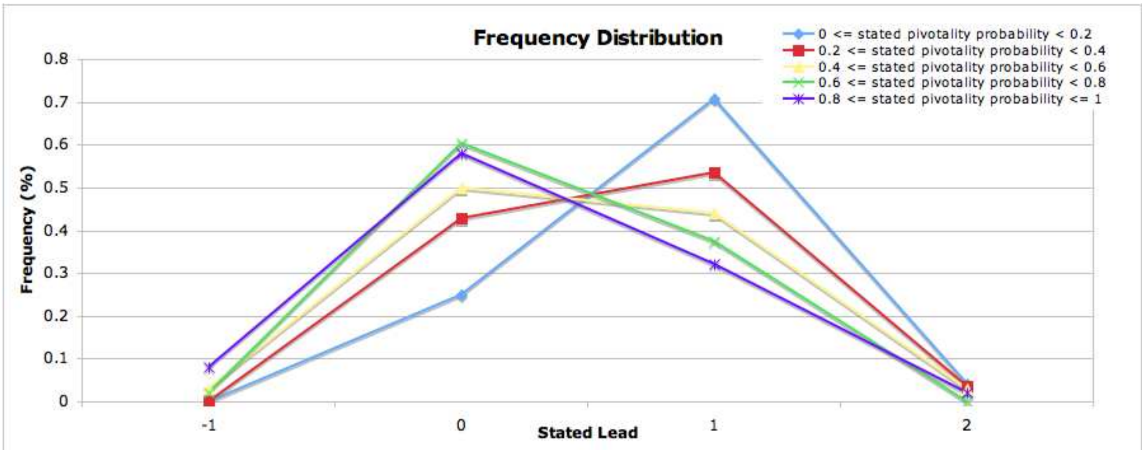

Figure 3.2: Frequency Distribution of Stated Leads: *CCMajority*

B.2) since I would like focus on discussing the results of *CCMajority* and *CPMajority*. As expected, *Voting Cost* is significantly negative in the two tables, *lead of the majority if in majority* and *lead = 0 or -1* are significantly positive in Table 3.5, and *Belief of being Pivotal* is significantly positive in Table B.2. These results are consistent with the predictions of the pivotal voter model.

However, to my surprise, *Belief of being Pivotal* is significantly negative in Table 3.5, implying that in *CCMajority* and *CPMajority*, subjects were more likely to vote when they believed that the probability that they would be pivotal was low. This result contradicts another result that *lead = 0 or -1* is significantly positive in Table 3.5 since it suggests that subjects were more likely to vote when they believed their own vote would change the election outcome. To explain this contradiction, the literature has provided an explanation: *the bandwagon effects*. However, the negative significance of *lead of the majority if in majority* in Table 3.5 shows that subjects were less likely to vote when they believed that the lead of their group would be large, implying that the bandwagon effects did not emerge in my experiment.

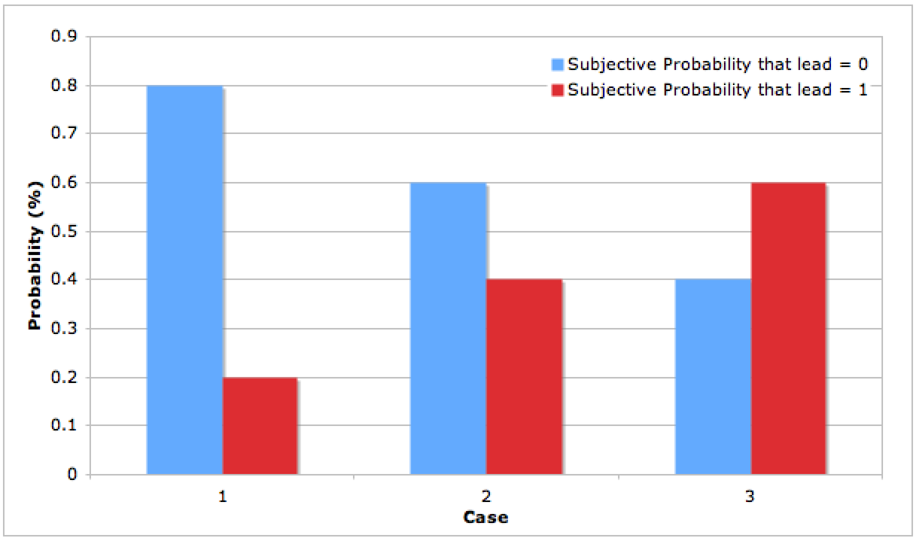

Figure 3.3: Example

To solve the contradiction, I separated the *CCMajority* data into five groups based on subjects' stated pivotality probabilities. Then, I calculated the frequency distribution of subjects' stated leads for each group. It is noteworthy that the minimum lead in *CCMajority* is -1, meaning that subjects in *CCMajority* would either be pivotal or win the election without voting. Figure 3.2 shows that subjects who stated a high pivotality probability, say $0.8 \leqslant$ the stated pivotality probability $\leqslant 1$, were more likely to guess that there would be a tie without their own vote. In contrast, subjects who stated a low pivotality probability, say $0 \leqslant$ the stated pivotality probability < 0.2, were more likely to guess that there would be a lead of their group without their own vote. According to Figure 3.2, the negative significance of *Belief of being Pivotal* in *CCMajority* implies that subjects were more willing to vote when they believed their group would have a lead with a high probability (i.e., their pivotality probability was low) than when they believed their group would have a lead with a low probability (i.e., their pivotality probability was high).

But if subjects believed their group would win with a *very* high probability regardless of their own vote, their voting propensity became low. This is shown by the positive significance of *lead = 0 or -1* and the negative significance of *lead of the majority if in majority*. I use the following example to explain this idea clearly. Figure 3.3 provides three cases for a voter i. Note that *lead* is defined as i's group's votes (not including i's own vote) *minus* i's competing group's votes, which is the same as the variable in Table 3.5. Case 1: i' belief of being pivotal is very high and i's belief that i's group would win without i's vote is low. Case 2: i believes that the situation in which i will be pivotal is most likely to happen, but i also believes that i's group would win without i's vote is very likely to happen. Case 3: i believes that i's group would win without i's vote is most likely to happen. The pivotal voter model predicts that i is more likely to vote for Case 1 than for Case 2, and more likely to vote for Case 2 than for Case 3. But based on the results from Table 3.5 and Figure 3.2, I would expect that i is least likely to vote for Case 3, but more likely to vote for Case 2 than for Case 1. More precisely, given that i believes that "the situation where i will be pivotal" is most likely to happen, I claim that i's voting propensity increases with i's predictions of i's group's advantage (i.e., *lead* > 1).

Psychological Explanation. A good explanation for the discussion above comes from Psychology. My hypothesis is that leading in *interim* stages has a positive psychological impact on performance in tournaments—in fact, many studies have demonstrated this phenomenon. Theoretically, Krumer (2013) studied a best-of-two contest between two teams, where the winner is the player who wins in both stages. He demonstrated that winning in the first stage provides a psychological advantage in the second stage.

Experimentally, Duffy and Tavits (2008) tested individuals' voting behavior in the laboratory. Before each election, they randomly decided which group would win in the event of a tie (the *advantaged* group) and viewed it as proxying for a preelection poll announcing a lead to one candidate. The pivotal voter model predicts lower turnout for the *advantaged* group. However, their experimental data showed that the turnout was statistically significantly higher for the *advantaged* group than that for the *disadvantaged* group, which is very similar to what was found in my paper.[9]

Empirically, Gonzalez-Diaz and Palacios-Huerta (2010) used data from chess tournaments and found that a player who draws the white pieces in the first game has a significant advantage to win the entire contest. In their data, "subjects who play with the white pieces win 28 percent of the chess games whereas those who play with the black pieces win just 18 percent (the remaining 54 percent are draws) in chess tournaments. But given that in a match both players play exactly the same amount of games with the same colors, no player is given an advantage in terms of playing more frequently with the white pieces. Therefore, they attributed their finding to the psychological effect that players who begin playing with the white pieces are randomly given a greater opportunity to lead in the partial score during the match, and leading has a drastic psychological impact on performance in this competitive situation" (pp. 7-8).

As a result, if we view the stage where subjects were informed of which situation they were in as the first stage of the tournament and view the stage where subjects had to decide whether or not to vote as the second stage of the tournament, being assigned to *CCMajority* can be viewed as leading in the first stage of the tournament, resulting in higher voter turnout than what the theory predicts.

Comparison of the Information-Revealing Mechanisms. The frequency distributions of subjects' stated leads for *CPMajority* and *PCMajority* are displayed in Figures B.5 and B.7, respectively. In these two situations, there are more subjects stating *lead* $= -1$ than in *CCMajority*, so the distributions in Figures B.5 and B.7 are similar to each

[9] See Duffy and Tavits (2008), pp. 613-614 for more details.

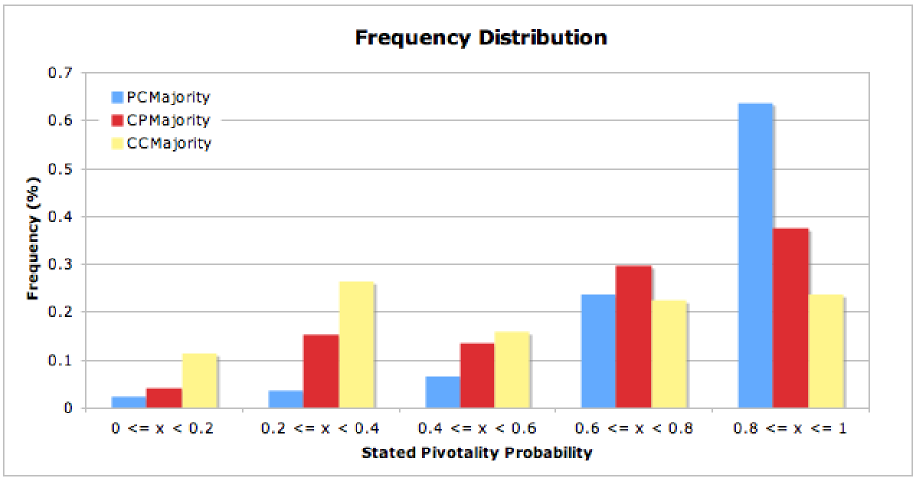

Figure 3.4: Frequency Distribution of Stated Pivotality Probabilities

other but not similar to the distributions in Figure 3.2. But if we condider the cumulative distribution functions for the stated leads of different stated-pivotality-probability groups, then we obtain the same result as what was found from Figure 3.2; that is, subjects who stated a high pivotality probability were more likely to guess that they would be pivotal in the election, while subjects who stated a low pivotality probability were more likely to guess that there would be a lead of their group without their own vote.[10] Figures for *CPMajority* and *PCMajority* are presented the Appendix B.1.

Recall that Table 3.4 displays that in *PCMajority*, the observed turnout rate ($\hat{p}_B(3, 0.6)$) is not significantly different from the Nash equilibrium prediction ($p^*_B(3, 0.6)$), and is not significantly different from the the best-response-to-subjective-belief turnout rate ($\hat{\hat{p}}_B(3, 0.6)$). This implies that subjects were not more willing to vote in *PCMajority*, when compared with the theoretical predictions, which is different from what we found in *CCMajority* and *CPMajority*. Figure 3.4, which displays displays the frequency distributions of subjects'

[10] I also ran a regression for *PCMajority* and obtained a negative coefficient of *Belief of being Pivotal* just like the regression results from *CCMajority* and *CPMajority*.

stated pivotality probabilities for *PCMajority*, *CPMajority*, and *CCMajority*, explains this inconsistency. As can be seen, compared with the *CCMajority* and *CPMajority* subjects, the *PCMajority* subjects were much more likely to guess that they would be pivotal in the election, and were much less likely to guess that their group would have a lead without their own vote. Their guess is very reasonable because according to the setting of the experiments, the *PCMajority* subjects' competing group (i.e., the A group) would have at least 3 votes with a relatively high probability of 0.6. Therefore, unlike being in *CCMajority* or in *CPMajority*, when subjects were informed of being in *PCMajority*, most of them did not view it as leading in the tournament, and thus the psychological effect mentioned above did not emerge on their voting behavior.

One aim of the present paper is to compare the two information-revealing mechanisms: polls and campaigns. I therefore calculated the frequency distributions of subjects' stated leads and the frequency distributions of subjects' stated pivotality probabilities for *CPFaceMinority* and *PCFaceMinority*, and found that only few *CPFaceMinority* and *PCFaceMinority* subjects guessed that their groups would have a lead without their own votes.[11] This implies that when compared with campaigns, it is more difficult to cause the psychological effect mentioned above by polls. This is reinforced by the facts from Tables 3.3 and 3.4, where the observed turnout rates are close to the best-response-to-subjective-belief turnout rates in *CPFaceMinority* and *PCFaceMinority*. In conclusion, the present study demonstrates that the information about being in an advantageous position revealed through campaigns would encourage a higher turnout than the best response to voters' belief of being pivotal due to the psychological effect, while it is more difficult for polls to cause the same effect. Result 3 summarizes the discussions above.

Result 3. *When subjects were informed of being in an advantageous position by cam-*

[11] I did not put the relative figures in the paper.

Table 3.6: Ratios of Actual to Hypothetical Best Response

Ratios of Actual to Best Response Payoffs							
Situation	Ratio	Situation	Ratio	Situation	Ratio	Situation	Ratio
CCMajority	1.052	*CPMajority*	1.065	*PCMajority*	1.012	*PPMajority*	1.040
CCMinority	1.166	*CPMinority*	1.305	*PCMinority*	1.276	*PPMinority*	1.034
Tie1	1.083	*CPFaceMajority*	1.216	*PCFaceMajority*	1.175		
Tie3	1.049	*CPFaceMinority*	1.070	*PCFaceMinority*	0.990		

paigns, their turnout became significantly higher than the best response to their belief of being pivotal, which can be attributed to that leading in an interim stage has a positive psychological impact on performance in tournaments. On the other hand, when compared with campaigns, it is more difficult for polls to cause the same effect.

Payoff Efficiency. Finally, I would like to examine the payoff efficiency of subjects' decisions relative to best response to see why *CCMajority* and *CPMajority* subjects did not move toward the *rational choice*[12] over time. Specifically, I followed Duffy and Tavits (2008) to calculate the payoffs subjects would have earned if they had played best responses to their subjective probabilities of pivotality in each period. Table 3.6 reports the ratio of actual payoffs to hypothetical best response payoffs for each situation. We see that subjects earned slightly higher payoffs than they would have had they played best responses to their subjective pivotality probabilities in *CCMajority* and *CPMajority.* This finding suggests that, while subjects did not play best responses to their stated beliefs in *CCMajority* and *CPMajority* (due to the psychological effect), they didn't seem to have been monetarily worse off as the result, so it is reasonable that they did not move toward the rational choice predictions (Duffy and Tavits (2008), p.613).

[12]Here *rational choice* refers to subjects' best responses to their subjective probabilities of pivotality, in terms of monetary payoffs.

Table 3.7: Belief Formation - Dependent Variable: Belief of being Pivotal

Treatment CC	*Majority*	*Minority*	*Tie1*	*Tie3*
Belief at t-1	0.286***	0.183***	0.672***	0.681***
	(0.0975)	(0.0519)	(0.0615)	(0.0934)
Observation at t-1	-0.00276	0.0892***	0.0715***	
	(0.0385)	(0.0278)	(0.0195)	
N	188	188	316	244
Treatment CP	*Majority*	*Minority*	*FaceMajority*	*FaceMinority*
Belief at t-1	0.608***	0.484***	0.416***	0.575***
	(0.0882)	(0.0897)	(0.0799)	(0.0861)
Observation at t-1	0.0980**	0.0878**	0.00511	0.0236
	(0.0419)	(0.0362)	(0.0325)	(0.0314)
N	263	241	263	241
Treatment PC	*Majority*	*Minority*	*FaceMajority*	*FaceMinority*
Belief at t-1	0.317***	0.539***	0.257**	0.300**
	(0.0767)	(0.110)	(0.104)	(0.118)
Observation at t-1	0.0438	0.0264	0.0253	0.0198
	(0.0452)	(0.0232)	(0.0277)	(0.0338)
N	304	229	304	230

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Discussion for Puzzle 2

Table 3.4 shows that the CP and PC treatment subjects overestimating their beliefs of being pivotal caused higher turnout in *Minority* and in *FaceMinority* but underestimating those beliefs caused lower turnout in *Majority* and in *FaceMajority* than the corresponding Nash equilibrium predictions (Puzzle 2). In contrast, almost all CC and PP treatment subjects formed pivotality beliefs consistent with the corresponding Nash equilibrium predictions.

In order to understand how subjects formed their beliefs, I ran a OLS regression for each situation, with robust standard errors clustered on individuals. Three independent

Table 3.8: Turnout Rates–Representativeness-Based Turnout Rates ($\tilde{p}$)

	No. of Subjects	R_A;π_A	R_B;π_B	$\hat{p}_A$	$\tilde{p}_A$	$\hat{p}_B$	$\tilde{p}_B$
CC	26	1	1	0.635	-	0.635	-
		3	1	0.659	-	0.402	-
		1	3	0.402	-	0.659	-
		3	3	0.870	-	0.870	-
CP	28	1	0.4	0.554	0.542	0.677	0.645
		3	0.4	0.794	0.743	0.533	0.589
PC	30	0.6	1	0.661	0.649	0.634	0.495
		0.6	3	0.609	0.683	0.746	0.786
PP	28	0.6	0.4	0.735	0.663	0.692	0.611

variables were *Period*, *Belief at t-1* (i.e., each subject's belief of being pivotal in the last period), and *Observation at t-1* (i.e., a dummy variable equal to one for a subject if this subject was pivotal in the last period). *Period* is insignificant in every regression, suggesting that beliefs did not change significantly over time. Table 3.7 displays the results of *Belief at t-1* and *Observation at t-1*. As shown, in each situation the coefficient of *Belief at t-1* is very significant, while the coefficient of *Observation at t-1* is insignificant and small in magnitude. This shows that for a given period, subjects did not use the historical data of actual decisiveness to adjust their beliefs of being pivotal but formed their beliefs by following their prior subjective beliefs about pivotality. This may be because of the setting of the experiments: In each of the CC, CP, and PC treatment, one of the four situations would randomly emerge in each period, making it difficult for subjects to learn from the actual outcomes of each situation.

In the real world, voters would experience the same types of elections every several years, not every year. Further, the situation for the current election may be different from the situation for the last election. As a result, it may not be easy for voters to learn from historical election outcomes, just like the setting of the experiments in the present paper. Hence, it is important to know what made subjects form a higher or lower *prior* belief about pivotality than the Nash equilibrium value for each situation. Nonetheless, I don't have enough data to study this question for now, so I leave this question open for future work. A possible explanation is from Kahneman and Tversky (1972) that "people follow a heuristic called *representativeness* to evaluate the probability of an uncertain event by the degree to which it is similar in essential properties to its parent population" (p. 431). This conjecture is supported by the findings reported in Table 3.8, where each representativeness-based turnout rate (denoted $\tilde{p}$) in CP, PC, or PP treatment is a weighted average of turnout rates in the situations of the CC treatment.[13]

3.5 Conclusion

This paper is an experimental examination of information revelation in a voting model. Typically parties can conduct public events, such as rallies or demonstrations that reveal their level of support in hopes this might influence voter turnout and the outcome of the election. How effective is this? I compare two information-revealing mechanisms in the Palfrey-Rosenthal pivotal voter model: one through which active supporters show their support without paying costs ("polls"), which can be viewed as cheap talk; the other where active supporters have to pay their time (active participation in "campaigns") or money (e.g., contributing to super PACs) to support their preferred candidates, thus providing more certainty about the actual level of support. To capture the difference between the two mechanisms, I assume that polls reveal the distribution of active supporters of a party,

[13] In other words, *CPMinority* turnout rate was calculated by $0.6 \times$ *CCTie1* turnout *plus* $0.4 \times$ *CCMinority* turnout (i.e., $0.542 = 0.6 \times 0.635 + 0.4 \times 0.402$), *CPMajority* turnout rate was calculated by $0.4 \times$ *CCTie3* turnout *plus* $0.6 \times$ *CCMajority* turnout (i.e., $0.794 = 0.4 \times 0.87 + 0.6 \times 0.659$), and so on.

while the campaigns provide the actual numbers of the active supporters of that party.

There are two main experimental findings. First, in most of the situations, subjects followed the main ideas of the Palfrey-Rosenthal pivotal voter model, with appropriately responding to the cost of voting and the belief of being pivotal. Second, however, when subjects were informed of being in an advantageous position by campaigns, their turnout became significantly higher than the best response to their pivotality belief. On the other hand, compared with campaigns, it is more difficult for polls to cause the same effect.

A possible explanation for the second finding comes from psychological studies on momentum effects. Specifically, leading in interim stages has a positive psychological impact on performance in tournaments. Therefore, an election can be viewed as a tournament with two stages, and being informed by campaigns that the preferred party is the favorite in the election can be viewed as leading in the first stage, which causes a positive effect on participants' propensity to vote in the second stage. Mago, Samak, and Sheremeta (2013) have examined the psychological momentum effect in a best-of-three contest. I will design a new experiment to test this effect in a best-of-two contest (which is what this paper is about). I expect to find that winning the first stage of the contest has a positive psychological effect on encouraging contestants to put in more effort in the second stage.

Chapter 4

Rallying Strategy in Two-Party Elections

4.1 Introduction

"In 2000, Nader wanted to achieve at least a 5% size of the presidential vote in order to secure public funding for the Green Party's candidate in 2004. But to do so, he needed to convince voters that it was possible for him to generate that large of a share of the vote. He attempted to do so with rallies."–Rebecca B. Morton (2006)

A dramatic transformation in voter mobilization has taken place over the past half-century, with candidates, parties, and countless businesses and organizations spending large amounts of resources to influence voters.[1] Mobilization tools include direct mail and telephone campaigns, door-to-door canvassing, TV advertising, speeches, and rallies. Rallies can serve as coordination mechanisms in multi-candidate races, especially for can-

[1] See Gerber and Green (2000) p.653 and Druckman et al. (2011) p.422.

didates who are trying to project images of strong current support among voters.[2] In the final days of a campaign, a successful rally can strengthen existing support and encourage less enthusiastic voters to cast their ballots.[3] Empirical evidence of these effects has been gathered by Finkel and Schrott (1995), Lazarsfeld, Berelson, and Gaudet (1944), and Mattlin (2004).

The goal of this research is to analyze candidates' rallying strategies in two-party races. This paper views political rallies as an information-revealing mechanism that allows candidates to project images of strong current support among voters. Compared with previous studies on campaign effects, this project starts from investigating voting behavior based on the Palfrey and Rosenthal (1985) (P-R) pivotal voter model. Then, the mechanism through which the support is shown in rallies is demonstrated through the informational impact in the P-R pivotal voter model. More specifically, in my model, there are two types of supporters: base supporters (those who always turn out to vote for their preferred candidates) and passive supporters (those who vote strategically). A randomly chosen voter may be a base supporter (π probability) or a passive supporter ($1 - \pi$ probability). The probability π is common knowledge, and voters' types are independent draws. But the realized number of base supporters is unknown unless a rally is held. If a rally is held, base supporters will automatically attend the rally organized by the candidate they support, and passive supporters will stay away. Hence, by holding a rally, candidates and supporters learn the realized number of base supporters.

A two-stage game is used to study the signaling purpose of rallies. In the first stage of my model, two candidates simultaneously decide whether or not to organize rallies. The candidates do not know how many people will show up when they decide whether or not to hold rallies. That is, the information about the numbers of base and passive supporters

[2] See Morton (2006) p.201.
[3] See Mattlin (2004) p.162.

can only be revealed by holding rallies. If there is no rally during the election, the only known information is π. In the second stage, passive supporters decide whether or not to vote based on their observations of rally outcomes. According to the Palfrey and Rosenthal (1985) turnout model, if the cost of voting for passive supporters exceeds zero, they will vote if they perceive that their votes are pivotal. In such situations, candidates can use rallies to disseminate information about their chances of winning. For a candidate, if a rally can encourage the passive supporters of his party to vote or discourage the passive supporters of the competing party from voting, then this candidate has an incentive to hold the rally.

Rally decisions depend on π and the size difference between one's party and the competing party. To further investigate the effects of holding a rally, I study two cases. One is the case where the sizes of the parties are equal; the other is the case where π values are equal. For the first case, my model predicts that when the sizes are equal, the party with a smaller π is more likely hold a rally (Hypothesis 1). This is because the party with a smaller π can eliminate the disadvantage of the lower ratio of base supporters by holding a rally. Otherwise, its passive supporters will believe that their chance of winning is lower than the competing party, leading to their lack of willingness to vote. On the other hand, the party with a higher π should not hold a rally since if it does not hold a rally, its passive supporters will believe that they have a chance to win due to the higher π. But if a rally is held and few of its base supporters show up at the rally, its passive supporters will be discouraged from voting. For the second case, my model predicts that when the π values of the two parties are equal and the size of a party is twice as big as that of another party, the big party will hold a rally, while the small party will not (Hypothesis 2). The intuition is as follows. Since the big party has a size advantage, if it can further show that it has many base supporters, then small party passive supporters will believe that their candidate is very likely to lose, increasing their lack of willingness to vote. On the other hand, the small party should not hold a rally since holding a rally cannot help to eliminate its size disadvantage.

To further investigate Hypotheses 1 and 2, I consider empirical data from U.S. presidential elections. Reliable state-by-state data on rallying strategies of presidential candidates can be found in Shaw (1999a). Shaw (1999a) provides the data on "candidate appearances," which are recorded as the total number of visits made to each state and D.C. for political rallies in the 1988, 1992, and 1996 U.S. presidential elections. Therefore, data on candidate appearances provided by Shaw (1999a) can stand as proxy for candidates' rallying strategies. The empirical data show that in most of the battleground states, if partisanship leans to the Democratic (Republican), Republican (Democratic) Party organized more candidate appearances than the Democratic (Republican) Party did, supporting Hypothesis 1. The empirical data also show that in most of the Base Democratic (Republican) states, the Democratic (Republican) Party organized more candidate appearances than the Republican (Democratic) Party did, supporting Hypothesis 2.

The rest of the paper proceeds as follows. Section 4.2 introduces the model and compares winning probabilities of holding a rally with those of not holding a rally. Further, it presents definitions of equilibria, followed by applying equilibrium analysis to a study of real-world situations. In Section 4.3, I explore the effects of holding a rally in two cases, followed by deriving two hypotheses. Section 4.4 uses empirical data to examine the hypotheses and the effectiveness of the model. Section 5 concludes.

4.2 The Model

4.2.1 The Benchmark Model

My model is based on Palfrey and Rosenthal (1985) and Levine and Palfrey (2007) turnout models, in which voters have privately known voting costs. A total of $\bar{N}$ voters can choose between candidates 1 and 2. Each voter belongs to one of two parties, T_1 or T_2, with N_1 voters in T_1 and N_2 voters in T_2, such that $N_1 + N_2 = \bar{N}$ and $N_1 \leqslant N_2$. T_1 voters prefer candidate 1, and T_2 voters prefer candidate 2. Voters can be further categorized into two types: base supporters and passive supporters. It is assumed that base supporters have zero voting costs, which causes that voting is considered a dominant strategy. For passive supporter A, voting cost is denoted as c_A and is set to be greater than zero for any A. In addition, c_A is independently drawn from a common density function $f(c)$, and is privately known by A before A decides whether or not to vote. The density function of the cost distribution, $f(c)$, is common knowledge and is assumed to be positive everywhere on its support.

A voter in T_1 is a base supporter with probability π_1 and a passive supporter with probability $1 - \pi_1$, where π_1 is commonly known by all, and types are independent draws. Hence, the number of T_1 base supporters is a random variable with a binomial distribution with parameters N_1 and π_1. Similarly, a voter in T_2 is a base supporter with probability π_2 and a passive supporter with probability $1 - \pi_2$, where π_2 is commonly known by all, and types are independent draws. Therefore, the number of T_2 base supporters is a random variable with a binomial distribution with parameters N_2 and π_2.

An election process can be modeled as a two-stage game. In the first stage, candidates 1 and 2 simultaneously decide whether or not to conduct rallies. It is assumed that base supporters will automatically attend, and passive supporters will not.[4] The candidates do

[4] An implicit assumption here is that the cost of attending the rallies is zero for base supporters and un-

not know how many people will show up when they decide whether or not to hold rallies. That is, the information about the realized numbers of base and passive supporters can only be revealed by holding rallies. If there is no rally during the election, the only known information are (N_1, N_2) and (π_1, π_2). Hence, by holding rallies, candidates and supporters learn the realized numbers of base supporters.

In the second stage, an election is held, and base supporters vote regardless of the rally outcome, while passive supporters decide whether or not to vote based on their observations of the numbers of base supporters who attend their respective rallies. To vote, passive supporter A must pay voting cost c_A. Whichever candidate receives more votes wins the election. In the event of a tie, a fair coin is tossed to decide the winner. If candidate 1 wins, then candidate 1 and all T_1 voters receive a reward of H and candidate 2 as well as all T_2 voters receive a reward of $L < H$. The opposite occurs if candidate 2 wins. These rewards are common knowledge.

I assume that in the second stage, passive supporters in the same party use the same decision rule in equilibrium. According to Palfrey and Rosenthal (1985), a quasi-symmetric equilibrium consists of a pair of critical points $(\hat{c}_1, \hat{c}_2)$ such that any passive supporter A in T_1 votes if and only if $c_A < \hat{c}_1$, and any passive supporter A in T_2 votes if and only if $c_A < \hat{c}_2$. A quasi-symmetric equilibrium implies an aggregate voting probability for passive supporters in each party, $(\hat{p}_1, \hat{p}_2)$, given by:

$$\hat{p}_1 = \int_0^{\hat{c}_1} f(c)dc = F(\hat{c}_1) \tag{4.1}$$

$$\hat{p}_2 = \int_0^{\hat{c}_2} f(c)dc = F(\hat{c}_2). \tag{4.2}$$

acceptably high for passive supporters. Readers may challenge the zero rally cost assumption as unrealistic, but the key issue is whether the organizing of rallies and size of base support encourage passive supporters to vote. Thus, adding positive rally costs into the model would make it more complex without providing new insight.

Since $(\hat{c}_1, \hat{c}_2)$ is an equilibrium, for an interior solution, a passive supporter with a cost equal to $(\hat{c}_1, \hat{c}_2)$ should be indifferent between voting and abstaining. As a result,

$$\hat{c}_1 = \frac{H-L}{2}\hat{q}_1 \tag{4.3}$$

$$\hat{c}_2 = \frac{H-L}{2}\hat{q}_2 \tag{4.4}$$

where $\hat{q}_1$ ($\hat{q}_2$) is the probability that a vote cast by a passive supporter in the T_1 (T_2) party will be pivotal (i.e., make or break a tie), given the equilibrium voting strategies of all other voters in both parties.

Let R_1 and R_2 represent the numbers of the base supporters attending the rallies held by candidates 1 and 2, respectively. In the cases where candidate i does not hold a rally, R_i is defined as an empty set (i.e., $R_i = \emptyset$). The values of $(\hat{c}_1, \hat{c}_2)$, $(\hat{p}_1, \hat{p}_2)$, and $(\hat{q}_1, \hat{q}_2)$ depend on candidate actions, (R_1, R_2), and (π_1, π_2). More precisely, if both candidates hold rallies, the values depend on (R_1, R_2); if only one candidate, say candidate 1, holds a rally, the values depend on R_1 and π_2; and if no candidates hold rallies, the values only depend on (π_1, π_2). The calculations of these values are shown in Appendix C.1.

Given those values resulting from candidate actions, $Prob_i(win|R_1, R_2)$ denotes the conditional probability of candidate i winning, $Prob_i(lose|R_1, R_2)$ the conditional probability of candidate i losing, and $Prob_i(tie|R_1, R_2)$ the conditional probability of a tie. Note that $Prob_i(tie|R_1, R_2) = Prob_j(tie|R_1, R_2)$ and $Prob_i(win|R_1, R_2) = Prob_j(lose|R_1, R_2)$, where j is i's opposing candidate. The calculations of these values are also shown in Appendix C.1. Since if it is a tie, candidate i has a probability of 0.5 to win, for the following discussions I define candidate i's conditional winning probability given (R_1, R_2) as $Prob_i(W|R_1, R_2) \equiv 0.5Prob_i(tie|R_1, R_2) + Prob_i(win|R_1, R_2)$.

In the first stage, as stated, both candidates simultaneously decide whether or not to hold rallies. Given conditional winning probabilities $Prob_i(W|R_1, R_2)$, I can compute unconditional winning probabilities of holding and of not holding rallies. The unconditional winning probability for candidate i is denoted as $W_i(s_1, s_2)$, where $s_i = Y$ if candidate i holds a rally and $s_i = N$ otherwise. And note that the unconditional winning probability for i's competitor, candidate j, is $W_j(s_1, s_2) = 1 - W_i(s_1, s_2)$.

There are three possible action profiles: both candidates hold rallies, only one candidate does, or neither candidate does. For the following discussions, without loss of generosity, I take candidate 1 as an example. If both candidates hold rallies, the probability of candidate 1 winning is

$$W_1(Y,Y) = \sum_{R_1=0}^{N_1} \sum_{R_2=0}^{N_2} \binom{N_1}{R_1} \binom{N_2}{R_2} \pi_1^{R_1}(1-\pi_1)^{N_1-R_1} \pi_2^{R_2}(1-\pi_2)^{N_2-R_2} Prob_1(W|R_1, R_2). \tag{4.5}$$

If candidate 1 holds a rally but candidate 2 does not, the probability of candidate 1 winning is

$$W_1(Y,N) = \sum_{R_1=0}^{N_1} \binom{N_1}{R_1} \pi_1^{R_1}(1-\pi_1)^{N_1-R_1} Prob_1(W|R_1, \emptyset). \tag{4.6}$$

Similarly, if candidate 1 does not hold a rally but candidate 2 does. Then

$$W_1(N,Y) = \sum_{R_2=0}^{N_2} \binom{N_2}{R_2} \pi_2^{R_2}(1-\pi_2)^{N_2-R_2} Prob_1(W|\emptyset, R_2). \tag{4.7}$$

If neither candidate holds a rally,

$$W_1(N,N) = Prob_1(W|\emptyset, \emptyset). \tag{4.8}$$

To compare the winning probability of holding a rally with that of not holding a rally, it is helpful to study them with graphs. In the following, without loss of generosity, I study how holding a rally affects the winning probability by taking candidate 1 as an example. Following Levine and Palfrey (2007), the payoffs used to calculate winning probabilities are $L = 5$ and $H = 105$, with a uniform distribution of voting costs ranging from 0 to 55.

Candidate 2 Holds a Rally

I first assume that candidate 2 holds a rally to study the winning probabilities $W_1(Y, Y)$ and $W_1(N, Y)$. Figure 4.1 consists of three subfigures. Each shows candidate 1's winning probabilities of holding a rally and of not holding a rally under a pair (π_1, π_2) given that $N_1 = 3$, $N_2 = 6$, and candidate 2 holds a rally. The top two subfigures share the same π_2 but different π_1, and the left two subfigures share the same π_1 but different π_2.

There are four bars and a line in each subfigure. The number r, where $r \in \{0, 1, 2, 3\}$, on top of a bar represents the rally turnout (i.e., $R_1 = r$). For convenience, I call a bar with a number r 'r-bar' in the following discussions. The height of a r-bar represents candidate 1's conditional winning probability given $R_1 = r$, and it can be expressed as

$$\sum_{R_2=0}^{N_2} \binom{N_2}{R_2} \pi_2^{R_2} (1 - \pi_2)^{N_2 - R_2} Prob_1(W|r, R_2),$$

implying that π_2 determines the heights of r-bars. This is shown by the left two subfigures: The width of the r-bar, where $r \in \{0, 1, 2, 3\}$, in the top subfigure is the same as it in the bottom subfigure, but the heights of the r-bars in the two subfigures are different.

The width of a r-bar represents the probability that $R_1 = r$ emerges, and it can be expressed as

$$\binom{N_1}{r} \pi_1^{R_1} (1 - \pi_1)^{N_1 - R_1},$$

implying that π_1 determines the widths of r-bars. This is shown by the top two subfigures

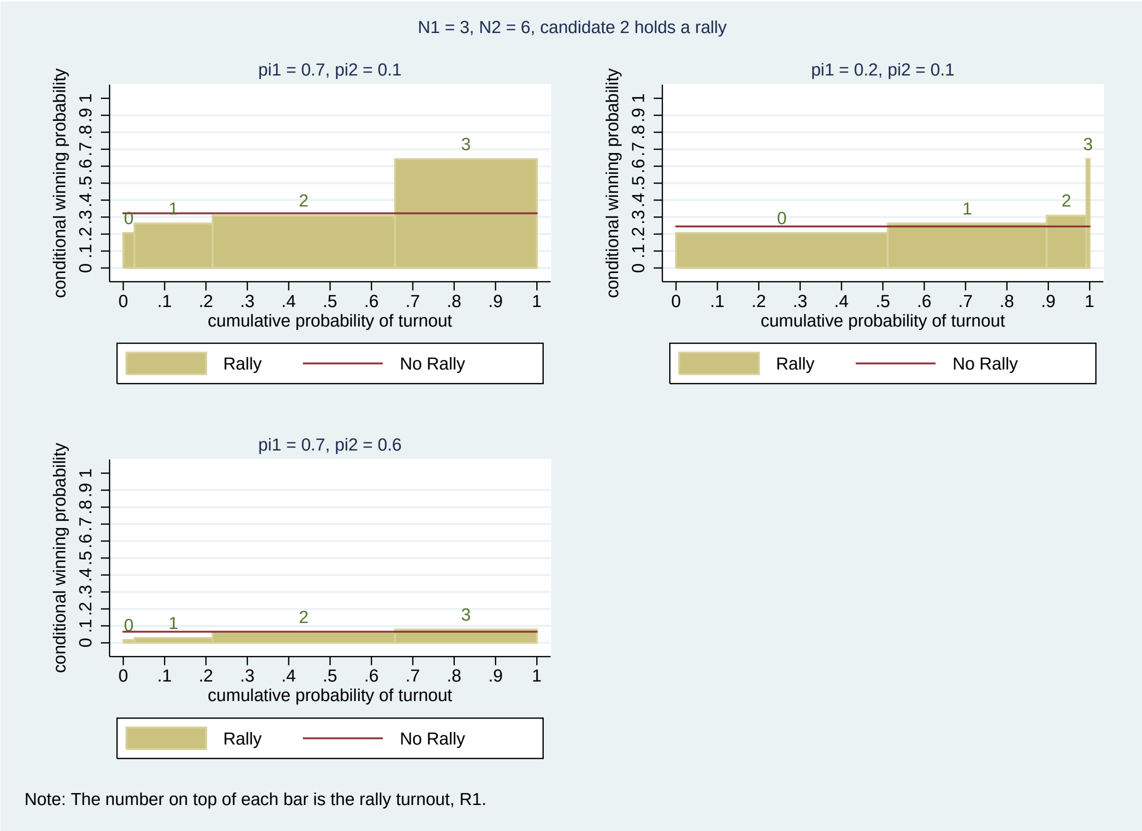

Figure 4.1: Candidate 1's winning probability in the case where $N_1 = 3$, $N_2 = 6$, and candidate 2 holds a rally.

where the heights of r-bars are the same, but the widths of r-bars are different. Note that the sum of the widths of r-bars is 1; that is,

$$\sum_{R_1=0}^{N_1} \binom{N_1}{r} \pi_1^{R_1}(1-\pi_1)^{N_1-R_1} = 1.$$

Accordingly, from each subfigure, candidate 1's (unconditional) winning probability of holding a rally can be represented by the sum of the areas of r-bars, which is

$$\sum_{R_1=0}^{N_1} \left\{ \binom{N_1}{r} \pi_1^{R_1}(1-\pi_1)^{N_1-R_1} \times \sum_{R_2=0}^{N_2} \binom{N_2}{R_2} \pi_2^{R_2}(1-\pi_2)^{N_2-R_2} Prob_1(W|r, R_2) \right\}.$$

This is the same as $W_1(Y,Y)$ shown by equation (4.5). For convenience, I call this area $Area(Y,Y)$.

As to the line in each subfigure, the area calculated from the height of the line *times* the width 1 represents candidate 1's winning probability of not holding a rally, $W_1(N,Y)$. For convenience, I call this area $Area(N,Y)$. Candidate 1 should decide whether or not to hold a rally by comparing $Area(Y,Y)$ and $Area(N,Y)$. For example, the top left subfigure shows that when $\pi_1 = 0.7$ and $\pi_2 = 0.1$, candidate 1 should hold a rally since $Area(Y,Y)$ $> Area(N,Y)$ (i.e., the winning probability of holding a rally is higher than that of not holding a rally).

Candidate 2 Does Not Hold a Rally

Now suppose that candidate 2 does not hold a rally. Subfigures in Figure 4.2 show candidate 1's winning probabilities of holding a rally and those of not holding a rally given that $N_1 = 3$, $N_2 = 6$, and candidate 2 does not hold a rally. These subfigures show the same characteristics as Figure 4.1. More precisely, the different widths of r-bars in the top two subfigures show that π_1 determines the probability that $R_1 = r$, where $r \in \{0, 1, 2, 3\}$,

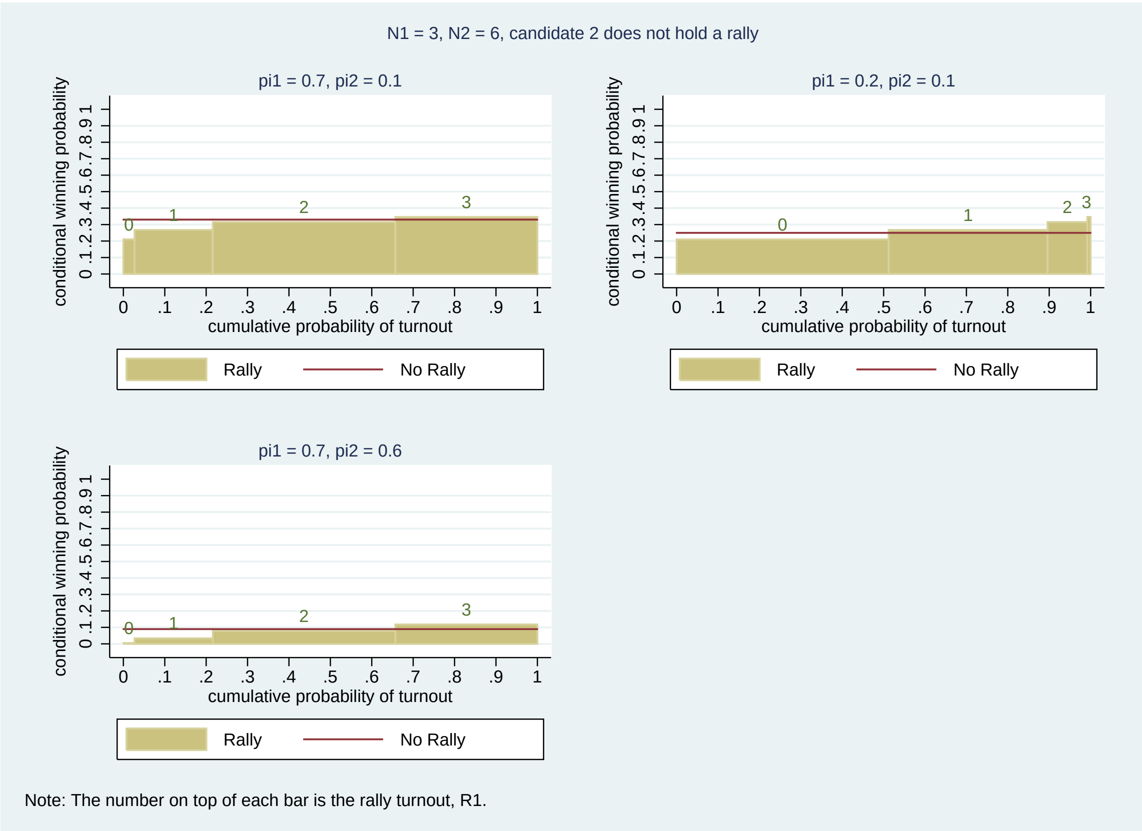

Figure 4.2: Candidate 1's winning probability in the case where $N_1 = 3$, $N_2 = 6$, and candidate 2 does not hold a rally.

and the different heights of r-bars in the left two subfigures show that π_2 determines the conditional winning probability given $R_1 = r$.

An important finding comes from comparing Figures 4.1 and 4.2. Figures 4.1 and 4.2 share the same values for each of the parameters N_1, N_2, π_1, and π_2, except that candidate 2 holds a rally in Figure 4.1 but not in Figure 4.2. Given this setting, I ask the following question: Should candidate 1 hold a rally when candidate 2 holds a rally or when candidate 2 does not hold a rally? I first compare the top subfigures in Figure 4.1 with those in Figure 4.2 to study the case where $\pi_2 = 0.1$. As shown, the 3-bar is much higher than the line in each of the top subfigures in Figure 4.1, while the 3-bar is only a little higher than the line in each of the top subfigures in Figure 4.2. In other words, when π_2 is low, candidate 1 should be more likely to hold a rally if candidate 2 holds a rally (Figure 4.1) than if candidate 2 does not hold a rally (Figure 4.2).

This is because when π_2 is low, if candidate 2 holds a rally, there will be a high probability that few T_2 base supporters show up at the rally. If it is the case, the event that $R_1 = 3$ will discourage T_2 passive supporters from voting, leading to the conditional winning probability given $R_1 = 3$ being high. On the other hand, if candidate 2 does not hold a rally, even in the case where R_1 is large and π_2 is low, T_2 passive supporters will still believe that candidate 2 has a chance to win since there are more voters in T_2. Therefore, T_2 passive supporters may still turn out to vote when $R_1 = 3$, leading to the conditional winning probability given $R_1 = 3$ being low. However, if π_2 is not so low, $\pi_2 = 0.6$ for example, the pattern in Figure 4.1 will be similar to that in Figure 4.2 (See the bottom subfigures in Figures 4.1 and 4.2).

Does a successful rally always increase the winning probability?

From Figures 4.1 and 4.2, candidate 1's conditional winning probability increases in R_1. However, having a successful rally (i.e., R_1 is large) does not always increase the

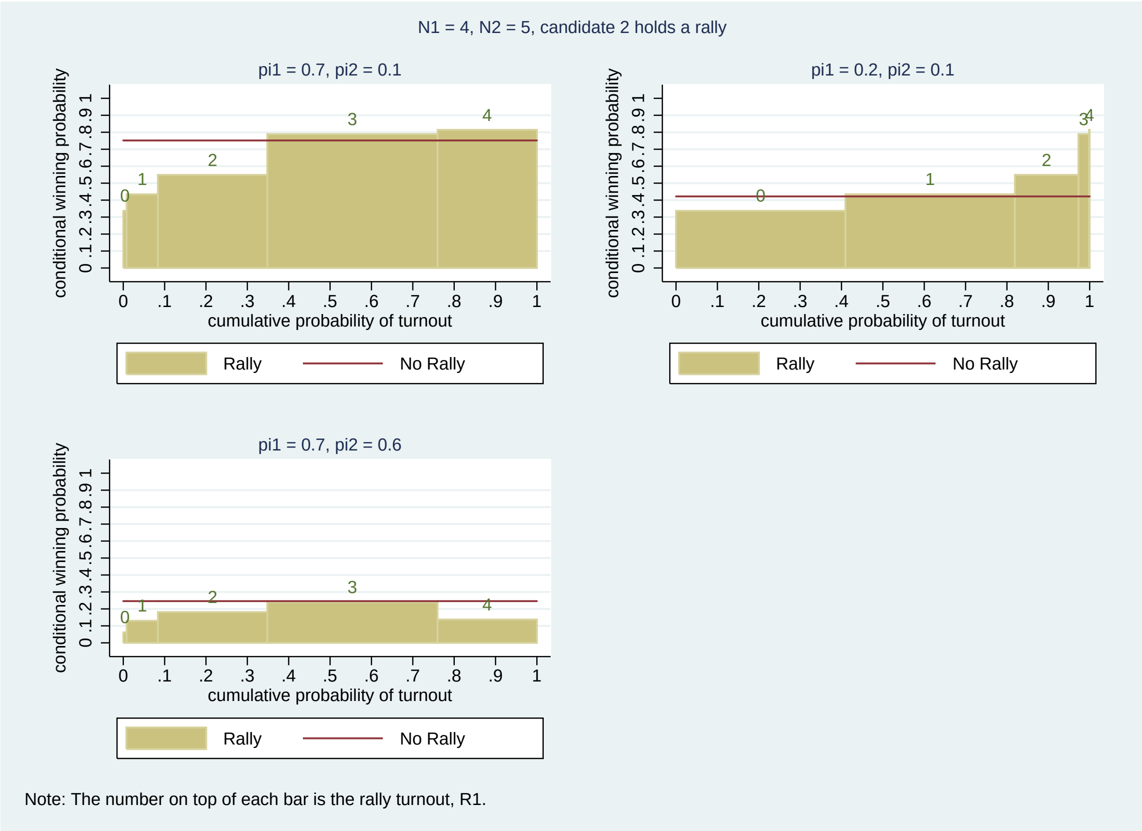

Figure 4.3: Candidate 1's winning probability in the case where $N_1 = 4$, $N_2 = 5$, and candidate 2 holds a rally.

conditional winning probability. This is because in addition to encouraging T_1 passive supporters to vote, a successful rally held by candidate 1 may also encourage T_2 passive supporters to vote if T_2 passive supporters believe that they need to vote to win the election after witnessing many T_1 base supporters showing up at the rally.

For example, consider the case where $N_1 = 4$ and $N_2 = 5$. The top subfigures in Figure 4.3 show that the conditional winning probabilities increase in R_1 when $\pi_2 = 0.1$, while the bottom subfigure shows that when $\pi_2 = 0.6$ the conditional winning probability given $R_1 = 4$ is lower than that given $R_1 = 3$ (i.e., the 4-bar is lower than the 3-bar). In other words, given that $\pi_1 = 0.7$, $\pi_2 = 0.6$, and candidate 2 holds a rally, for candidate 1, having a very successful rally decreases the conditional winning probability. This is because witnessing $R_1 = 4$ encourages T_2 passive supporters to vote if R_2 is not too small. If $\pi_2 = 0.6$, R_2 may not be too small, while it is very likely that R_2 is small if $\pi_2 = 0.1$. Hence, witnessing $R_1 = 4$ does not encourage T_2 passive supporters to vote in the top cases where $\pi_2 = 0.1$, while it encourages T_2 passive supporters to vote in the bottom case where $\pi_2 = 0.6$, leading to the conditional winning probability given $R_1 = 4$ being lower.

4.2.2 Equilibrium

After discussing the winning probabilities, I now move on to analyze equilibria. Since candidate i receives a reward of H if winning and receives a reward of L if losing,

$$U_i(s_1, s_2) = W_i(s_1, s_2) \times H + (1 - W_i(s_1, s_2)) \times L, \tag{4.9}$$

where $i \in \{1, 2\}$, $s_1 \in \{Y, N\}$, and $s_2 \in \{Y, N\}$. A payoff matrix can be obtained given any N_1, N_2, π_1, and π_2 (Table 4.1). The focus in this paper is on a particular class of equilibria in which candidates play pure actions in the first stage; in the second stage, passive supporters decide whether or not to vote according to the corresponding critical

Table 4.1: The Payoff Matrix

	Rally	No Rally
Rally	$(U_1(Y,Y), U_2(Y,Y))$	$(U_1(Y,N), U_2(Y,N))$
No Rally	$(U_1(N,Y), U_2(N,Y))$	$(U_1(N,N), U_2(N,N))$

point ($\hat{c}_1$, $\hat{c}_2$). There are four possible equilibria in this class.

Definition 1. *Rally Equilibrium: If $U_1(Y,Y) > U_1(N,Y)$ and $U_2(Y,Y) > U_2(Y,N)$, an equilibrium exists in which both candidates hold rallies in the first stage; this is referred to as a rally equilibrium.*

Definition 2. *Non-rally Equilibrium: If $U_1(N,N) > U_1(Y,N)$ and $U_2(N,N) > U_2(N,Y)$, the equilibrium represents both candidates refraining from holding first-stage rallies; this is referred to as a non-rally equilibrium.*

Definition 3. *T_1-Rally Equilibrium: If $U_1(Y,N) > U_1(N,N)$ and $U_2(Y,N) > U_2(Y,Y)$, the equilibrium consists of candidate 1 holding a rally and candidate 2 not holding a rally; this is referred to as a T_1-rally equilibrium.*

Definition 4. *T_2-Rally Equilibrium: If $U_1(N,Y) > U_1(Y,Y)$ and $U_2(N,Y) > U_2(N,N)$, the equilibrium consists of candidate 2 holding a rally and candidate 1 not holding a rally; this is referred to as a T_2-rally equilibrium.*

These equilibria can be displayed on equilibrium diagrams in three different cases: $N_2 = 2N_1$, $N_2 = N_1 + 1$, and $N_2 = N_1$. Since $N_2 \geqslant N_1$, there is greater interest in the case where $\pi_2 \leqslant \pi_1$ in the parameter set $\Omega = \{(\pi_1, \pi_2) : 0 < \pi_2 \leqslant \pi_1 < 1\}$. In addition to showing the equilibrium diagrams, to see if the model can explain empirical data, I also apply equilibrium analysis to a study of real-world situations in $N_2 = 2N_1$ and $N_2 = N_1 + 1$ cases.

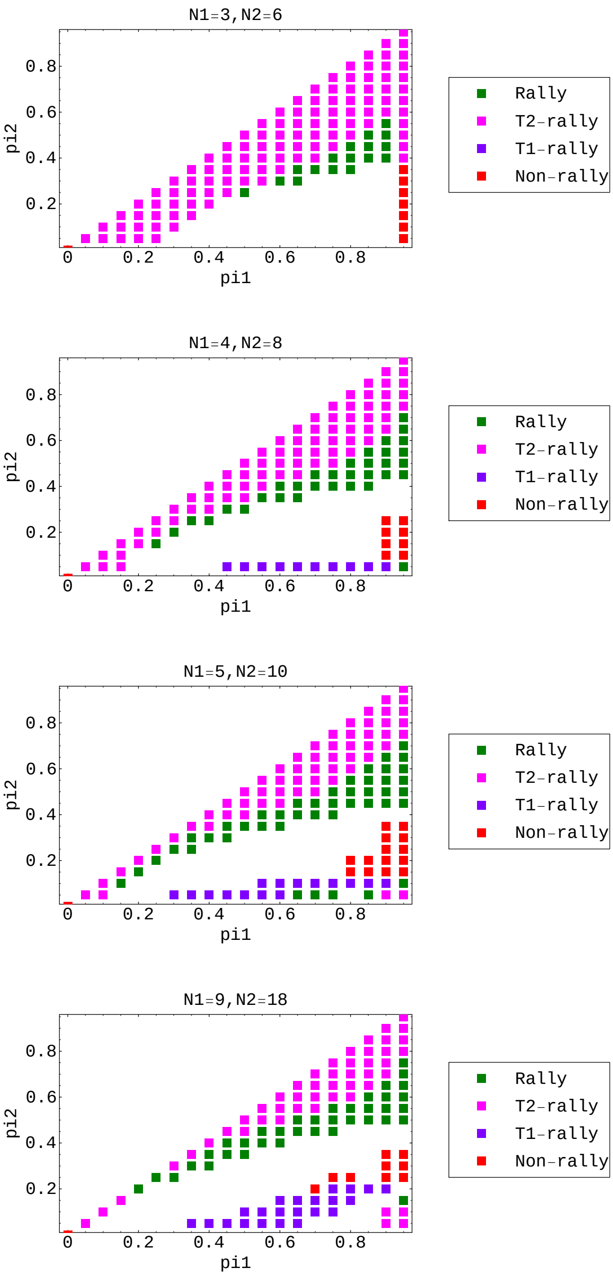

Figure 4.4: Equilibrium diagrams for $N_2 = 2N_1$.

Figure 4.4 presents equilibrium diagrams for different electorate sizes $\bar{N}$, with each diagram showing equilibria where $N_2 = 2N_1$. For each diagram, the horizontal axis represents π_1 and the vertical axis represents π_2. An equilibrium or equilibria may exist given any pair (π_1, π_2). Each diagram is divided into two areas along the diagonal line. The left-up triangle area will not be discussed since I only focus on the case where $\pi_2 \leqslant \pi_1$. In the right-down triangle area, green dots represent rally equilibria, pink dots T_2-rally equilibria, purple dots T_1-rally equilibria, red dots non-rally equilibria, and white spaces represent no equilibria.

Real-world Example of the $N_2 = 2N_1$ Case

To give an example of a $N_2 = 2N_1$ scenario, during the 2008 presidential election in Taiwan, opinion polls showed Kuomintang (KMT) candidate Ma Ying-jeou receiving between 49% and 55% voter support, and Democratic Progressive Party (DPP) candidate Frank Hsieh receiving 28%-31% (Lin (2009), Table 13).[5] The support percentage for candidate i during an election can be expressed as N_i, $i \in \{1, 2\}$. By labeling Frank Hsieh candidate 1 and Ma Ying-jeou candidate 2, support rates are expressed as $N_2 = 2N_1$.

Identifying π_1 and π_2 is the next step. Using Taiwan Electoral Democracy Survey (TEDS) election data,[6] Cheng (2007) used three indices to measures base DPP support: the concepts of Taiwanese consciousness, Taiwanese regime, and party preference. According to Cheng (2007), I compute π_1 and π_2 in Appendix C.2. Their ranges were 0.55-0.65 and 0.08-0.40, respectively.

Given $N_2 = 2N_1$, $\pi_1 \in [0.55, 0.65]$, and $\pi_2 \in [0.08, 0.40]$, according to Figure 4.4, a rally equilibrium or T_2-rally equilibrium was more likely to emerge, suggesting that candidate 2 conduct a rally regardless of candidate 1's decision. In the actual situation, Ma held rallies

[5] For details on opinion polls from various news agencies and organizations in Taiwan during the election campaign, visit http://tinyurl.com/7hvy4oc.

[6] TEDS: http://www.tedsnet.org/cubekm2/front/bin/home.phtml

starting on May 11, 2007; one of his most important rallies (known as the "Long Stay" rally) was held on July 11, 2007. Hsieh waited until November 12, 2007 to hold his first rally, indicating that Ma decided to hold rallies regardless of Hsieh's decision–an example of a T_2-rally equilibrium. My model predictions are consistent with the actual case.

Real-world Example of the $N_2 = N_1 + 1$ Case

Next, consider the case where $N_2 = N_1 + 1$. Equilibrium diagrams for different $\bar{N}$ electorate sizes are shown in Figure 4.5; each diagram shows the equilibria where $N_2 = N_1 + 1$. In another example involving Taiwan electoral politics, in 2004 opinion polls showed that the KMT candidate Lien Chan had 38%-42% support, and DPP candidate Chen Shui-bian had 36%-40% (Lin (2009), Table 13). The small gap was reflected in the actual election, which Chen won by 0.22%. This can be analyzed as an example of $N_2 = N_1 + 1$, where Chen is candidate 1 and Lien is candidate 2. Similar to the $N_2 = 2N_1$ case, to find π_1 and π_2 I used data from the 2004 TEDS to calculate Cheng's (2007) indices. I compute the potential π_1 and π_2 in Appendix C.2. The π_1 and π_2 ranges were 0.36 to 0.48 and 0.13 to 0.44, respectively. Given $N_2 = N_1 + 1$, $\pi_1 \in [0.36, 0.48]$, and $\pi_2 \in [0.13, 0.44]$, according to Figure 4.5, a T_1-rally equilibrium was more likely to emerge if π_1 was small, and a T_2-rally equilibrium was more likely to emerge if π_1 was large.

In the actual 2004 presidential campaign, there were two major mass rallies: a "228 Hand-in-Hand Rally" organized by the DPP on February 28, and a "313" pan-blue (meaning all pro-KMT parties) rally hled on March 13. At the beginning of the campaign, the prevailing belief was that Lien would win. However, unlike the $N_2 = 2N_1$ example in which Frank Hsieh waited until very late to organize rallies, the DPP held a very early rally in September of 2003, believing that they could overcome Lien's narrow lead. The Hand-in-Hand rally was exceptionally successfully, with about two million people forming

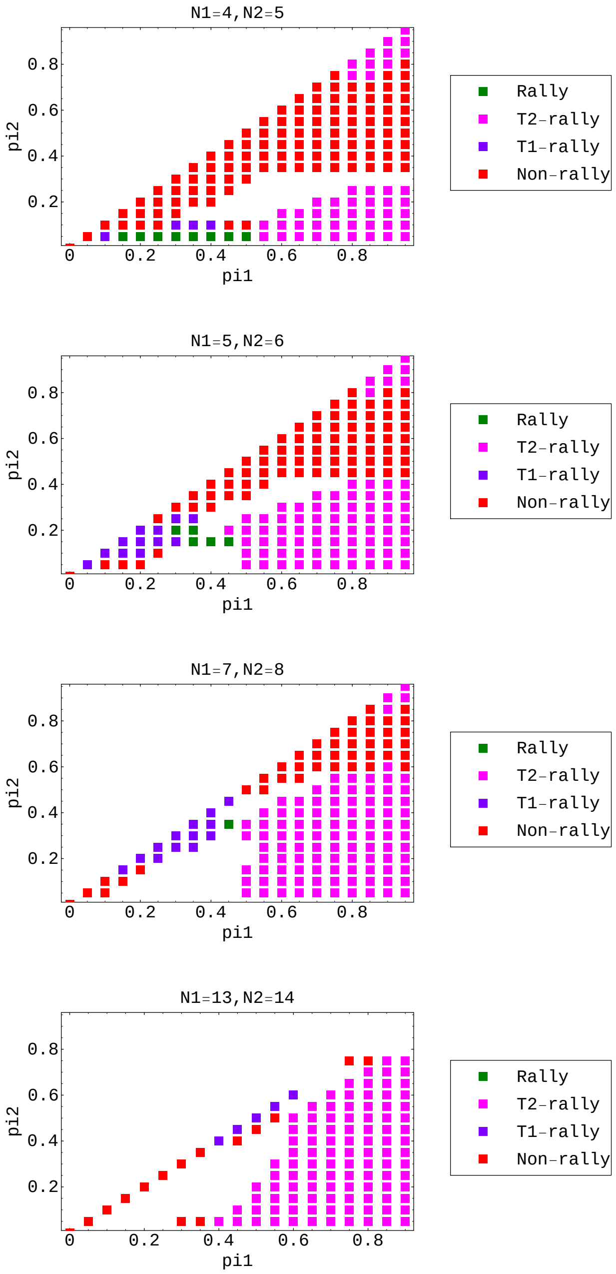

Figure 4.5: Equilibrium diagrams for $N_2 = N_1 + 1$.

a human chain across the island.[7] Until then, the KMT did not have a mass rally plan,[8] therefore this can be viewed as a T_1-rally equilibrium example, in which Chen held a mass rally but Lien did not. This might be because the π_1 value was underestimated before the DPP rally outcome was realized. And this situation is consistent with the prediction of the model–that is, a T_1-rally equilibrium emerged when π_1 was small.

Lien's lead narrowed significantly following the Hand-in-Hand event,[9] with some polls showing that Chen had taken the lead. According to a *China Times* poll of 3,391 eligible voters, 40 percent backed Chen and 38 percent favored Lien. To rally its traditional support base, the pro-KMT coalition held 24 separate 313 pan-blue rallies on the same date that were also said to attract 2 million participants.[10] This situation is consistent with a T_2-rally equilibrium–that is, after seeing the success of the Hand-in-Hand rally, Lien found that the π_1 value was larger than estimated, encouraging him to organize his own rally.

The $N_2 = N_1$ Case

For the $N_2 = N_1$ case, diagram shown in Figure 4.6 is symmetric along the diagonal, therefore only the parameter set $\Omega = \{(\pi_1, \pi_2) : 0 < \pi_2 \leqslant \pi_1 < 1\}$ will be considered. And the results of another parameter set $\hat{\Omega} = \{(\pi_1, \pi_2) : 0 < \pi_1 \leqslant \pi_2 < 1\}$ can be easily inferred. The figure shows equilibrium diagrams for different electorate sizes $\bar{N}$, with each diagram showing equilibria when $N_1 = N_2$. According to Figure 4.6, I have the following observation: When $N_1 = N_2$, a T_2-rally equilibrium is more likely to exist when $\pi_2 < \pi_1$. This observation will be further discussed in the next section.

[7] Clark (2004), p.32
[8] Mattlin (2004), p.13
[9] Wikipedia: Republic of China presidential election, 2004
[10] *Taipei Times* (March 7, 2004) and Mattlin (2004).

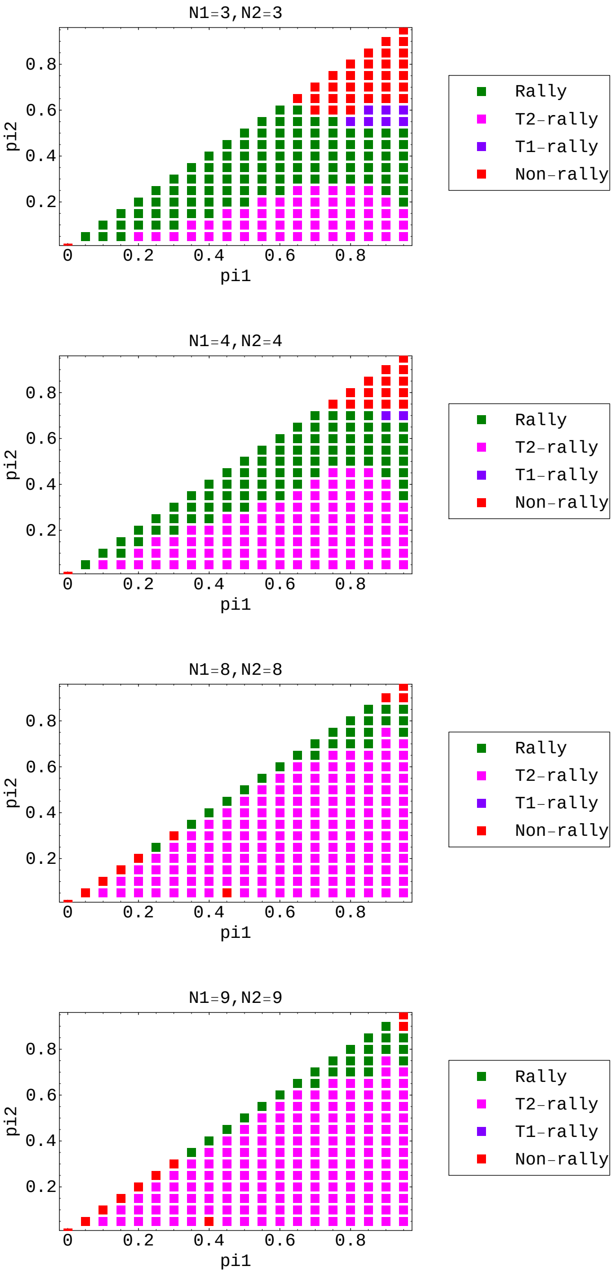

Figure 4.6: Equilibrium diagrams for $N_1 = N_2$.

4.3 Effects of Holding a Rally

Figures 4.4-4.6 show that given different N_1, N_2, π_1, and π_2 values, different equilibrium outcomes emerge. This is because positive and negative effects may emerge simultaneously when a rally is held, and in different cases, different effects are dominant. From candidate i's point of view, if i holds a rally, it may encourage T_i passive supporters to vote and/or discourage passive supporters of T_i's competing party from voting, which is the positive effect. On the other hand, it may also discourage T_i passive supporters from voting and/or encourage passive supporters of T_i's competing party to vote, which is the negative effect. For any case, if the positive effect of holding a rally is larger than the negative one, i should hold a rally. Therefore, we should ask the following question: Under what circumstances should candidate i hold a rally?

To answer this question, it is helpful to study the effects of holding a rally by fixing $N_1 = N_2$ and fixing $\pi_1 = \pi_2$, respectively. Hence, in the following discussions, I will first study the case where $N_1 = N_2$ and $\pi_1 > \pi_2$. In this case, I call the party with the higher π the strong party, and call the party with the lower π the weak party. I, then, study the case where $\pi_1 = \pi_2$ and $N_1 < N_2$. In this case, I call the party with the bigger N the big party, and call the party with the smaller N the small party.

4.3.1 Strong Party vs. Weak Party

Consider the case where $N_1 = N_2$ but $\pi_1 > \pi_2$. Since $\pi_1 > \pi_2$, T_1 is the strong party and T_2 is the weak party in this subsection. Recall that subsection 4.2.2 observes that given $N_1 = N_2$, a T_2-rally equilibrium is more likely to exist when $\pi_1 > \pi_2$. According to this observation, an equilibrium where the weak party holds a rally while the strong party does not is more likely to exist when $N_1 = N_2$. For convenience, I call this equilibrium a "weak party rally equilibrium".

To analyze this observation, I show candidates' winning probabilities of holding and not holding rallies with graphs. Figure 4.7 shows four subfigures for the case where $N_1 = N_2 = 6$, $\pi_1 = 0.8$, and $\pi_2 = 0.4$. The top two show candidate 2's winning probabilities in the case where candidate 1 holds a rally (top left subfigure) and in the case where candidate 1 does not hold a rally (top right subfigure). The bottom two show candidate 1's winning probabilities in the case where candidate 2 holds a rally (bottom left subfigure) and in the case where candidate 2 does not hold a rally (bottom right subfigure). From the top two subfigures, candidate 2's dominant strategy is to hold a rally regardless of candidate 1's strategy. On the other hand, candidate 1's dominant strategy is not to hold a rally regardless of candidate 2's strategy, as shown by the bottom two subfigures. As a result, there is a unique equilibrium, which is the weak party rally equilibrium, in this case.

The intuition is as follows. For candidate 2, who is supported by the weak party, if he does not hold a rally, the smaller π_2 will discourage T_2 passive supporters from voting since they don't think candidate 2 has a chance to win due to $\pi_2 < \pi_1$. However, if candidate 2 holds a rally, the disadvantage of the smaller π_2 is eliminated when many T_2 base supporters show up at the rally. We can see this from each of the top subfigures: The 3-bar, 4-bar, 5-bar, and 6-bar are all higher than the line, leading to the winning probability of holding a rally being larger than that of not holding a rally. As a result, when $N_1 = N_2$, holding a rally is the weak party candidate's dominant strategy since it can eliminate the disadvantage of the smaller π.

On the other hand, candidate 1's dominant strategy is not to hold a rally. This is because even if candidate 1 does not hold a rally, T_1 passive supporters will believe that candidate 1 has a chance to win due to $\pi_1 > \pi_2$, leading to their willingness to vote. Therefore, the winning probability of not holding a rally is high, as shown by the lines of the bottom subfigures. However, if candidate 1 holds a rally, even if $\pi_1 > \pi_2$, there is still

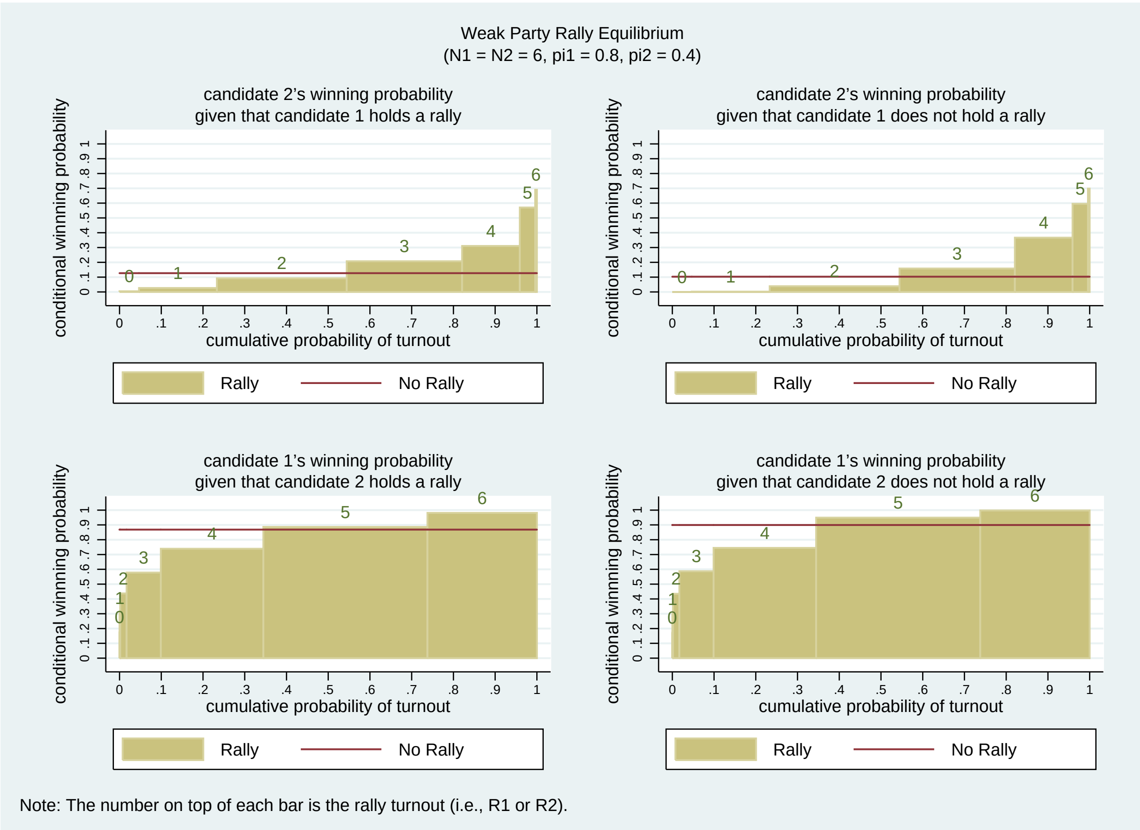

Figure 4.7: Candidates' winning probabilities in the case where $N_1 = N_2 = 6$, $\pi_1 = 0.8$, and $\pi_2 = 0.4$.

a chance that few T_1 base supporters show up at the rally, leading to a lower conditional winning probability. This can be seen from each of the bottom subfigures: The 0-bar, 1-bar, 2-bar, 3-bar, and 4-bar are all lower than the line, resulting in the winning probability of holding a rally being smaller than that of not holding a rally. In conclusion, I have a hypothesis as follows.

Hypothesis 1. *Suppose that $N_1 = N_2$ and $\pi_1 > \pi_2$. A weak party rally equilibrium is more likely to exist because the weak party candidate has an incentive to eliminate the disadvantage of the smaller π by holding a rally.*

4.3.2 Big Party vs. Small Party

Now consider another case where $\pi_1 = \pi_2$ but $N_2 = 2N_1$. Since $N_2 = 2N_1$, T_1 is the small party and T_2 is the big party in this subsection. Recall that Figure 4.4 shows four equilibrium diagrams for the $N_2 = 2N_1$ case. According to Figure 4.4, I observe that an equilibrium where the big party holds a rally while the small party does not is more likely to exist when $N_2 = 2N_1$ and $\pi_1 = \pi_2$. For convenience, I call this equilibrium a "big party rally equilibrium".

To analyze this observation, I take the Figure 4.8 case as an example. Figure 4.8 shows that there is a unique big party rally equilibrium in the case where $N_1 = 4$, $N_2 = 8$, and $\pi_1 = \pi_2 = 0.6$.[11] This is because for candidate 1, who is supported by the small party, holding a rally cannot help to eliminate the size disadvantage of T_1 even if many T_1 base supporters show up at the rally. This is shown by the top subfigures in Figure 4.8 that the

[11] The top two subfigures in Figure 4.7 show candidate 1's winning probabilities in the case where candidate 2 holds a rally (top left subfigure) and in the case where candidate 2 does not hold a rally (top right subfigure). The bottom two show candidate 2's winning probabilities in the case where candidate 1 holds a rally (bottom left subfigure) and in the case where candidate 1 does not hold a rally (bottom right subfigure). From the top two subfigures, candidate 1's dominant strategy is to hold a rally regardless of candidate 2's strategy. On the other hand, candidate 2's dominant strategy is not to hold a rally regardless of candidate 1's strategy, as shown by the bottom two subfigures.

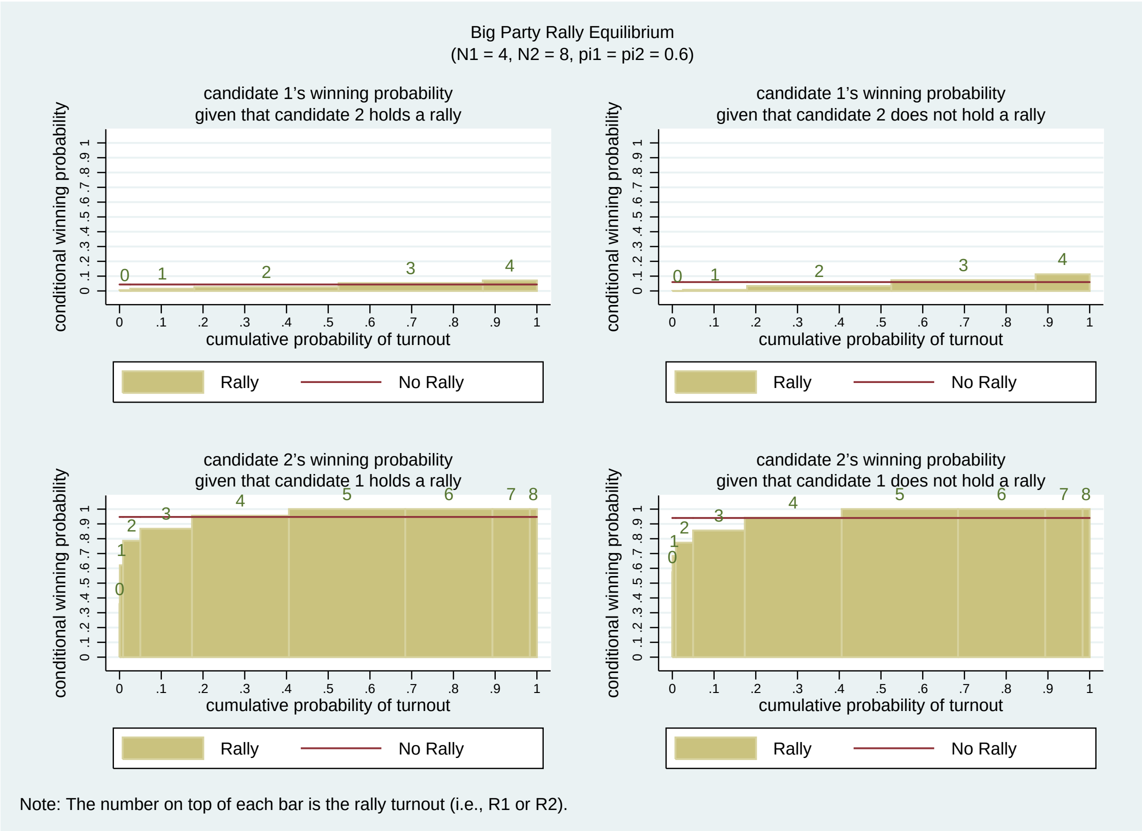

Figure 4.8: Candidates' winning probabilities in the case where $N_1 = 4$, $N_2 = 8$, $\pi_1 = \pi_2 = 0.6$.

3-bars and 4-bars are only a little higher than the lines. Moreover, if few T_1 base supporters show up at the rally, the conditional winning probabilities will be lower than the winning probability of not holding a rally, as shown by the 0-bars, 1-bars, and 2-bars.

On the other hand, candidate 2, who is supported by the big party, should hold a rally to prevent T_1 passive supporters from voting. This is because N_2 is much larger than N_1, leading to candidate 2 winning the election for sure as long as more than four T_2 base supporters show up at the rally (Figure 4.8, bottom subfigures). As a result, I have another hypothesis as follows.

Hypothesis 2. *Suppose that $N_2 = 2N_1$ and $\pi_1 = \pi_2$. A big party rally equilibrium is more likely to exist because the big party candidate has an incentive to prevent the passive supporters of the small party from voting by holding a rally.*

4.4 Testing the Model

To examine the effectiveness of the model, I tested Hypothesis 1 and Hypothesis 2 with empirical data from the 1988, 1992, and 1996 U.S. Presidential elections since rich empirical statewide data on these three elections can be obtained from existing studies. Three pieces of information are essential: (1) Democratic Party's rallying strategy and Republican Party's rallying strategy, (2) Democratic Party's voter support and Republican Party's voter support respectively representing N_1 and N_2, and (3) Democratic Party's base support and Republican Party's base support respectively representing π_1 and π_2.

Reliable state-by-state data on rallying strategies of presidential candidates can be found in Shaw (1999a). Shaw (1999a) provides the data for the variable "candidate appearances," which are recorded as the total number of visits made to each state and D.C. for political rallies in the 1988, 1992, and 1996 U.S. presidential elections. Therefore, candidate appearance data provided by Shaw (1999a) can stand as proxy for each party's rallying strategies. To normalize the data, in each elections, I calculated the percentage of candidate appearances in each state for each party, which is a party's number of candidate appearances in a state divided by that party's total number of candidate appearances.

The Democratic Party's voter support and the Republican party's voter support were drawn from Shaw (1999b). According to Shaw (1999b), campaigns tended to sort states into one of five categories: 1. Base Republican; 2. Lean Republican; 3. Battleground; 4. Lean Democratic; 5. Base Democratic. This information can stand as proxy for the voter support of a party in a state. More specifically, states categorized into Base Republican (Base Democratic) by Shaw (1999b) can be viewed as examples of $N_2 = 2N_1$, where the Democratic (Republican) Party is candidate 1 and the Republican (Democratic) Party is candidate 2.

With the data on each party's rallying strategy and the data on each party's voter support, I can test Hypothesis 2, which predicts that given a state where one party has big voter support and the other has small voter support, the party with big voter support is more likely to hold rallies. Information regarding a party's base support which represents π_1 or π_2 are not necessary for this test because Hypothesis 2 holds as long as π_1 is not very different from π_2, as shown by Figure 4.4 in Section 4.2.2. Table 4.2 presents the Base Democratic states in the 1988, 1992, or 1996 U.S. presidential election and the percentage of candidate appearances in each state. As shown, in most of the Base Democratic states, the Democratic Party organized more candidate appearances than the Republican party did. For example, in the 1996 U.S. Presidential election, there were 11 Base Democratic states with a higher percentage of Democratic candidate appearances, while there were only 2 Base Democratic states with a higher percentage of Republican candidate appearances. Similar findings are shown in Table 4.3, which presents the Base Republican states in the 1996, 1992, or 1988 U.S. presidential election and the percentage of candidate appearances in each state. The data in Tables 4.2 and 4.3 support Hypothesis 2.

Hypothesis 1 predicts that, given a state where two parties have similar voter support, the party with weak base support in that state organizes more candidate appearances than the party with strong base support. Therefore, to test Hypothesis 1, states categorized into "Lean Republican," "Battleground," or "Lean Democratic" in Shaw (1999b), which are the states where two parties have similar voter support, were considered. For convenience, I call these states battlegrounds. In addition to each party's voter support and each party's rallying strategies, information regarding each party's base support that represents π_1 or π_2 is essential for testing Hypothesis 1. The Democratic Party's base support and the Republican party's base support were drawn from Norrander (2001), which presents state-level public opinion values produced with the data from the American National Election Study's survey of Senate races in 1988, 1990, and 1992. I used the state partisanship data reported by Norrander (2001) as proxy for a party's base support in each state for the 1992 and 1996 U.S. presidential elections.

Table 4.4 presents the percentage of candidate appearances in each battleground state in the 1992 and 1996 U.S. Presidential elections. The state partisanship data taken from Norrander (2001) are presented in the second column, with the high partisanship number indicating a strong attachment to the Republican Party and the low partisanship number indicating a strong attachment to the Democratic Party. It is noteworthy that Shaw (1999b) categorizes LA, NV, and NM into "Battleground" for the 1996 U.S. presidential election. I therefore used the mean of the partisanship numbers of LA, NV, and NM, which is 2.82, as the standard. States with the partisanship number higher than 2.82 were categorized to have a stronger Republican party base, and states with the partisanship number lower than 2.82 were categorized to have a stronger Democratic party base. In other words, according to Hypothesis 1, states with the partisanship number higher (lower) than 2.82 are expected to have a higher percentage of democratic (republican) candidate appearances. It is shown on Table 4.4 that in the 1992 U.S. Presidential election, twenty-three battlegrounds received candidate appearances. Of these, fifteen are consistent with Hypothesis 1: CT, OR, ME, MO, GA, FL, and NC have partisanship numbers higher than 2.82 and also have higher percentages of democratic candidate appearances, and TN, LA, NM, WI, PA, AL, TX, and MT have partisanship numbers lower than 2.82 and also have higher percentages of republican candidate appearances. In other words, more than 65 percent of states in the 1992 U.S. Presidential election are consistent with Hypothesis 1. With the same idea, Table 4.4 shows more than 72 percent of states in the 1996 U.S. Presidential election are consistent with Hypothesis 1.

Table 4.2: Candidate Appearances in Base Democratic States, 1988, 1992, and 1996

	1996		1992		1988	
State	Rep. App.	Dem. App.	Rep. App.	Dem. App.	Rep. App.	Dem. App.
AR	0	2.4	0	2.15	-	-
CA	-[a]	-	1.12	3.23	-	-
CT	2.21	0.8	-	-	-	-
DC	5.15	10.4	0	0	0.88	4
DE	0	0	-	-	-	-
HI	0	0	0	0	0	0
IL	-	-	2.25	3.23	-	-
IA	2.21	1.6	1.12	1.08	0.88	0
MD	0	0	2.25	2.15	0.88	1.6
MA	0	1.6	1.12	1.08	2.63	9.6
ME	0	0.8	-	-	-	-
MN	0	0.8	0	0	0	0
NY	0.74	5.6	1.12	2.15	-	-
OR	0	1.6	-	-	-	-
RI	0	0.8	0	0	0	0.8
VT	0	0	0	1.08	-	-
WA	0	1.6	-	-	-	-
WI	0	0.8	-	-	-	-
WV	0	0.8	0	0	0	0
Number of Base Democratic states	17		13		8	
Number of states w/ candidate app.	13		8		5	
Number of states w/ more Dem. app.	11		5		4	
Fit of Hypothesis 2	0.846		0.625		0.8	

[a] The sign "-" means that Shaw (1999b) does not categorize this state into "Base Democratic" in the 1988, 1992, or 1996 U.S. presidential election.

Table 4.3: Candidate Appearances in Base Republican States, 1988, 1992, and 1996

	1996		1992		1988	
State	Rep. App.	Dem. App.	Rep. App.	Dem. App.	Rep. App.	Dem. App.
AL	0.74	0.8	-	-	0	0
AK	0	0	0	0	0	0
AR	-[a]	-	-	-	0.88	0.8
AZ	-	-	0	0	0	0
CO	-	-	-	-	4.39	3.2
FL	-	-	-	-	0	0
GA	-	-	-	-	0	0
LA	-	-	-	-	0	1.6
ID	0	0	0	0	0	0
IN	0	0	0	2.15	0.88	0
KS	2.21	0	0	0	0	0
KY	-	-	-	-	3.51	1.6
MS	0	0	1.12	1.08	0	0
MT	0	0	-	-	0.88	0.8
NE	0.74	0	0	1.08	0.88	0
NV	-	-	0	1.08	0	0
NH	-	-	0	0	0	0
NM	-	-	-	-	0.88	0
NC	1.47	0.8	-	-	0.88	1.6
ND	0	0	0	0	0	0
OK	0	0	2.25	0	0.88	0
SC	0.74	0	1.12	2.15	0	0
SD	-	-	-	-	0.88	2.4
TN	-	-	-	-	0.88	0.8
TX	1.47	3.2	-	-	-	-
UT	0.74	0	1.12	1.08	0	0
VA	-	-	3.37	3.23	0	0.8
WY	0	5.6	0	0	0	0
Number of Base Democratic states	15		15		27	
Number of states w/ candidate app.	10		8		14	
Number of states w/ more Dem. app.	7		4		11	
Fit of Hypothesis 2	0.7		0.5		0.786	

[a] The sign "-" means that Shaw (1999b) does not categorize this state into "Base Republican" in the 1988, 1992, or 1996 U.S. presidential election.

Table 4.4: Candidate Appearances in Battleground States, 1992 and 1996

State	Partisanship	1996 Rep. App.	1996 Dem. App.	1992 Rep. App.	1992 Dem. App.
AL	2.80	-[a]	-	1.12	0
AZ	3.24	2.21	3.2	-	-
CA	2.66	16.91	7.2	-	-
CO	3.15	4.41	4.8	2.25	2.15
CT	2.97	-	-	1.12	2.15
DE	3.09	-	-	1.12	1.08
FL	3.26	8.09	4	3.37	5.38
GA	2.82	4.41	0.8	3.37	5.38
IL	2.90	4.41	4	-	-
KY	2.85	3.68	4	4.49	3.23
LA	2.58	2.94	1.6	4.49	2.15
MI	3.02	3.68	4.8	10.11	8.6
ME	2.90	-	-	0	1.08
MO	2.80	3.68	2.4	5.62	6.45
MT	2.78	0	0	1.12	0
NV	3.33	2.21	0.8	-	-
NH	3.24	0.74	2.4	-	-
NJ	3.15	4.41	2.4	5.62	5.38
NM	2.55	2.21	4	2.25	2.15
NC	2.94	-	-	3.37	5.38
OH	2.69	6.62	8	6.74	7.53
OK	2.51	-	-	2.25	0
OR	2.91	-	-	1.12	2.15
PA	2.75	3.68	1.6	4.49	3.23
SD	3.06	0.74	1.6	2.25	1.08
TN	2.79	4.41	1.6	3.37	0
TX	2.91	-	-	7.87	2.15
WA	2.91	-	-	1.12	1.08
WI	2.63	-	-	5.62	4.3
Number of battleground states		19		23	
Number of states w/ candidate app.		18		23	
Number of states w/ Party Id < 2.82 and more Rep. app. or w/ Party Id > 2.82 and more Dem. app.		13		15	
Fit of Hypothesis 1		0.722		0.652	

[a] The sign "-" means that Shaw (1999b) does not categorize this state into "Lean Republican," "Battleground," or "Lean Democratic" in the 1992 or 1996 U.S. presidential election.

4.5 Conclusion

This paper investigates candidates' rallying strategies in two-party races. It views campaign rallies as an information-revealing mechanism that allows candidates to project images of strong current support among voters. Compared with previous studies on campaign effects, this research starts from investigating voting behavior based on the Palfrey and Rosenthal (1985) (P-R) pivotal voter model. Then, the mechanism through which the support is shown in rallies is demonstrated through the informational impact in the P-R pivotal voter model.

There are two types of voters in the model: base supporters (those who always turn out to vote for their preferred candidates) and passive supporters (those who vote strategically). The idea is that if a candidate holds a rally, base supporters will automatically attend the rally organized by the candidate they support, but passive supporters will stay away. Hence, by holding a rally, candidates and supporters learn the realized number of the base supporters. Afterwards, passive supporters decide whether or not to vote based on their observations of rally outcomes. Therefore, candidates can use rallies to disseminate information about their chances of winning to make passive supporters believe that their votes will change the election outcome, leading to their willingness to vote.

According to the model, two hypotheses are derived: (1) when the sizes of the two parties are equal but base support is unequal, the party with a smaller probability of strong base support is more likely to hold a rally, and (2) when two parties are different in size but have the same chances of strong base support, the larger party is more likely to hold a rally. To test the hypotheses, three U.S. Presidential elections (1988, 1992, and 1996) are studied. Empirical analysis of these three elections shows that in most of the battleground states, if partisanship leans to the Democratic (Republican), the Republican (Democratic) Party organized more candidate appearances than the Democratic (Republican) Party did, supporting Hypothesis 1. The empirical data also show that in most of the Base Democratic (Republican) states, the Democratic (Republican) Party organized more candidate appearances than the Republican (Democratic) Party did, supporting Hypothesis 2.

Appendix A

Appendix for Chapter 1

A.1 Proof of Proposition 1

For a player i of a team, say team A, given that there are N_A contributors on team A and N_B contributors on team B. If i is a contributor and team A wins the competition, i's utility is equal to i's material payoff minus some disutility that is generated by the difference between i's payoff and the payoff of free-riders,

$$\left(\frac{g}{n}N_A + \frac{g}{n}N_B\right);$$

if team A loses the competition, i's utility is 0.

On the other hand, if i is a free-rider and team A wins the competition, i's utility is equal to i's material payoff minus some disutility that is generated by the difference between i's payoff and the payoff of contributors,

$$\left(1 + \frac{g}{n}N_A + \frac{g}{n}N_B\right);$$

if team A loses the competition, i's utility is 1.

To analyze the equilibria, let N_A^*, N_B^* denote the number of contributors on team A and the number of contributors on team B, respectively, in equilibrium. Then, for a contributor i, the necessary and sufficient condition for the equilibrium is

$$\left\{(\frac{1}{2}+\frac{N_A^*-N_B^*}{2n})(\frac{g}{n}N_A^*+\frac{g}{n}N_B^*)+(\frac{1}{2}+\frac{N_B^*-N_A^*}{2n})(0)\right\}$$
$$-\left\{(\frac{1}{2}+\frac{(N_A^*-1)-N_B^*}{2n})(1+\frac{g}{n}(N_A^*-1)+\frac{g}{n}N_B^*)+(\frac{1}{2}+\frac{N_B^*-(N_A^*-1)}{2n})(1)\right\}\geqslant 0 \qquad (1a)$$

Similarly, for a free-rider i, the necessary and sufficient condition for the equilibrium is

$$\left\{(\frac{1}{2}+\frac{N_A^*-N_B^*}{2n})(1+\frac{g}{n}N_A^*+\frac{g}{n}N_B^*)+(\frac{1}{2}+\frac{N_B^*-N_A^*}{2n})(1)\right\}$$
$$-\left\{(\frac{1}{2}+\frac{(N_A^*+1)-N_B^*}{2n})(0+\frac{g}{n}(N_A^*+1)+\frac{g}{n}N_B^*)+(\frac{1}{2}+\frac{N_B^*-(N_A^*+1)}{2n})(0)\right\}\geqslant 0 \qquad (2a)$$

In the same way, we can get similar equilibrium conditions for a player on team B with the exchange N_A^* and N_B^*.

There are potentially two types of symmetric equilibria. One type has $N_A^*=N_B^*=0$, and one has $N_A^*=N_B^*=n$. The first is that no player chooses to contribute the token to the common account in equilibrium; i.e., all players are free-riders. Substituting $N_A^*=N_B^*=0$ into (2a), the necessary and sufficient condition for this equilibrium is

$$\frac{g}{n}\leqslant\frac{2n}{n+1}.$$

Next, consider the equilibrium where $N_A^*=N_B^*=n$, which is that every player chooses to contribute the token in equilibrium; i.e., all players are contributors. Substituting $N_A^*=N_B^*=n$ into (1a), the necessary and sufficient condition for this equilibrium is

$$\frac{g}{n}\geqslant\frac{2n}{3n-1}.$$

A.2 Proof of Proposition 2

When the parameter γ_i is considered, for a contributor i, the condition that should be satisfied in equilibrium becomes

$$\left\{(\frac{1}{2}+\frac{N_A^*-N_B^*}{2n})(\frac{g}{n}N_A^*+\frac{g}{n}N_B^*)+(\frac{1}{2}+\frac{N_B^*-N_A^*}{2n})(0)\right\}$$
$$-\left\{(\frac{1}{2}+\frac{(N_A^*-1)-N_B^*}{2n})(1+\frac{g}{n}(N_A^*-1)+\frac{g}{n}N_B^*)+(\frac{1}{2}+\frac{N_B^*-(N_A^*-1)}{2n})(1)-\gamma_i\right\}\geqslant 0,$$

while the condition for a free-rider i is the same as what has been shown in the proof for Proposition 1. Then, following the same ideas presented in the proof for Proposition 1, we can prove Proposition 2(a) and Proposition 2(b).

A.3 Experimental Data at the Individual Level

Eighty participants participated in the TT treatment. For each participant i, let J denote i's belief about the number of contributors (not including i) on i's own team and K denote and the the number of contributors on i's competing team. Given a pair of (J, K), I define "the percentage of contributions in the (J, K) situation" for i as

$$\frac{\#\text{ obs. that } i \text{ contributed in the } (J,K) \text{ situation}}{\#\text{ obs. that } i \text{ in the } (J,K) \text{ situation}}.$$

Among the 80 participants, 21 participants always stated $J < K$ and contributed (Table A.1), and 14 participants always stated $J \geqslant K$ and never contributed (Table A.2). Let C_i^{JK} denote the percentage of contributions of i when $J \geqslant K$ and C_i^{KJ} denote the percentage of contributions of i when $J < K$. Thirty-one participants were with $C_i^{JK} < C_i^{KJ}$. More importantly, they always contributed when $J < K$ and seldom contributed when $J \geqslant K$ (Table A.3). Fourteen participants were with $C_i^{JK} \geqslant C_i^{KJ}$. As shown in Table A.4, they did not show a significant difference in contribution between when $J < K$ and when $J \geqslant K$. In summary, most of the participants were substantially more willing to contribute when $J < K$ than when $J \geqslant K$, and this contribution behavior did not change with the sizes of J and K.

Table A.1: Percentage of beliefs of the participants who always contributed

K, J	0	1	2	3
0	0	0	0	0
1	0	0.043	0.010	0
2	0.014	0.15	0.143	0.033
3	0	0.024	0.410	0.048
4	0	0.005	0.024	0.095

* This table presents the percentages of beliefs of the participants who always contributed. For example, when $J = K = 2$, the number in the table is 0.143. It means that 30 observations reported $J = K = 2$, leading to a percentage of 0.143, or $\frac{30}{210}$.

Table A.2: Percentage of beliefs of the participants who never contributed

K, J	0	1	2	3
0	0.214	0.007	0	0
1	0.014	0.2	0.014	0
2	0	0.093	0.307	0.007
3	0	0	0.029	0.093
4	0.014	0	0	0.007

* This table presents the percentage of beliefs of the participants who never contributed. For example, when $J = K = 2$, the number in the table is 0.307. It means that 43 observations reported $J = K = 2$, leading to a percentage of 0.307, or $\frac{43}{140}$.

Table A.3: Percentage of contributions of the participants with $C_i^{JK} < C_i^{KJ}$

K, J	0	1	2	3
0	0.17, $\frac{1}{6}$	0.00, $\frac{0}{1}$	0.00, $\frac{0}{1}$	1.00, $\frac{1}{1}$
1	0.83, $\frac{5}{6}$	0.05, $\frac{1}{20}$	0.00, $\frac{0}{4}$	0.00, $\frac{0}{1}$
2	-, $\frac{0}{0}$	0.68, $\frac{28}{41}$	0.18, $\frac{10}{57}$	0.00, $\frac{0}{3}$
3	1.00, $\frac{2}{2}$	0.75, $\frac{3}{4}$	0.73, $\frac{55}{75}$	0.14, $\frac{5}{37}$
4	-, $\frac{0}{0}$	1.00, $\frac{1}{1}$	1.00, $\frac{6}{6}$	0.93, $\frac{13}{14}$

* This table presents the percentages of contributions of the participants with $C_i^{JK} < C_i^{KJ}$. For example, when $J = K = 2$, the numbers in the table are 0.18 and $\frac{10}{57}$. It means that there are 57 observations reporting $J = K = 2$, and the contribution percentage is 0.18, or $\frac{10}{57}$.

Table A.4: Percentage of contributions of the participants with $C_i^{JK} \geqslant C_i^{KJ}$

K, J	0	1	2	3
0	1.00, $\frac{2}{2}$	0.00, $\frac{0}{1}$	1.00, $\frac{1}{1}$	-, $\frac{0}{0}$
1	0.33, $\frac{1}{3}$	0.75, $\frac{6}{8}$	0.67, $\frac{6}{9}$	1.00, $\frac{1}{1}$
2	0.00, $\frac{0}{3}$	0.48, $\frac{12}{25}$	0.52, $\frac{14}{27}$	0.70, $\frac{7}{10}$
3	1.00, $\frac{1}{1}$	0.55, $\frac{5}{9}$	0.57, $\frac{12}{21}$	0.47, $\frac{8}{17}$
4	0.33, $\frac{1}{3}$	0.50, $\frac{1}{2}$	-, $\frac{0}{0}$	1.00, $\frac{7}{7}$

* This table presents the percentages of contributions of the participants with $C_i^{JK} \geqslant C_i^{KJ}$. For example, when $J = K = 2$, the numbers in the table are 0.52 and $\frac{14}{27}$. It means that there are 27 observations reporting $J = K = 2$, and the contribution percentage is 0.52, or $\frac{14}{27}$.

A.4 Estimation and Quantal Response Equilibrium

In the following model I use player i on team A as an example. Recall that in the team tournament model, teams compete against each other for prizes that are shared equally among team members. The set of competition outcomes to player i is denoted by $C_1 = \{w, l\}$ if i chooses to contribute and is denoted by $C_0 = \{w, l\}$ if i chooses not to contribute, where w represents that team A wins the competition and l represents that team A loses the competition. Suppose that there are J contributors (not including i) on team A and K contributors on team B. Then, the set of events to player i is denoted by $Z = C_1 \times C_0$. Let $P_{JK}^A = \{p_{bd}^A(J, K) : b \in C_1, d \in C_0\}$ be the set of probability measures on Z where $p_{bd}^A(J, K)$ is calculated by the distribution function $F(\epsilon^h)$ that satisfies equation (2.3) and

$\sum_{b\in C_1}\sum_{d\in C_0} p^A_{bd}(J,K) = 1$. More specifically, according to equation (2.3),

$$\begin{aligned}
P^A_{ww}(J,K) &= \int\int I\{[y^A > y^B|J,K,x^A_i = 1]\bigcap[y^A > y^B|J,K,x^A_i = 0]\}d\epsilon^A d\epsilon^B \\
&= \int\int I\{[\epsilon^B - \epsilon^A < 1 + J - K]\bigcap[\epsilon^B - \epsilon^A < J - K]\}d\epsilon^A d\epsilon^B \\
&= \int\int I\{\epsilon^B - \epsilon^A < J - K\}d\epsilon^A d\epsilon^B \\
&= Pr(\epsilon^B - \epsilon^A < J - K) = \frac{1}{2} + \frac{J-K}{2n},
\end{aligned}$$

$$\begin{aligned}
P^A_{ll}(J,K) &= \int\int I\{[y^A < y^B|J,K,x^A_i = 1]\bigcap[y^A < y^B|J,K,x^A_i = 0]\}d\epsilon^A d\epsilon^B \\
&= \int\int I\{[\epsilon^B - \epsilon^A > 1 + J - K]\bigcap[\epsilon^B - \epsilon^A > J - K]\}d\epsilon^A d\epsilon^B \\
&= \int\int I\{\epsilon^B - \epsilon^A > 1 + J - K\}d\epsilon^A d\epsilon^B \\
&= 1 - Pr(\epsilon^B - \epsilon^A < K - J - 1) = \frac{1}{2} + \frac{K-J-1}{2n},
\end{aligned}$$

$$\begin{aligned}
P^A_{lw}(J,K) &= \int\int I\{[y^A < y^B|J,K,x^A_i = 1]\bigcap[y^A > y^B|J,K,x^A_i = 0]\}d\epsilon^A d\epsilon^B \\
&= \int\int I\{[\epsilon^B - \epsilon^A > 1 + J - K]\bigcap[\epsilon^B - \epsilon^A < J - K]\}d\epsilon^A d\epsilon^B = 0,
\end{aligned}$$

$$\begin{aligned}
P^A_{wl}(J,K) &= \int\int I\{[y^A > y^B|J,K,x^A_i = 1]\bigcap[y^A < y^B|J,K,x^A_i = 0]\}d\epsilon^A d\epsilon^B \\
&= 1 - P^A_{ww}(J,K) - P^A_{ll}(J,K) - P^A_{lw}(J,K) = \frac{1}{2n}.
\end{aligned}$$

For an element $(b,d) \in Z$, let $u^A_{bdi1}(J,K,\gamma_i)$ denote i's payoff when i chooses to contribute and the event is (b,d). Similarly, let $u^A_{bdi0}(J,K,\gamma_i)$ denote i's payoff when i chooses not to contribute. Therefore, given that there are J contributors (not including i) on team

A and K contributors on team B, if i decides to contribute effort, the expected payoff (denoted as $EU_C^A(\gamma)$ in the main text) will be

$$u_{i1}^A(J,K,\gamma_i) = \sum_{b\in C_1}\sum_{d\in C_0} p_{bd}^A(J,K) \times u_{bdi1}^A(J,K,\gamma_i), \tag{A.1}$$

where $u_{bdi1}^A(J,K,\gamma_i)$ can be calculated according to equations (2.4) and (2.5). To allow a small amount of bounded rationality, let

$$\hat{u}_{ia}^A(J,K,\gamma_i) = u_{ia}^A(J,K,\gamma_i) + \eta_{ia}^A$$

where the vector of perturbations $\eta_i^A = (\eta_{i1}^A, \eta_{i0}^A)$ is drawn from a joint density f_i. Based on individual choice behavior research (Luce (1959); McFadden (1973); McKelvey and Palfrey (1995)), assume that every η_{ia}^A is an independent draw from an extreme value distribution with cumulative density function $F_i(\eta_{ia}^A) = e^{-e^{-\lambda\eta_{ia}^A-\alpha}}$, where α is Euler's constant, and η_{ia}^A is i.i.d. across all a yielding the logit choice probabilities. Therefore, given that there are J contributors (not including i) on team A and K contributors on team B, the probability that i decides to contribute effort is

$$Pr(\hat{u}_{i1}^A(J,K,\gamma_i) \geqslant \hat{u}_{i0}^A(J,K,\gamma_i)) = \frac{e^{\lambda u_{i1}^A(J,K,\gamma_i)}}{e^{\lambda u_{i1}^A(J,K,\gamma_i)} + e^{\lambda u_{i0}^A(J,K,\gamma_i)}}. \tag{A.2}$$

Let $\sigma_{i1}^A(J,K,\gamma_i,\lambda)$ denote the probability that i contributes effort. Note that the parameter λ is the inverse of the error level.

From the experiment I derived each participant's decision–s_{ia}^h, $i = 1,...,n$, $a \in \{1,0\}$, $h \in \{A,B\}$, and each participant's beliefs about the number of contributors on his or her own team and the number of contributors on the competing team–j_i^h and k_i^h for each period. Given these observations, the parameters γ_i and λ can be estimated by a maximum likelihood method. However, it is difficult to obtain accurate estimates of these subject-specific parameters for each individual since the data were insufficient. Hence, I assumed that $\gamma_i = \gamma$ for all participants. The maximum likelihood estimates of γ and λ then can be obtained by the following log-likelihood function:

$$\ln L(\gamma, \lambda | s_{i1}^h, j_i^h, k_i^h) = \sum_{h \in \{A,B\}} \sum_{i=1}^{n} s_{i1}^h \ln \left[\sigma_{i1}^h (j_i^h, k_i^h, \gamma, \lambda) \right] + (1 - s_{i1}^h) \ln \left[(1 - \sigma_{i1}^h (j_i^h, k_i^h, \gamma, \lambda)) \right]. \tag{A.3}$$

Next, I show how to calculate the quantal response equilibrium (QRE). Let the set of pure strategies available to player i on team A to be denoted by $S_i^A = \{s_{i1}^A, s_{i0}^A\}$, with $S = \times_i^h S_i^h$ and $h \in \{A, B\}$, where s_{i1}^A means that i chooses to contribute effort, and s_{i0}^A indicates no contribution. Let Δ_i^A denote the set of all probability measures on S_i^A. Let $\Delta = \times_i^h \Delta_i^h$ denote the set of probability measures on S, with elements $q = (q_1^A, ..., q_n^A, q_1^B, ..., q_n^B)$. For simplicity, let q_{ia}^A represent $q_i^A(s_{ia}^A)$. Consider a symmetric QRE, where $q_{i1}^h = \pi$ for $i = 1, ..., n$ and $h \in \{A, B\}$. Then, in equilibrium the probability that player i chooses to contribute effort becomes

$$q_{i1}^A = \pi = \sum_{k=1}^{n} \sum_{j=1}^{n-1} \pi^{j+k} (1-\pi)^{2n-1-j-k} \binom{n-1}{j} \binom{n}{k} \times \sigma_{i1}^A (j, k, \gamma, \lambda). \tag{A.4}$$

Appendix B

Appendix for Chapter 2

B.1 Figures and Tables

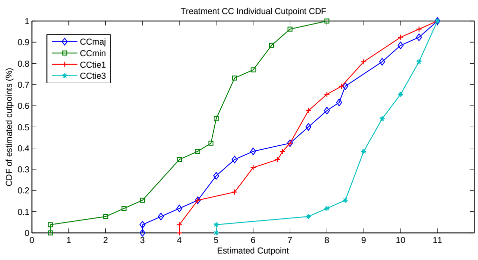

Figure B.1: Treatment CC Cutpoint CDF

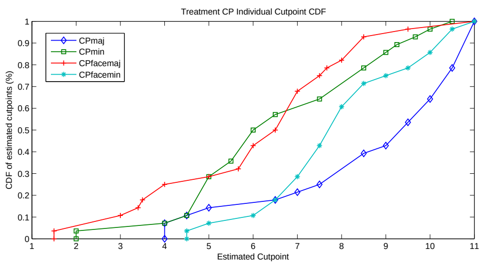

Figure B.2: Treatment CP Cutpoint CDF

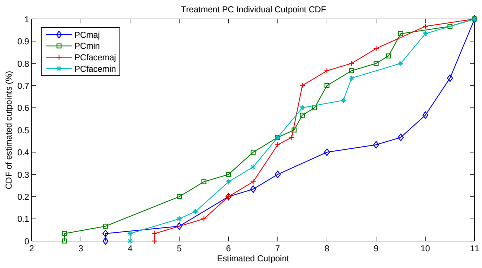

Figure B.3: Treatment *PC* Cutpoint CDF

Table B.1: Fraction of Positive Paired Cutoff Differences

Within-Subject Competition Effect			
CCTie1 − CCMajority	*CCTie1 − CCMinority*	*CCTie3 − CCMajority*	*CCTie3 − CCMinority*
0.462 (0.1)	0.731 (2.6)	0.769 (2.2)	0.962 (4.6)

Within-Subject Size Effect	Within-Subject Underdog Effect
CCTie3 − CCTie1	*CCMinority − CCMajority*
0.808 (2.1)	0.192 (-2.5)

Note: With the estimated cutpoint for each subject, I followed Table 6 of Levine and Palfrey (2007) to consider the difference in each subject's cutpoint between being in different situations in the *CC* treatment, and calculate the fraction of these differences that are positive to test H1-H3. As can be seen, when subjects were in *CCMajority*, their cutpoints were higher than the Nash equilibrium prediction, leading to failure to support the hypotheses of the *CCTie1 − CCMajority* competition effect and the underdog effect. This finding is consistent with the analysis of H1-H3 hypotheses at the aggregate level. (Average difference in parentheses.)

Table B.2: Probit Regressions (Marginal Effects Reported): No *Majority* Situation

Dependent variable: *Vote*	*CC*	*CP*	*PC*
Voting Cost	-0.130***	-0.168***	-0.140***
	(0.0153)	(0.0163)	(0.0132)
Period	-0.00429**	-0.00297	0.000621
	(0.00204)	(0.00198)	(0.00176)
Belief of being Pivotal	0.207**	0.530***	0.184*
	(0.0998)	(0.124)	(0.102)
Voted at t-1	0.00251	-0.00164	0.0983
	(0.0591)	(0.0755)	(0.0766)
Won at t-1	-0.00372	-0.0162***	-0.00655
	(0.00310)	(0.00518)	(0.00409)
Voted and Won at t-1	0.00705	0.0152***	0.00243
	(0.00457)	(0.00526)	(0.00579)
Tie1 Situation	-0.333***		
	(0.0765)		
Minority Situation	-0.662***	0.0470	0.0135
	(0.0927)	(0.0661)	(0.0515)
FaceMinority Situation		0.195***	0.0817
		(0.0525)	(0.0574)
N	808	809	830

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

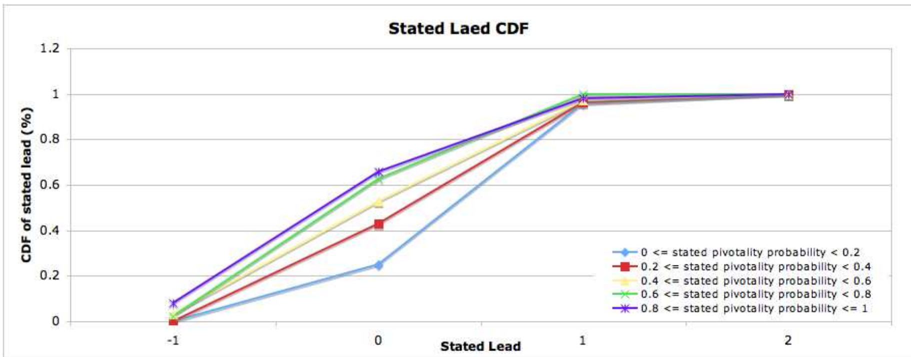

Figure B.4: Stated Lead CDF: *CCMajority*

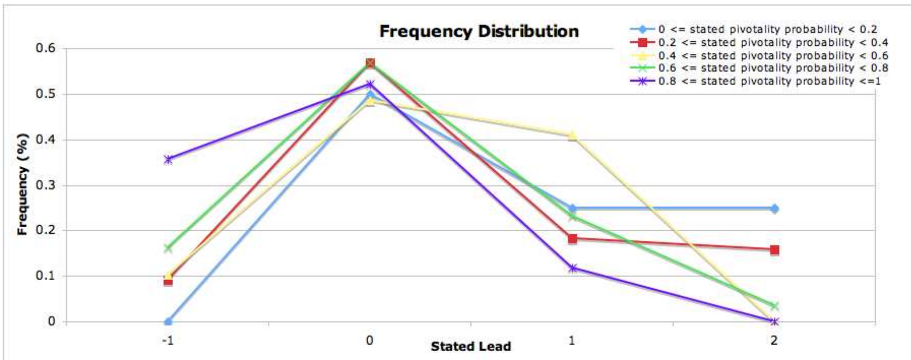

Figure B.5: Frequency Distribution of Stated Leads: *CPMajority*

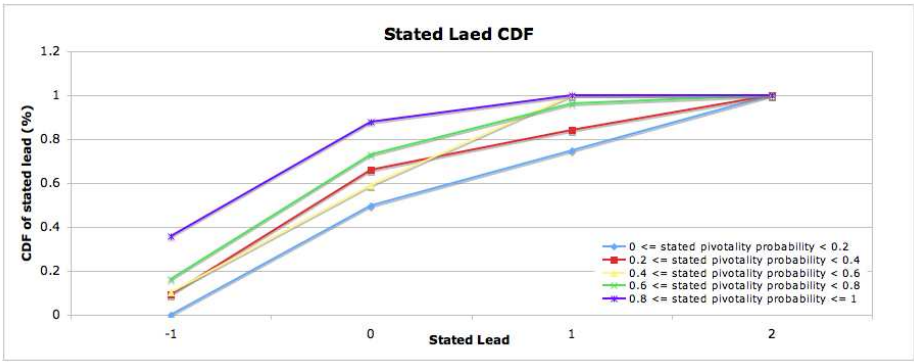

Figure B.6: Stated Lead CDF: *CPMajority*

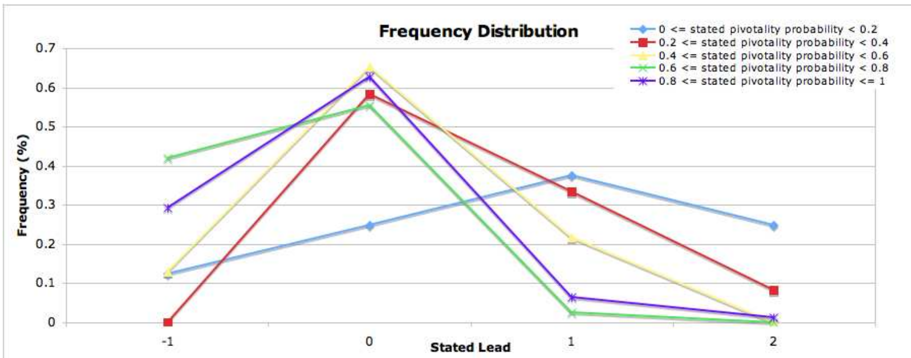

Figure B.7: Frequency Distribution of Stated Leads: *PCMajority*

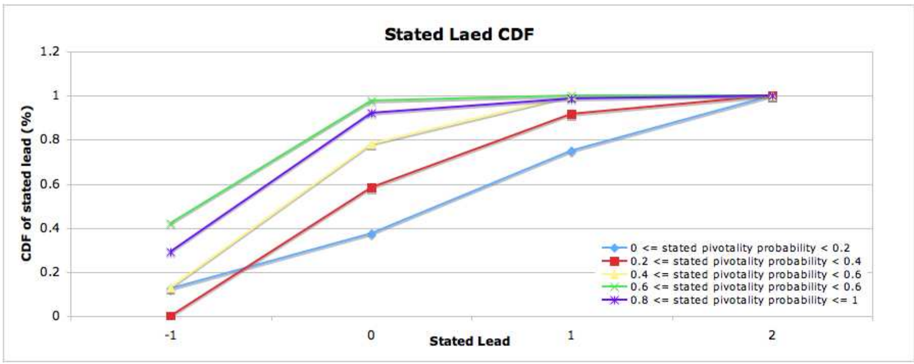

Figure B.8: Stated Lead CDF: *PCMajority*

Appendix C

Appendix for Chapter 3

C.1 The Conditional Winning Probabilities

First, if there are n passive supporters, and each passive supporter has a probability p of voting, then the probability of an event in which exactly k passive supporters turn out to vote is denoted as

$$P_p(k|p, n) = \binom{n}{k} p^k (1-p)^{n-k}.$$

Note that in the case that $n = 0$, p is not well-defined since there are no passive supporters. In such cases, $P_p(k|p, n) = 1$ and $\sum_k P_p(k|p, n) = 1$, thus ensuring that the formulas in the following sections are well-defined. Second, suppose there are n voters, and that each individual voter is either a base supporter (π probability) or passive supporter ($1 - \pi$ probability), and that each passive supporter turns out to vote with probability p. In this scenario, the probability of exactly k voters casting their ballots is denoted as

$$P_{all}(k|p, \pi, n) = \sum_{x=0}^{k} \binom{n}{x, k-x, n-k} \pi^x ((1-\pi)p)^{k-x} ((1-\pi)(1-p))^{n-k}.$$

C.1.1 Both Candidates Hold Rallies

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.

Given R_1 base supporters attending the rally held by candidate 1 and R_2 base supporters attending the rally held by candidate 2, the probability of a passive supporter in party T_1 or T_2 making or breaking a tie is expressed as

$$\begin{aligned} q_1^* = & \sum_{k=\max\{R_1,R_2\}}^{\min\{N_1-1,N_2\}} \left\{ \; P_p(k - R_1|p_1^*, N_1 - R_1 - 1) \cdot P_p(k - R_2|p_2^*, N_2 - R_2) \; \right\} \\ & + \sum_{k=r_1}^{\min\{N_1-1,N_2-1\}} \left\{ \; P_p(k - R_1|p_1,^* N_1 - R_1 - 1) \cdot P_p(k + 1 - R_2|p_2^*, N_2 - R_2) \; \right\} \end{aligned} \quad \text{(C.1)}$$

$$\begin{aligned} q_2^* = & \sum_{k=\max\{R_1,R_2\}}^{\min\{N_1,N_2-1\}} \left\{ \; P_p(k - R_2|p_2^*, N_2 - R_2 - 1) \cdot P_p(k - R_1|p_1^*, N_1 - R_1) \; \right\} \\ & + \sum_{k=r_2}^{\min\{N_1-1,N_2-1\}} \left\{ \; P_p(k - R_2|p_2^*, N_2 - R_2 - 1) \cdot P_p(k + 1 - R_1|p_1^*, N_1 - R_1) \; \right\} \end{aligned} \quad \text{(C.2)}$$

where $r_i = \max\{R_1, R_2\} - 1$ if $R_i < R_j$, otherwise $r_i = \max\{R_1, R_2\}$. From equations (4.1)-(4.4), (C.1) and (C.2) it is possible to solve the aggregate voting probability of passive supporters for each party, (p_1^*, p_2^*).

When both candidates conduct rallies in the first stage and when $R_1 = N_1$ and $R_2 = N_2$, $Prob_1(tie|R_1, R_2) = 1$ if $N_1 = N_2$, $Prob_1(win|R_1, R_2) = 1$ if $N_1 > N_2$ and $Prob_1(lose|R_1, R_2) = 1$ if $N_1 < N_2$. In all other cases,

$$Prob_1(tie|R_1, R_2) = \sum_{k=\max\{R_1,R_2\}}^{\min\{N_1,N_2\}} \left\{ \; P_p(k - R_1|p_1^*, N_1 - R_1) \cdot P_p(k - R_2|p_2^*, N_2 - R_2) \; \right\},$$

$$Prob_1(win|R_1, R_2) = \sum_{k=r}^{N_1} \left\{ \; P_p(k - R_1|p_1^*, N_1 - R_1) \cdot \textstyle\sum_{y=1}^{N_1} P_p(k - y - R_2|p_2^*, N_2 - R_2) \; \right\},$$

where $r = \max\{R_1, R_2+1\}$ if $R_2 = N_2$, otherwise $r = R_1$.

C.1.2 Only One Candidate Holds a Rally

Let (c_1^{**}, c_2^{**}), (p_1^{**}, p_2^{**}) and (q_1^{**}, q_2^{**}) be the equilibrium values of $(\hat{c}_1, \hat{c}_2)$, $(\hat{p}_1, \hat{p}_2)$ and $(\hat{q}_1, \hat{q}_2)$ respectively.

Without loss of generality, assume that candidate 1 conducts a rally and candidate 2 does not. Recall that a randomly chosen voter in T_2 may be a base supporter (π_2 probability) or a passive supporter ($1-\pi_2$ probability). Given π_2 and R_1 base supporters attending the candidate 1 rally, equations (C.1) and (C.2) become

$$\begin{aligned} q_1^{**} = & \sum_{k=R_1}^{\min\{N_1-1, N_2\}} \left\{ P_p(k-R_1|p_1^{**}, N_1-R_1-1) \cdot P_{all}(k|p_2^{**}, \pi_2, N_2) \right\} \\ + & \sum_{k=R_1}^{\min\{N_1-1, N_2-1\}} \left\{ P_p(k-R_1|p_1^{**}, N_1-R_1-1) \cdot P_{all}(k+1|p_2^{**}, \pi_2, N_2) \right\} \end{aligned} \tag{C.3}$$

$$\begin{aligned} q_2^{**} = & \sum_{k=R_1}^{\min\{N_1, N_2-1\}} \left\{ P_{all}(k|p_2^{**}, \pi_2, N_2-1) \cdot P_p(k-R_1|p_1^{**}, N_1-R_1) \right\} \\ + & \sum_{k=\max\{R_1-1,0\}}^{\min\{N_1-1, N_2-1\}} \left\{ P_{all}(k|p_2^{**}, \pi_2, N_2-1) \cdot P_p(k+1-R_1|p_1^{**}, N_1-R_1) \right\} \end{aligned} \tag{C.4}$$

According to equations (4.1)-(4.4), (C.3) and (C.4), it is possible to solve the aggregate voting probability for passive supporters in each party, (p_1^{**}, p_2^{**}), in this case.

Given that candidate 1 holds a rally and candidate 2 does not,

$$Prob_1(tie|R_1,\emptyset) = \sum_{k=R_1}^{\min\{N_1,N_2\}} \left\{ P_p(k-R_1|p_1^{**},N_1-R_1)\cdot P_{all}(k|p_2^{**},\pi_2,N_2) \right\},$$

$$Prob_1(win|R_1,\emptyset) = \sum_{k=R_1}^{N_1} \left\{ P_p(k-R_1|p_1^{**},N_1-R_1)\cdot \textstyle\sum_{y=1}^{N_1} P_{all}(k-y|p_2^{**},\pi_2,N_2) \right\}.$$

C.1.3 Neither Candidate Holds a Rally

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

Given that a randomly chosen voter in T_1 may be a base supporter (π_1 probability) or a passive supporter ($1-\pi_1$ probability), and a randomly chosen voter in T_2 may be a base supporter (π_2 probability) or a passive supporter ($1-\pi_2$ probability), equations (C.1) and (C.2) become

$$\begin{aligned}\tilde{q}_1 = & \sum_{k=0}^{\min\{N_1-1,N_2\}} \left\{ P_{all}(k|\tilde{p}_1,\pi_1,N_1-1)\cdot P_{all}(k|\tilde{p}_2,\pi_2,N_2) \right\} \\ & + \sum_{k=0}^{\min\{N_1-1,N_2-1\}} \left\{ P_{all}(k|\tilde{p}_1,\pi_1,N_1-1)\cdot P_{all}(k+1|\tilde{p}_2,\pi_2,N_2) \right\}\end{aligned} \tag{C.5}$$

$$\begin{aligned}\tilde{q}_2 = & \sum_{k=0}^{\min\{N_1,N_2-1\}} \left\{ P_{all}(k|\tilde{p}_2,\pi_2,N_2-1)\cdot P_{all}(k|\tilde{p}_1,\pi_1,N_1) \right\} \\ & + \sum_{k=0}^{\min\{N_1-1,N_2-1\}} \left\{ P_{all}(k|\tilde{p}_2,\pi_2,N_2-1)\cdot P_{all}(k+1|\tilde{p}_1,\pi_1,N_1) \right\}\end{aligned} \tag{C.6}$$

According to equations (4.1)-(4.4), (C.5) and (C.6), it is possible to solve the aggregate voting probability of passive supporters for each party, $(\tilde{p}_1,\tilde{p}_2)$, in this case.

If neither candidate holds a rally,

$$Prob_1(tie|\emptyset,\emptyset) = \sum_{k=0}^{\min\{N_1,N_2\}} \left\{ P_{all}(k|\tilde{p}_1,\pi_1,N_1) \cdot P_{all}(k|\tilde{p}_2,\pi_2,N_2) \right\},$$

$$Prob_1(win|\emptyset,\emptyset) = \sum_{k=1}^{N_1} \left\{ P_{all}(k|\tilde{p}_1,\pi_1,N_1) \cdot \sum_{y=1}^{N_1} P_{all}(k-y|\tilde{p}_2,\pi_2,N_2) \right\}.$$

C.2 Compute π_1 and π_2

Cheng (2007) use 2004 and 2005 TEDS data to show that base DPP supporters constituted approximately 20% of the electorate, and that the probability of a base DPP supporter voting for DPP candidates was approximately 90%, inferring that DPP base supporters represented approximately 18% of the electorate ($0.2 \times 0.9 = 0.18$). However, ratios of base supporters to electorates (hereafter, B/E ratio) can change over time, therefore for the 2008 presidential election we also calculated a B/E ratio based on 2008 TEDS data. TEDS data include Taiwanese consciousness and the party preference data, but not Taiwanese regime data. Using Cheng's method, for the party identification index we determined that 21.78% of 2008 voters were DPP identifiers. This figure was used as an upper boundary for DPP B/E ratio.

Since there is no existing data on KMT base supporters, I measured the ratio of KMT base supporters to the overall electorate by calculating Cheng's indices with 2008 TEDS data. For the first index (the Taiwanese and Chinese consciousness), the number of KMT base supporters identified from the Chinese consciousness data was approximately 5.1% of the electorate. The number of KMT identifiers according to the third index (party preferenc) was 27.47% of the electorate. Since TEDS does not have the necessary data for calculating the second index for 2008, it was assumed from the first and third indices that KMT base supporters constituted between 5.1% and 27.47% of the overall electorate.

The π_1 and π_2 values for the $N_2 = 2N_1$ case are computed in the following way. Since $\pi_1 \times N_1/\bar{N} = 0.18$, $\bar{N} = N_1 + N_2 = 3N_1$, $\pi_1 = 0.18 \times 3 = 0.55$. From $\pi_1 \times N_1/\bar{N} = 0.2178$, $\pi_1 = 0.6534$. Also, $\pi_2 \times N_2/\bar{N} = 0.051$, $N = N_1 + N_2 = 1.5N_2$ and $\pi_2 = 0.051 \times 1.5 = 0.0765$. From $\pi_2 \times N_2/\bar{N} = 0.2747$, $\pi_2 = 0.41205$. The π_1 and π_2 values for the $N_2 = N_1 + 1$ case are computed in the following way. According to Cheng (2007) Table 8, the DPP and KMT B/E ratios are ranged from 18.0%-23.8% and 6.3%-21.8%, respectively. Since $\pi_1 \times N_1/\bar{N} = 0.18$, $N = N_1 + N_2 = 2N_1 + 1$, $\pi_1 \approx 0.18 \times 2 = 0.36$. From $\pi_1 \times N_1/\bar{N} = 0.238$, $\pi_1 \approx 0.476$. Also, $\pi_2 \times N_2/\bar{N} = 0.063$, $\bar{N} = N_1 + N_2 = 2N_2 - 1$ and $\pi_2 \approx 0.063 \times 2 = 0.126$. From $\pi_2 \times N_2/\bar{N} = 0.218$, $\pi_2 \approx 0.436$.

Bibliography

Adams, J. Stacy. 1963. "Toward an Understanding of Inequity." *Journal of Abnormal and Social Psychology* 67 (5):422–36.

Agranov, Marina, Jacob K. Goeree, Julian Romero, and Leeat Yariv. 2012. "What Makes Voters Turn Out: The Effects of Polls and Beliefs."

Bornstein, Gary and Ido Erev. 1994. "The Enhancing Effect of Intergroup Competition on Group Performance." *International Journal of Conflict Management* 5 (3):271–283.

Cappelen, Alexander W., Astri Drange Hole, Erik Ø. Sø rensen, and Bertil Tungodden. 2007. "The Pluralism of Fairness Ideals: An Experimental Approach." *American Economic Review* 97 (3):818.

Cheng, Su-feng. 2007. "A Preliminary Study on Deep-Green Voters." *Questions and Research* 46 (1):33–57.

Clark, Cal. 2004. "Taiwan's 2004 Presidential Election: The End of Chen Shui-bian's "Strategic Ambiguity on Cross-Strait Relations?" *East Asia* 21 (4):25–37.

Downs, Anthony. 1957. *An Economic Theory of Democracy.* New York: Harper & Row.

Druckman, James N., Donald P. Green, James H. Kuklinski, and Lupia Arthur. 2011.

Cambridge Handbook of Experimental Political Science. New York: Cambridge University Press.

Duffy, John and Margit Tavits. 2008. "Beliefs and Voting Decisions : A Test of the Pivotal Voter Model." *American Journal of Political Science* 52 (3):603–618.

Erev, Ido, Gary Bornstein, and Rachely Galili. 1993. "Constructive Intergoup Competition as a Solution to the Free Rider Problem: A Field Experiment." *Journal of Experimental Social Psychology* 29:463–478.

Fehr, Ernst and Klaus M. Schmidt. 1999. "A Theory of Fairness, Competition, and Cooperation." *Quarterly journal of Economics* 114 (3):817–868.

Finkel, Steven E. and Peter R. Schrott. 1995. "Campaign Effects on Voter Choice in the German Election of 1990." *British Journal of Political Science* 25 (3):349–377.

Fischbacher, Urs. 2007. "z-Tree : Zurich toolbox for ready-made economic experiments." *Experimental Economics* 10 (2):171–178.

Gelman, Andrew, Nate Silver, and Aaron Edlin. 2012. "What Is the Probability Your Vote Will Make a Difference?" *Economic Inquiry* 50 (2):321–326.

Gerber, Alan S. and Donald P. Green. 2000. "The Effects of Canvassing, Telephone Calls, and Direct Mail on Voter Turnout: A Field Experiment." *American Political Science Review* :653–663.

Gonzalez-Diaz, Julio and Ignacio Palacios-Huerta. 2010. "Pawns of the Emotions: Psychological Elements in Cognitively Sophisticated Humans."

Grober, Jens and Arthur Schram. 2010. "Public Opinion Polls, Voter Turnout, and Welfare: An Experimental Study." *American Journal of Political Science* 54 (3):700–717.

Guillen, Pablo and Danielle Merrett. 2010. "Efficient Inter-Group Competition and the Provision of Public Goods."

Gunnthorsdottir, Anna and Amnon Rapoport. 2006. "Embedding social dilemmas in intergroup competition reduces free-riding." *Organizational Behavior and Human Decision Processes* 101 (2):184–199.

Halevy, Nir, Gary Bornstein, and Lilach Sagiv. 2008. ""In-Group Love" and "Out-Group Hate" as Motives for Individual Participation in Intergroup Conflict." *Psychological science* 19 (4):405–11.

Halevy, Nir, Eileen Y. Chou, Taya R. Cohen, and Gary Bornstein. 2010. "Relative Deprivation and Intergroup Competition." *Group Processes & Intergroup Relations* 13 (6):685–700.

Halevy, Nir, Ori Weisel, and Gary Bornstein. 2012. "In-Group Love and Out-Group Hate in Repeated Interaction Between Groups." *Journal of Behavioral Decision Making* 25 (2):188–195.

Holbrook, Thomas M. and Scott D. McClurg. 2005. "The Mobilization of Core Supporters: Campaigns, Turnout, and Electoral Composition in United States Presidential Elections." *American Journal of Political Science* 49 (4):689–703.

Holmstrom, Bengt. 1982. "Moral Hazard in Teams." *The Bell Journal of Economics* 13 (2):324–340.

Homans, George Caspar. 1974. *Social Behavior: Its Elementary Forms (Revised Edition).* New York: Harcourt Brace.

Kahneman, Daniel and Amos Tversky. 1972. "Subjective Probability: A Judgment of Representativeness." *Cognitive psychology* 3:430–454.

Karni, Edi. 2009. "A Mechanism for Eliciting Probabilities." *Econometrica* 77 (2):603–606.

Klor, Esteban F. and Eyal Winter. 2006. "The Welfare Effects of Public Opinion Polls." *International Journal of Game Theory* 35 (3):379–394.

Kreps, David M., Paul Milgrom, John Roberts, and Robert Wilson. 1982. "Rational Cooperation in the Finitely Repeated Prisoners' Dilemma." *Journal of Economic Theory* 27 (2):245–252.

Krumer, Alex. 2013. "Best-of-Two Contests with Psychological Effects." *Theory and Decision* 75 (1):85–100.

Lazarsfeld, PF, B Berelson, and H. Gaudet. 1944. *The people's choice*. 111. New York: Columbia University Press.

Levine, David K. and Thomas R. Palfrey. 2007. "The Paradox of Voter Participation? A Laboratory Study." *American Political Science Review* 101 (1):143.

Lin, Jun-Ting. 2009. *Xuanju zaoshi huodong dui xuanmin toupiao xingwei yingxiang zhi yanjiu (The Effects of Rallies on Voting Behavior)*. Ph.D. thesis, FUDAN UNIVERSITY, SHANGHAI, CHINA.

Luce, R. Duncan. 1959. *Individual Choice Behavior*. New York: Wesley.

Mago, Shakun, Anya Samak, and Roman Sheremeta. 2013. "Facing Your Opponents: Social Identification and Information Feedback in Contests." *Chapman University, ESI Working Paper* .

Marino, Anthony M. and Ján Zábojník. 2004. "Internal Competition for Corporate Resources and Incentives in Teams." *RAND Journal of Economics* 35 (4):710–727.

Mattlin, Mikael. 2004. "Referendum as a Form of Zaoshi : The Instrumental Domestic Political Functions of Taiwan's Referendum Ploy." *Issues & Studies* 40 (2):155–185.

McFadden, Daniel. 1973. *Conditional Logit Analysis of Qualitative Choice Behavior*. Institute of Urban & Regional Development, University of California.

McKelvey, Richard D. and Thomas R. Palfrey. 1995. "Quantal Response Equilibria for Normal Form Games." *Games and Economic Behavior* 10 (1):6–38.

Morton, R.B. 2006. *Analyzing Elections*. New York: W. W. Norton & Company.

Mui, Vai-Lam. 1995. "The Economics of Envy." *Journal of Economic Behavior & Organization* 26:311–336.

Nalbantian, Haig R. and Andrew Schotter. 1997. "Productivity under Group incentives: An Experimental Study." *The American Economic Review* :314–341.

Nikiforakis, Nikos. 2008. "Punishment and Counter-punishment in Public Good Games: Can We Really Govern Ourselves?" *Journal of Public Economics* 92 (1-2):91–112.

Norrander, Barbara. 2001. "Measuring State Public Opinion with the Senate National Election Study." *State Politics & Policy Quarterly* 1 (1):111–125.

Palfrey, Thomas R. and Howard Rosenthal. 1985. "Voter Participation and Strategic Uncertainty." *The American Political Science Review* :62–78.

Rapoport, Amnon and Gary Bornstein. 1987. "Intergroup Competition for the Provision of Binary Public Goods." *Psychological Review* 94 (3):291–299.

Shaw, Daron R. 1999a. "The Effect of TV Ads and Candidate Appearances on Statewide Presidential Votes, 1988-96." *American Political Science Review* 93 (2):345–361.

———. 1999b. "The Methods behind the Madness: Presidential Electoral College Strategies, 1988-1996." *Journal of Politics* 61 (4):893–913.