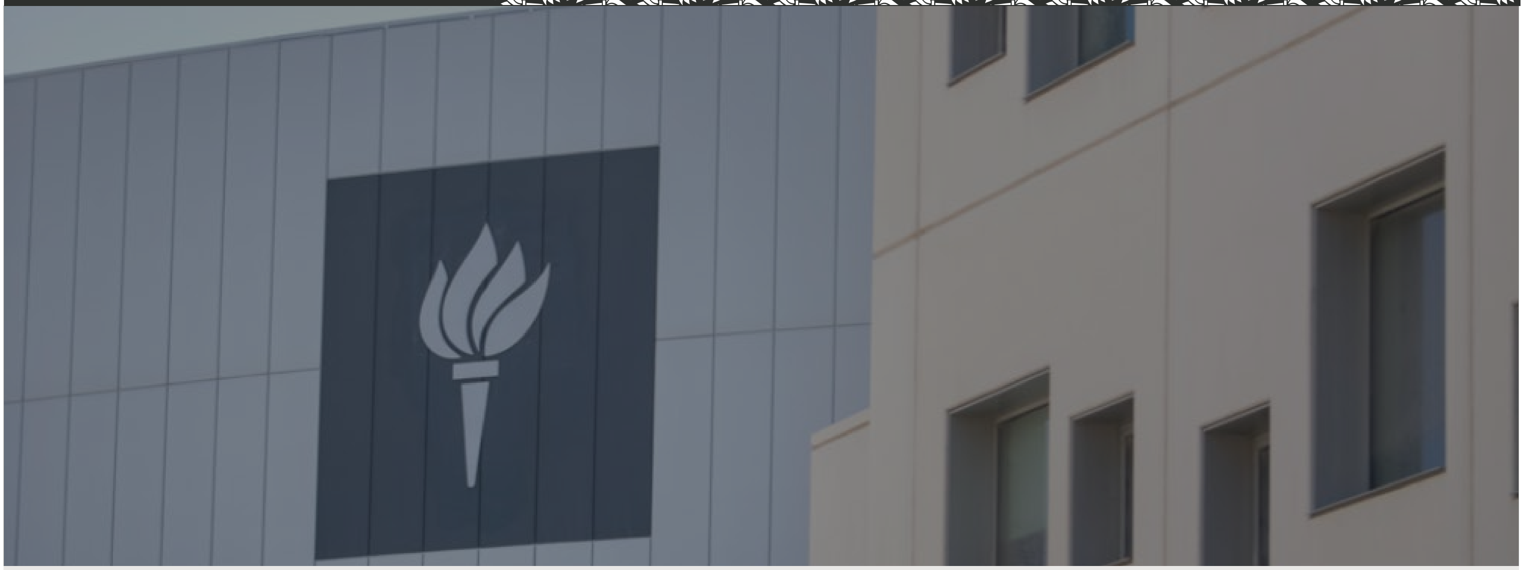

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Marco Battaglini, Rebecca B. Morton, and
Eleonora Patacchini

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ABSTRACT

We present an informational theory of public protests, according to which public protests allow citizens to aggregate privately dispersed information and signal it to the policy maker. The model predicts that information sharing of signals within social groups can facilitate information aggregation when the social groups are sufficiently large even when it is not predicted with individual signals. We use experiments in the laboratory and on Amazon Mechanical Turk to test these predictions. We find that information sharing in social groups significantly affects citizens' protest decisions and as a consequence mitigates the effects of high conflict, leading to greater efficiency in policy makers' choices. Our experiments highlight that social media can play an important role in protests beyond simply a way in which citizens can coordinate their actions; and indeed that the information aggregation and the coordination motives behind public protests are intimately connected and cannot be conceptually separated.

Marco Battaglini
Department of Economics
Uris Hall
Cornell University
Ithaca, NY 14850
and EIEF, CEPR
and also NBER
battaglini@cornell.edu

Rebecca B. Morton
New York University
NYC and Abu Dhabi
19 West 4th St. 2nd Floor
New York, NY 10012
rebecca.morton@nyu.edu

Eleonora Patacchini
Department of Economics
Cornell University
430 Uris Hall
Ithaca, NY 14853
and CEPR
ep454@cornell.edu

1 Introduction

Even in democratic systems, most common decisions are delegated to one or a few representatives who have monopoly power over decision-making. These include elected officials in the public sector, or boards of directors and CEOs in the private sector. In these contexts, a very common way to influence the decision maker's choices is to organize a petition, such as an explicit petition with signatures, a walkout or some other form of public protest. Only in the past two years, we have seen many prominent examples of these phenomena: in October 2017, a thousand economists signed a petition to call upon the American Economic Association to drop job search site Economics Job Market Rumors, which was accused of sexism; in January 2018, over 50,000 people signed a petition calling YouTube to cancel controversial video blogger Paul Logan's channel; in March 2018, tens of thousands of students organized a walkout from school to petition for gun control after the mass shooting in Parkland, Florida.[1] These activities are becoming more common since a number of websites are exclusively dedicated to providing the infrastructure for online petitions such as *Change.org*, *ipetitions.com*, *Gopetitions.com* and many others. On March 8, 2018 the magazine *Elle UK* published an article entitled: "5 Feminist Petitions You Can Sign In Under 5 Minutes To Commemorate International Women's Day."[2]

The diffusion of petitions and public protests as ways to influence decision makers is often linked to the diffusion of social media and this perception is influencing how government and private companies respond to these phenomena. As social media has expanded throughout the world a number of governments, worried about the use of social media during times of unrest and protests from citizens over public policies, have instituted measures to limit access as in for example China, India, Iran, Turkey, and Uganda.[3] Similarly,

[1] For the first example, see Morath in the *Wall Street Journal*, 26 October 2017; for the second, see Agerholm in the *Independent*, 3 January 2018; for the third, see Heim and Lang in the *Washington Post*, 14 March 2018.

[2] See O'Malley in Elle UK, 8 March 2018, retrieved on 19/03/2018 from http://www.elleuk.com/life-and-culture/culture/news/a42205/feminist-petitions-international-womens-day/.

[3] See for example Simon Denyer, "China's scary lesson to the world: Censoring the internet works," The Washington Post, May 23, 2016; Emily Dreyfuss, "Uganda's regressive social media tax stays, at least for now," Wired, July 19, 2018; Sophie Hutchinson, BBC News, "Social media plays major role in Turkey protests," June 4, 2013; Krishna Pokharel and Newley Purnell, "India Temporarily Pulls Plug on Mobile Services in Delhi to Curb Protests," The Wall Street Journal, December 19, 2019; and Marilia Brocchetto and Dakin Andone, "Iran restricts social media as anti-government protests enter 4th day," CNN, Sept. 4, 2018.

private companies have responded to employees' activism by restricting the information that can be shared in internal web forums.[4] Most think of social media communications during protests as a way of coordinating disparate individuals who are already convinced. But social media interactions are also a way in which social groups share concerns and information about public policies among each other when they are still uncertain in their opinions. These facts raise a number of questions. What is the relationship between public activism and social media? Does the coordination and information sharing that protesters do in social media lead to better or worse outcomes?

In this paper, we investigate the effects of information sharing in social groups on protest choices theoretically and using controlled experiments, both in the laboratory and on Amazon Mechanical Turk. By conducting an experiment, we are able to control for the exact events observed by the policy maker before choosing an action and the informed agents' private information, to an extent that would be impossible with conventional field data.

We find that information sharing can lead to individuals making protest decisions based on the experiences of the majority in their group rather than simply their own personal experiences. When citizens protest to reflect the overall experience of their social groups, then their protests can be more effective in conveying information to policy makers, particularly those whose ex ante policy preferences may be significantly different from citizens' such that they are not easily persuaded. In this way, information sharing within social groups can result in more informationally efficient protest choices by citizens and to more efficient public policies as a consequence. Banning social media use during times of unrest may not only limit the ability of protesters to coordinate their actions but also the extent that their actions convey useful information to policy makers.

In the theoretical model, the players are one policy maker and a finite number n of citizens. The policy maker is faced with the problem of choosing one of two policies, A or B. The optimal policy depends on the state of the world, a variable that may take two values, a or b. The players have the same prior over the two states and they agree

[4] In November 2019, for example, Google has suspended two employees involved with the walkout of November 2018 for sharing information in the company web forum. One of the suspended employees has also claimed that Google deleted critical questions and memes that employees had posted to company wide forums. See Los Angeles Times [2019].

that policy A is better in state a and policy B is better in state b. They, however, have different payoffs in the two states: the policy maker, absent any other signal would choose B; the citizens would choose A. Essentially, the conflict between the players relies on the fact that citizens and the policy maker face different type I (choose A in state b) and Type II (choose B in state a) errors, so they are willing to choose different actions at the ex ante or interim stage. A fraction of the citizens receive an informative signal on the true state. When there is no information sharing within social groups of citizens, the Baseline game, after signals are privately observed and before the policy action is selected, citizens independently choose to protest or sign a petition. In the information sharing game, citizens choose to protest after observing the entire vector of signals in their group. In both cases, the policy maker chooses the policy after observing the citizens' actions.

The theory shows that there are two factors determining whether information aggregation is possible: the first, perhaps unsurprisingly, is the conflict in the preferences of the policy maker and the citizens; the second is the precision of the citizens' individual signals. No matter what the size of the population is, information aggregation is possible only if, for a given precision of the individual signals, the conflict in ex ante preferences is sufficiently small; or, for a given level of conflict, the precision of the individual signals is sufficiently high. Even in cases in which information aggregation is impossible with independent agents, however, we show that information aggregation is achievable when agents can share information through social groups before taking actions. For any level of precision of the individual signals, the larger is the social group, the easier it is to aggregate information through protests and petitions.

The reason why protests may fail to achieve information aggregation is that the policy maker cannot commit to a decision rule. Indeed, if the decision maker could commit to change policy after a given turnout of protesters, then protests would work as elections and information aggregation would generally be guaranteed, as in the classic results on information aggregation in elections à la Condorcet.[5] Without commitment, the problem for information aggregation can be described as follows. In equilibrium, there must be a threshold over which the policy maker changes policy from B to A. Importantly, and differently from an election, at this threshold, the policy maker must be willing to choose A

[5] See Austen-Smith and Banks [1996], Fedderesen and Pesendorfer [1996, 1997, 1999] and for a more specific discussion Battaglini [2016].

given the observed signals. At the same time, citizens must be willing to use a separating strategy (that is a strategy that depends on the signal). A necessary condition for signaling to happen is that citizens with the signal least favorable to A are willing to not protest conditional on being pivotal (that is on being able to affect the policy maker's decision). Roughly speaking, conditioning on being pivotal means that the citizens condition on the event in which the number of protesters is close to the number that is sufficient to convince the policy maker to choose A. But if this number is sufficiently large to convince the policy maker who is biased against A, then it is going to also *strictly* convince the citizen that A is the best option if the individual signal received by the citizen is not sufficiently precise. In this case, an informative equilibrium is impossible: the endogenous informative content of the pivotal event is so strong that citizens are willing to disregard their private informative signal.

Sharing information in social groups helps in achieving information aggregation because it relaxes the incentive compatibility constraint for revealing the signals informatively. The intuition for this phenomenon is that when citizens can share signals in a group, it is as if the group receives one, single but more informative signal with an associated number of realizations equal to the number of members of the group. The precision of the aggregate information of the social group may indeed be sufficiently high to counterbalance the reasoning described above: even if in the pivotal event the policy maker is willing to select A, groups with sufficiently precise information in favor of B are willing to refrain from being active.

In our experiments we first examine the extent that conflict can lead to failure in information aggregation through protests when there is no information sharing within groups. While we find that citizens tend to use strategies that are more informative than predicted by the theory (a behavioral phenomenon that is typical in experiments of signaling games as ours), we find strong support for our theoretical prediction that high conflict will lead to citizens' protests being less informative and policy makers paying less attention to protests in both data samples. We also find evidence in support of our prediction that conflict decreases efficiency of policy maker choices, significantly so in our data from Mechanical Turk and qualitative evidence in our lab sample.

When we add information sharing through social groups, we find strong support for our prediction that when citizens share information within social groups prior to making their protest decisions the effects of high conflict are mitigated. With information sharing, the protests are significantly more informative in both data samples, policy makers pay more attention to protests (in both samples when the citizen population is small), and policy makers make more informationally efficient choices (in the Mechanical Turk sample).

The remainder of the paper is organized as follows. In the following subsection we discuss the related literature. In Section 2 and 3 we present our model and theoretical analysis. In Section 4 we discuss our experimental design and predictions. In Sections 5 and 6 we present our experimental results. We conclude in Section 7 with a discussion of the results and of future research.

1.1 Related literature

Much of the previous literature on protest has modelled protests as coordination games in which protest are successful only if an exogenous threshold of participation is reached.[6] In this context protests do not convey information on the quality of the policy to the decision makers: the focus is instead on whether citizens can coordinate on passing the threshold, whether multiple equilibria are possible, and the extent to which the probability of protests depends on the fundamentals. On the contrary, the focus of our theory and related experiments is on information aggregation of dispersed information concerning the quality of alternative policies, and thus on the impact of protests on the quality of the policy maker's beliefs and decisions, an issue that we feel is important but still understudied, both theoretically and empirically. The two issues (coordination and information aggregation) are naturally interconnected. Indeed, our work shows that the issue of coordination can not be separated from the issue of information aggregation in the presence of heterogenous signals, and vice-versa. Membership to a social group induces citizens to share signals and thus coordinate actions; it also relaxes the incentive compatibility constraints for information transmission with the policy-maker. These results emerge because we provide an explicit modelling of the policy-maker's response to the protests.

[6] See Olson [1965], Tullock [1971] and Shelling [1971] for classic results. More recently, see Boix and Slovik [2009], Edmond [2013], Shadmehr and Bernhardt [2011], Barbera and Jackson [2018] and Ananyev et al. [2019] among others. Another line of research is presented by Passarelli and Tabellini [2017] who see protests are an emotional reaction to unfair treatment and study the implication of this on policy-making.

The idea that petitions and public protests can allow the aggregation of information dispersed among citizens was first suggested by Condorcet [1785] as a normative theory of elections, in light of which elections work as mechanisms to aggregate information dispersed in the electorate, and in its modern form, by Austen-Smith and Banks [1996], Feddersen and Pesendorfer [1996, 1997, 1999] and others. The idea was applied to study public protests or polls by Lohmann [1993,1994], Banerjee and Somanathan [2001], Battaglini and Benabou [2003], Morgan and Stocken [2008], Battaglini [2016] and a number of follow up papers.[7] This literature, however, so far has been exclusively theoretical. The theoretical framework presented here is inspired by Battaglini [2016], but, contrary to this work, it is designed to be implementable in an experiment with a finite number of players.[8]

From an empirical point of view, information aggregation with protests has not been extensively studied because it is difficult to conclusively establish a causal effect of the size of public activism on politician beliefs and policy choices with field data. Laboratory experiments allow us to control for otherwise unobserved private signals: this is the reason why we have chosen this tool to test the predictions of our model. A related complementary work that highlights the importance of this line of research is Wouters and Walgrave [2017]. They present an experiment in which they expose Belgian national and regional politicians to manipulated television news on public protests. They identify a number of features of protests that affect the politicians' attitudes toward the issues the protests are about (notably size and whether protesters agree with themselves). Contrary to our work, these authors do not have a theoretical model and sharp hypothesis to test, other that the generic fact that politicians respond to how the protests are portrayed on television. These authors, moreover, do not look at the effect of social groups on the effectiveness of protests in terms of policy choices; and can not assess the welfare effects of public activism.

In addition to the works cited above, our paper is related to two other strands of

[7] For recent related contributions on this front see, among others, Ali and Bohren [2019], Eckmecki and Lauermann [2019], Salas [2019].

[8] In Battaglini [2016] it is assumed that the number of voters is a realization from a Poisson distribution with mean n. This implies that the number of players is with positive probability arbitrarily large independently from its expected value. In the model presented below we assume there are $n+1$ players, where n is a finite number.

literature. First, it is related to a recent strand of empirical papers proposing original identification strategies to study the causal effect of social media on the occurrence of public protest using field data. Enikolopov, Makarin and Petrova [2016] showed that the penetration of the Russian social network VK increased the probability of protests; and Manacorda and Tesei [2016] showed that mobile phones are instrumental to mass mobilization during economic downturns. Our theory and experiments extend and complement these results by providing a theoretical background of why social media makes protests more effective, and by using lab experiments to test the theory in ways that would be impossible using field data.

Second, our work is related to the experimental literature on information aggregation in elections (see Guarnaschelli, McKelvey and Palfrey [2000], Battaglini Morton and Palfrey [2007, 2008, 2010] among others). This literature aims at studying with laboratory experiments whether elections aggregate information as predicted in the Condorcet Jury Theorem and related results. This literature has been recently extended to allow for preplay communication of voters in networks by Buechel and Mechtenberg [2019] and Pogorelskiy and Shum [2019]. Compared to these papers, we consider simpler social networks and communication mechanisms in the networks, but we study information aggregation in a different and more complex setting in which a decision is not determined by a voting rule, but by a policy-maker without commitment.

2 Model

Consider a model in which a policy maker has to choose between two policies, A and B and there are two possible states of the world. The policy maker believes that policy A is optimal in state a and policy B is optimal in state b. Formally, the policy maker's preference is $V(p, \theta)$, where $p = A, B$ is the policy and $\theta = a, b$ is the state of the world. The prior probability that the state is θ is $\mu(\theta)$ with $\mu(a) = 1/2$. If we define $V(\theta) = V(A, \theta) - V(B, \theta)$ to be the net expected benefit of A in state θ, then $V(a) > 0$ and $V(b) < 0$. The policy maker is willing to choose A if

$$V = -V(a)/V(b) \geq 1.$$

We assume that $V < 1$, so that, with no additional information, the policy maker chooses B.

There is a population of n citizens. Citizens' utilities are described by $v(p, \theta)$, where p is the policy and θ is the state of the world. If we define $v(\theta) = v(A, \theta) - v(B, \theta)$, we assume $v(a) > 0$ and $v(b) < 0$. This implies that citizens agree that A is the best policy in state a and B is the best policy in state b. A citizen is willing to choose A if

$$v = -v(a)/v(b) \geq 1.$$

We assume that the policy maker and the citizens have different willingness to choose A. Specifically, we assume $v > V$. Citizens are therefore more predisposed to choosing A than the policy maker is. The difference between v and V provides a natural way to measure the conflict of interest between the policy maker and the citizens.

Citizens observe a private informative signal t with distribution $r(t;\theta)$, support $\mathcal{T} = \{0, 1\}$. We assume that $r(0, b) = r(1, a) = r > 1/2$ and $r(0, a) = r(1, b) = 1-r$. This signal therefore satisfies a standard monotone likelihood ratio property, implying that the posterior $\mu(a; t)$ of a citizen with signal t is increasing in t.

After observing the private signal, each citizen chooses whether to protest against the policy maker's default policy B or to stay home. The policy maker observes the number of protesters and then chooses a policy that maximizes her utility.

In Section 5 we discuss how we model social networks in this environment. Until then, we assume that citizens act independently. In this case, a strategy for the policy maker is a function from the observed number of protesters to a probability of choosing A, i.e., $\rho : N \to [0, 1]$. A strategy for a citizen is a function from the signal to a probability of protesting, i.e., $\sigma : \mathcal{T} \to [0, 1]$.

Given the strategies described in the previous section, the probability that a citizen protests in state θ when the strategy is σ is:

$$\phi(\theta; \sigma) = r(0; \theta)\sigma(0) + r(1; \theta)\sigma(1).$$

From Bayes' rule, the posterior probability that the state is a if Q citizens protest is then:

$$\Gamma_n(a; Q, \sigma) = \frac{B_n(Q; \phi(a; \sigma))}{\sum_{\theta=a,b} B_n(Q; \phi(\theta; \sigma))}. \tag{1}$$

where $B_n(Q, \phi(\theta;\sigma)) = \begin{pmatrix} n \\ Q \end{pmatrix} \phi(a;\sigma)^Q (1-\phi(a;\sigma))^{n-Q}$ is a binomial distribution with n trials, and probability of success $\phi(\theta;\sigma)$. The public protest game described above always has an equilibrium in which the policy maker ignores the protesters and chooses B with probability one: in such an equilibrium citizens use uninformative, state-uncontingent strategies.[9] In the following we study the conditions under which the policy maker's decision is influenced by the "wisdom of the crowd," i.e., the citizens' actions. We assume that with complete information the policy maker would change his mind if she observed a sufficiently large number of signals pointing at a. A sufficient condition for this is that $\Gamma_n(a;Q,\sigma) > 1/(1+V)$, that is:

$$r > \underline{r} = \frac{1}{1+V^{1/n}} \tag{2}$$

Note that (2) is very easily satisfied for $r > 1/2$, since $V^{1/n}$ converges very quickly to one as n increases. We assume (2) is satisfied for the remainder of the paper.

With asymmetric information, citizens' protests can affect the policy maker's action only if they are informative on the state of the world. We say that σ, ρ is an *informative equilibrium* if citizens use informative strategies and so the probability of protesting is higher in state a, the state in which the policy maker's default policy is incorrect: $\phi(a;\sigma) > \phi(b;\sigma)$. In this case the probability of a is increasing in Q and there is a Q^* such that the policy maker is willing to choose A if and only if $Q > Q^*$.[10]

Informativeness of an equilibrium is only a minimal requirement for public protests to be useful: even if public protests are informative, information transmission can be minimal and the policy maker's mistake can be significant; even when the population is arbitrarily large, informativeness may converge to zero as $n \to \infty$. The probability of a mistake in an informative equilibrium σ, ρ, is $M(\sigma,\rho) = (1-\mu)\Pr(A, b;\sigma,\rho) + \mu \Pr(B, a;\sigma,\rho)$, where $\Pr(p,\theta;\sigma,\rho)$ is the probability that policy p is chosen in state θ. We say that *full information aggregation* is achievable if there is a sequence of informative equilibria σ_n, ρ_n for environments with population n such that $M(\sigma_n,\rho_n)$ converges to zero as $n \to \infty$.

[9] An example will be presented in Section 2.1.

[10] We can also have informative equilibria in which citizens "protest" to show support to the policy maker and stay home to signal their disagreement: in this case $\phi(a;\sigma) < \phi(b;\sigma)$. There is no loss of generality to focus on the most natural case in which a protest is interpreted as a sign that citizens protests to induce a change in the policy maker's action.

3 Theoretical predictions

In Section 2.1 we provide a characterization of the equilibrium strategies. In Section 2.2. we use the characterization to study when an informative equilibrium exists. In Section 2.3 we present numerical examples that we will use in the experimental analysis.

3.1 Equilibrium characterization

The policy maker's optimal choice depends on his posterior belief $\Gamma_n(a; Q, \sigma)$ given the citizens' strategy σ. When citizens use informative strategies, $\Gamma_n(a; Q, \sigma)$ is increasing in Q and the policy maker always finds it optimal to follow a cut-off rule. Let $Q_n(\sigma, \rho)$ be the minimal Q such that:

$$\Gamma_n(a; Q, \sigma) \geq \mu^*. \tag{3}$$

The policy maker strictly prefers B if $Q < Q_n(\sigma, \rho)$ and A if $Q > Q_n(\sigma, \rho)$; if $Q = Q_n(\sigma, \rho)$ the policy maker is indifferent if $Q_n(\sigma, \rho)$ satisfies (3) with equality and strictly prefers A otherwise. To account for the possibility of the policy maker using mixed strategies, it is convenient to represent the policy maker's strategy $\rho_n(Q)$ as a function of a threshold q_n on the real line:

$$\rho_n(Q) = \begin{cases} 0 & Q < \lfloor q_n \rfloor \\ \lceil q_n \rceil - q_n & Q = \lfloor q_n \rfloor \\ 1 & Q > \lfloor q_n \rfloor \end{cases}. \tag{4}$$

where $\lfloor x \rfloor$ and $\lceil x \rceil$ are, respectively, the largest integer less than or equal to x and the smallest integer greater than x. When q_n is an integer, (4) describes a simple cut-off rule for action in pure strategies: type q_n is the smallest number of protesters that induces the policy maker to choose A with probability one; so that B is chosen if and only if less than q_n citizens protest. When q_n is not an integer, then $\lceil q_n \rceil$ is the smallest number of protesters that induces the policy maker to choose A with probability one. A policy maker that observes $\lfloor q_n \rfloor$ chooses A with probability $\lceil q_n \rceil - q_n$; a policy maker that observes less than $\lfloor q_n \rfloor$ chooses B with probability one. Following a strategy described by (4) is optimal for a policy maker if and only if $q_n \in [Q_n(\sigma, \rho), Q_n(\sigma, \rho) + 1]$, with $q_n = Q_n(\sigma, \rho)$ if $\Gamma_n(a; Q_n(\sigma, \rho), \sigma) > \mu^*$. In this case we say that q_n is optimal given the citizens' strategy.

The citizens' strategies depend on their posterior belief, conditioning on being pivotal, i.e. conditioning on being able to affect the policy maker's decision. To evaluate the citizens' decision, define $\varphi_n(\theta;\sigma,\rho)$ to be the pivot probability in state θ given an expected population size n and the strategies σ,ρ. The pivot probability is the increase in the probability that A is chosen, as induced by a citizen's decision to protest. The pivot probability in state θ is:

$$\varphi_n(\theta;\sigma,\rho) = \left[\begin{array}{c} \beta_n \cdot B_{n-1}(Q_n(\sigma,\rho) - 1, \phi(\theta;\sigma)) \\ +(1-\beta_n)\cdot B_{n-1}(Q_n(\sigma,\rho), \phi(\theta;\sigma)) \end{array} \right], \tag{5}$$

where β_n is the probability that A is chosen if $Q_n(\sigma,\rho)$ citizens are protesting and, recall, $B_{n-1}(Q_n(\sigma,\rho)-1,\phi(\theta;\sigma))$ is the binomial with $n-1$ draws, $Q_n(\sigma,\rho)-1$ successes and probability of success $\phi(\theta;\sigma)$. A citizen is pivotal in only two events, when $Q_n(\sigma,\rho)-1$ or $Q_n(\sigma,\rho)$ other citizens are protesting (corresponding, respectively, to the first and second term in (5)). In the first event, a citizen's protest increases the probability of A from zero to β_n; in the second event, a citizen's protest increases the probability of A from β_n to one.

A citizen chooses to protest if the expected benefit of the protest is non negative:

$$v(a)\varphi_n(a;\sigma,\rho)\mu(a;t) + v(b)\varphi_n(b;\sigma,\rho)\mu(b;t) \geq 0. \tag{6}$$

We can rewrite this condition as:

$$\frac{\mu(a;t)}{\mu(b;t)} \geq -\frac{v(b)\varphi_n(b;\sigma,\rho)}{v(a)\varphi_n(a;\sigma,\rho)} = \frac{\varphi_n(b;\sigma,\rho)}{v\cdot\varphi_n(a;\sigma,\rho)}. \tag{7}$$

The monotone likelihood assumption on citizens' signals implies that there is a $t_n(\sigma,\rho) \in [0,1]$ such that only citizens with $t \geq t_n(\sigma,\rho)$ find it optimal to protest and citizens with $t < t_n(\sigma,\rho)$ find it strictly optimal not to protest; if $t_n(\sigma,\rho)$ satisfies (7) with equality then citizens with $t = t_n(\sigma,\rho)$ are indifferent and are willing to randomize their action. As with the policy maker, a citizen's equilibrium strategy σ_n can be conveniently represented as a continuous function of a threshold $\tau_n \in [0,2]$ as follows:

$$\sigma_n(t) = \begin{cases} 0 & t < \lfloor \tau_n \rfloor \\ \lceil \tau_n \rceil - \tau_n & t = \lfloor \tau_n \rfloor \\ 1 & t > \lfloor \tau_n \rfloor \end{cases}. \tag{8}$$

Following a strategy described by (8) is optimal for a citizen if and only if

$$\tau_n \in [t_n(\sigma,\rho), t_n(\sigma,\rho)+1],$$

with $\tau_n = t_n(\sigma, \rho)$ if (7) is strict at $\tau = t_n(\sigma, \rho)$. In this case, we say that τ_n is optimal given q_n.

The representations of the strategies in (4) and (8) allow to characterize an equilibrium in terms of two real numbers and simple cut-off strategies:

Proposition 1. *An informative equilibrium is characterized by a pair of thresholds* τ_n^*, q_n^* *such that* q_n^* *is optimal given* τ_n^**, and* τ_n^* *is optimal given* q_n^**.*

It is easy to see that an equilibrium of this game always exists. For example, $\sigma(t) = 1/2$ for all t and $\rho(Q) = 0$ for all Q is an equilibrium. In this case the probability of a protest is the same in both states: $\phi(a; \sigma) = \phi(b; \sigma) = 1/2$. This implies that the policy maker's posterior $\Gamma_n(a; Q, \sigma)$ is independent from Q, implying that $\rho(Q) = 0$ is optimal. Since the policy maker is unresponsive to Q, $\sigma(t) = 1/2$ is optimal for the citizens as well.

3.2 Information aggregation with public protests

The key question we intend to study is when informative public protests are possible. Our first result is an impossibility condition that characterizes an upperbound on the precision of the signals below which information aggregation is impossible.

Assume an informative equilibrium exists. Then there must be a threshold Q_n such that the policy maker is willing to choose A if and only if the number of protesting citizens Q is at least Q_n. At this threshold the policy maker's posterior probability must be sufficiently large: $\Gamma_n(a; Q_n, \sigma) \geq \mu^*$. This inequality can be rewritten as:

$$\frac{P(Q_n, \phi(a; \sigma_n))}{P(Q_n, \phi(b; \sigma_n))} \geq \frac{1}{V}, \tag{9}$$

The equilibrium, however, is informative only if there is separation of the citizens' types. This is possible only if, at the very minimum, the citizens with the lowest signal are willing to be inactive. By condition (7), we must have:

$$\frac{\varphi_n(a; \sigma, \rho)}{\varphi_n(b; \sigma, \rho)} \leq \frac{1}{v}\left(\frac{1}{\mu(a; 0)} - 1\right). \tag{10}$$

where recall that $\mu(a; 0)$ is the posterior probability of state a of a citizen who observes the lowest signal, $t = 0$. An informative equilibrium exists only if both (9) and (10) are satisfied. We now show that when conflict is sufficiently high and/or the precision of the individual signals is sufficiently low, these conditions are incompatible.

The left hand sides of (9) and (10) are intimately connected. The left hand side of (9) is the ratio between the probabilities of having Q_n protesters in, respectively, state a and in state b. The left hand side of (10) is the ratio of the pivot probabilities in, respectively, state a and b. As can be seen from (5), the pivot probability in state θ is a convex combination of the probabilities that Q_n and $Q_n - 1$ citizens are active in state θ (since a citizen is pivotal only in these two events).[11] There is therefore, a well defined relationship between the left hand sides of (9) and (10). As formally shown in the proof of Lemma 1, the relationship between them can be bounded as follows:

$$\frac{\varphi_n(a;\sigma_n,\rho)}{\varphi_n(b;\sigma_n,\rho)} \geq \frac{B_n(Q_n,\phi(a;\sigma_n))}{B_n(Q_n,\phi(b;\sigma_n))}\left(\frac{1}{r}-1\right). \tag{11}$$

Using (11) we can now connect (9) and (10) and obtain the following necessary condition for information aggregation:

$$\begin{aligned}\frac{1}{v}\left(\frac{1}{\mu(a;0)}-1\right) &\geq \frac{\varphi_n(a;\sigma,\rho)}{\varphi_n(b;\sigma,\rho)} \geq \frac{B_n(Q_n,\phi(a;\sigma_n))}{B_n(Q_n,\phi(b;\sigma_n))}\left(\frac{1}{r}-1\right)\\ &\geq \frac{1}{V}\left(\frac{1}{r}-1\right)\end{aligned}$$

The first and last inequality follow from (9)-(10), the second inequality follows from (11). We conclude that an informative equilibrium does not exist in our example *if* $V < V_*(v,r) = v\left(r^{-1}-1\right)^2$. Remarkably, when this condition is not satisfied, an informative equilibrium does not exist even if the number of informed citizens is arbitrarily large. We have:

Proposition 2. *No informative equilibrium exists if:*

$$V < V_*(v,r) = v\left(r^{-1}-1\right)^2. \tag{12}$$

Proposition 1 highlights a key difference between our public protests game and the voting games studied in the *Condorcet Jury Theorem* literature in which the policy maker can commit to a response function, the voting rule. In these cases, as first shown by Feddersen and Pesendorfer [1996], not only does an informative equilibrium exist, but full information aggregation is achieved as the size of the population increases, independently

[11] The weights in the convex combination depend on the policy-maker's strategy (the probability of choosing A with Q_n protesters).

from the cut-off rules that are used. Conversely, when the policy maker cannot commit to a response plan, the fact that citizens receive informative signals is not sufficient for information transmission. Indeed when the condition of Lemma 1 is satisfied, no information is transferred at all, no matter how large the number of informed citizens is.

In what situations will public protests be useful and allow the policy maker to improve her choice when conflict is sufficiently small? The following result characterizes a simple sufficient condition for the existence of an informative equilibrium.

Proposition 3. *An informative equilibrium exists if:*

$$V \geq V^*(v, r) = \left[v\left(r^{-1} - 1\right)\right]^{\frac{1}{1-1/n}}. \tag{13}$$

It is easy to verify that $V^*(v, r)$ is positive, larger than $V_*(v, r)$ and smaller than v. This condition implies that if conflict is sufficiently small, information transmission is possible for any population size.[12] As the precision of the individual signals increases, moreover, $v\left(r^{-1} - 1\right)$ converges to zero, so the condition of Proposition 2 is satisfied for any V.

The next result establishes that full information aggregation is possible if (13) is satisfied.

Proposition 4. *If $V \geq V^*(v, r)$ we achieve full information aggregation as $n \to \infty$.*

Proposition 4 rationalizes the belief in "the power of the numbers" according to which large protests can help significantly improving policy outcomes, but it qualifies the result highlighting that the result requires conflict to be sufficiently low and or the precision of the individual signals to be sufficiently high.

3.3 Social groups

We model the effect of social media assuming that each citizen is affiliated to one of m groups of size G, so the size of the population is $n = Gm$. Citizens in a group can communicate and share their signals.

Consider the problem faced by the citizen in a social group. When citizens share their information, each citizen in a group receives an informative signal corresponding to the

[12] Recall that $V < v$ and $|V - v|$ is a measure of the conflict between citizens and the policy maker: a larger V, therefore, corresponds to a smaller conflict.

number of citizens with a $t = 1$ (instead of $t = 0$) realization. This aggregate signal $\widetilde{t}$ has support $\widetilde{\mathcal{T}} = \{0, .., G\}$ and distribution $r_G(t;\theta) = \mathcal{B}_G(t;\theta)$, where $\mathcal{B}_G(t,\theta)$ is a binomial with mean rG when the state is a, i.e. $B_G(t; rG)$; and the binomial with mean $(1-r)G$ when the state is b, i.e. $B_G(t; (1-r)G)$.

The game with social groups can be analyzed using the results of the previous sections. Given the strategies of the policy maker, citizens in a social circle find it optimal to truthfully share their information and coordinate their actions as if they were a single player since they have no conflict. Similarly, the policy maker finds it optimal to treat each group as an individual agent if all groups act in a coordinated way. This implies that the extended game with m groups of size G can be treated as a game with m individual with signal $r_G(t;\theta)$. We have:

Proposition 4. *With a social group of size G, an informative equilibrium exists if $V \geq V_G^*(v) = v\left(r^{-1} - 1\right)^G$.*

The intuition for Proposition 4 is as follows. When the size of groups is G and their members share signals, the likelihood ratio of receiving $\widetilde{t}$ signals is now $r(\widetilde{t}; a)/r(\widetilde{t}; b) = \left(\frac{1-r}{r}\right)^{G-2\widetilde{t}}$. As g increases, the posterior probability that the state is a after signals $\widetilde{t} = 0$ converges to zero: these groups are going to be willing to abstain from protesting even when there is a very large conflict.

A drawback of having social groups (at least as described above) is that each group now behaves as a single player: all members are predicted to protest or not protest together. The number of independent signals that are available to the policy maker is not smaller. Of course this is still an advantage when the policy maker would be unable to get any information by citizens acting independently.

3.4 Discussion

In this section we discuss some key assumptions of the model.

Signal precision and overconfidence. In the previous analysis we have assumed that the signals are only partially informative, that is the likelihood ratio $r(t;a)/(t;b)$ is bounded for any signal t. Consider now a version in which the signal is continuous in $\left[\underline{t}, \overline{t}\right]$ and, for example we have $r(t;b)/(t;a) \to \infty$ as $t \to \underline{t}$. In this case, citizens with signals at or close to the lower bound would find it optimal not to protest because they surely (or almost surely) know that the state is b. In this case we would always have an informative equilibrium.[13] The existence of arbitrarily precise signals is a theoretical possibility, but probably not a realistic one: it is indeed natural to assume that citizens are only imperfectly informed, indeed typically poorly informed. The case with highly precise signals is, however, interesting for another, perhaps more plausible, reason: a citizen may be overconfident regarding the precision of their signal, a phenomenon that is well documented in the psychology literature (see for instance Kahneman et al. [1982]). Sufficiently overconfident citizens would find it optimal to act according to their signal even if this is not justified by Bayesian updating. This may be an important factor determining the success of petitions and/or protests in aggregating information. We will return to this aspect in Section 5 when we discuss the experimental results.

Direct costs/benefits of signing petitions. In the analysis above we have assumed that the cost of signing a petition is zero, which seems a realistic assumption in all examples discussed in the introduction. There are environments in which it may be natural to assume that citizens face a direct cost/benefit of signing a petition. The rational for a direct benefit from signing a petition is that citizens may receive utility from expressing their opinion (see for example Brennan and Lomasky [1993]); the rationale for a cost is that the act of signing a petition or participating to a protest may be time consuming or it may involve a penalty (especially in a non democratic country). Allowing for a cost of sending a message (i.e., the signature of the petition) naturally makes signalling easier since it improves the ability of the informed agents to separate. Battaglini and Benabou [2003] have studied the case of public protests with costly actions and they have shown that a separating equilibrium always exists. Ekmecki and Lauermann [2018] have extended the model in Battaglini to allow for cost/benefits of protesting. The interesting question, however is the extent to which the amount of information transmitted is significant when the number of citizens is large and the precision of individual signals is not very high. With many senders the probability of being pivotal is small and converges to zero as $n \to \infty$, so any citizen with a strictly positive cost, or a strictly positive benefit of signing a petition would act uninformatively. If any information is revealed, it must be revealed

[13] Of course this possibility is contemplated in the statement of Proposition 1, since the case with arbitrarily precise signals corresponds to a case with a large r (in which case condition 12 does not hold).

only by citizens who have a positive but arbitrarily small cost of sending the message, if such types exist.[14] In Battaglini it is shown that with a finite number of types (i.e. a finite number of possible cost/benefit types of sending the message), the same results as in Section 2.1-2.2 hold with essentially no modifications. It is easy to see that even assuming continuous types and any number of citizens even (and especially) if arbitrarily large, results remain necessarily qualitatively unchanged. In the original model by Battaglini [2016] citizens are a realization of a Poisson random variable with mean n. In this case we can technically speaking have an "informative" equilibrium even for low precision of individual signals. This would happen only because with a Poisson there is a probability that any arbitrarily large number of citizens exists: so even if the strategy used by the citizens is very uninformative because only a tiny fraction of types are informative (those marginally above zero), the policy maker may change policy if it happens that there is a very large realization of the number of existing citizens (a technical problem with the assumption of a Poisson number of citizens is that the Poisson is unbounded above). Even in these cases, however, the probability that the policy maker is affected by the citizens would be arbitrarily small: these would be informative equilibria only by name. In the model presented above, moreover, this possibility is not allowed because the number of possible voters is not unbounded. In this case, for any number n of citizens, there is always a threshold on individual informativeness below which no information is revealed as in Proposition 1.

Instrumental vs. expressive preferences. Another key underlying assumption of the model is that players have instrumental preferences, that is they care only about the policy outcome. This assumption has been criticized in the political science literature. It has been argued that, in addition to caring about policies, voters may have direct preference for expressing their opinion (Brennan and Lomasky [1993]), they may be motivated by self-image considerations (Della Vigna et al. [2015]), or ethical concerns (Coate and Conlin [2004], Feddersen and Sandroni [2006]).[15] The theory presented above is not necessarily excluding the presence of these factors: many different factors may concur in determining equilibrium behavior. Some of these "behavioral" effects are automatically controlled for

[14] It is clear from the logic of Proposition 1 discussed in Section 3.2 that citizens with a negative cost would be biased toward being uninformative even more than citizens with a zero cost.

[15] See Feddersen [2004] for a survey.

in the experiment, for example self image considerations are controlled since the subjects play anonymously. A behavioral factor that may be present and that is especially relevant is the possibility of expressive preferences. Expressive preferences may be of two types – myopic expressiveness in which a citizen receives utility from protesting regardless of his or her signal in order to express their preferences for a given state of the world or truthful expressiveness in which a citizen receives utility for truthfully revealing the signal. If some citizens are myopic expressive then obviously the possibility of information aggregation decreases as the information received by policy makers becomes noisier. Truthful expressiveness can have the opposite effect. As mentioned, expressive preferences have been discussed in the political science literature. They are especially relevant in this context because the communication game we are studying is a variant of a cheap talk game in which there is one receiver (the policy maker), but many senders (the citizens). There is ample evidence that senders in cheap talk game tend to reveal more information than predicted in equilibrium, supportive of truthful expressiveness.[16] Preferences for being truthful may play an important role in our environment also because even if citizens have instrumental preferences, they may have a hard time computing the pivot probabilities (as documented by Duffy and Tavits [2008]). If the citizens underestimate the probability of being pivotal, then expressive preferences may dominate their decisions.

4 Experimental Design

4.1 Basic Procedures

In order to evaluate the theoretical predictions, we conducted two experiments, labeled Exp 1 and 2 (both of which were approved prior to implementation by relevant university institutional review board). In both experiments we varied the conflict between the policy maker and citizens as well as the existence of social groups among the protesters who share information. Exp 1 was conducted at the Center for Experimental Social Science (CESS) at New York University with 177 subjects in 21 sessions.[17] Exp 2 was conducted via

[16] See for example Dickhaut, McCabe, and Mukherji (1995), Blume, Dejong, Kim, and Sprinkle (1998; 2001), Cai and Wang (2006), Sanchez-Pages and Vorsatz (2007; 2009), Wang, Spezio, and Camerer (2010), Battaglini and Makarov [2014] and Battaglini et al. [2019].

[17] No subjects participated in more than one session. The subject pool at CESS is drawn from the large and diverse undergraduate population at the university.

Amazon Mechanical Turk with 721 subjects in 40 sessions.[18] We conducted the sessions on Mechanical Turk as it allowed us to have larger groups of potential protestors than is feasible in the laboratory as well as providing a larger and more varied subject pool than one can recruit to most laboratories in the same of period of time. A number of studies have shown that behavior of subjects in similar games on Mechanical Turk are comparable to behavior in more conventional laboratory experiments.[19]

The experimental games followed the theory closely. In each game, subjects in a session were assigned as either citizens or policy makers. However, we used a neutral frame labeling citizens as "first movers" and policy makers as "second movers." Subject identities and assignments were anonymous and all subject communication took place via the internet.[20] We conducted two types of sessions: small groups (21 sessions in Exp 1 and 37 sessions in Exp 2) and large groups (3 sessions in Exp 2). In the small group sessions we recruited 5 protesters and 1-6 policy makers and in the large group sessions we recruited 50 of each.

Each policy maker's payoffs depended purely on whether he or she chose the jar that matched the true jar as described below. Hence, policy makers were not in a game with each other, but made independent choices. Only one policy maker's choice determined the payoffs for the protesters, which was randomly determined after a session was completed. We chose this procedure in order to increase the number of observations of policy maker

[18] No subject participated in more than one session. We screened subjects such that they were based in the US (and thus their identieis had been verified by Amazon), had prior experience on Mturk, and an evaluation score of 90% or higher. We also screen subjects such that if they had participated before, even if they dropped off before completing the experiment, they were not able to join the experiment again. Subjects were further screened through an incentivized quiz that they took after reading the instructions but before embarking on the experiment. That is, subjects were given 7 quiz questions about the game structure. If a subject answered a question wrong they were shown a message which explained the right answer and given a chance to answer the question again. If they answered the question wrong the second time, they failed the quiz and were paid $1 for their participation but not allowed to continue the experiment. The quiz was also incentivized. For every question they answered correctly the first time they received a reward of $0.10. In total 900 subjects started the experiment, of which 14 subjects dropped out before the quiz and 151 took the quiz but failed it and were screened out. A further 12 subjects dropped off after the quiz (probably due to internet issues). Two subjects' choices were not recorded for all rounds due to computer failures. These subjects' choices if they completed some of the game rounds are not included in the data as their choices could not be used for the experiment although they were paid for their participation. Subjects who completed the entire experiment earned on average $9.24 and took on average 15 to 20 minutes to complete the experiment.

[19] See for example Berinsky et al. 2012 and Levay et al. 2016.

[20] The experiment was programed in Javascript and Php. The program is available from the authors. Screenshots are presented in the Supplemental Online Appendix.

behavior without changing the nature of the game. In Exp 1, since it took place in the laboratory, all subjects were aware of the number of protestors in a session and the number of potential policy makers. In Exp 2, all subjects in a session were aware of the number of protesters in the session as well. However, in Exp 2 protesters were told that their payoffs depended on the choice of a single policy maker (which was truthful) and policy makers were told that their choices determined the payoffs for both themselves and all the protesters in their session (which was not always truthful depending on whether they were randomly chosen to so determine). Therefore, we engaged in a form of deception by not revealing to the subjects in Exp 2 that the actual policy maker in the game was drawn from a pool of policy makers and that not all the policy maker choices determined the payoffs of the protesters.

Our experiments focus on two main aspects of the theory: the effect of conflict in preferences on information aggregation through protests and the extent that information sharing within social groups increases information aggregation through protests. We have the following expectations: Holding signal quality constant, we expect that increasing conflict will reduce the likelihood of information aggregation and holding preferences constant, we expect that when citizens share information in social groups, the likelihood of information aggregation will increase.

We therefore conducted two basic games in the sessions: Baseline and Social Information, using a between subjects design in comparing game types. We describe the games in more detail below. In order to evaluate the effects of conflict we conducted experiments using the Baseline game, varying the payoffs between Low and High Conflict (as explained below) using a medium signal quality of $r = 0.60$. In order to evaluate the effects of Social Information we used the High Conflict payoffs with the Social Information game which allowed for sharing of information within social groups.

4.2 Baseline Game & Payoff Variations

In order to explain the structure of the games, we first describe a session in Exp 1 in the Laboratory in the Baseline game. Typically ten subjects were recruited to the laboratory and received instructions on how the game worked for both roles, after which they took a short quiz on the instructions. If they answered a question wrong, they were given a second chance and an explanation of the answer. They where then randomly assigned as either citizens or policy makers (in the experiment they were referred to as First or Second Movers). The subjects were shown on their computer screens two jars with 100 balls: a Silver Jar with 60 silver and 40 gold balls and a Gold Jar had 60 gold and 40 silver balls. They were told that the computer would randomly choose with 50-50% probability one of the jars as the "True Jar." Subjects were not told the jar selected by the computer, but shown a jar with colorless balls. Each Citizen then privately chose one of the balls to reveal its color and thus receive an informative yet noisy signal as to the color of the True Jar. The color shown was a random draw from the probabilities given by the jars such that each protestor's signal was a new independent draw with replacement and did not depend on the actual ball clicked on the computer monitor. After receiving their signals, citizens were given the opportunity to send the following message to policy makers: "Do not choose the Silver Jar." As will become evident below, with no additional information other than the ex ante probabilities of the True Jar's color, the policy maker's expected payoffs were maximized by choosing the Silver Jar. Hence, the message conveyed a protest against the policy maker's expected payoff maximizing choice.

After the citizens made their choices, the number of messages sent were revealed to the policy makers who then chose either the Gold or Silver Jar. The True Jar was then revealed and one of the policy maker's choices was randomly chosen to determine the payoffs for the citizens. Subjects were then told the potential payoffs for that round depending on their role. The game was repeated for a total of 50 rounds with 4 periods randomly chosen for payment at the end of the game.

In Exp 2 on Mechanical Turk there were a number of modifications given the constraints of conducting the experiment online. On Mechanical Turk the citizens were recruited first and made choices for 30 periods without feedback.[21] After all the citizens

[21] We thus had 360 subjects as first movers altogether play the game for 10,800 periods. Due to a programming problem in which on a rare occasion the software did not record their choices, the data for 21 of the periods for a few of the citizen subjects are missing with on average less than 1 choice in 1 period per session missing with no more than 4 choices in 4 periods in any one session missing (we do not have missing data for policy makers). When such data was not recorded, then policy makers were told the number of messages received only for the citizens whose choices were recorded. From the user interface the software error was not noticeable. We excluded the periods with missing data entirely from the empirical analysis reported below. As the subjects received no feedback between periods as to the identify of the true jar, there is no reason to believe that the fact that these observations were not recorded by the program had any affect on behavior of the subjects in subsequent periods.

had chosen in all the periods, then policy makers were recruited to make choices. For each period, the policy makers were told the sum of messages sent and then chose a jar (Silver or Gold). As with citizens, there was no feedback between periods. After all the policy makers had chosen in all 30 periods, one of the periods was randomly chosen for payment. Payoffs were determined and all subjects were given their payment.

To study how behavior changes with incentives and thus the effects of conflict, we used two different payoff combinations for the players in the Baseline game: Low and High Conflict. These payoffs in dollars are presented below in Table 1. Note that in both the Low and High Conflict Treatments, the policy makers' ex ante payoffs are maximized by choosing Silver, while the citizens' ex ante payoffs are maximized by choosing Gold. Yet, the theory makes starkly different predictions about behavior in the two treatments. As can be easily verified using condition (12) in Proposition 2, in the High Conflict Treatment the unique equilibrium prediction is that the decisions to send messages (protest) are independent of the colors of the balls (signals) observed by citizens and that policy makers as a consequence in equilbrium should ignore the protests and always choose the Silver Jar. In the Low Conflict Treatment, on the contrary, an informative equilibrium exists in which potential protesters respond to their signals in an informative manner and policy makers respond accordingly to the messages received.[22]

Table 1: Payoffs in Baseline Games

	Low Conflict	True Jar is Gold	True Jar is Silver
Policy Makers	Gold is Selected	\$8	-2
	Silver is Selected	-2	9
Citizens	Gold is Selected	\$10	-2
	Silver is Selected	-2	8
	High Conflict	True Jar is Gold	True Jar is Silver
Policy Makers	Gold is Selected	\$1	-2
	Silver is Selected	-2	8
Citizens	Gold is Selected	\$18	-2
	Silver is Selected	-2	1

As discussed in Section 3.5, in previous experiments on cheap talk games subjects have shown a propensity for communicating even in situations in which it is not rational to do

[22] This can be verified using condition (13) in Proposition 3.

so, engaging in excessive informative communication. Hence, we expect that even in the High Conflict Baseline game, protesters will be more likely to send messages when they see a Silver ball than when they see a Gold ball. Yet, we expect that information aggregation (messages sent) and the reactions by policy makers to protesters will be greater in the Low Conflict game than in the High Conflict game.

4.3 Social Information Game & Summary of Treatments

In order to evaluate Proposition 5 (the effects of social information), we also conducted sessions in which citizens were organized into groups who shared signals. That is, after each citizen chose his or her ball and learned its color, the citizens also were told the colors of the balls chosen by the other members of their social group. Note that we do not endogenous information sharing among citizens as our focus is the effects of such sharing on information aggregation rather than the decision to share information. In our design all citizens have the same preferences and thus they have no incentive not to share information. Nevertheless, we believe that future research should allow for endogenous information sharing among citizens and also the possibility of false information being shared as well, especially given that our results demonstrate the value of information sharing.

In Exp 2, since citizens were not necessarily online simultaneously, in order to provide this information all the draws for all the citizens within each social group were made when the session was created and then randomly assigned to the citizens by period within each social group. In Exp 1 we also used the same design to minimize differences between the two studies. After learning the distribution of signals in their social groups, citizens again chose whether to send the message to the policy makers. Policy makers only learned the number of messages sent, not the distribution of signals. In the Social Information game we used the same payoffs as in the High Conflict game. As in the Baseline game, we conducted two variants, one with 5 protesters and 1-5 policy makers and one with 50 of each. As in the Baseline game, one policy maker's choices was randomly chosen to determine payoffs. In both the 5 and 50 citizen sessions, the citizens were divided into social groups of 5. Therefore in the smaller games, there was one social group, but in the larger games there were 10 social groups. In the Social Information game we also used

$r = 0.60$. Given the parameters in the Social Information game, there exists an informative equilibrium in which citizens used the social information to convey informative messages that are then responded to by the policy makers.

Table 2 below summarizes the treatments conducted.

Table 2: Treatments and Sessions

Payoffs	Citizens	Policy Makers	r	Groups	Sessions	Subjects
Exp 2 Baseline Games						
Low	5	5	0.60	NA	10	100
Low	50	50	0.60	NA	1	100
High	5	5	0.60	NA	12	120
High	50	50	0.60	NA	1	100
Exp 2 Social Information Games						
High	5	4-5	0.60	1	10	99
High	50	51	0.60	10	1	100
Exp 1 Baseline Games						
Low	5	5	0.60	NA	6	60
High	5	1-5	0.60	NA	4	36
Exp 1 Social Information Games						
High	5	1-5	0.60	1	9	67

4.4 Experimental Predictions

Our treatments allow us to evaluate a number of predictions concerning policy maker, citizen behavior, and the effectiveness of protests. We expect that when conflict is high in the Baseline games, citizens' protests will be less informative, that policy makers will respond to protests less, and that policy makers will make less efficient choices. In contrast, we expect that when citizens share social information, citizens' protests will be more informative, that policy makers will respond to protests more, and that policy makers will make more efficient chocies. Thus, with respect to citizens, we expect their signaling behavior to be least informative in the High Conflict Baseline games as compared to the Low Conflict Baseline games and the High Conflict Social Information games. Similarly, we expect that policy makers will respond to the protests of citizens the least in the High Conflict Baseline games as compared to the other two. Finally, as a consequence of the behavior of citizens and policy makers, we expect that policy makers will make the least efficient choices in the High Conflict Baseline games as compared to the other two. These predictions are summarized below:

Prediction 1 (Effect of Conflict on Citizen Behavior) *We expect that in the Baseline games, citizens' protest behavior will be less informative in the High Conflict games than in the Low Conflict games.*

Prediction 2 (Effect of Conflict on Policy Maker Behavior) *We expect that in the Baseline games, policy makers will be less likely to respond to protests in the High Conflict games than in the Low Conflict games and will make less efficient choices in the High Conflict games.*

Prediction 3 (Effect of Social Information on Citizen Behavior) *We expect that in the Social Information games, citizens' protest behavior will be more informative than in the Baseline games.*

Prediction 4 (Effect of Social Information on Policy Maker Behavior) *We expect that in the Social Information games, policy makers will be more likely to respond to protests than in the Baseline games and will make more efficient choices in the Social Information games.*

5 Empirical Analysis of the Effects of Conflict

We begin our analysis with an examination of the effects of conflict on citizen and policy maker behavior and the extent that their choices support Predictions 1 and 2 above. First, we consider how conflict affects citizen behavior.

5.1 Citizen Behavior and Prediction 1

Table 3 shows the raw data on citizen's strategies representing the frequencies of protesting conditioning in the individual signals by conflict and number of citizens. We find evidence in support of Prediction 1. That is, we find that while conflict level appears to have little effect on the extent that citizens send messages when they receive a Gold signal, they are much more likely to send message when receiving a Silver signal in the High Conflict treatment. Thus, we find that subjects' behavior does appear to be conditional on the Conflict level and the signal they receive.

Table 3: Percent Citizens Send Messages in Baseline Game

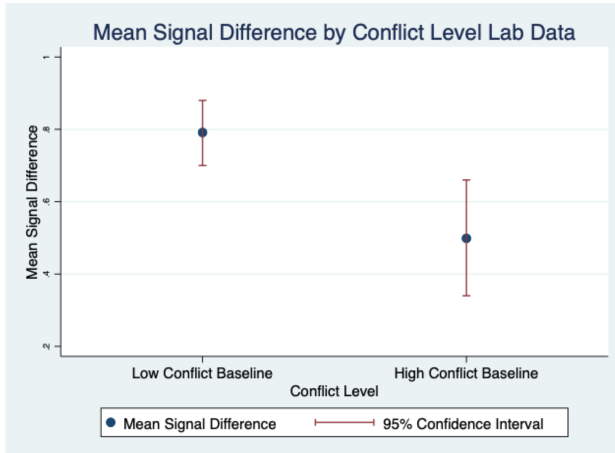
Experiment	Number of Citizens	Signal Type	Low Conflict	High Conflict
Exp 1	Five	Gold	89%	83%
		Silver	15%	35%
Exp 1	Fifty	Gold	75%	82%
		Silver	14%	38%
Exp 2	Five	Gold	92%	89%
		Silver	12%	40%

But it is important to remember that the numbers in the table do not reflect individual subjects' signaling behavior, but their behavior in the aggregate, and do not control for repeated observations by subject. Therefore, we conduct two types of analyses in order to evaluate whether there are statistically significant differences across treatments in message behavior: (1) We calculate the mean signaling behavior for each subject across rounds and (2) We estimate probit equations of the probability a citizen sends a message in which we control for repeated observations by clustering by subject and adding in controls for the round of choice.

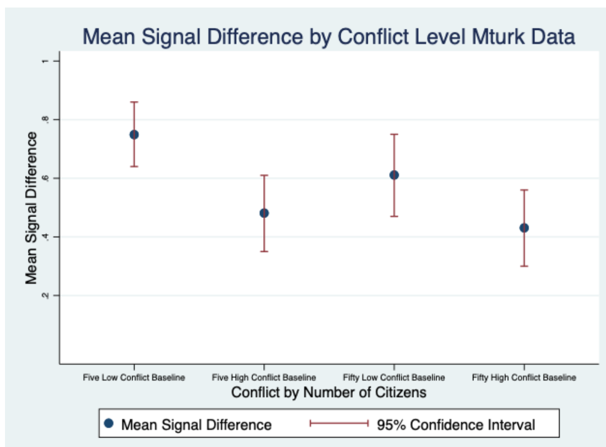
In our first approach, we calculate for each individual subject his or her messaging strategy in terms of Mean Signal Difference, MSD_{ij} for subject i in session j. To calculate MSD_{ij} we estimate the mean message strategy for the player when receiving a Gold Signal (and should send a message in the Low Conflict Treatment) and the mean message strategy for that player when receiving a Silver Signal (and should not send a message in the Low Conflict Treatment) and find the difference between the two. That is, if a subject sends a message in a round we coded that choice with a 1 and if a subject did not we coded that choice with a 0. We then calculated the average messaging strategy for each subject for all the rounds that he or she received a Gold Signal and the average for each subject for all the rounds that he or she received a Silver Signal. If the subject always sent a message when she received a Gold Signal and never sent a message when she received a Silver Signal, then the first average equals 1, the second average equals 0 and the $MSD_{ij}$for that subject equals 1. Hence, the closer the MSD_{ij} is to 1, the more informative the subject's signaling strategy.

Figures 1a,b: Effects of Treatment on Mean Signal Difference

(a) Exp 1 Results



(b) Exp 2 Results



Figures 1a,b below present the mean of the MSD_{ij} with confidence intervals by treatment and numbers of citizens. In our statistical comparisons we use both parametric (t statistic) and nonparametric (Mann-Whitney z statistic) measures. We find that the MSD_{ij} in the Low Conflict treatment is significantly greater than in the High Conflict treatment in all cases in both Exp 1 and Exp 2, supporting Prediction 1 (note that the only slight exception is that the fifty citizen case is significant only in the nonparametric test and for a one-tailed version of the parametric test).[23]

[23]The t statistic for the comparison of Low Conflict with High Conflict for five citizens in Exp 1 = 3.27, Pr = 0.00 and in Exp 2 is 3.12, Pr = 0.00 . The t statistic for the fifty citizen comparison of Low and High is 1.88, Pr = 0.06. The z statistics for the nonparametric tests = 2.71, Pr = 0.01; = 2.93, Pr = 0.00; and 2.35, Pr = 0.02; respectively.

In our second approach we estimate probit equations of the probability a citizen sends a message in which we control for repeated observations by clustering by subject and adding controls for rounds of choice which are reported in Tables B1 and B2 in the Supplemental Online Appendix B and Figures 2a,b below. The null case in the probits is the Low Conflict treatment with a Silver Signal. For each treatment we measure both the treatment and the effect of the signal. In unreported analyses we estimated of the five and fifty citizen cases in Exp 2 separately and find no differences in the qualitative relationships observed, so we report a combined estimation here.

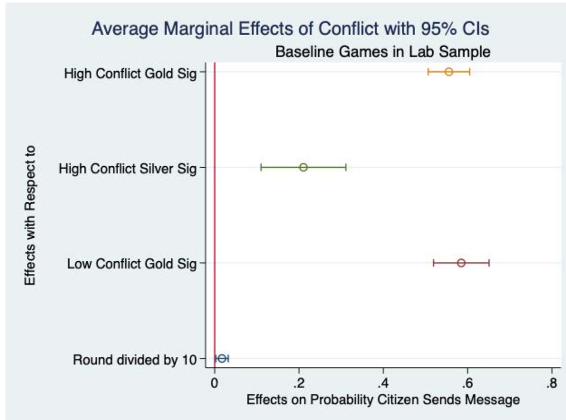
We find that in the Low Conflict treatment subjects are as expected significantly more likely to send a message if they receive a Gold Signal as compared to when they receive a Silver Signal in both Exp 1 and Exp 2. We also find that in the High Conflict treatment subjects are significantly more likely to send messages with a Gold Signal, but that that they are also significantly more likely to send messages when they receive a Silver Signal than those in the Low Conflict treatment, as expected in both Exp 1 and Exp 2. Thus, the messages of subjects in the High Conflict treatment are more noisy and more messages are sent in these treatments. We hence find strong support for Prediction 1, our High Conflict treatment significantly reduces the informativeness of citizens' protests.

The fact that citizens use strategies that are more informative than predicted in equilibrium is not surprising in light of the existing experimental literature on cheap talk. The game we are studying is indeed a cheap talk game in which the citizens are senders and the policy maker is the receiver. The experimental literature on cheap talk has been unanimous in showing that in these games senders tend to be informative even when not predicted by the theory, though the comparative statics of cheap talk games with respect to the informativeness of the strategies is typically in line with theoretical predictions: exactly what we find here.[24] The only difference is that here we are considering a more general game in which there are multiple (potentially an arbitrarily large number of) senders, and the senders' signals and the policy space are binary.

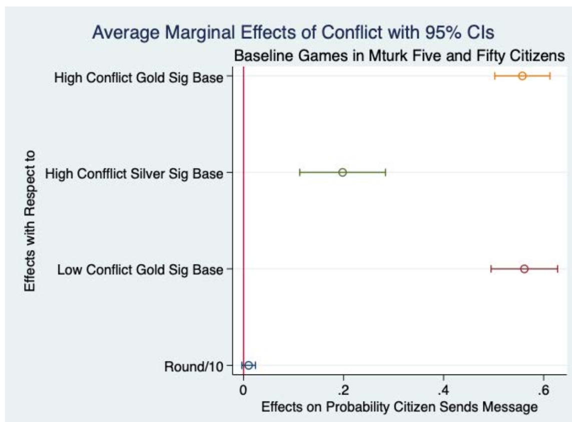
Figures 2a,b: Effects Estimated in Probits of Citizens' Choices

(a) Exp 1 Results

[24] See footnote 13 for references.



(b) Exp 2 Results (Five and Fifty Citizens Combined)



5.2 Policy Maker Behavior and Prediction 2

5.2.1 How Responsive are Policy Makers?

With protests less informative, how is policy maker behavior affected? According to Prediction 2, we expect policy makers to be less responsive to citizen protests and to make less efficient choices in the Baseline games when conflict increases. If policy makers are responsive to protests, then we expect them to be more likely to choose the Gold Jar as the number of protests increases. If the policy maker is responsive, we expect the relationship to be nonlinear: when the number of protesters is sufficiently small, the marginal effect of a protester is zero since the policy-maker remains on policy B, the ex ante optimal policy; when the number of protesters is very high, the marginal effect of a protester is still zero, since the policy maker has already shifted to policy A. It is only for intermediate numbers of protesters that a marginal protester can have a large impact on the probability of a decision.

We have not explicitly computed the exact threshold on the number of protesters at which the policy maker shifts from B to A since it is not necessary for us to test the qualitative implication of the theory and it would be unrealistic to assume that the citizens adopt the exact theoretical threshold: more realistically we should expect a distribution of thresholds centered at the midpoints; and therefore to find a small marginal effect for low and high levels of turnout; and a higher marginal effect for intermediate values. We therefore considered 3 regions: a low turnout region with 0 to 2 protesters with $n = 5$ and 0 to 24 with $n = 50$; a medium turnout region with 2 to 3 with $n = 5$ and 24 to 25 with $n = 50$; and the remaining high turnout region with 3 to 5 and 25 to 50 with $n = 50$. We expect that the marginal effect of a protester is higher for the intermediate region: if we find no effect, it may be that we have selected the cutoff incorrectly and we are underestimating the nonlinearity; if we find the effect, then we have evidence of the nonlinear effect discussed above. What we care showing in the experiment is that there is evidence that the policy maker uses a threshold on the number of protesters and that this threshold (i.e. the peacemaker's responsiveness) depends on the treatment as predicted.

Figures 3a,b,c illustrate how the mean percentage of policy makers who choose the Gold Jar changes as the sum of messages sent changes by Conflict Level in both Exp 1 & 2. As the figures illustrate, we find the nonlinear relationship expected. Furthermore, we find support for Prediction 2 in that policy makers are much more likely to respond to protests as they increase in the Low Conflict games than in the High Conflict ones. Hence, we find strong evidence that policy makers are much less responsive to protests when there is high conflict in both experiments.

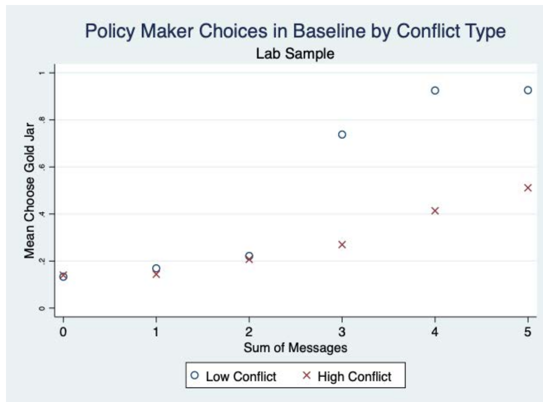
The raw data supports our predictions, but are these differences significant? Since we have repeated observations by subject and possible behavior changes over time, in order to determine the statistical significance of our results we estimate probit analyses of the effect of the number of messages sent by citizens in each treatment on the decision to choose Gold (clustered by subject to control for repeated observations of subjects' choices and adding in round variables). The results of the probit analyses are reported in Tables B3,4 in the Supplemental Online Appendix B and shown in Figures 4a,b,c below.

In the probit analyses, since we expect that the sum of messages will have a nonlinear effect on choices, we use a spline estimation procedure, estimating the effects of increasing the sum of messages on the probability a policy maker chooses gold for three separate intervals. In the five citizen case, we estimate the effect of increasing the messages in each treatment (Low and High Conflict) in the interval 0 to 2 with the independent variables Sum Msgs Low Conflict 0-2 and Sum Msgs High Conflict 0-2, respectively. We created similar variables with the suffix 2-3 for the effect of increasing the messages in the interval 2 to 3 and 3-5 for the effect of increasing the messages in the interval from 3 to 5. For the fifty citizen case, we create similar variables with the intervals as 0 to 24, 24 to 26, and 26 to 50.[25] In the estimation the null case is when Sum Msgs Low Conflict 0-2 = 1 or Sum Msgs Low Conflict 0-24 = 1.

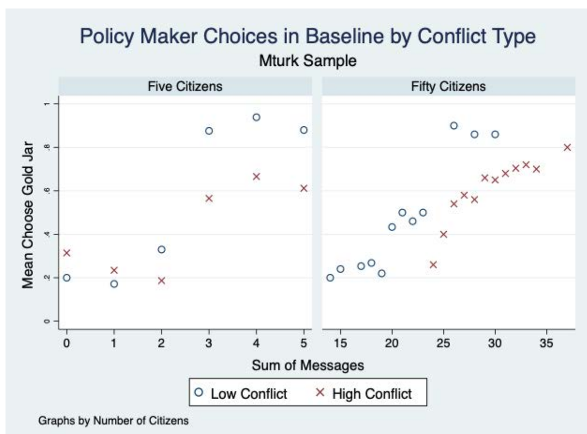
[25] While the five citizen case the best placement of the intervals is easy, in the fifty citizen case we compared different intervals with similar qualitative relationships as is reported here. We also investigated other intervals in the fifty citizen case, but more than three intervals resulting in high collinearity across independent variables and other breakpoints had lower goodness of fit.

Figures 3a,b,c: Effect of Conflict on Policy Makers' Responses to Protests

(a) Exp 1 Results



(b) & (c) Exp 2 Results

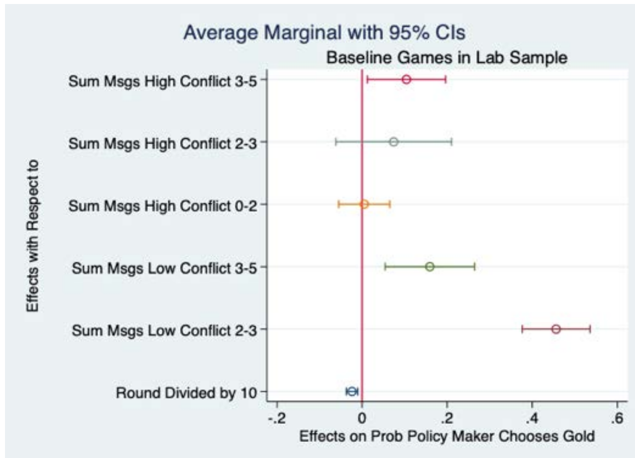


As expected, we find that the responses to the sum of messages sent by the policy makers is highly nonlinear in the Low Conflict case. The function of response can be interpreted as representation of the empirical strategy $\rho_n(Q)$ described in (4). We find that for both five and fifty citizens, the size of the effect of moving from 0 to 2 messages received is always significantly smaller than the effect of moving from 2 to 3 for all treatments.

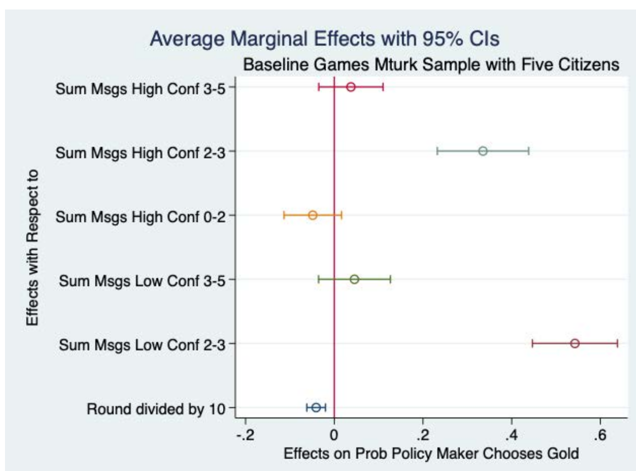
Figures 4a,b,c: Effects Estimated in Probit of Policy Maker Choices

Null Case Baseline Game with Low Conflict 0-2 & 0-24

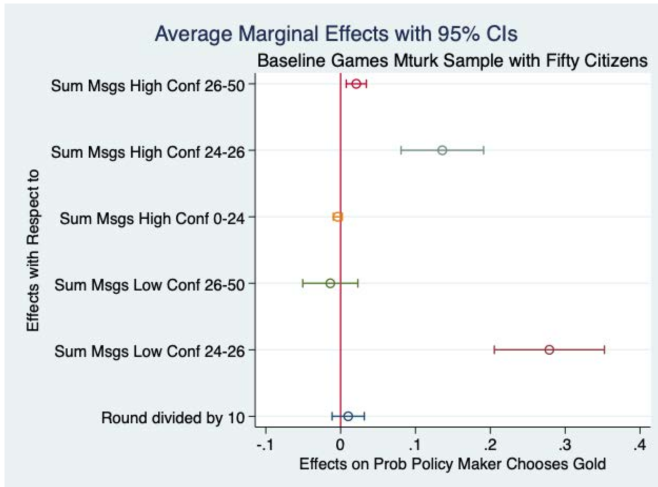
(a) Exp 1 Results



(b) Exp 2 Results for Five Citizens



(c) Exp 2 Results for Fifty Citizens



Notably, we find significant evidence of a treatment effect in the comparison between Low Conflict and High Conflict on policy maker responsiveness, supporting Prediction 2 in all three estimations. In Exp 1, we find that in the High Conflict Treatment policy makers only respond significantly to increases in the sum of messages from 3-5. In Exp 2, although policy makers respond nonlinearly to the sum of messages with High Conflict payoffs, the effect of the sum changes from 2-3 (24-26) is significantly less than the effect of the same variable in the Low Conflict treatment for five (fifty) citizens. Hence, we see that policy makers are much less responsive to the sum of messages they receive under High Conflict than Low Conflict supporting Prediction 2.

5.2.2 How Efficient are Policy Makers' Choices?

As is obvious in Figures C1a,b,c in Supplemental Online Appendix C, the number of messages sent by citizens is an endogenous variable and affected by treatment, so in order to calculate a better measure of the effect of treatment on policy maker behavior we measure the effect of treatment on the informational efficiency of policy makers' choices, which is also part of Prediction 2. In order to control for differences in draws that may occur between treatments as well as the number of citizens in the game (theoretically we might expect more efficient choices as the number of citizens increases), we used as a benchmark the choice that would have been made by the policy makers if they could directly observe the citizens' signals.[26] We then compared the choices made by policy makers to this hypothetical informationally efficient choice.[27] If the policy maker made the same choice as would have been made if fully informed, we coded those choices with a success or 1, with failure coded 0. We then, for each policy maker, we calculated the percentage of times they made the informationally efficient choice in all rounds, which we labeled as the policy maker's Mean Efficiency, ME_{ij} for policy maker i in session j. Figures 5a,b below present mean values of ME_{ij} and confidence intervals by conflict level and number of potential protesters in Exp 1 and 2.

Figures 5a,b present a number of results that are supportive of our Predictions. In the comparisons, we use both parametric t tests and the nonparametric Mann-Whitney z test. We find that, as expected, efficiency is significantly lower in both tests when we compare the High Conflict Treatment to the Low Conflict Treatment in the Baseline game with both five and fifty citizens in Exp 2.[28] We find a similar negative effect of High Conflict on efficiency in Exp 1, but the relationship is not significant.[29]

Furthermore, an intersting finding is that, holding conflict level constant, we find that efficiency is not significantly higher when there are 50 citizens as compared to five citizens in Exp 2.[30] This result means that decision of a fully informed policy maker is not statistically more efficient than the decision of a policy maker observing public protests with $n = 50$ than with $n = 5$.

[26] Although the program was relatively effective in randomizing both the true jar and the signals, there was still variation across treatments which would confound a comparison of simply whether the policy maker chose the correct jar as a measure of efficiency. Specifically, the mean number of signals that matched the correct jar in the 5 citizen case varied from 2.86 in the Low Conflict Baseline game in Exp 1 to 3.15 in the High Conflict 1 Baseline game in Exp 2. With 50 citizens in Exp 2, the mean number ranged from 29.2 in the Low Conflict Baseline Game to 30.37 in the High Conflict 1 Social Information game.

[27] Let m be the number of 1 signals (i.e the one for gold). A fully informed policy maker would choose as follows: with low conflict and $n = 5$, gold would be selected if $m \geq 3$; with low conflict and $n = 50$, gold would be selected if $m \geq 26$; with high conflict and $n = 5$, gold would be selected if $m \geq 4$; with high conflict and $n = 5$, gold would be selected if $m \geq 27$.

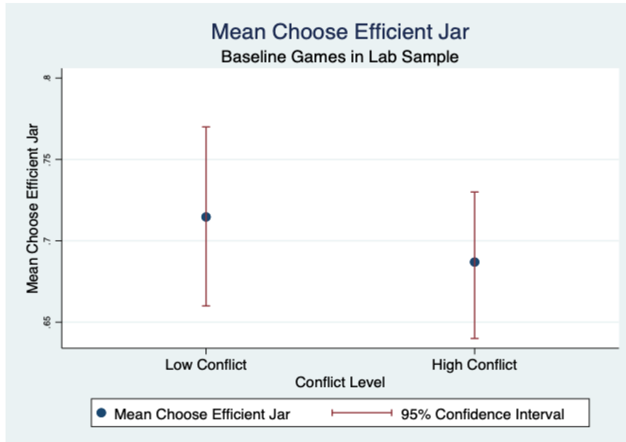
[28] The t statistic for the comparison of Low Conflict with High Conflict with 5 citizens in Exp 2 = 4.31, Pr = 0.00 and the z statistic = 4.06, Pr = 0.00. For the 50 citizen case the two statistics are 2.07, Pr = 0.04 and 3.05, Pr = 0.00, respectively.

[29] The t statistic = 0.72, Pr = 0.47 for two-tailed test. The z statistic for the Mann-Whitney test = 0.59, Pr = 0.55.

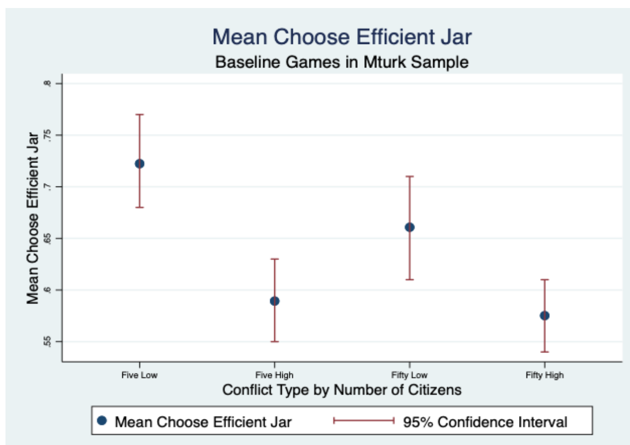
[30] The t statistic for the comparison of five and fifty citizens in the baseline game under the low conflict treatment = 1.78, Pr = 0.08 and for the high conflict treatment = 0.56, Pr = 0.58. The z statistics for the two comparisons = 1.27, Pr = 0.20 and 0.34, Pr = 0.73.

Figures 5a,b: Mean Efficiency by Treatment

(a) Exp 1 Results



(b) Exp 2 Results



5.3 Effects of Conflict: Summary

We find significant effects of conflict on citizen behavior in support of Prediction 1 in both Exp 1 and 2. Citizens' messaging is significantly more noisy when conflict is high than it is low. We also find support for Prediction 2, policy makers are less responsive to citizen protests when conflict is high than when it is low. We find some evidence of less efficient policy choices with high conflict in Exp 2 and suggestive evidence in Exp 1. Our results suggest then that conflict does reduce the effectiveness of protests, even in a common value setting where if the truth were known there would be no disagreement between citizens and the policy maker.

6 Effects of Social Information on Citizen Behavior

Our theoretical analysis suggests that if citizens were divided into social groups and shared their information, even when there is high conflict, protests are informative and can be effective in improving policy making. In this section we evaluate our Predictions 3 and 4, begininig with Prediction 3, that citizen protests will be more informative with social information.

6.1 Citizen Behavior and Prediction 3

In the previous Section we evaluated how informative citizen choices were by comparing their MSD_{ij} by conflict level. However, such a comparison does not make sense as a way of measuring the informativeness of citizen behavior under social information since citizens' behavior should not be a function of their individual signals, but the distribution of signals in their social groups. Therefore, to compare the informativeness of citizen behavior in the Baseline and Social Information games, we calculate a measure of how much citizens respond to the distributions on average which we label subjects' Mean Distribution Difference or MDD_{ij}. To calculate MDD_{ij} we estimate the mean messaging strategy for a citizen when the majority of signals in her social group is Gold (and should send a message in the Social Information game) and the mean messaging strategy for that citizen when the majority of signals in her social group is Silver (and should not send a message in the Social Information game) and find the difference between the two for each citizen. That is, if a citizen sends a message in a round we coded that choice with a 1 and if a citizen did not we coded that choice with a 0. We then calculated the average messaging strategy for each citizen for all the rounds in which the majority of signals were Gold and the average for each citizen for all the rounds in which the majority of signals were Silver and calculated the difference. If the citizen always sent a message when the majority were Gold and never sent a message when the majority were Silver, then the first average equals 1, the second average equals 0 and the MDD_{ij} for that subject equals 1. Hence, the closer the MDD_{ij} is to 1, the more informative the citizen's signaling strategy of the distribution of signals in the subject's social group. We calculated this difference for citizens in the Baseline and Social Information games. If with Social Information citizens' messaging is more informative, then the MDD_{ij} should be significantly higher than in the Baseline games. In the Baseline games when the number of citizens were five, the social group is the total group of citizens. We randomly assigned citizens to social groups of five for the calculation with fifty citizens using the same procedure in which they were randomly assigned in the Social Information games.

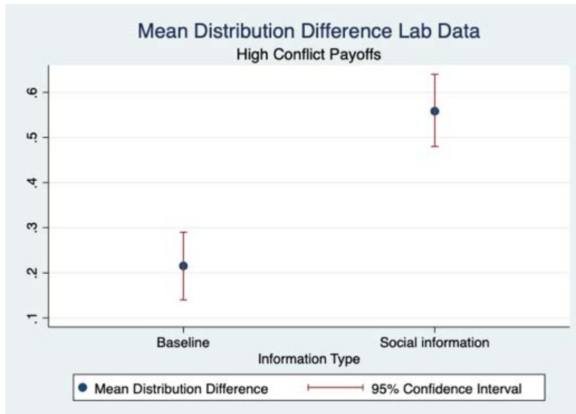
Our MDD_{ij} measures are presented in Figures 6a,b. We find that citizens are significantly more likely to send messages reflecting the distribution of signals in their social groups in the Social Information games than in the Baseline ones in both the lab and mturk data and for both five and fifty citizen cases.[31]

In addition to our calculation of our MDD_{ij} measures, we also estimated probit equations of citizen's probability of sending a message as above in our evaluation of Prediction 1 as a function of social information under the High Conflict payoffs. Since we expect that citizens will respond to the distribution of gold signals received in their social groups, we used a spline estimation procedure similar to the one used in Figures 5a,b,c. That is, we created variables Sum Gold Sigs Social 0-2 for the case where the number of gold signals was between 0 and 2 and citizens received social information, etc. We created similar measures for the Baseline games as well. The null case in the estimations is a Baseline game in which the citizen received a silver signal. The results of these estimations are presented in Figures 7a,b and in the Supplemental Online Appendix B in Tables B5,6. As above, we clustered standard errors by subjects.

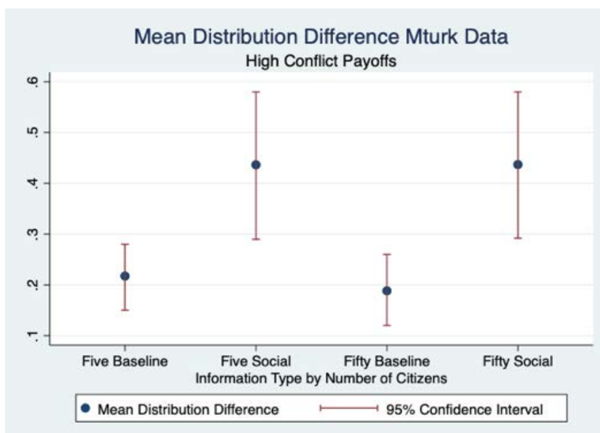
[31] The t statistic for the comparison in the lab data =6.38, Pr = 0.00. The t statistic for the comparison in the Mturk data for five citizens = 2.79, Pr = 0.01 and for fifty citizens =3.08, Pr = 0.00. The Mann Whitney z statistics for the same comparisons = 4.87, Pr = 0.00; 3.38, Pr = 0.00; and 2.89, Pr = 0.00; respectively.

Figures 6a,b: Effects of Treatment on Mean Distribution Difference

(a) Exp 1 Results



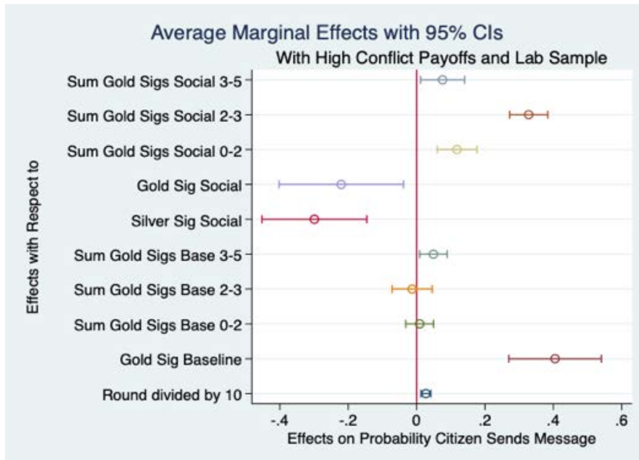
(b) Exp 2 Results



As in Figures 6a,b,c, our probit estimations provide strong evidence that citizens are responding to the distribution of signals in their social groups more than their own signals and significantly more than citizens in the Baseline games in both Exp 1 and 2. Hence, we find strong evidence that citizens' messaging behavior is more informative with social information.

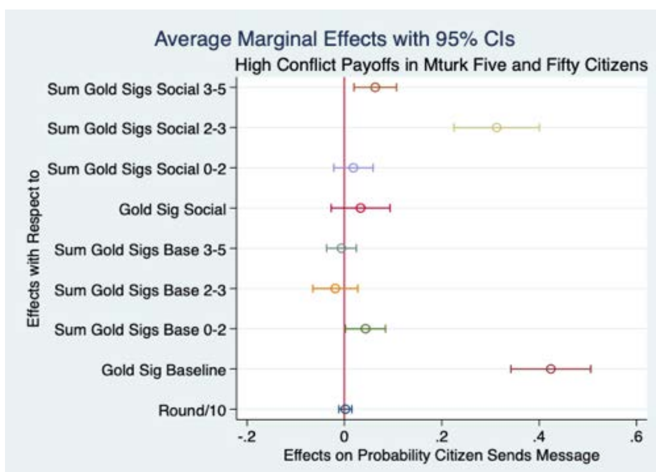
Figures 7a,b: Spline Probits of the Effects of Social Information on Citizen Messaging Behavior

(a) Exp 1 Results



(b) Exp 2 Results

(Silver Signal Social Information case dropped due to Collinearity)



6.2 Policy Maker Behavior and Prediction 4

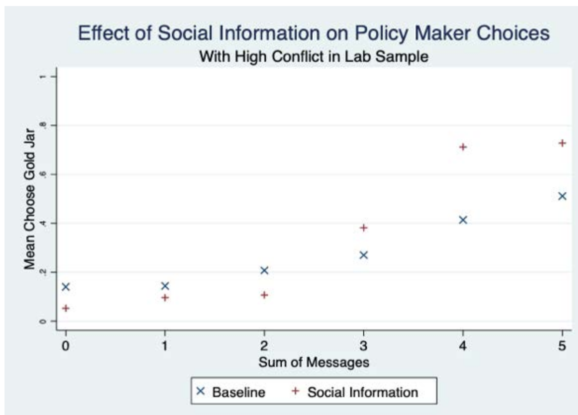
We now turn to our Prediction 4, that policy makers will respond more to citizen messages and make more efficient choices with social information than in the Baseline games. As above, we first consider the extent that policy makers are responding more to the messages they receive under social information and then address the efficiency of their choices.

6.2.1 How Responsive are Policy Makers?

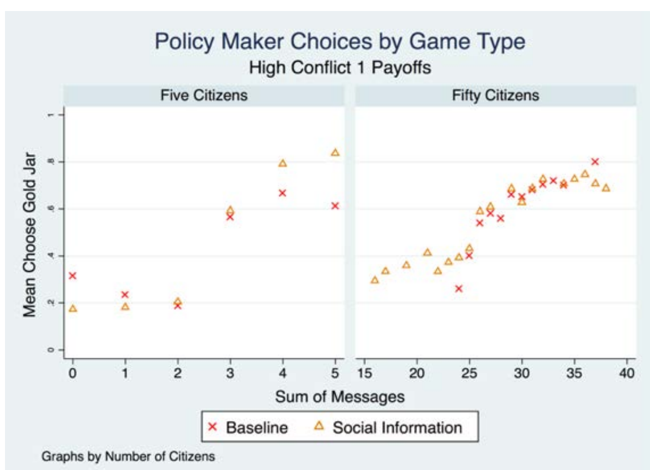
Figures 8a,b,c present a summary of policy makers' tendency to choose the gold jar as a function of the number of messages they receive. We find that policy makers appear more responsive in Exp 1 and to some extent with five citizens in Exp 2, but do not appear to be so with fifty citizens in Exp 2.

Figures 8a,b,c: Effect of Social Information on Policy Makers' Responses

(a) Exp 1 Results



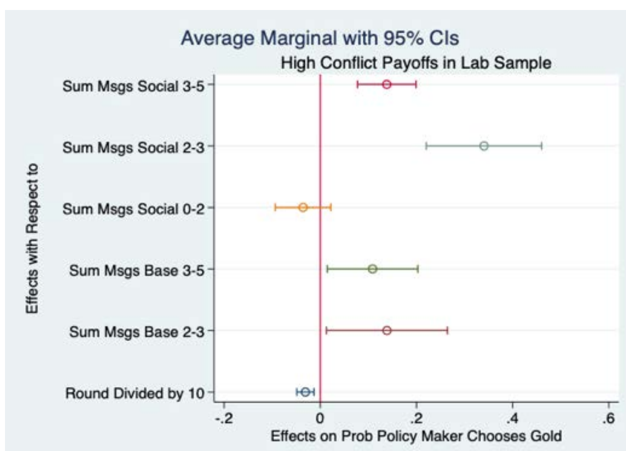
(b) & (c) Exp 2 Results



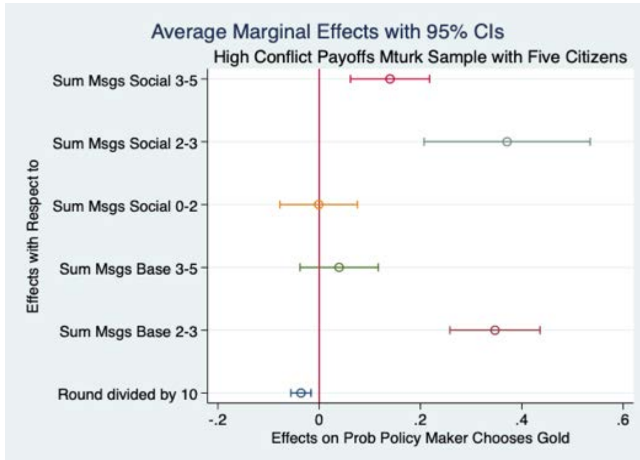
In order to determine if the differences we observe are significant, we estimate spline probit equations as in Figures 4a,b,c for a comparison of the Baseline games and Social Information ones under the High Conflict Payoffs, which are prested in Figures 9a,b,c below and reported on in the Supplemental Online Appendix in Tables B7,8. As above, we find the strongest evidence that policy makers are more responsive to citizens' protests in Exp 1 (the effects of increasing the number of messages from 2-3 is significantly greater with social information), our lab sample, and little evidence of greater responsiveness in Exp 2 with either five or fifty citizens. These differences may reflect either the fact that the subjects in Exp 1 received feedback after each round and thus had a greater opportunity to learn the benefit of responding to the protests, whereas such learning was not possible for policy makers in Exp 2 or that subjects in the lab were more focused on the task at hand. In unreported analysis of policy maker choices over time in the lab, however, we find little evidence that the differences we observe between treatments is greater in later periods than earlier ones, which suggests that the difference in behavior between our lab and Mturk samples does not reflect learning differences.

Figures 9a,b,c: Effects Estimated in Probit of Policy Maker Choices Null Case Baseline Game 0-2 & 0-24

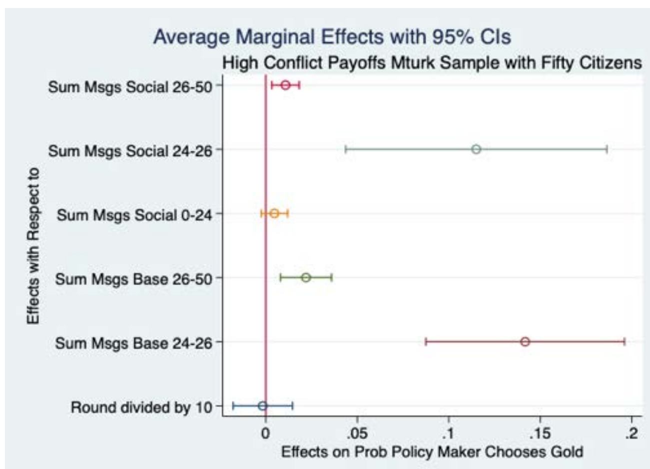
(a) Exp 1 Results



(b) Exp 2 Results for Five Citizens



(c) Exp 2 Results for Fifty Citizens



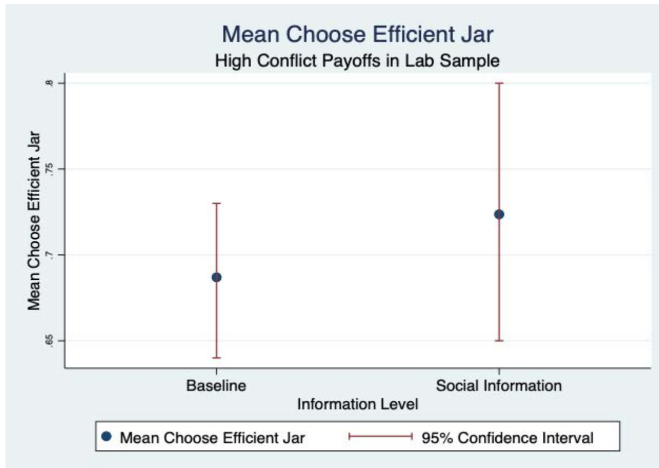
6.2.2 How Efficient are Policy Makers' Choices?

In Figures 10a,b we summarize the effects of social information on the likelihood that policy makers choose the jar they would have chosen if fully informed as to the signals received by the citizens. We find qualitative evidence that policy makers make the informationally efficient choice more often with social information, but the difference is only statistically significant in Exp 2 for five citizens using both parametric and nonparametric tests and for fifty citizens using a parametric test.[32]

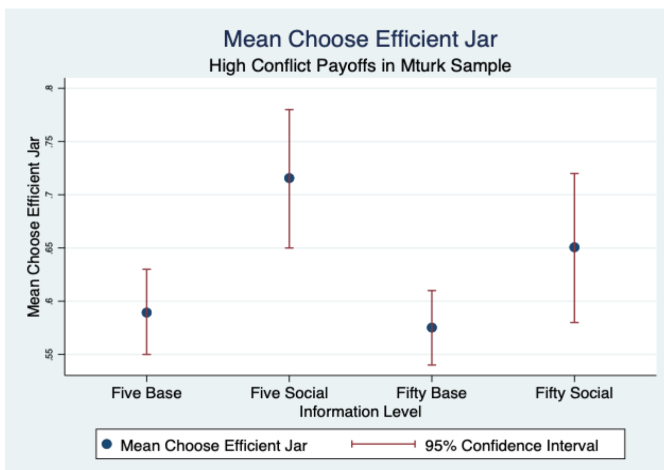
[32] For Exp 1, the t statistic = 0.86, Pr = 0.40 and the z statistic = 1.06, Pr =0.30. For Exp 2, for five citizens the values = 3.22, Pr = 0.00 and 3.66, Pr = 0.00. For fifty citizens the values = 2.07, Pr = 0.04 and 1.79, Pr = 0.09.

Figures 10a,b: Mean Efficiency by Treatment

(a) Exp 1 Results



(b) Exp 2 Results



7 Conclusions

In this paper, we have presented an informational theory of public protests, according to which public protests and petitions allow citizens to aggregate privately dispersed information and signal it to the policy maker. The model predicts that information aggregation depends on the precision of the individual signals and the level of conflict with the policy maker. Even for large populations, information aggregation by public protests or petitions is possible only if, for a given precision of the individual signals, the conflict in ex ante preferences is sufficiently small; or, for a given level of conflict, the precision of the individual signals is sufficiently high. The important point however is that even for the cases where information aggregation is impossible with independent agents, we show that information aggregation is achievable when agents can share information through social groups before taking actions.

We have used experiments on Amazon Mechanical Turk and in the laboratory to test these predictions. Our evidence confirms that public protests allow for information aggregation of dispersed information and can enable policy makers to improve their choices when conflict is low and signals are relatively precise. Both informed citizens and policy makers react to incentives as predicted by the theory, so that information transmission and the quality of policy choices improve when conflict is low. When conflict is high, moreover, we find that policy makers are significantly less likely to make efficient choices and that protests provide less information to policy makers.

Consistently with the theory, we have found that information sharing in social groups significantly affects citizens' protest decisions and as a consequence mitigates the effects of high conflict leading to greater efficiency in policy makers' choices. Our experiments highlight that social media can play an important role in protests beyond simply a way in which citizens can coordinate their actions; through information sharing use of social media in protests can lead to protests that are more informative to policy makers and more effective in changing policies. Limitations on social media use not only hurts the ability of citizens to coordinate, but also the extent that protests aggregate information, particularly when there are conflicts between citizens and policy makers in preferences.

One important caveat with this conclusion, however, is that in our design the information sharing is automatic, not a choice of the citizens. Our focus in this study is to examine the effects of information sharing in social groups on information aggregation through protests and policy makers' decisions given that such sharing occurs, rather than studying the decisions that citizens make in choosing whether to share information in social groups or not. In our design citizens all have common interests and therefore we would expect that information sharing would occur if a choice, since there would be no gain from withholding their own signals from their colleagues. Our design also abstracts away from the possibility of false information being shared within social groups either by accident or maliciously. In order to fully understand the informational role that social groups can play in protests, future research should explore how endogenous information sharing and the possibility of false information affects our results.

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8 Supplemental Online Appendix A: Proofs of Propositions

8.1 Proof of Proposition 2

Assume by way of contradiction that an informative equilibrium exists and $V < V_*(v, r)$. Define $Q^* = \min_{Q \geq 0} \{Q \text{ s.t. } \Gamma_n(a; Q, \sigma^*) \geq \mu^*\}$. In correspondence to an informative equilibrium, assuming its existence, it must be that Q^* is finite for any (finite) n. By definition of μ^*, we must have:

$$\frac{B_n(Q^*, \phi(a; \sigma^*))}{B_n(Q^*, \phi(b; \sigma^*))} \geq \frac{1}{V}, \tag{14}$$

For any informative equilibrium, moreover, we need that type $t = 0$ is willing to stay inactive, otherwise all types would be active and no information would be revealed by the citizens' actions. This requires:

$$\frac{1}{v}\left(\frac{1}{\mu(a; 0)} - 1\right) = \frac{1}{v}\left(\frac{1}{r} - 1\right)^{-1} \geq \frac{\varphi_n(a; \sigma^*, \rho^*)}{\varphi_n(b; \sigma^*, \rho^*)}, \tag{15}$$

for any n. Observe that we can write:

$$\begin{aligned}
\frac{\varphi_n(a; \sigma^*, \rho^*)}{\varphi_n(b; \sigma^*, \rho^*)} &= \frac{\rho(Q^*) \cdot B_{n-1}(Q^* - 1, \phi(a; \sigma^*)) + (1 - \rho(Q^*)) \cdot B_{n-1}(Q^*, \phi(a; \sigma^*))}{\rho(Q^*) \cdot B_{n-1}(Q^* - 1, \phi(b; \sigma^*)) + (1 - \rho(Q^*)) \cdot B_{n-1}(Q^*, \phi(b; \sigma^*))} \\
&= \frac{B_n(Q^*, \phi(a; \sigma^*))}{B_n(Q^*, \phi(b; \sigma^*))} \cdot \frac{\left[\begin{array}{c} (1 - \rho(Q^*)) \cdot \frac{B_{n-1}(Q^*, \phi(a; \sigma^*))}{B_n(Q^*, \phi(a; \sigma^*))} \\ +\rho(Q^*) \cdot \frac{B_{n-1}(Q^* - 1, \phi(a; \sigma^*))}{B_n(Q^*, \phi(a; \sigma^*))} \end{array}\right]}{\left[\begin{array}{c} (1 - \rho(Q^*)) \cdot \frac{B_{n-1}(Q^*, \phi(b; \sigma^*))}{B_n(Q^*, \phi(b; \sigma^*))} \\ +\rho(Q^*) \cdot \frac{B_{n-1}(Q^* - 1, \phi(b; \sigma^*))}{B_n(Q^*, \phi(b; \sigma^*))} \end{array}\right]} \\
&= \frac{B_n(Q^*, \phi(a; \sigma^*))}{B_n(Q^*, \phi(b; \sigma^*))} \cdot \frac{\left[\begin{array}{c} (1 - \rho(Q^*)) \cdot \frac{n-Q}{n} \frac{1}{1 - \phi(a; \sigma^*)} \\ +\rho(Q^*) \cdot \frac{Q}{n} \frac{1}{\phi(a; \sigma^*)} \end{array}\right]}{\left[\begin{array}{c} (1 - \rho(Q^*)) \cdot \frac{n-Q}{n} \frac{1}{1 - \phi(b; \sigma^*)} \\ +\rho(Q^*) \cdot \frac{Q}{n} \frac{1}{\phi(b; \sigma^*)} \end{array}\right]} \\
&\geq \frac{B_n(Q^*, \phi(a; \sigma^*))}{B_n(Q^*, \phi(b; \sigma^*))} \cdot \frac{\phi(b; \sigma^*)}{\phi(a; \sigma^*)}
\end{aligned} \tag{16}$$

where $\rho(Q^*)$ is the probability that A is chosen if Q^* protesters are observed. The following lemma is useful to complete the argument:

Lemma A1. *For any pair of strategies σ, ρ, we have:* $\frac{\phi(b; \sigma, \rho)}{\phi(a; \sigma, \rho)} \geq \frac{r(1; b)}{r(1; a)} = \left(\frac{1}{r} - 1\right)$.

Proof. *Let* τ^* be the threshold associated to σ^* according to (8). Assume first $\tau^* \geq 1$. Then we have:

$$\frac{\phi\left(b;\sigma,\rho\right)}{\phi\left(a;\sigma,\rho\right)} = \frac{\left(2-\tau^*\right)r(1;b)}{\left(2-\tau^*\right)r(1;a)} = \frac{r(1;b)}{r(1;a)}$$

We will now show that $\frac{r(1;b)}{r(1;a)} \leq \frac{\phi(b;\sigma,\rho)}{\phi(a;\sigma,\rho)}$ for $\tau^* \in [0,1]$. To this end note that for $\tau^* \in [0,1]$:

$$\begin{aligned}\frac{\phi\left(b;\sigma,\rho\right)}{\phi\left(a;\sigma,\rho\right)} &= \frac{r(1;b)+\left(1-\tau^*\right)r(0;b)}{r(1;a)+\left(1-\tau^*\right)r(0;a)} = \frac{r(1;b)}{r(1;a)} \cdot \frac{1+\left(1-\tau^*\right)\frac{r(0;b)}{r(1;b)}}{1+\left(1-\tau^*\right)\frac{r(0;a)}{r(1;a)}} \\ &\geq \frac{r(1;b)}{r(1;a)} = \left(\frac{1}{r}-1\right)\end{aligned}$$

where the first inequality follows from the monotone likelihood ratio property. We conclude that $\frac{\phi(b;\sigma,\rho)}{\phi(a;\sigma,\rho)} \geq (\frac{1}{r}-1)$ for any σ, ρ. ■

From Lemma A1 and (16) we have:

$$\frac{B_n(Q^*, \phi\left(a;\sigma^*\right))}{B_n(Q^*, \phi\left(b;\sigma^*\right))} \leq \frac{\varphi_n\left(a;\sigma^*,\rho^*\right)}{\varphi_n\left(b;\sigma^*,\rho^*\right)} / \left(\frac{1}{r}-1\right) \tag{17}$$

Combing this inequality with (14) and (15), we have:

$$\begin{aligned}\frac{1}{v}\left(\frac{1}{r}-1\right)^{-1} &\geq \frac{\varphi_n(a;\sigma^*,\rho^*)}{\varphi_n(b;\sigma^*,\rho^*)} \geq \left(\frac{1}{r}-1\right)\frac{B_n(Q^*, \phi\left(a;\sigma^*\right))}{B_n(Q^*, \phi\left(b;\sigma^*\right))} \\ &\geq \frac{1}{V}\left(\frac{1}{r}-1\right).\end{aligned}$$

This implies that $V \geq V_*(v,r)$, a contradiction. ■

8.2 Proof of Proposition 3

Recall that strategies σ, ρ can be represented by two thresholds τ, q with $\tau \in [0,2]$ and $q \in [0, n+1]$. In the rest of this section, we will represent the policy maker's posterior $\Gamma_n(\theta; Q, \sigma)$, the pivot probabilities $\varphi_n\left(\theta;\sigma,\rho\right)$, and probability of action as $\phi\left(a;\sigma\right)$ as, respectively, $\Gamma_n(\theta; Q, \tau)$, $\varphi_n\left(\theta;\tau,q\right)$ and $\phi\left(a;\tau\right)$. We proceed in two steps.

Step 1. First we consider a modified game in which we force the lowest type (i.e. a citizen with a signal $t=0$) to be inactive with positive probability and the highest type (i.e. a citizen with a signal $t=1$) to be active with positive probability. Define $\underline{\tau}$ as the solution to:

$$\frac{B_n(n, \phi\left(a;\underline{\tau}\right))}{B_n(n, \phi\left(b;\underline{\tau}\right))} = \left[\frac{r(0;a)(1-\tau)+r(1;a)}{r(0;b)(1-\tau)+r(1;b)}\right]^n = \frac{1}{V} \tag{18}$$

Note that (2) implies that $\underline{\tau} \in (0,1)$. In the modified game we restrict the strategy space imposing $\tau \in [\underline{\tau}, 2-l]$ for some $l \in (0,1)$. We now have a modified game in which $\tau \in [\underline{\tau}, 2-l]$ and $q \in [0, n+1]$. We can prove that an informative equilibrium exists in this modified game by applying the Kakutani fixed point theorem (see the proof of Lemma 2 in Battaglini [2017] for details).

Step 2. We then prove that if $V \geq V^*(v,r)$, then any equilibrium of the modified game is also an equilibrium of the original game. Since the policy maker's strategy space is unrestricted, the strategy described by q^* is a best response for the planner given (τ^*, q^*) in the original game. To show that the strategy described by τ^* is also a best response for the citizens in the original game, we proceed in three sub-steps.

Step 2.1. Assume first that $\tau^* \in (\underline{\tau}, 2-l)$. In this case, by construction types $t < t(\tau^*, q^*)$ and type $t = t(\tau^*, q^*)$ if $\frac{\mu(a;t(\tau^*,q^*))}{\mu(b;t(\tau^*,q^*))} < \frac{1}{v}\frac{\varphi_n(b;\tau^*,q^*)}{\varphi_n(a;\tau^*,q^*)}$ find it optimal to abstain; type $t = t(\tau^*, q^*)$ if $\frac{\mu(a;t(\tau^*,q^*))}{\mu(b;t(\tau^*,q^*))} = \frac{1}{v}\frac{\varphi_n(b;\tau^*,q^*)}{\varphi_n(a;\tau^*,q^*)}$ is indifferent; and types $t > t(\tau^*, q^*)$ find it optimal to be active: this is exactly the action prescribed by τ^*. It follows that τ^* is an optimal reaction function given (τ^*, q^*). We conclude that (τ^*, q^*) is a Nash equilibrium of the full game.

Step 2.2. Assume now that $\tau^* = \underline{\tau}$ in the modified game. We now prove that either we have a contradiction or $\tau^* = \underline{\tau}$ is a best reply in the original game. If $\tau^* = \underline{\tau}$, then the agent can be pivotal only if $n-1$ out of $n-1$ other citizens are protesting. By definition of $\underline{\tau}$, we must have:

$$\frac{\varphi_n(a;\tau^*,q^*)}{\varphi_n(b;\tau^*,q^*)} = \left[\frac{r(0;a)(1-\underline{\tau}) + r(1;a)}{r(0;b)(1-\underline{\tau}) + r(1;b)}\right]^{n-1} = \left(\frac{1}{V}\right)^{1-\frac{1}{n}} \tag{19}$$

Since $V \geq V^*(v,r)$, using (19) we have:

$$\frac{\varphi_n(a;\tau^*,q^*)}{\varphi_n(b;\tau^*,q^*)} = \left(\frac{1}{V}\right)^{1-\frac{1}{n}} \leq \frac{1}{v}\left(\frac{1}{1-r} - 1\right), \tag{20}$$

It follows that:

$$\frac{1}{v}\left(\frac{1}{\mu(a,0)-1}\right) \geq \frac{\varphi_n(a;\tau^*,q^*)}{\varphi_n(b;\tau^*,q^*)} \tag{21}$$

If (21) is satisfied as an equality, then $\tau^* = \underline{\tau}$ is a vest reply for the citizens in the original game. If instead (21) is strict, then a citizens, that after observing a signal $t = 0$, strictly prefers not to protest, i.e. $\tau^* = \underline{\tau}$ is too small: it follows that $\tau^* = 1 + l$ can not describe an optimal reaction function for a citizen in the set $[1 + l, 2 - l]$, a contradiction.

Step 2.3. Assume now that $\tau^* = 2 - l$, to prove that (τ^*, q^*) is an equilibrium we need to prove that either τ^* is a best reply in the original game, or it can not be a best reply in the restricted game. Define

$$\widetilde{Q}(\tau^*) = \min \left\{ Q \in \{0, .., n\} \ \ a.t. \ \Gamma_n(a; Q, \tau^*) \geq \mu^* \right\}.$$

Naturally $\widetilde{Q}(\tau^*) < n$ by (2) and, since $V < 1$, $\widetilde{Q}(\tau^*) > 0$. Consider the problem faced by a voter of type $t = 1$. Using similar steps as in (16) we can show that:

$$\frac{\varphi_n (a; \tau^*, q^*)}{\varphi_n (b; \tau^*, q^*)} \geq \left(\frac{1}{r} - 1 \right) \cdot \frac{B_n(\widetilde{Q}(\tau^*), \phi (a; \tau^*))}{B_n(\widetilde{Q}(\tau^*), \phi (b; \tau^*))} \tag{22}$$

We conclude that:

$$\frac{1}{v} \leq \frac{1}{V} \leq \frac{B_n(\widetilde{Q}(\tau^*), \phi (a; \tau^*))}{B_n(\widetilde{Q}(\tau^*), \phi (b; \tau^*))} \leq \frac{\varphi_n (a; \tau^*, q^*)}{\varphi_n (b; \tau^*, q^*)} / \left(\frac{1}{r} - 1 \right)$$

Implying that:

$$\frac{1}{v} \left(\frac{1}{\mu(a; 1)} - 1 \right) = \frac{1}{v} \left(\frac{1}{r} - 1 \right) \leq \frac{\varphi_n (a; \tau^*, q^*)}{\varphi_n (b; \tau^*, q^*)} \tag{23}$$

We now have two possibilities. If the inequality in (23) is satisfied as equality, then $\tau^* = 2 - l$ is a best reply in the original game. If instead it is satisfied as a strict inequality, then and agent with a signal $t = 1$ strictly prefers to be active (so τ^* is too large), implying that $\tau^* = 2 - l$ can not describe an optimal reaction function for a citizen in the restricted game. ■

8.3 Proof of Proposition 5

Note that the argument in Proposition 2 does not depend on the fact that we have two signals only in $\mathcal{T} = \{0, 1\}$. The same argument applies when we have $\mathcal{T} = \{0, 1, ..., T\}$ with a distribution $r(t; \theta)$ $\theta = a, b$ that satisfies the monotone likelihoods ratio property. In the more general model with $\mathcal{T}$ signals, the condition for Proposition 2 is $V \geq \frac{\mu(a;t=0)}{1-\mu(a;t=0)} v$, where $t = 0$ is the lowest signal. When we have m groups of size G and a binary signal $\{0, 1\}$, the agents in the group share the signals and act as a single player: we have an informative equilibrium in this game if an only if we have an informative equilibrium in the game with m players, G signals with distribution $B_G(t; r(1;\theta))$. We therefore conclude that we have an informative signal in the game with groups of size G if $V \geq \frac{\mu(a;\text{ G signals=0})}{1-\mu(a;\text{ G signals=0})}v$, since the "lowest signal" in this case corresponds to the case in which all members of the group receive $t = 0$. It follows that an informative equilibrium is possible if $V \geq \frac{\mu(a;t=0)}{1-\mu(a;t=0)}v = (\frac{1-r}{r})^G v$. ■

9 Supplemental Online Appendix B: Additional Empirical Results

9.1 Effects of Conflict

9.1.1 Citizen Probit Exp 1

Table B1: Prob. Citizens Send Messages in Exp 1 by Conflict

(Null Case Low Conflict Silver Signal, Clustered by Subj.)

	dy/dx	Std. Err.	z	P > $\|z\|$
Round divided by 10	0.02	0.01	2.30	0.02
Low Conflict Gold Signal Baseline	0.58	0.03	17.40	0.00
High Conflict Silver Signal Baselione	0.21	0.05	4.10	0.00
High Conflict Gold Signal Baseline	0.56	0.03	22.20	0.00
No. of Observations	2,850			
Pseudo R^2	0.40			
Clusters	57			

9.1.2 Citizen Probit Exp 2

Table B2: Prob. Citizens Send Messages in Exp 2 by Conflict

(Null Case Low Conflict Silver Signal, Clustered by Subj)

(Five and Fifty Citizen Cases Combined)

	dy/dx	Std. Err.	z	P > $\|z\|$
Round divided by 10	0.01	0.01	1.46	0.15
Low Conflict Gold Signal Baseline	0.56	0.03	16.54	0.00
High Conflict Silver Signal Baseline	0.20	0.04	4.53	0.00
High Conflict Gold Signal Baseline	0.56	0.03	19.80	0.00
No. of Observations	5,730			
Pseudo R^2	0.28			
Clusters	210			

9.1.3 Policy Maker Probit Exp 1

Table B3: Prob. Policy Maker Chooses Gold in Exp 1 by Conflict

(Null Case Msgs Low Conflict Base 0-2, Clustered by Subj.)

	dy/dx	Std. Err.	z	P > $\|z\|$
Round divided by 10	-0.02	0.01	-3.50	0.00
Msgs Low Conflict Base 2-3	0.46	0.04	11.21	0.00
Msgs Low Conflict Base 3-5	0.16	0.05	2.97	0.00
Msgs High Conflict Base 0-2	0.00	0.03	0.16	0.87
Msgs High Conflict Base 2-3	0.07	0.07	1.07	0.29
Msgs High Conflict Base 3-5	0.10	0.05	2.22	0.03
No. of Observations	2,650			
Pseudo R^2	0.24			
Clusters	53			

9.1.4 Policy Maker Probits Exp 2

Table B4: Prob. Policy Maker Chooses Gold in Exp 2 by Conflict

(Null Case Low Conflict Zero Messages, Clustered by Subj., Baseline Games)

	Five Citizens Case				Fifty Citizens Case			
	dy/dx	Std. Err.	z	P>|z|	dy/dx	Std. Err.	z	P>|z|
Round divided by 10	-0.04	0.01	-3.82	0.00	0.01	0.01	0.92	0.36
Msgs Low Conflict S2	0.54	0.05	11.09	0.00	0.28	0.04	7.44	0.00
Msgs Low Conflict S3	0.05	0.04	1.10	0.27	-0.01	0.02	-0.73	0.46
Msgs High Conflict S1	-0.05	0.03	-1.46	0.14	-0.00	0.00	-1.26	0.21
Msgs High Conflict S2	0.34	0.05	6.38	0.00	0.14	0.03	4.83	0.00
Msgs High Conflict S3	0.04	0.04	1.02	0.31	0.02	0.01	3.05	0.00
No. of Observations	3,230				2,500			
Pseudo R^2	0.22				0.11			
Clusters	110				100			
	S1: 0-2, S2: 2-3, S3: 3-5				S1: 0-24, S2: 24-26, S3: 26-50			

9.2 Effects of Social Information

9.2.1 Citizen Probit Exp 1

Table B5: Prob. Citizens Send Messages in Exp 1 By Infor
(Null Case Silver Signal Baseline, Clustered by Subj, High Conflict Payoffs)

	dy/dx	Std. Err.	z	$P > \|z\|$
Round divided by 10	0.03	0.01	3.72	0.00
Gold Sig Baseline	0.40	0.07	5.86	0.00
Sum Gold Sigs Base 0-2	0.01	0.02	0.42	0.67
Sum Gold Sigs Base 2-3	-0.01	0.03	-0.43	0.67
Sum Gold Sigs Base 3-5	0.05	0.02	2,40	0.02
Silver Sig Social	-0.30	0.08	-3.82	0.00
Gold Sig Social	-0.22	0.09	-2.37	0.02
Sum Gold Sigs Social 0-2	0.12	0.03	3.98	0.00
Sum Gold Sigs Social 2-3	0.33	0.03	11.50	0.00
Sum Gold Sigs Social 3-5	0.08	0.03	2.32	0.02
No. of Observations			3,600	
Pseudo R^2			0.26	
Clusters			72	

9.2.2 Citizen Probit Exp 2

Table B6: Prob. Citizens Send Messages in Exp 2 By Infor
(Null Case Silver Signal Baseline, Clustered by Subj, High Conflict Payoffs)
(Five and Fifty Citizen Cases Combined)
(Silver Signal Social Information omitted due to colinearity)

	dy/dx	Std. Err.	z	$P > \|z\|$
Round divided by 10	0.00	0.01	0.31	0.76
Gold Sig Baseline	0.43	0.04	10.13	0.00
Sum Gold Sigs Base 0-2	0.04	0.02	2.07	0.04
Sum Gold Sigs Base 2-3	-0.02	0.02	-0.79	0.43
Sum Gold Sigs Base 3-5	-0.01	0.02	-0.38	0.71
Gold Sig Social	0.03	0.03	1.08	0.28
Sum Gold Sigs Social 0-2	0.02	0.02	0.90	0.37
Sum Gold Sigs Social 2-3	0.31	0.04	7.00	0.00
Sum Gold Sigs Social 3-5	0.06	0.02	2.84	0.00
No. of Observations			6,005	
Pseudo R^2			0.17	
Clusters			210	

9.2.3 Policy Maker Probit Exp 1

Table B7: Prob. Policy Maker Chooses Gold in Exp 1 by Infor

(Null Case Msgs Low Conflict Base 0-2, Clustered by Subj.)

	dy/dx	Std. Err.	z	P > $\|z\|$
Round divided by 10	-0.03	0.01	-3.43	0.00
Msgs High Conflict Base 2-3	0.14	0.06	2.16	0.03
Msgs High Conflict Base 3-5	0.11	0.05	2.27	0.02
Msgs High Conflict Social 0-2	-0.04	0.03	-1.22	0.22
Msgs High Conflict Social 2-3	0.34	0.06	5.56	0.00
Msgs High Conflict Social 3-5	0.14	0.03	4.46	0.00
No. of Observations			2,250	
Pseudo R^2			0.19	
Clusters			45	

9.2.4 Policy Maker Probits Exp 2

Table B6: Prob. Policy Maker Chooses Gold in Exp 2 by Infor

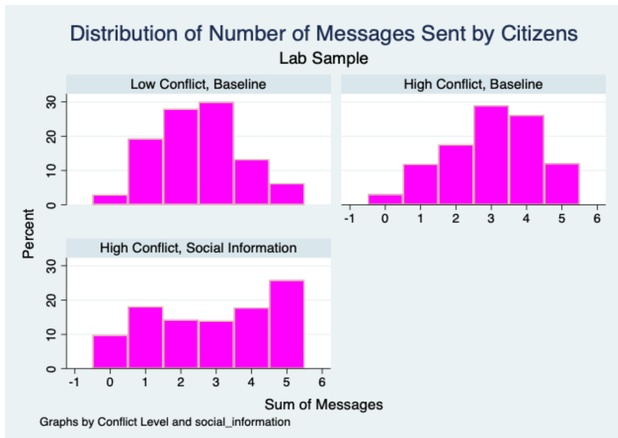
(Null Case Low Conflict Zero Messages, Clustered by Subj., High Conflict Payoffs)

	Five Citizens Case				Fifty Citizens Case			
	dy/dx	Std. Err.	z	P>|z|	dy/dx	Std. Err.	z	P>|z|
Round divided by 10	-0.04	0.01	-3.53	0.00	-0.00	0.01	-0.20	0.84
Msgs Baseline S2	0.35	0.05	7.65	0.00	0.14	0.03	5.12	0.00
Msgs Baseline S3	0.04	0.04	1.00	0.32	0.02	0.01	3.11	0.00
Msgs Social S1	-0.00	0.04	-0.03	0.98	0.00	0.00	1.28	0.20
Msgs Social S2	0.37	0.08	4.44	0.00	0.12	0.04	3.16	0.00
Msgs Social S3	0.14	0.04	3.51	0.00	0.01	0.00	2.83	0.01
No. of Observations	3,225				2,780			
Pseudo R^2	0.17				0.08			
Clusters	109				101			
	S1: 0-2, S2: 2-3, S3: 3-5				S1: 0-24, S2: 24-26, S3: 26-50			

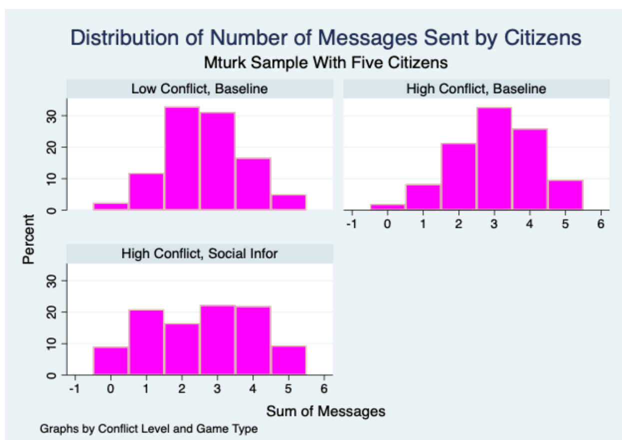
10 Supplemental Online Appendix C: Additional Figures

Figures C1: Histograms of the Sum of Messages Sent

(a) Exp 1



(b) Exp 2 Five Citizens



(c) Exp 2 Fifty Citizens