Voting with Endogenous Information Acquisition: Theory and Evidence

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Abstract

The standard model of jury voting with exogenously given noisy but informative signals about the true state of the world predicts that the efficiency of group decision-making increases unambiguously with the group size. However, once signal acquisition is made a costly, endogenous decision, there are important free-riding consideration that counterbalance the information aggregation effect. If the cost of acquiring information is fixed, then rational voters have disincentives to purchase information as the impact of their votes becomes smaller with a larger group size. An implication of this trade-off between information aggregation and free-riding is that there will exist an optimal group size for given voting costs and signal precisions. We investigate the extent to which these trade-offs are relevant in an laboratory experiment with human subjects where we very the group size, the cost to voting and the signal precision. We find in most settings, a pronounced tendency to over-acquire information relative to equilibrium predictions and we offer several possible explanations for this finding.

JEL Codes: C72, D72, D81.
Keywords: Voting, Condorcet Jury Model, Information Aggregation, Endogenous Information Acquisition

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1 Introduction

Condorcet's jury theorem (Condorcet 1785) asserts that if a group of individuals have common preferences with regard to some binary outcome (e.g., convicting the guilty or acquitting the innocent) and independent, noisy but informative private signals about the true state of the world (e.g., guilt or innocence) then, under majority rule, the correct outcome is more likely to be achieved as the number of voters is increased. Feddersen and Pesendorfer (1997) have shown that this result is robust to strategic or insincere voting, where voters may rationally vote against their private information; even if voters vote strategically against their signals, they do so in an optimal way, and as a consequence, information aggregation continues to improve with increasing group size. An implication of these results for optimal voting mechanisms is that, under the maintained assumptions, we can always make a voting mechanism better by adding more voters. However, this result assumes that private signals about the true but unknown state of the world are costless and exogenously provided. In this paper we study the question of endogenous and costly information aggregation where voters must first decide whether to acquire a costly signal about the true state of the world prior to voting to convict or acquit. In particular, we present the results from a laboratory experiment designed to explore how the number of players, the cost of information and the informativeness of signals matter for information aggregation by juries or committees.

The basic set-up of our experiment is the Condorcet jury model in which voters must make a decision as a group about whether to convict or acquit a defendant, based on private noisy signals about whether the defendant is guilty or innocent. When signals are freely provided to voters, the voters can do better - make the correct decision with a higher probability - with a larger group size. However, this group size effect no longer holds when information is endogenous and its acquisition involves a costly decision. If voters are asked to buy private signals at a fixed cost to be better informed about the true (but unknown) state of the world, then there is an important free-riding consideration that counterbalances the larger group size, better information aggregation effect. As we add one more voter to a group, and as long as this voter still has an incentive to acquire information (with positive probability), the information aggregation effect implies a higher probability of making a correct group decision (a positive effect on the efficiency of group decisions). On the other hand, the entire group of voters are less likely to acquire information as we add one more voter because the likelihood that any single vote will be pivotal now diminishes with increases in the group size, i.e., free-riding motivations with regard to information acquisition introduce a negative effect on the efficiency. As we increase the group size with any fixed voting rule, the information aggregation effect is dominant at first and hence we have an increase in the efficiency of group decision-making up to a certain group size. Beyond that group size, the free-riding effect becomes dominant, resulting in a decrease in efficiency. Persico (2004) and Koriyama and Szentes (2009) show the existence of an upper bound on the optimal group size in Condorcet jury environments with costly information acquisition.

Those theoretical papers provide us with testable hypotheses that we evaluate in our laboratory experiment. In particular, increases in the group size should result in an increase in efficiency under the free information treatment. However, under costly information, efficiency should only increase up to a certain group size and then drop off to a minimal level. The reason for the latter drop-off in efficiency arises from a (possibly) huge decrease in the rate of information acquisition as the group size increases. Depending on the choice of parameters, all voters may have an incentive to acquire information up to a certain group size, but beyond that group size no individual has an incentive to acquire information. The result is a dramatic fall in the efficiency of group decision-making with endogenous information. Thus the theory puts an upper bound on the optimal group size when information choice is endogenous, and one purpose of our experiment is to determine whether this upper bound really matters among the laboratory subjects who are asked to make a decision about the purchase of costly information. In addition to increasing group size, we also vary the cost of information acquisition and the precision of the signal processes. Changes in these model variables can have similar effects on the efficiency of group decision-making as we discuss in detail.

The rest of the paper proceeds as follows. In section 2 we discuss related literature. Section 3 presents the theoretical models and the equilibrium predictions. In section 4 we outline our experimental design and in section 5 we state our research hypotheses with numerical predictions under the parameter setups that are used in the experiments. In section 6 we present our main findings and we also we offer several explanations for why, in certain treatments, information acquisition departs from theoretical predictions. Finally, section 7 concludes with a summary of our main findings and some suggestions for future research.

2 Related Literature

As noted in the introduction, the theory of endogenous information acquisition in the Condorcet jury model set-up begins with Persico (2004). He observes that if agents must decide whether to privately gather costly and noisy information that is then aggregated to reach a collective decision, the information acquisition decision is properly viewed as a free-rider problem with the result that information acquisition will generally be less than the social optimum. As a consequence, the optimal voting rule must take account of the precision of the the noisy information. Rules that require a high degree of consensus (e.g., near-unanimity) can only be optimal if the signal precision is sufficiently high so that free-riding in information acquisition is deterred. If signals are not very precise, then the optimal voting rule cannot be too demanding. An implication of this observation is that for any given signal precision and voting rule there will exist an optimal committee size, and in contrast to the standard Condorcet Jury Theorem, larger committees will not always be welfare-improving. Mukhopadhaya (2003) and Koriyama and Szentes (2009) also explore the Condorcet Jury model under endogenous information acquisition and show that larger than optimal committee sizes do lead to social welfare losses relative to smaller committee sizes, but that these losses might not be so great. Gerardi and Yariv (2008) take a mechanism design approach and show that the optimal voting mechanism is in general not ex-post efficient; distoritions have to be introduced to ensure that agents have incentives to acquire information. Martinelli (2006, 2007) and Oliveros (2013) also study endogenous, costly and noisy information acquisition but consider the case where the signal precision is the choice variable, with more precise signals being more costly. Martinelli shows that if the marginal cost of the signal precision is zero at the lowest level of precision then voters acquire some information even in large electorates and that the voting outcome is asymptotically efficient. Oliveros (2013) adds abstention and shows that those acquiring more precise information do not necessarily abstain less often.

Early experimental studies of the Condorcet jury model focus on the case of exognenous information provision: Guarnaschelli, McKelvey and Palfrey (2000), Battaglini, Morton and Palfrey (2010), Goeree and Yariv (2011) and Bhattacharya, Duffy and Kim (2014). More recent experimental studies of the jury model have also explored the consequences of endogenous information acquisition: Großer and Seebauer (2013) and Elbittar, Gomberg, Martinelli and Palfrey (2014).[1] Großer and Seebauer (2013) study costly information acquisition by groups of size 3 or 7 and focus on the question of whether compulsory rather than voluntary voting, where abstention is allowed provides greater incentives for voters to acquire information (it does). Elbittar, Gomberg, Martinelli and Palfrey (2014) explore endogenous information acquisition under a voluntary voting mechanism focusing on the extent to which the voting rule, majority or unanimity matters for information acquisition and participation in voting. By contrast, we focus only on the majority rule, compulsory voting setting where we vary not only the group size, but also the cost of acquiring information (signals) about the true state of the world as well as the precision of those signals. Our design thus enables a more complete assessment of the comparative statics implications of group size, information cost, and signal precision for information acquisition all under the majority rule, compulsory voting mechanism.

3 The Model

Our experiments are based on the standard Condorcet Jury model set-up with the addition of an endogenous information acquisition stage that takes place prior to the voting stage. Within this environment we consider the comparative statics implications of varying the information acquisition cost, c, the group size, N, and the signal precision, x.

In all of our experimental settings (or "treatments") a group consisting of an odd number, N, of individuals faces a choice between two alternatives, labeled R (Red) and B (Blue). The group's choice is made in an election decided by majority rule, that is, the alternative, R or B that receives more than $N/2$ votes is the group's decision. It is common knowledge among voters that there are two equally likely states of nature, ρ and β, i.e., all voters have the common prior $\Pr[\rho] = \Pr[\beta] = .5$. Alternative R is commonly known to be the better choice in state ρ while alternative B is commonly known to be better choice in state β. Specifically, in state ρ each group member earns a payoff of $M > 0$ if R is the alternative chosen by the group and 0 if B is the chosen alternative. In state β the payoffs from R and B are reversed. Formally, we have

[1]We only became aware of these studies after we had begun working on this project.

$$\begin{aligned} U(R|\rho) &= U(B|\beta) = M, \\ U(R|\beta) &= U(B|\rho) = 0. \end{aligned}$$

Prior to the voting decision, each individual may acquire a costly private signal regarding the true state of nature. This signal can take on one of two values, either r or b. The probability of receiving a particular signal depends on the true state of nature. Specifically, each subject choosing to acquire a signal receives a conditionally independent signal where

$$\Pr[r|\rho] = \Pr[b|\beta] = x.$$

Voters who do not acquire a signal have no more information about the true state of the world than the initial common prior that the two states are equally likely.

We suppose $1/2 < x \leq 1$ so that signals are informative but possibly noisy. More precisely we will consider cases where $1/2 < x < 1$, so that the signal is noisy but informative as well as cases where $x = 1$, and the signal (if purchased) is perfectly informative. The latter eliminates fundamental uncertainty so that the voter only faces strategic uncertainty as to the information acquisition choies of other voters. Given that $x > 1/2$ signal r is associated with state ρ while the signal b is associated with state β (we may say r is the correct signal in state ρ while b is the correct signal in state β). It can be easily checked that when the signal precision is *symmetric* the posterior probabilities that signals are matched with the correct states are the same in both states and given by the signal precision parameter x:

$$\Pr[\rho|r] = \Pr[\beta|b] = x.$$

It is important to note that if information is free, $c = 0$, then each individual gets *at no cost* a private signal whose conditional probability is as above. However, if information is costly, then each individual can decide whether to acquire this private signal *at a fixed cost* $c > 0$. In the latter case, an individual's payoff is $U(A|\omega) - c$, where A is the group decision outcome and ω is the state of nature (i.e., payoffs are either $M - c$ or $-c$, depending on the correctness of group decision), if she acquires a private signal. Payoffs are the same as before, i.e., $U(A|\omega)$, if she doesn't acquire a signal.

Having specified the preferences and information structure of the model, we next discuss the strategies, equilibrium conditions and equilibrium predictions for each of the two voting mechanisms that we explore in our experiment. We restrict attention to symmetric equilibria in weakly undominated strategies as these are the most relevant equilibrium concepts given the information that is available to subjects in our experiment. In particular, we require that in equilibrium (*i*) all voters of the same signal type play the same strategies and (*ii*) no voter uses a weakly dominated strategy. We will discuss later the possibility of multiple, or more precisely asymmetric, equilibria, but our design involves the choice of parameters that entails a unique symmetric equilibrium (in weakly undominated strategies).

3.1 Voting with Free Information

When information is free, the strategy of a voter is a specification of two probabilities (v_r, v_b) where v_r is the probability of voting for alternative R given an r signal and v_b is the probability of voting for B given a b signal (that is, v_s is the probability of voting according to one's signal s, or voting *sincerely*). When $c = 0$, there exists a unique symmetric equilibrium in weakly undominated strategies. In this equilibrium, we obtain a sincere voting equilibrium ($v_r^* = v_b^* = 1$) if the signal precision is symmetric (i.e., $\Pr[r|\rho] = \Pr[b|\beta]$) and voting is by majority rule (as in our model).[2]

In a sincere voting equilibrium, an individual must strictly prefer voting according to his/her signal, $s \in \{r, b\}$, conditional on her vote being pivotal (given that the other individuals are also playing equilibrium strategies). This observation yields the following equilibrium conditions:

$$\begin{aligned} U(R|r) - U(B|r) &\equiv \frac{M}{2}\{\Pr[\rho|r]\Pr[Piv|\rho] - \Pr[\beta|r]\Pr[Piv|\beta]\} > 0, \\ U(B|b) - U(R|b) &\equiv \frac{M}{2}\{\Pr[\beta|b]\Pr[Piv|\beta] - \Pr[\rho|b]\Pr[Piv|\rho]\} > 0, \end{aligned}$$

[2]However, sincere voting equilibrium is in general not robust to the introduction of asymmetry in the voting environment. We often have an equilibrium in which voters with one signal type always vote for the signal (vote *sincerely*, i.e. $v_s^* = 1$) while those with the other signal type mix between the two alternatives (i.e., $v_{-s}^* \in (0, 1)$), e.g., if signal precision is asymmetric ($\Pr[r|\rho] \neq \Pr[b|\beta]$) or if voting outcome is decided by supermajority/unanimity rule.

where $U(A|s)$ is the payoff the voter gets when alternative $A \in \{R, B\}$ is chosen and her signal (type) is $s \in \{r, b\}$; and $\Pr[Piv|\omega]$ is the probability that the voter's vote is pivotal in state $\omega \in \{\rho, \beta\}$. A vote is pivotal only when both alternatives R and B get the same number of votes. Since the pivot probabilities depend on voter strategies (v_s), we can check the above conditions by fixing strategies ($v_r^* = v_b^* = 1$) and assigning values for the model parameters. We can also easily obtain, under sincere voting strategies, the probability of making a correct group decision (our measure for the efficiency of group decision).

3.2 Voting with Costly Information

When information is costly, we must consider not only the voting strategy but also the information acquisition strategy which we denote by $\sigma \in [0, 1]$, where $\sigma = 1$ (denoted σ_1) means "acquire information," while $\sigma = 0$ (denoted σ_0) means "do not acquire information," and $\sigma \in (0, 1)$ denotes the probability with which a voter acquires information. As most of our experimental treatments involve $c > 0$, the voter's information acquisition strategy σ, as opposed to their voting strategy, v_s, will be the main focus of our paper. One reason for focusing on the information acquisition strategy is that in the symmetric equilibrium that we consider, all voters who choose to acquire costly information will continue to vote sincerely according to the signal they receive, i.e., conditional on purchasing a signal, $v_s = 1$, just as in the case where information is costless. Voters who don't acquire information in the costly information case simply randomize over the two alternative with equal probability, consistent with the commonly held prior belief that the two possible states of the world are equally likely. Thus, an equilibrium in the majority rule, symmetric signal precision environment that we consider is essentially characterized by the equilibrium information acquisition probability, σ^*, alone.

Under costly information acquisition, there may exist multiple equilibria (including asymmetric equilibria) where individuals acquire information with positive probability ($\sigma^* > 0$).[3] However, we always choose our parameter values such that voting game in our experiment has a unique symmetric

[3] Since subjects are randomly matched to form a different group in each round of a session (which will be explained in detail in the next section about experimental design), we doubt that subjects could find a way to coordinate on the play of asymmetric equilibrium.

equilibrium. We report a zero information acquisition equilibrium ($\sigma^* = 0$) only when there doesn't exist an equilibrium with positive information acquisition.

When we have an interior solution, $\sigma^* \in (0, 1)$, a voter must be indifferent between acquiring and not acquiring information. This observation yields the following equilibrium conditions:

$$\begin{aligned} U(\sigma_1) &\equiv \frac{M}{2}\{Pr[\rho|r]\Pr[Piv|\rho] + Pr[\beta|b]\Pr[Piv|\beta]\} - c \\ &= \frac{M}{2}\{\frac{1}{2}\Pr[Piv|\rho] + \frac{1}{2}\Pr[Piv|\beta]\} \equiv U(\sigma_0) \end{aligned}$$

Of course, the above condition holds with strict inequality when we have a corner solution, e.g., $U(\sigma_1) > U(\sigma_0)$ if $\sigma^* = 1$ in which case every voter acquires information for certain in equilibrium. Again, the solution value σ^* is then used for the calculation of efficiency.

4 Experimental Design

We consider three main treatment variables: 1) the group size N, 2) the information cost c and (3) the signal precision x. We adopt a between subjects experimental design so that in each session subjects only make decisions under a single set of treatment variables.[4]

The experiment is presented to subjects as an abstract group decision-making task using neutral language that avoided any direct reference to voting, elections, jury deliberation, etc., so as not to trigger some other possible (non-theoretical) motivations for voting (e.g., civic duty, the sanction of peers, etc.).

Each session consisted of a multiple of N inexperienced subjects and 25 rounds. At the start of each and every round, subjects were randomly allocated to groups of size N and this random assignment was public knowledge.[5]

[4]That is, in each session, the group size N, information cost c and signal precision x is held fixed for all rounds of the session.

[5]Our intention was to eliminate repeated game dynamics enabling, for instance, coordination on asymmetric equilibria or other collusive outcomes thereby making our symmetric equilibrium predictions more salient.

Each group of size N is then assigned to either a red jar (state ρ) or a blue jar (state β) with equal probability, thus fixing the true state of nature for each group. No subject knows which jar is assigned to her group. The assignment of groups and jars are determined randomly at the start of each new round so as to avoid possible repeated game dynamics. Subjects *do* know that it is equally likely that their group is assigned to a red or a blue jar at the start of each round, that is, we took care to implement this common prior belief among the subjects.

The red jar was known to contain a fraction x of *red* balls (signal r) and a fraction $1 - x$ of *blue* balls (signal b) while the blue jar was known to contain a fraction x of *blue* balls and a fraction $1 - x$ of *red* balls. We fix this signal precision either at $x = 0.7$ or at $x = 1$ in a given session, and these signal precisions were made public knowledge in the written instructions. We thus implement symmetric signal precisions so as to facilitate subjects' understanding of equilibrium strategies in the compound decision making situations of information acquisition and voting. In addition, as we have previously noted, symmetric signal precisions rule out strategic (insincere) voting under the majority rule compulsory voting mechanism that we employ.

The sequence of moves in a round of the free (c=0) information treatment sessions was as follows. First, each subject blindly and simultaneously drew a ball (with replacement) from her group's (randomly assigned) jar. This is done virtually in our computerized experiment; subjects click on one of 10 balls on their decision screen and the color of their chosen ball is revealed.[6] While the subject observes the color of the ball she has drawn, she does not observe the color of any other subject's selections or the color of the jar from which she has drawn a ball. The group's common and publicly known objective is to correctly determine the jar, "red" or "blue", that has been assigned to their group.

After subjects have drawn a ball (signal) and observed its color, they next make a "choice" (i.e., vote) between "red" or "blue", with the understanding that their group's decision is red if a majority of group members choose red and the group's decision is blue otherwise and that the group's aim is to correctly assess the jar (red or blue) that is assigned to the group. We can't have a tie for any group size N since N is always chosen to be odd, so a

[6] For each round and for each subject, the assignment of colors to the 10 ball choices the subject faces are made randomly according to whether the jar the subject is drawing from is the red (in which case percentage x of the balls are *red*) or blue (in which case percentage x balls are *blue*).

group's decision is either red or blue.

In sessions of treatments with costly information acquisition, the sequence of moves was similar to the costless case, but the first choice that each subject made was whether or not to pay the cost $c > 0$, to draw a ball from her group's jar. If a subject decided to draw a ball, then she drew a ball from her group's jar where the composition of red and blue balls was exactly the same as described for the free information case. Differently from the free information case, subjects who chose not to draw a ball had to wait until other group members (if any) finished drawing a ball. After the information acquisition decision was made and any voters who chose to pay the cost of drawing a ball had drawn their ball and observed its color, play proceeded to making a choice between red or blue for the color of the group's jar. All voters, regardless of whether or not they chose to draw a ball had to make a decision red or blue as to the color of their group's jar for that round. The group's decision was again determined according to majority rule.

Payoffs in each round were determined as follows. If the group's decision via majority rule was correct, i.e., the group's decision is red (blue) and the jar assigned to that group is in fact the red (blue) jar, then each of N members of a group received at least 100 points ($M = 100$). If the group's decision is incorrect, then each of the N members of the group received at least 0 points. Adjustments to these payoffs depended on whether there was a positive cost to information acquisition and if so, whether the subject chose to pay that cost to acquire information. Specifically, in treatments where $c > 0$, we endowed each subject with c points at the start of each round. If a voter decided not to draw a ball (buy information), then she kept her endowment of c points and also earned the group-wide payoff in points as well, which depended on whether the group got the decision correct (100 points) or incorrect (0 points). Thus, by not acquiring information, the subject earned either $100 + c$ or c points depending on her group's decision under majority rule. By choosing to acquire information, the subject agreed to give up her endowment of c points for the period, so that her total earnings would be either 100 or 0 points depending again on whether the group decision was correct or not. Notice that we have implemented the cost of drawing a ball (obtaining a signal) as an *opportunity cost*, so as to avoid the possibility of negative payoffs.[7] We vary the magnitude of information acquisition cost

[7]Levine and Palfrey (2007) and Bhattacharya et al. (2014) implement voting costs in this same manner.

$c \in \{5, 8, 15, 25\}$. The parameterization of the payoff function (i.e., the value of c) was held constant across all rounds of a session and subjects were paid the cumulative total of their points earned from all rounds played.

Following 25 rounds of play, the session was over. Subjects' point totals from all 25 rounds of play were converted into dollars at the fixed and known rate of 1 point = \$0.01 and these dollar earnings were then paid to them in cash and in private. In addition, subjects were given a \$5 cash show-up payment.

Treatment Conditions			No. of Sessions	Session Labels	No. Subjects per Session	No. of Rounds per Session
N	c	x				
3	0	0.7	4	VFI 1-4	6	25
3	5	0.7	4	VCI 1-4	6	25
3	8	0.7	4	VCI 5-8	6	25
7	0	0.7	1	VFI 5	14	25
7	5	0.7	4	VCI 9-12	14	25
7	8	0.7	4	VCI 13-16	14	25
13	8	0.7	4	VCI 17-20	26	25
7	15	0.7	2	VCI 21-22	14	25
3	8	1	4	VCI 23-26	6	25
7	8	1	4	VCI 27-30	14	25

Table 1: The Experimental Design

Table 1 summarizes our experimental design, which involves 5 voting sessions with with free information (VFI) and 30 voting sessions with with costly information (VCI) Subjects were recruited from the undergraduate population of the University of Pittsburgh and the experiment is conducted in the Pittsburgh Experimental Economics Laboratory. No subject was allowed to participate in more than one session of this experiment.

5 Research Hypotheses

Table 2 shows symmetric equilibrium predictions for each combination (N, c, x) of treatment variables in our experiment.

x=0.7	$N=3$		$N=7$		$N=13$	
	σ^*	w^*	σ^*	w^*	σ^*	w^*
$c=0$	n/a	0.784	n/a	0.874	n/a	0.938
5	1	0.784	0.6693	0.773	0	0.5
8	1	0.784	0	0.5	0	0.5
15	0	0.5	0	0.5	0	0.5
x=1	$N=3$		$N=7$		$N=13$	
	σ^*	w^*	σ^*	w^*	σ^*	w^*
$c=5$	0.8944	0.992	0.5621	0.955	0.3561	0.912
8	0.8246	0.978	0.4472	0.902	0.2359	0.810
15	0.6325	0.911	0.1163	0.625	0	0.5

[*] σ^* = Equilibrium rate of information acquisition.
[†] w^* = Equilibrium efficiency.

Table 2: Symmetric Equilibrium Predictions

Based on the equilibrium predictions shown in Table 2, we formulate four main research hypotheses concerning the effect of our three treatment variables on the frequency of information acquisition (and hence on the frequency of a group's making correct decisions - the efficiency of group decision-making always moves in the same direction as the rate of information acquisition, as Table 2 reveals).

H0. Condorcet Jury theorem: When information is free and informative, group decisions under majority rule improve as the group size increases.

If information is free ($c = 0$), then there is only an information aggregation effect, so we should observe an increase in the efficiency of group decision as we increase the group size. This is the main conclusion of Condorcet's (1785) original jury model where information was also assumed to be free and informative and represents the first application of the law of large numbers in the social sciences. While this treatment is not the main focus of our analysis, it serves as a benchmark case and we are not aware of any prior experiments that test this simple information aggregation hypothesis.

H1. Group size effect: For any fixed (positive) information

cost and signal precision $(c, x) \in \{5, 8, 15\} \times \{0.7, 1\}$, the frequency of information acquisition decreases as we increase the group size from $N = 3$ to $N = 5$, and to $N = 13$.

If information is costly, then a free-riding incentive effect arises that competes with the information aggregation effect, and for any fixed cost c and fixed precision x, the free-riding effect will eventually dominate the information aggregation effect so that we reach a group size at which the aggregation incentive to acquire information totally disappears (σ^* drops to 0). This drop occurs because the probability that an individual's vote is pivotal decreases and converges to zero as the group size becomes large. In general, whenever information is costly to acquire, the equilibrium rate of information acquisition and group decision efficiency decreases as we increase the group size beyond a certain point.

H2. Cost effect: For any fixed group size and signal precision $(N, x) \in \{3, 7, 13\} \times \{0.7, 1\}$, the frequency of information acquisition decreases as we increase the information acquisition cost c.

The effect of information cost is straightforward: the higher the cost of information acquisition, the less likely people are to acquire information. However, there might be some salience issue. For example, theoretically speaking, an information cost of $c = 8$ should be sufficiently large enough to dissuade voters from acquiring any information. Behaviorally speaking, voters may feel that such a cost level is not sufficiently large enough compared to the level of benefit from a correct group decision (100 points), and therefore they may continue to acquire information with a positive frequency. Hence, it is of interest to consider whether we will obtain the cost effect as cleanly as predicted by the theory.

H3. Signal precision effect: For some fixed group size and information cost (N, c), the frequency of information acquisition can decrease as we increase the signal precision from $x = 0.7$ to $x = 1$.

As we increase the signal precision, there are again two effects that work against one another. On the one hand, a more precise signal will induce individuals to invest in information with a higher frequency holding the cost of information acquisition constant. On the other hand, a better quality of information makes an individual's vote less likely to be pivotal since those who have acquired the more precise signal are now more likely to vote for the correct alternative. Overall, whether voters acquire information with a higher frequency depends on which effect is dominant. Here, if subjects are purely decision-theoretic and don't fully understand the strategic interactions associated with the collective decision problem at hand, then the frequency of information acquisition will increase whenever we increase the signal precision. However, if and only when they reason game-theoretically, they will acquire information less frequently, facing a more precise signal, especially for relatively smaller group size and information costs (see Table 2).

These four hypotheses H1-H4 are the main hypotheses to be tested against our experimental data.

6 Experimental Results

We discuss our experimental findings at both the aggregate and the individual level. We first focus on aggregate level findings which we use to address hypothese H1-H4.

6.1 Aggregate Data

Tables 3-4 report the aggregate proportions of information acquisition and efficiency achieved for treatments with signal precision $x = 0.7$ and $x = 1$ respectively, over all rounds of all sessions of all treatments as well as the average proportions over all sessions of each treatment combination (N, c, x). Figure 1 shows the average frequency of information acquisition and the average level of efficiency.

We first observe in Table 3 that when information is free ($c = 0$) and signals are noisy but informative, ($x = 0.7$) that efficiency is increasing with the group size in support of the Condorcet Jury theorem, [H0]. In particular, we see that efficiency averages 76 percent in the $c = 0$, $x = .7$ and $N = 3$ treatment, while it is higher at 84 percent in the $c = 0$, $x = .7$ and $N = 7$

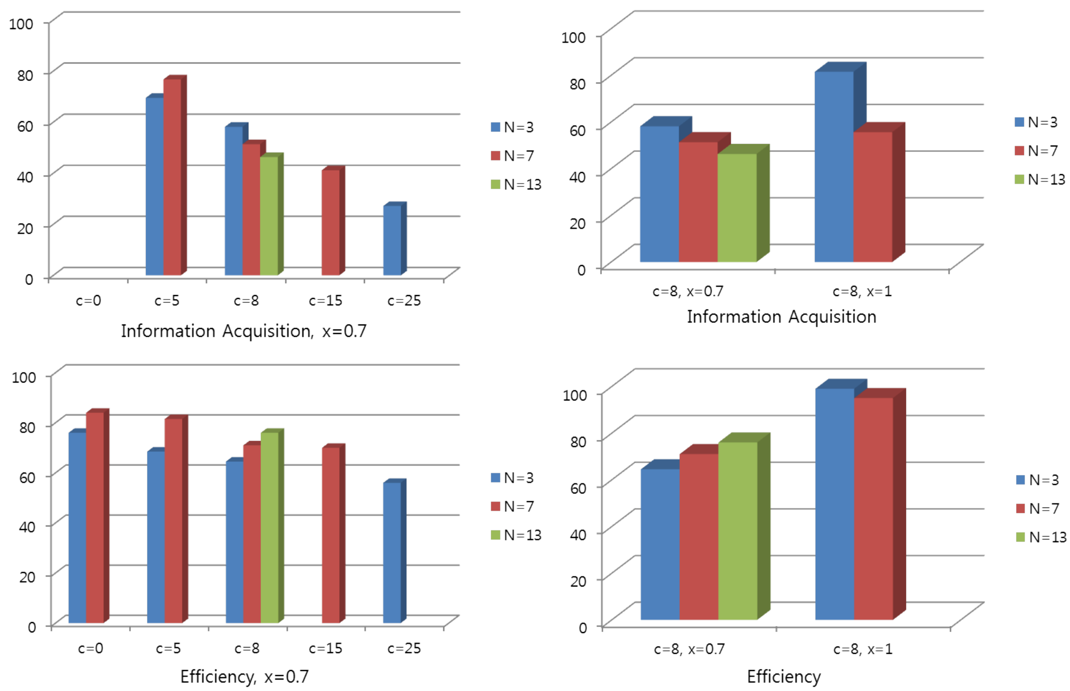

Figure 1: Overall Frequency of Information Acquisition and Efficiency

treatment.[8] Thus with free information, a larger group size yields higher efficiency.

We next look at the group size effect, [H1]. Fixing $c = 5$ and $x = 0.7$ Table 3 reveals that the mean frequency of information acquisition increases as N is increased from 3 to 7, rising from 69.5% to 76.7% but the difference is not statistically significant according to Mann-Whitney tests on session-level averages ($p > .10$). By contrast, the theory predicts a movement in the opposite direction from 100% information acquisition to 66.9%). Next, fixing $c = 8$ and $x = 0.7$, Table 3 indicates that the mean frequency of information acquisition decreases slightly as N is increased from 3 to 7 and finally to 13, from 58.17% to 51.36% to 46.31%, respectively. These differences are again not statistically significant ($p > .10$). Still, the decline in the frequency of information acquistion as N is increased *is* consistent with the theory, though the magnitude of the acquisition frequencies departs substantially from theoretical predictions: the theory predicts a movement from 100% when $N = 3$ to 0% frequency of information acquisition when $N = 7$ or 13.

Remarkably, at Table 4 reveals, the group size effect is much more clear when signals are perfectly precise signal ($x = 1$). In that case, the mean frequency of information acquisition drops significantly from 81.5% when $N = 3$ to 55.64% when $N = 7$ ($p < .02$). The theoretical prediction is that 82.4% purchase information when $N = 3$ falling to 44.72% when $N = 7$. Hence, in this case, not only do the experimental data reflect the group size effect, but in addition, the mean frequencies of information acquisition are closer to the theoretical predictions for both group sizes $N = 3$ and $N = 7$. This may be because we have interior predictions at $x = 1$ whereas mostly boundary predictions, either 0% or 100%, at $x = 0.7$. Moreover, the elimination of noise in the signal seems to make subjects understand the free-riding effect more clearly.

We next turn to the information cost effect [H2]. Fixing $N = 3$ and $x = 0.7$, the first column of Table 3 reveals that an increase in the cost of acquiring information from $c = 5$ to $c = 8$ results in a decrease in the frequency of information acquisition from 69.5% to 58.17%; but this decrease is not statistically significant ($p > .10$). However, as we further increase the cost

[8] We only have a single observation of the $n = 7$ treatment and so we cannot perform statistical tests. However, we suspect that more sessions would not overturn this finding so long as subjects voted sincerely with their signal choice, as in that case the hypothesis just reflects the more accurate information aggregation that is possible with a larger group size.

to $c = 25$, the frequency of information purchase drops more dramatically to 27.1% and this drop is statistically significant ($p < 0.03$ in the comparison of $c = 8$ vs. $c = 25$). Fixing $N = 7$ and $x = 0.7$, the same increase in the cost of acquiring information from $c = 5$ to $c = 8$ results in a decrease in the frequency of information acquisition from 76.71% to 51.36% - theory predicts a fall from 66.93% to 0% - and this decrease is marginally significant ($p = 0.08$). For $N = 7$ (and $x = 0.7$), we further increased that cost to $c = 15$ (just two observations) and this resulted in an even lower mean frequency of information acquisition of 41.15%, but still much higher than the rational choice prediction of 0%.

We finally consider the signal precision effect [H3]. Fixing $N = 3$ and $c = 8$, Tables 3-4 reveal that an increase in the signal precision from $x = 0.7$ to $x = 1$ results in an increase in the mean frequency of information acquisition from 58.17% to 81.5% and this difference is statistically significant ($p = 0.04$). The theoretical prediction, by contrast, is for a decrease from 100% to 82.46%. On the other hand, fixing $N = 7$ and $c = 8$, an increase in the signal precision from $x = 0.7$ to $x = 1$ results in a slight increase in the frequency of information acquisition - from 51.36% when $x = 0.7$ to 55.64% when $x = 1$. This difference is not statistically significant ($p > .10$). Still, the increase is consistent with the theoretical prediction, which calls for an increase in information acquistion from 0% to 44.72% as x is increased from 0.7 to 1.

Table 5 shows the average frequencies of information acquisition and efficiency disaggregated according to the first 13 rounds and the last 12 rounds of each session. There is no clear pattern, or much evidence of learning (or equilibrium behavior), for the change in the mean frequency of information acquisition as we go from the first-half to the second-half of these sessions. These frequencies increased or decreased, depending on specific treatments or sessions. Although the frequency of information acquisition has dropped under many treatment conditions, the mean level of efficiency has almost always increased when we compare the first-half with the second-half. Hence there is some evidence that subjects learn to achieve a better group decision outcome over time, although we fail to find evidence for their behavior converging to equilibrium predictions.

Summarizing, using session level means, there is poor evidence in support of the point predictions of the theory (except in the case where $x = 1$) and some mixed evidence with regard to the comparative statics predictions of the theory across treatments. We next turn our attention to exploring individual subject behavior in further detail so as to determine whether our aggregate measures (session means) may be masking any larger behavioral differences across treatment conditions.

6.2 Individual Behavior

Figure 2 shows the cumulative distributions of the frequency of information acquisition over all rounds, for signal precision $x = 0.7$. Figure 3 compares the same distributions between different signal precisions for various levels of group sizes and information costs.

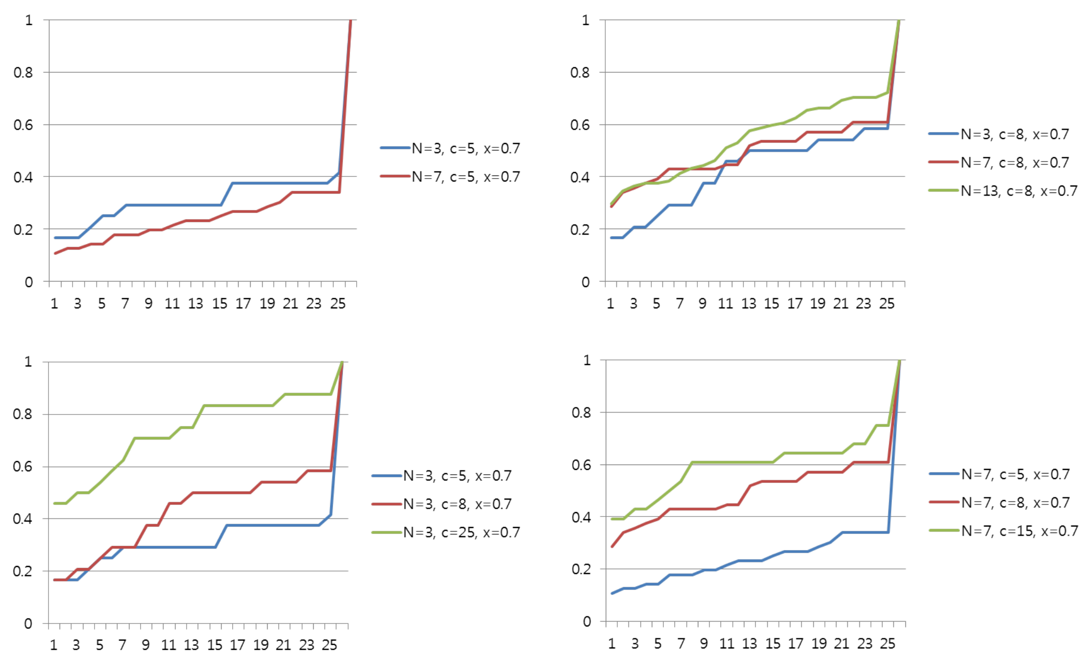

Figure 2: Distribution of the Individual Frequencies of Information Acquisition over All 25 Rounds, $x = 0.7$

Consider first the case where the signal precision is fixed at $x = 0.7$. When $c = 5$, the upper left panel of Figure 2 reveals that the cumulative frequency of information purchase when $N = 7$ stochastically dominates the cumulative frequency of information purchase when $N = 3$, which is completely opposite to theoretical predictions. By contrast, when $c = 8$, the upper right panel of figure 2 reveals that increases in group size largely follow the comparative static prediction that information acquisition decreases as the group size gets larger. Indeed, for this case, the cumulative frequency of information purchase when $N = 3$ stochastically dominates the cumulative frequency of information purchase when $N = 13$. The bottom two panels of Figure 2 confirm that the individual distributions follow the comparative static prediction that increases in information cost are associated with less information acquisition for groups of size $N = 3$ and $N = 7$ (we administered only one cost level $c = 8$ for the larger group size $N = 13$). Indeed, for $N = 7$ we see clearly that the cumulative frequency of information acquisition when $c = 5$ stochastically dominates the cumulative frequency of information acquisition when $c = 8$, which in turn stochastically dominates the cumulative frequency of information acquisition when $c = 15$

The cumulative frequency distributions in Figure 3 enable us to examine the effect of changes in signal precision. Here we fix $c = 8$ as this is the only cost level we administered for signal precision $x = 1$. We find that the equilibrium effect of signal precision could not be found well in our data for either group sizes $N = 3$ and $N = 7$. We found that the frequency of information acquisition has invariably increased as we increase the level of signal precision from $x = 0.7$ to $x = 1$. However, the theory predicts, depending on specific parameter values, sometimes a decrease (e.g., from 100% to 82.46% for $N = 3$, $c = 8$) and sometimes an increase (e.g., from 0% to 44.72% for $N = 7$, $c = 8$), again as a consequence of competition between information aggregation effect and free-riding effect (pivot effect). In this regard, our data may be better explained by decision-theoretic predictions that dictates higher frequency of information acquisition as the quality of information becomes better. The proportion of the subjects who behave according to decision-theoretic principle should be large enough to sway the overall results in their favor while the game-theoretic reasoning is so subtle here that the latter type of subjects fail to grasp such incentives.

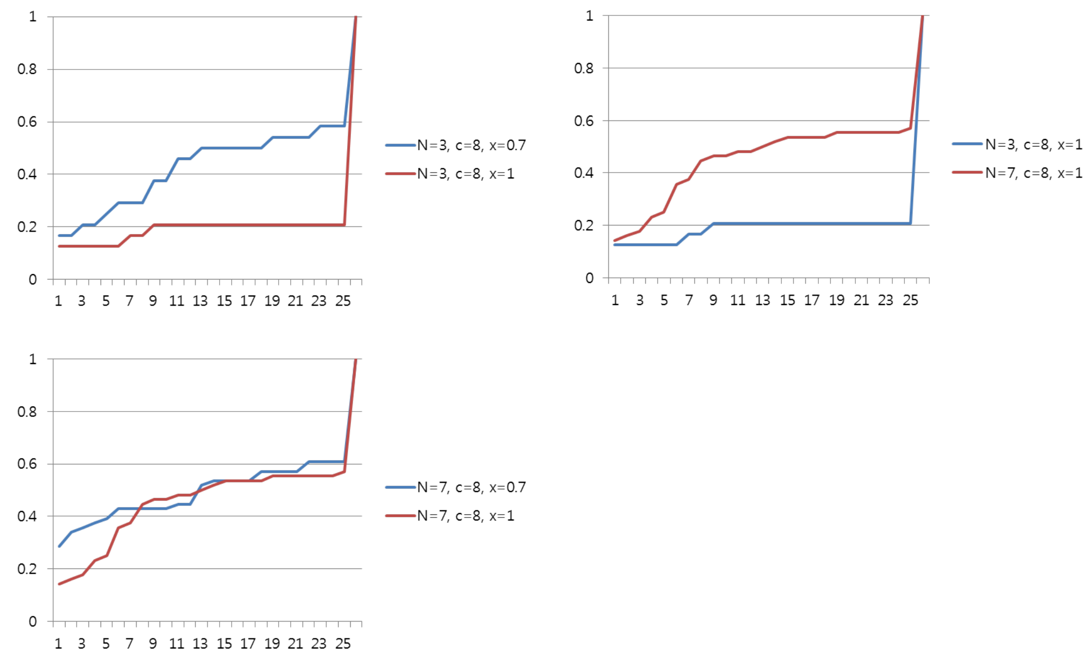

Figure 3: Comparison of Individual Distributions across Different Signal Precisions

6.3 Behavioral Models

As we have seen, in some treatments of our experiment subjects under-acquire information relative to the symmetric Nash equilibrium prediction, e.g., the case where $N = 3$, $c = 8$ and $x = 0.7$. On the other hand, we often see that with a single change of a treatment variable we move from under- to over-acquisition of information as for example in the case where $N = 7$, $c = 8$ and $x = 0.7$. In this section we present several possible explanations for the observed over- or under-acquisition of information in our experimental data.

6.3.1 Subjects act as decision theorists rather than game theorists

Suppose that subjects under-weight or dismiss completely the strategic interaction that is involved in the collective action voting game. As an extreme case, let us suppose that subjects perceive the game to be one where $N = 1$ and so in effect, they are lone decision-makers. If $N = 1$, then it is rational to acquire information at the fixed cost c so long as $M(x - 1/2) \geq c$ and to not acquire information otherwise. In our parameterization, we have $M = 100$. Thus for our $x = 0.7$ treatment, it becomes rational to acquire information if $c < 20$, while for our $x = 1$ treatment it is rational to acquire information so long as $c < 50$. These cost thresholds are satisfied for *all* of our treatments, with the sole exception of the $x = .7$, $c = 25$ treatment (that is why we chose to implement that treatment). In that treatment, both the decision-theoretic and game-theoretic incentives are perfectly aligned and thus subjects should never choose to acquire information. Note that while the characterization of subjects as decision theorists can explain *over*–acquisition of information in our $x = 0.7$ treatments with $c < 20$ it cannot explain *under*–acquisition of information as in the $N = 3$, $x = 0.7$ treatments where $c = 5$ or $c = 8$.

In an effort to address the extent to which subjects might be ignoring strategic considerations, we classified each subject based on their information acquisition decisions. Specifically, we classified each subject according to one of three distinct types: 1) those who *never buy* (NB) information in all 25 rounds of the experiment 2) those who *switch* (S) at least once during the 25 rounds between buying and not buying information, and 3) those who *always buy* (AB) information in all 25 rounds. Table 6 shows the proportion of these three subject types for each treatment condition (N, c, x).

Let us first focus on the $x = 0.7$, $c = 8$ treatments, where we observe that the share of AB-types in the population steadily decreases as we increase N from 3 to 7 to 13. The game-theoretic equilibrium prediction calls for a 100 percent frequency of AB-types when N=3 and a drop-off to 0 percent AB-types (and 100 percent NB-types) for the $N = 7$ and $N = 13$ treatments. By contrast, the decision-theoretic prediction is for 100 percent AB-types in all three of these treatments. The steady but more gradual decline in AB-types as N is increased as reported in Table 6 suggests that decision costs as opposed to strategic, group-size considerations alone may be playing a role in the behavior of some of our AB-type subjects.

Consider next the case where $x = 0.7$ and $N = 7$ and c is varied from 5 to 8 to 15. The game-theoretic equilibrium prediction is that subjects should acquire information on average 66.9 percent of the time when $c = 5$, but should never acquire information when c increases to 8 or 15. By contrast, the decision-theoretic prediction again calls for 100 percent AB-types in all three of these treatments as c is always less than 20. Table 6reveals that there is indeed a much larger percentage of AB-types when $c = 5$ than when

$c = 8$ or $c = 15$, but that the percentage of AB-types remains strictly greater than 0 in the latter two cases in violation of game-theoretic equilibrium predictions but consistent with the notion that some subjects may be acting as decision-theorists.

Similarly, in the case where $x = 0.7$ and $N = 3$, we observe a steady decline in the frequency of AB-types as the cost, c, increases from 5 to 8 to 25, which is again inconsistent with the game-theoretic equilibrium prediction that there should be 100 percent AB-types when $c = 5$ or $c = 8$ and a decline to 0 percent AB-types when $c = 25$. As noted earlier in connection with Table 3, fixing $N = 3$ and $x = .7$, there *is* a large and statistically significant drop-off in the frequency of information acquisition as we move from $c = 8$ to $c = 25$. By contrast, under the same treatment conditions, the increase in costs from $c = 5$ to $c = 8$ results in a statistically insignificant drop in the frequency of information acquisition. However, inconsistent with the decision-theoretic explanation, the frequency of AB types is *not* equal to 100 percent when $c = 5$ or 8 nor is it equal to 0 when $c = 25$.

Finally, consider the case where $x = 1.0$ and $c = 8$ In this case, the game–theoretic equilibrium predictions are closer to matching the distribution of subject types than the decision-theoretic predictions. In particular, when $N = 3$ the game-theoretic equilibrium prediction is for 82.5 percent of subjects to acquire information, while when $N = 7$ the prediction is for 44.7 percent of subjects to acquire information. The decision-theoretic prediction is for all subjects to always acquire information in both of these treatments as c is always less than 50. Table 6 reveals that the frequency of AB-types falls from 79.7 percent when $N = 3$ to 42.86 percent when $N = 7$ instead of remaining constant at 100 percent as would be consistent with the decision-theoretic approach.

Summarizing, the evidence on individual behavior suggests that when $x < 1$, the player population could be characterized as a mixture of game-theoretic and decision-theoretic player types; decision-theoretic reasoning can account for over-acquisition of information in all but one of our treatments (the one where $c = 25$), though not *under*–acquisition of information as is often observed in our treatments where $N = 3$. By contrast, when $x = 1.0$, the distribution of player types is more closely aligned with game-theoretic equilibrium predictions as opposed to decision-theoretic predictions. The latter finding suggests that subjects may compensate for the greater noise in the imperfect signal ($x = .7$) treatments by ignoring strategic considerations and acting more like decision-theorists. Again, we must qualify this conclusion by noting that it cannot explain under-acquisition of information that we observe in some of our treatments.

6.3.2 Quantal Response equilibrium

A second possible explanation for why the frequency of information acquisition is at odds with theoretical predictions is that the experimental environment in which voters are operating is a noisy one and so the appropriate best response function is not the theoretical one, but instead a noisy best response function that conditions on the actual distribution of subject decisions. The idea of finding equilibria that comprise mutual best responses to the empirical distribution of actual and possibly noisy behavior, as opposed to the theoretical ideal has been formalized as the concept of a quantal response equilibrium by McKelvey and Palfrey (1995). In this section we estimate the quantal response equilibrium predictions for our experimental data and we compare these with the Nash equilibrium predictions.

In the quantal response equilibrium model, we calculate the information acquisition choice probabilities as (quantal response) functions of the expected payoffs. Given the slope λ of the logistic quantal response function, the information acquisition choice strategy of a subject can be written as:

$$\sigma(\lambda) \quad = \quad \frac{1}{1+\exp[-\lambda\{U(\sigma_1)-U(\sigma_0)\}]}. \tag{1}$$

where, as before, σ_1 means "acquire information," while σ_0 means "do not acquire information." Here, λ is understood to measure the "degree of rationality"; $\lambda = 0$ corresponds to random behavior whereas $\lambda = \infty$ corresponds to equilibrium behavior (perfect rationality). We can also specify voting strategies in a similar way. The likelihood function to maximize is then proportional to:

$$\mathcal{L}(\lambda) = \sigma(\lambda)^{\sigma_1}\,[1-\sigma(\lambda)]^{\sigma_0} \tag{2}$$

In all instances, we use pooled data from all sessions of a given treatment in maximizing the above likelihood function. The results of our maximum likelihood estimation are reported in Table 7.

6.3.3 Risk aversion

A third possible explanation for information acquisition decisions being at odds with theoretical predictions is that we have assumed that agents are risk neutral with respect to uncertain money earnings. This assumption can be relaxed by allowing agents to be risk averse with respect to uncertain monetary payoffs. To consider this explanation, we proceed as follows...[I added Sourav' note here]

Suppose the probability of being pivotal is q and the probability of getting the right outcome conditional on NOT being pivotal is p.

Both of these are functions of other voters' search probabilities.

Now, suppose that the utility function of an individual is $u(z)$, where z is the amount of money earnings. Let us normalize $u(0) = 0$ and $u(1) = 1$. Denote the signal precision by $x > \frac{1}{2}$.

The following table lists the outcomes for different actions

$$\begin{array}{cc} PIVOTAL \ wp \ q & NOT \ PIVOTAL \ wp \ 1-q \\ Acquire: \begin{bmatrix} u(1)=1 & wp \ x \\ u(0)=0 & wp \ (1-x) \end{bmatrix} & Acquire: \begin{bmatrix} u(1)=1 & wp \ p \\ u(0)=0 & wp \ (1-p) \end{bmatrix} \\ Not \ Acquire: \begin{bmatrix} u(1+c) & wp \ \frac{1}{2} \\ u(c) & wp \ \frac{1}{2} \end{bmatrix} & Not \ Acquire: \begin{bmatrix} u(1+c) & wp \ p \\ u(c) & wp \ (1-p) \end{bmatrix} \end{array}$$

Therefore, the payoff from information acquisition is given by

$$u(A) = qx + (1-q)p,$$

while the payoff from not acquiring information is given by

$$u(NA) = u(1+c)\left[\frac{1}{2}q + (1-q)p\right] + u(c)\left[\frac{1}{2}q + (1-q)(1-p)\right]$$

Notice that given our normalization, the "shape" of the utility function only affects $u(NA)$. Suppose we have linear utilities, which, given our normalization, must mean that $u(z) = z$.

In that case, utility from not acquiring information is

$$\begin{aligned} u^L(NA) &= [u(1)+u(c)]\left[\frac{1}{2}q + (1-q)p\right] + u(c)\left[\frac{1}{2}q + (1-q)(1-p)\right] \\ &= u(1)\left[\frac{1}{2}q + (1-q)p\right] + u(c) \\ &= \left[\frac{1}{2}q + (1-q)p\right] + c \end{aligned}$$

Next, we find conditions on the shape of the utility function for which $u(NA)$ is greater than or less than $u^L(NA)$.

$$\begin{aligned}
u(NA) &= u(1+c)\left[\frac{1}{2}q+(1-q)p\right]+u(c)\left[\frac{1}{2}q+(1-q)(1-p)\right] \\
&= [u(1+c)-u(1)-u(c)]\left[\frac{1}{2}q+(1-q)p\right]+u(c)\left[\frac{1}{2}q+(1-q)(1-p)\right] \\
&\quad +[u(1)+u(c)]\left[\frac{1}{2}q+(1-q)p\right] \\
&= [u(1+c)-u(1)-u(c)]\left[\frac{1}{2}q+(1-q)p\right]+u(1)\left[\frac{1}{2}q+(1-q)p\right]+u(c) \\
&= [u(1+c)-u(1)-u(c)]\left[\frac{1}{2}q+(1-q)p\right]+\left[\frac{1}{2}q+(1-q)p\right]+u(c) \\
&= [u(1+c)-u(1)-u(c)]\left[\frac{1}{2}q+(1-q)p\right]+u^L(NA)+u(c)-c
\end{aligned}$$

Writing $\frac{1}{2}q+(1-q)p=t$, we have the following expression

$$\begin{aligned}
&u(NA)-u^L(NA) \\
= \; &[u(c)-c]-t[u(1)+u(c)-u(1+c)]
\end{aligned}$$

Assuming that $u(x)$ is convex, from our normalization that $u(0)=0$ and $u(1)=1$, we have $[u(c)-c]>0$ and $u(1)+u(c)-u(1+c)>0$.

Therefore, $u(NA)<u^L(NA)$ if and only if

$$t>\frac{u(c)-c}{1+u(c)-u(1+c)}$$

In other words, if the utility function is sufficiently more curved at $1+c$ compared to c, the above condition holds. Notice also that $t=\frac{1}{2}q+(1-q)p$ is the likelihood of getting the right outcome conditional on not acquiring information. Since $q<\frac{1}{2}<p$, we must have $t\in(\frac{1}{2},p)$.

If we have $u(NA)<u^L(NA)$, in settings where everyone is risk neutral and equilibrium involves mixing between acquiring and not acquiring information, if one individual's utility function changes to $u(NA)$ from $u^L(NA)$, she will acquire information with a small probability.

Now, what kind of utility functions lead to this being satisfied (or not)? A priori, it is hard to say. Call the RHS $U(c)$

With CARA utility function (suitably normalized): $u(x) = \frac{1-e^{-\alpha x}}{1-e^{-\alpha}}$, $\alpha > 0$, for any c, $U(c|\alpha)$ is increasing in α. In particular, for any $c < 1$, there is some $\overline{\alpha}$ such that if some subject has CARA utility function with $\alpha < \overline{\alpha}$ (i.e., low enough risk aversion), then $U(c|\alpha) < \frac{1}{2}$, therefore guaranteeing that $t > U(c|\alpha)$ for all t. Of course, for specific values of c and t, the range of α for which $t > U(c|\alpha)$ is much larger. For example, if we have an observed welfare of $p = 0.75$, t is at least 0.625 (assuming $q = \frac{1}{2}$ which is the theoretical maximum), any α less than 0.9 works for $c = 0.05$ and any α less than 0.8 works for $c = 0.8$.

Notice that small deviations from linearity make it more likely for us to have $u(NA) - u^L(NA) > 0$.

Interesting observation: Fix some c and thus, some value of $U(c)$. An increase in n may make t go up (which is always the case with observed data in our experiment since t is increasing in p and decreasing in q). It is now possible that, for low n, we have $t < U(c)$ - i.e. $u(NA) > u^L(NA)$ which will tend to underacquisition compared to the linear case and for large n we will have $t > U(c)$ which will lead to overacquisition compared to the linear case.

EQUILIBRIUM ANALYSIS

Suppose the utility of money for all voters is given by $u(x)$. Moreover, we have $u(0) = 0$ and $u(1) = 1$. Assume that there are $2n + 1$ voters

Suppose also that in equilibrium, voters acquire information with probability $\sigma \in [0, 1]$.

Also, assume that on not acquiring information, voters vote for each alternative with probability $v = \frac{1}{2}$.

Then, the probability of a random voter voting for the correct alternative (i.e., R in state ρ or B in state β) is

$$v = \sigma x + (1 - \sigma)\frac{1}{2}$$

and the probability of voting for the wrong alternative is

$$1 - v = \sigma(1 - x) + (1 - \sigma)\frac{1}{2}$$

Then, the probability of a voter being pivotal in a given state ($\Pr(piv|\rho) = \Pr(piv|\beta)$) is

$$q(\sigma) = \binom{2n}{n} [v(1 - v)]^n$$

Probability of obtaining the right outcome conditional on NOT being pivotal is

$$p(\sigma) = \sum_{r=n+1}^{2n} \binom{2n}{r} [v]^r [1-v]^{2n-r}$$

Therefore, payoff from acquisition is

$$U^A(\sigma) = qx + (1-q)p$$

Payoff fron not acquiring information is

$$U^{NA}(\sigma) = u(1+c)\left[\frac{1}{2}q + (1-q)p\right] + u(c)\left[\frac{1}{2}q + (1-q)(1-p)\right]$$

We now find the equilibrium in the usual way: if there is some $\sigma^* \in [0,1]$ for which $U^A(\sigma) = U^{NA}(\sigma)$, then σ^* is an equilibrium. Otherwise, we have a corner solution.

7 Conclusion

We found rather poor support for the comparative statics predictions of the rational choice theory of endogenous information acquisition and voting. We observe that our subjects generally over-invest in costly information, hence the extent of free-riding is not as large as predicted. Many subjects appear to be ignoring strategic considerations and acting as lone decision-theorists. If $N = 1$, the one should buy information if $M(x-1/2) \geq c$. In our setting with $M = 100$, if $x = 0.7$, then one would buy information as long as $c \leq 20$, and if $x = 1$, as long as $c \leq 50$, which is always the case under all of our treatment conditions. This characterization of subjects (at least some part of them) as decision theorists can explain over-acquisition of information, but not under-acquisition of information in the $N = 3$, $x = 0.7$ treatments. We found relatively clear information cost effect. Increasing the cost from $c = 5$ to $c = 8$ to $c = 15$ shrinks the expected gains from information acquisition and some subjects (but not enough) are responsive to this change. We suspect that a quantal response model (noisy best response) can help to rationalize our findings. The results seem more promising for the theory when $x = 1$, where perhaps free-riding incentives are most clear. For example, under

$x = 1$, if everyone else acquires information, the probability that one's vote is decisive (pivot probability) becomes zero, which must dissuade him strongly from informed voting.

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x=0.7	$N=3$		$N=7$		$N=13$	
	$\hat{\sigma}$	$\hat{w}$	$\hat{\sigma}$	$\hat{w}$	$\hat{\sigma}$	$\hat{w}$
	n/a	68	n/a	84		
$c=0$	n/a	78				
	n/a	72				
	n/a	86				
Overall	n/a	76	n/a	84	n/a	
Predicted	n/a	78.4	n/a	87.4	n/a	93.8
	54.67	62	64.00	76		
$c=5$	76.00	76	82.57	80		
	64.00	70	74.57	86		
	83.33	66	85.71	84		
Overall	69.50	68.5	76.71	81.5		
Predicted	100	78.4	66.93	77.3	0	50
	60.00	68	34.00	58	44.15	70
$c=8$	35.33	62	75.14	82	61.69	82
	74.00	66	36.00	70	38.77	78
	63.33	62	60.29	74	40.62	74
Overall	58.17	64.5	51.36	71	46.31	76
Predicted	100	78.4	0	50	0	50
			28.29	66		
$c=15$			54.00	74		
Overall			41.15	70		
Predicted	0	50	0	50	0	50
	34	54				
$c=25$	8.67	48				
	24	52				
	42	70				
Overall	27.17	56				
Predicted	0	50	0	50	0	50

* $\hat{\sigma}$ = Observed frequency of information acquisition (%).
† $\hat{w}$ = Observed efficiency (%).

Table 3: Results by Session for $x = 0.7$

x=1	$N=3$		$N=7$	
	$\hat{\sigma}$	$\hat{w}$	$\hat{\sigma}$	$\hat{w}$
	88.67	100	51.43	92
$c=8$	83.33	100	52.86	94
	70.67	96	64.57	98
	83.33	100	53.71	96
Overall	81.50	99	55.64	95
Predicted	82.46	97.8	44.72	90.2

* $\hat{\sigma}$ = Observed frequency of information acquisition (%).
† $\hat{w}$ = Observed efficiency (%).

Table 4: Results by Session for $x=1$

x=0.7	N = 3		N = 7		N = 13	
	$\hat{\sigma}$	$\hat{w}$	$\hat{\sigma}$	$\hat{w}$	$\hat{\sigma}$	$\hat{w}$
$c = 0$	n/a	76	n/a	84		
1st 13 rds	n/a	75	n/a	84.615		
2nd 12 rds	n/a	77.08	n/a	83.335		
Predicted	n/a	78.4	n/a	87.4	n/a	93.8
$c = 5$	69.5	68.5	76.71	81.5		
1st 13 rds	71.47	66.35	76.785	77.88		
2nd 12 rds	67.36	70.83	76.635	85.42		
Predicted	100	78.4	66.93	77.3	0	50
$c = 8$	58.17	64.5	51.36	71	46.31	76
1st 13 rds	58.97	60.58	52.335	69.23	47.34	78.85
2nd 12 rds	57.29	68.75	50.295	72.92	45.19	72.92
Predicted	100	78.4	0	50	0	50
$c = 15$			41.15	70		
1st 13 rds			39.56	69.23		
2nd 12 rds			42.86	70.83		
Predicted	0	50	0	50	0	50
$c = 25$	27.17	56				
1st 13 rds	27.565	51.925				
2nd 12 rds	26.74	60.42				
Predicted	0	50	0	50	0	50
x=1	N = 3		N = 7		N = 13	
	$\hat{\sigma}$	$\hat{w}$	$\hat{\sigma}$	$\hat{w}$	$\hat{\sigma}$	$\hat{w}$
$c = 8$	81.5	99	55.64	95		
1st 13 rds	81.73	100	58.38	95.19		
2nd 12 rds	81.25	97.92	52.68	94.8		
Predicted	82.46	97.8	44.72	90.2	23.59	81

* $\hat{\sigma}$ = Observed frequency of information acquisition (%).
† $\hat{w}$ = Observed efficiency (%).

Table 5: Session Average, Overall, First 13 rounds and Second 12 rounds

Precision	Cost	Type	All Rounds			First 13 Rounds			Last 12 Rounds		
			N=3	N=7	N=13	N=3	N=7	N=13	N=3	N=7	N=13
$x = 0.7$	$c = 5$	NB	16.67	10.71		16.67	10.71		25.00	14.29	
		S	25.00	23.22		25.00	23.22		12.50	16.07	
		AB	58.33	66.07		58.33	66.07		62.50	69.64	
	$c = 8$	NB	16.67	28.57	29.81	16.67	28.57	31.73	29.17	39.29	36.54
		S	41.66	32.14	42.31	41.66	32.14	37.50	25.00	17.85	31.73
		AB	41.67	39.29	27.88	41.67	39.29	30.77	45.83	42.86	31.73
	$c = 15$	NB		39.29			50.00			39.29	
		S		35.71			17.86			32.14	
		AB		25.00			32.14			28.57	
	$c = 25$	NB	45.83			50.00			54.17		
		S	41.67			37.50			29.17		
		AB	12.50			12.50			16.66		
$x = 1$	$c = 8$	NB	12.50	14.28		12.50	17.86		12.50	25.00	
		S	8.33	42.86		8.33	39.28		8.33	30.36	
		AB	79.17	42.86		79.17	42.86		79.17	44.64	

* NB = Subjects who *never buy* information (%).
† S = Subjects who *switch* between buying and non-buying (at least once) (%).
AB = Subjects who *always buy* information (%).

Table 6: Proportions of Different Subject Types

Precision	Cost	$N = 3$	$N = 7$	$N = 13$
$x = .7$	$c = 5$	$\hat{\sigma} = 0.6943$	$\hat{\sigma} = 0.6693$	
		$\hat{\lambda} = 9.7000$	$\hat{\lambda} = \infty$	
	$c = 8$	$\hat{\sigma} = 0.5817$	$\hat{\sigma} = 0.5000$	$\hat{\sigma} = 0.4632$
		$\hat{\lambda} = 11.3000$	0.0000	$\hat{\lambda} = 1.7000$
	$c = 15$		$\hat{\sigma} = 0.4130$	
			$\hat{\lambda} = 1.9000$	
	$c = 25$	$\hat{\sigma} = 0.2694$		
		$\hat{\lambda} = 3.3000$		
$x = 1.0$	$c = 8$	$\hat{\sigma} = 0.8150$	$\hat{\sigma} = 0.5000$	
		$\hat{\lambda} = 188.0000$	$\hat{\lambda} = 0.0000$	

Table 7: Quantal Response Equilibrium: Maximum Likelihood Estimates