Good-Citizen Lottery*

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Abstract

This paper examines the Good-Citizen Lottery, a budget-balanced institutional mechanism designed to collectively minimize public bads by using penalties from violators to fund a reward for one randomly-selected prosocial agent. Contrary to standard voluntary contribution models where cooperation decays in large groups, our game-theoretic model predicts the asymptotic stability of good-citizen behavior. This is driven by the budget-neutral nature of the lottery: as the group size grows, the decreased probability of winning the lottery is offset by the endogenously increasing prize pool (funded by more violators). Experimental evidence is consistent with this theoretical prediction: the proportion of good behavior is robust and weakly increases with group size. Finally, we show that this institutional success is further enhanced by a behavioral channel: individuals who subjectively overestimate small winning probabilities find the uncertain reward relatively more appealing, sustaining compliance levels above the risk-neutral benchmark.

JEL Classification: D73, C91, H41, K42

Keywords: Lottery, Public bads, Imperfect monitoring, Laboratory experiments

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1 Introduction

Good citizenship is often, if not always, unpaid. Consider a driver who wants to stop at a building that has no available parking spaces. Although it may cause various forms of social costs, parking illegally for two minutes might avoid detection, so he may be tempted to park in front of the building and sneak away from the scene shortly. Alternatively, the driver could take the time to find a legal parking spot, walk the extra distance, and pay the parking fee, all without receiving explicit acknowledgment for doing the "right thing." Good citizenship encompasses a wide range of behaviors, but this paper focuses on actions that are costly to the individual yet do not harm society.[1] In this framework, good citizens are those who voluntarily abstain from contributing to the production of public bads, such as reducing greenhouse gas emissions at home, recycling responsibly, refraining from littering, and paying for public transportation when monitoring is minimal.

The literature on public bads minimization has mostly focused on penalizing bad[2] citizens, while little attention has been paid to ways to encourage good citizenry. Another apparent solution to minimize social costs is to increase government spending on monitoring capacities or offsetting social costs, but this raises subsequent questions about the cost-effectiveness of government intervention. Having these issues in mind, my broader research question is how to facilitate good-citizen behaviors without imposing additional government expenses. This paper proposes a novel method to collectively minimize the production of public bads without requiring an external budget: a good-citizen lottery, hereinafter a *citizen lottery*. Under the status quo, each citizen decides how to behave based on their own benefits and costs. Under the lottery, one randomly-selected good citizen receives a lottery payment whose prize is funded by imperfectly-collected penalties from bad citizens.[3] Would this mechanism effectively decrease the proportion of bad citizens? If so, how does the mech-

[1] A concept of good citizens may be innocuously extended to law-abiding business owners and taxpayers. For example, the recent legalization of cannabis in some U.S. states forces legal cannabis sellers to compete against the opportunistic benefits of being an illegal seller. News reports indicate that California's first cannabis company filed for bankruptcy largely because they could not compete with illegal weed stores, which constitute more than 70 percent of the market in Los Angeles.

[2] Here the 'bad' citizen does not necessarily mean that the citizen's behavior is morally bad. Throughout this paper, I refer to behavior that renders a positive expected payoff to the individual but imposes a social cost via negative externality. Without proper monitoring capacity and penalization, this 'bad' behavior can be understood as economically 'rational' behavior.

[3] For three days in September 2010, the Swedish Road Safety Organization and Volkswagen trialed a 'speed camera lottery,' whereby drivers who drove under the speed limit were entered to win a lottery prize funded by fines paid by speeding drivers (Fact check. Last access: Jan 8, 2025.) To the best of my knowledge, this trial is the only known implementation of the budget-balanced good-citizen lottery described in this paper.

anism perform as the population size grows?

To understand the effect of the citizen lottery, I consider a game where citizens simultaneously choose one of two actions. One action, corresponding to a rent-seeking (or bad-citizen) behavior, involves a large benefit with some probability and a penalty with the complimentary probability. The other action, corresponding to a good-citizen behavior, comes with no benefits, but one of the good citizens is randomly selected to get an award whose value is the sum of the penalties collected by a fraction of bad citizens.

With a reasonable set of parameters, the equilibrium probability of good actions is asymptotically stable as the population size grows. The intuition relies on the budget-neutral nature of the mechanism. As the population grows, two forces interact. On one hand, a larger number of good citizens implies that the probability of winning the lottery approaches zero (a dilution effect). On the other hand, a larger population with the same fraction of good citizens implies a larger absolute number of bad citizens, which scales up the collected penalties and, consequently, the prize pool (a valuation effect). These two forces—the decreasing probability of winning and the increasing value of the prize—offset each other. This result stands in contrast to the typical prediction for voluntary contributions to public goods, where individual incentives to contribute asymptotically shrink to zero as the number of beneficiaries grows (Andreoni, 2006). In the citizen lottery, because the reward scales endogenously with the number of violators, the incentive to maintain good citizenship remains robust even in large populations. Furthermore, an increase in monitoring capacity increases the equilibrium probability of good actions, implying that this mechanism complements, rather than substitutes, standard enforcement efforts.

Experimental findings are consistent with these theoretical predictions. As the group size increases, the proportion of (neutrally framed) good-citizen behaviors remains stable and does not decay. Moreover, the *level* of good citizenship observed in the experiment is consistently higher than the risk-neutral theoretical benchmark. This "level shift" is primarily driven by subjects with a stronger tendency toward probability weighting: individuals who subjectively overestimate small winning probabilities find the lottery reward relatively more appealing than the standard model predicts. These insights reinforce the viability of the citizen lottery: the institutional structure ensures stability against group size, while psychological biases (probability weighting) enhance the overall compliance level. A supplementary online experiment with significantly larger group sizes (from 50 to 200) provides corroborating evidence, confirming that the proportion of good-citizen behaviors remains robust and well above theoretical predictions even as the group size scales up.

The remainder of this paper is organized as follows. The following subsection provides an overview of the relevant literature. Section 2 describes the model. Section 3 presents the theoretical analyses, and Section 4 describes the laboratory experiment. Section 5 reports the experimental findings, and Section 6 discusses various issues, including the supplementary evidence from an online experiment with larger group sizes. Section 7 concludes.

1.1 Literature Review

The use of lotteries in nonstandard contexts has gained considerable attention in recent years as an innovative mechanism to address diverse societal challenges. Kim (2021) explores the use of vaccination lotteries to examine how they promote vaccination uptake compared to a lump-sum subsidy, while Kim (2023) introduces a penalty lottery framework that endogenously makes citizens reveal their willingness to produce public bads. Gerardi et al. (2016) and Duffy and Matros (2014) examine the relationship between penalties for not turning out to vote and turnout lotteries, demonstrating their potential to incentivize voter participation. Kearney et al. (2010) and Filiz-Ozbay et al. (2015) advocate for savings lotteries as a tool to encourage financial discipline among individuals who did not have savings accounts. Morgan (2000) and Morgan and Sefton (2000) propose and experimentally examine the efficacy of lotteries as a method to fund public goods, showing that such mechanisms can overcome free-rider problems. The "regret lottery" that pays a randomly-selected employer who did not park in the facility worked as an effective tool to reduce car use (Gneezy, 2023), while inducing regret in others who were selected but disqualified due to car use. Other innovative applications include Björkman Nyqvist et al. (2019), who examine the effectiveness of a lottery to promote safer sexual behavior, and Volpp et al. (2008) and Levitt et al. (2016), who explore lotteries as a means to foster desirable habits, such as improving health outcomes and student achievement. Collectively, these studies underline the versatility of lotteries in motivating behaviors across a range of settings.

To the extent that the minimization of public bads corresponds to the provision of public goods, this study is related to the extensive experimental literature on public goods provision (Isaac et al., 1984; Isaac and Walker, 1988; Andreoni, 1990; Charness and Yang, 2014). However, a key distinction of the good-citizen lottery is its asymptotic behavior. A standard voluntary contribution mechanism (VCM) model without warm glow utility predicts that the voluntary contributions asymptotically decrease as the population size grows (Andreoni, 2006). In contrast, the budget-neutral design of the citizen lottery creates a countervailing force, the scaling prize, that stabilizes cooperation in large groups. Additionally, unlike standard VCM studies that often rely on framing effects to sustain cooperation (Andreoni, 1995), this study adopts an abstract and neutral framing to isolate the strategic incentives of the mechanism itself.

The most closely related work is Fabbri et al. (2019), who conducted a field experiment on a bus-ride lottery aimed at improving compliance with purchasing public transportation tickets. While their study offers valuable insights, there are three significant differences. First, this paper ensures budget balancedness, which imposes a natural constraint on the expected benefits of good-citizen behaviors and creates the endogenous stability described above. Second, rather than comparing the lottery mechanism to a no-lottery baseline, this study investigates how the group size and monitoring capacity influence the effectiveness of the lottery. Finally, it delves into individual heterogeneities that drive good-citizen behaviors, utilizing a behavioral channel (probability weighting)[4] to explain why compliance levels exceed risk-neutral predictions. These distinctions position the current study as a novel contribution to the literature on institutional design and the incentivization of prosocial behaviors.

2 Model

This section considers the simplest possible model. Although there are many avenues to extend this model, the fundamental tradeoff between two actions of each decision maker would still remain unchanged.

Suppose there are n citizens, indexed by $i \in \{1,\ldots,n\} \equiv N$, making a decision simultaneously.[5] Each citizen chooses one of two actions: one action is to safely abide by law, denoted by S, and another action is to violate it to accrue private benefits, V. Thus, the action space is $A = \{S,V\}^n$.

Citizen i accrues a benefit of acting V, $B_i > 0$.[6] Although the citizen of acting V can be monitored and fined F, the monitoring capacity is limited. Specifically, with probability $p \in (0,1)$, action V is monitored so that the citizen's payoff is $B - F < 0$, while with probability

[4] A recent policy experiment relying on this bias is the "Lucky Yatra" pilot introduced by Indian Railways in 2025. The scheme converted standard train tickets into lottery entries to incentivize fare compliance. While the initiative was designed to exploit the overestimation of small probabilities, subsequent reports indicated mixed operational results due to low public awareness. See *Storyboard18* (June 21, 2025), "Cannes Lions Grand Prix winner 'Lucky Yatra' fails to deliver for Indian Railways."

[5] This assumption of simultaneity does not mean that all the citizens must act at the same time. Rather, this assumption parsimoniously captures the imperfect information about other citizens' actions.

[6] Alternatively, one can consider a cost of acting S, which essentially works the same.

$1-p$, she enjoys the full benefit of B_i. The payoff of choosing S is 0 for the 'most' cases, but when selected as a winner of the lottery, it is kF, where k is the number of players who chose V and got monitored.

I made two parametric assumptions here. I assume that the monitoring capacity is determined by the external agency or the government, so p is exogenously given. Also, I assume $B_i - pF > 0$ for all i, so bad behavior is beneficial in expectation. The model becomes trivial otherwise: If $B_i - pF \leq 0$ for some i, such citizens will find that V is strictly dominated by S.

Before we analyze the model, I illustrate the key tradeoff with an example of three homogeneous citizens, $B_i = B$ for all $i \in \{1,2,3\}$. It can be easily understood as a variation of a coordination game. One clear prediction is that (S,S,S) can never be an equilibrium: Given that two other citizens play S, the expected payoff of playing V is $B - pF$, while the expected payoff of playing S is $0 (= 0 + 0F)$ since no penalties are collected. Since $B - pF > 0$, the citizen has an incentive to deviate to V. Under some parametric conditions, (V,V,V) cannot be an equilibrium either. Given that two other citizens play V, the expected payoff of playing S is $2pF$, where $2p$ is the expected number of citizens who got a penalty. So, as long as $2pF > B - pF$, or $\frac{B}{pF} < 3$, the citizen has an incentive to deviate to play S. (In other words, if $\frac{B}{pF} > 3$, the unique Nash equilibrium is (V,V,V).) When $3 > \frac{B}{pF}$, a symmetric mixed-strategy Nash equilibrium is for each citizen to play S with probability δ, where

$$\delta = \frac{3 - \sqrt{\frac{4B}{pF} - 3}}{2}.$$

Note that we assume $B - pF > 0$, so $\frac{4B}{pF} - 3 > 1$ and $\delta < 1$. Note also that $\delta > 0$ as long as $\frac{B}{pF} < 12$, which is an unbinding condition since we consider $\frac{B}{pF} < 3$. In words, if the monitoring capacity p is not too large ($\frac{B}{pF} < 3$), there is a symmetric equilibrium where citizens play a good-citizen behavior with some positive probability.

3 Theoretical Analysis

For notational simplicity, suppose there are $n+1$ citizens (instead of n citizens) so that each citizen's decision takes into account n other citizens' decisions. $(\delta)_{i=1}^{n+1}$ is a symmetric mixed-strategy Nash equilibrium if the expected payoff of playing S:

$$\begin{aligned}&\binom{n}{0}\delta^n(1-\delta)^0 0F+\binom{n}{1}\delta^{n-1}(1-\delta)\frac{pF}{n}+\binom{n}{2}\delta^{n-2}(1-\delta)^2\frac{2pF}{n-1}+\cdots+\binom{n}{n}\delta^0(1-\delta)^n npF\\ &=\sum_{i=1}^{n}\binom{n}{i}\delta^{n-i}(1-\delta)^i\frac{ipF}{n+1-i}\end{aligned} \tag{1}$$

is equal to the expected payoff of playing V:

$$B-pF, \tag{2}$$

where $\binom{n}{i}\delta^{n-i}(1-\delta)^i\frac{ipF}{n+1-i}$ is the expected payoff when i among n citizens playing V ($\binom{n}{i}\delta^{n-i}(1-\delta)^i$) so the citizen playing S expects to be the winner of the good-citizen lottery whose expected prize is ipF, with probability $\frac{1}{n+1-i}$. $\delta \in [0,1]$ such that

$$B-pF=\sum_{i=1}^{n}\binom{n}{i}\delta^{n-i}(1-\delta)^i\frac{ipF}{n+1-i}$$

is each citizen's equilibrium probability of playing S. Let $b := \frac{B}{pF}-1 \in (0,1)$, the normalized excess benefit to the expected cost. Then, δ is such that

$$b=\sum_{i=1}^{n}\binom{n}{i}\delta^{n-i}(1-\delta)^i\frac{i}{n+1-i} := R(\delta,n) \tag{3}$$

Equation 3 demonstrates the tradeoff of playing S versus V: Playing V renders the normalized excess benefit, but as more people play V, the expected size of the good-citizen lottery prize increases, leaving the opportunity cost of not playing S larger. This equation works as a basis for the comparative statistics. Note that the left-hand side of equation 3 is constant in n, and the right-hand side of it is constant in p, the comparative statistics on these parameters are straightforward. Before analyzing the equilibrium strategy and examining comparative statics, it is useful to observe that $R(\delta,n)$ has nice properties.

Lemma 1. *$R(\delta,n)=\sum_{k=1}^{n}(1-\delta)^k$. $R(0,n)=n$, $R(1,n)=0$, and $R(\delta,n)$ is monotone decreasing in $\delta \in [0,1]$.*

Proof: See Appendix.

Thanks to Lemma 1, the equilibrium probability of good-citizen behavior δ is such that

$$b = \sum_{k=1}^{n} (1-\delta)^k, \tag{4}$$

which is analytically tractable. The first comparative static regards the changes in n.

Proposition 1. *Let $b \in (0,n)$ be a constant and n be an integer. Let $\delta^*(n) \in (0,1)$ be the solution to $b = \sum_{k=1}^{n}(1-\delta)^k$. $\delta^*(n)$ is unique, and it is strictly increasing in n.*

Proof: See Appendix.

Proposition 1 demonstrates the most desirable feature of the citizen lottery: As the number of citizens gets larger, the probability of choosing S, or the proportion of good citizens, increases.

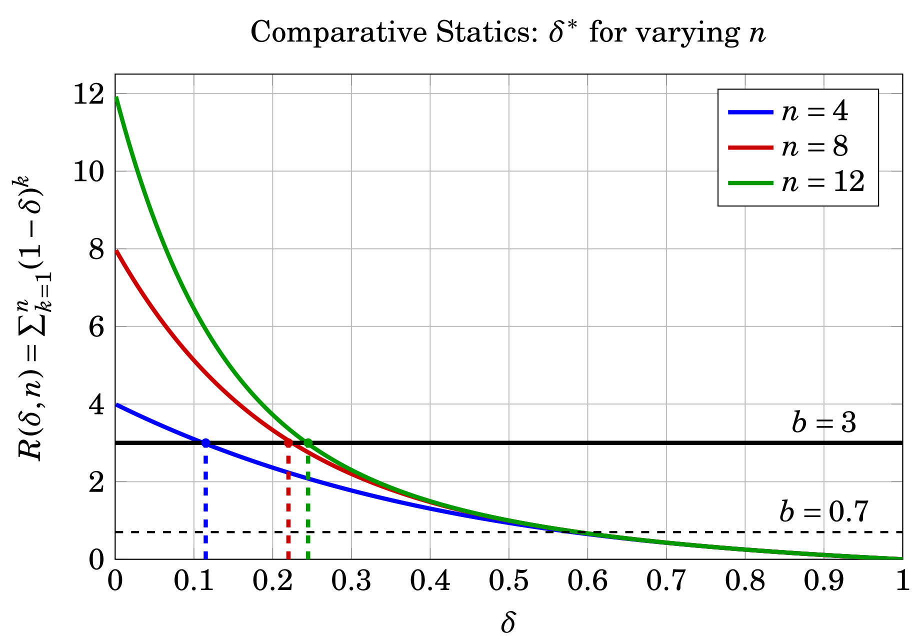


Figure 1: A larger population increases the proportion of good citizens.

Figure 1 illustrates Proposition 1 and demonstrate additional properties. The x-axis of the figure represents the value of δ ranging from 0 to 1, while the y-axis represents the value of the left- and right-hand sides of Equation 4. The left-hand side of it is invariant to the changes in n and δ, so it is depicted as a horizontal line: I arbitrarily chose $b = 3$ for illustration. The right-hand side of it, $R(\delta, n)$ decreases in δ from n to 0 (Lemma 1). The crossing point between the decreasing curve and a horizontal line describes the equilibrium strategy δ^*. As illustrated in Figure 1, $\delta^*(n)$ increases when n increases from 4 to 12. The intuition requires to understand two opposite forces describing the expected benefit of playing S: On one hand, given the same δ, having more population implies that the chance of being the lottery winner becomes smaller. For illustration, suppose that $n = 100,000$, and all other citizens' strategy is $\delta = 0.25$. Then the probability of getting a positive payoff when playing S is $\frac{1}{25,000}$, which is almost negligible. Thus, a larger n pushes down the citizen toward V. On the other hand, given the same δ, having more population implies that the prize size of the citizen lottery is larger. For the same illustration, the expected prize size is $75,000pF$ since there are 75,000 citizens playing V, and each one pays the expected penalty of pF. Thus, a larger n pushes up the citizen toward S. Proposition 1 shows that the upside force weakly dominates the downside one. Another noticeable observation is that when b is between 0 and 1, the equilibrium δ^*, would be almost stable: See the three downward-sloping curves almost coincide with a horizontal dashed line depicting $b = 0.7$. A formal argument for this observation is stated in Proposition 2.

Proposition 2. *Let $b \in (0,1)$ be a constant. The sequence $\{\delta^*(n)\}_{n=1}^{\infty}$, defined by the solution to $b = \sum_{k=1}^{n}(1-\delta)^k$, is a Cauchy sequence that converges to $\delta^*_\infty = \frac{1}{1+b}$. Furthermore, for any $n \geq 1$, the incremental change is bounded by $\delta^*(n+1) - \delta^*(n) < b^{n+1}$, implying that for $b \in (0,1)$, the sequence stabilizes exponentially fast.*

Proof: See Appendix.

Propositions 1 and 2 provide desirable properties of the citizen lottery. First, when the normalized excess benefit of V is high, a larger population size leads to a larger proportion of good citizens. This implies that the citizen lottery effectively deters many citizens to play V even though doing so is highly beneficial. Second, when the benefit of V is still positive but not that high, the proportion of good citizens are stable as the population size grows. This stability result may help a policymaker to make a reasonable prediction without concerning too much about population uncertainty. I will use this property when choosing parameters for the laboratory experiment.

The second comparative statistic regards the changes in p.

Proposition 3. $\frac{d\delta^*}{dp} > 0$ *for $b \in (0,n)$.*

Proof: The right-hand side of Equation 4 is constant in p and decreasing in δ. Since the left-hand side, $b = \frac{B}{pF} - 1$, decreases in p, δ^* that equates both hands increases. $\square$

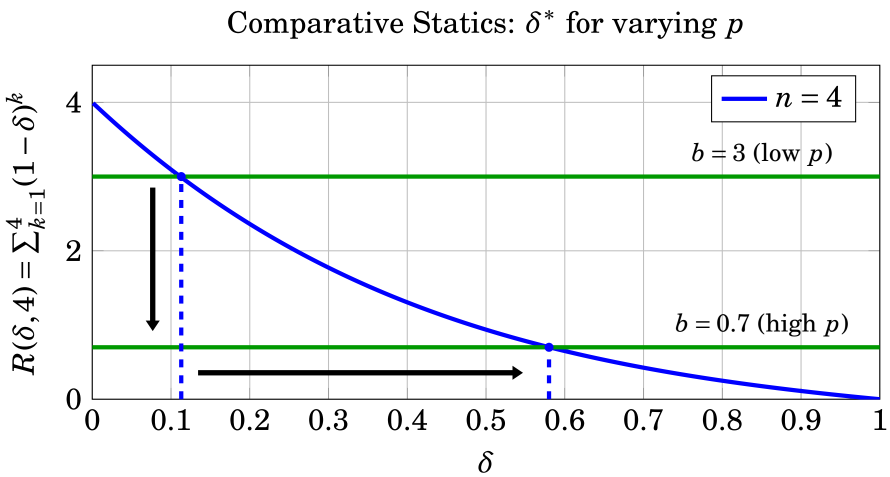


Figure 2: Monitoring capacity encourages good-citizen behaviors.

Figure 2 illustrates Proposition 3. As b decreases to b' due to the increase in the monitoring capacity, the equilibrium probability of playing S increases. Since the left-hand side of Equation 4 does not involve n, this holds for all n. Two dashed lines show how the equilibrium probability of playing S increases for $n=4$ when b is changed from 3 to 0.7. Although it may seem too straightforward that the better monitoring capacity decreases the excessive benefit of playing V, it is worth noting that the increase in $\delta^*(p)$ happens only when $b \in (0,n)$. When the normalized excess benefit of V is greater than n, that is, when p is too low, B is too large, or F is too small, the equilibrium probability of playing S is bounded at zero.

Risk preferences and subjective probability weighting are worth being mentioned as two important additional factors that could affect the citizens' decision. When it comes to the risk preferences, it is not straightforward to tell which action is more "risky". On the one hand, action V is risky because the payoff of B comes with probability $1-p$ and $B-F$ with probability p. On the other hand, action S is risky in the sense that the payoff of 0 is more likely to occur while the payoff of kF is possible with nonzero probability. Worse yet, the number of violators who got monitored, k, is a random variable, so it is hard to tell whether S is a riskier action when the population size, n, is relatively small.[7] A relatively straightforward claim is, for sufficiently large n, risk-averse subjects' δ would be larger. This

[7]To illustrate, consider an extreme case where there are only two citizens. Given the other citizen's probability of playing S is δ, action S is associated with a random payment of 0 with probability $1-(1-\delta)p$ or F with probability $(1-\delta)p$. Meanwhile, action V is associated with a random payment of B with probability $1-p$, and $B-F$ with probability p. Which one gives a larger expected payoff for a risk-averse citizen depends on the size of B, F, the monitoring capacity p, and the risk-aversion parameter.

is because the winning probability of the citizen lottery is negligible, while the payoff of V is volatile.

Claim 1. *When n is not sufficiently large, the relationship between risk preferences and likelihood of playing S is ambiguous.*

Another factor that the model does not take into account is the heterogeneous tendency of subjectively overestimate small probabilities (Tversky and Kahneman, 1992). Some people would buy lotteries, expecting that the chance of winning the lottery is greater than the objective probability (Blau et al., 2020), and such tendencies manifest in the 'Favorite–Longshot Bias' in betting markets (Thaler and Ziemba, 1988; Snowberg and Wolfers, 2010), where bettors accept negative expected value for the chance of a high payoff. Extending this observation to the case of the citizen lottery, I would expect that people with a tendency of subjective probability weighting would play S more.

Claim 2. *The more overestimate small probabilities, the more likely to play S.*

4 Experiment

To examine how the citizen lottery works in practice, I conducted a laboratory experiment, varying two key parameters, n and p. I consider the theoretical predictions and claims summarized in section 3 as null hypotheses for the experiment and design the experiment to test them clearly.

4.1 Experimental Design

An experiment is designed as follows: In each session of $N \in \{18, 20\}$ participants, they play 12 similar games, wherein each subject is randomly assigned to a group whose size is $n \in \{3, 6, 9, 18\}$ when $N = 18$ or $\{2, 5, 10, 20\}$ when $N = 20$.[8] Their task is to choose one of the two items: a white ball and a box.[9] Unwrapping the box, a subject gets a red ball with probability $p \in \{0.3, 0.5\}$ and a blue ball with probability $1 - p$. By getting a blue ball, a subject earns a payoff of $B + m$. A red ball is associated with a payoff of $B - F + m$, where

[8]It would be ideal to have all the sessions with the same number of participants, but due to unexpected no-shows I had to prepare for two different contingencies.

[9]To avoid any unobservable responses to the framed narratives, I consider abstract framing. A white ball and a box, respectively, correspond to actions S and V in section 2, but in any part of the experiment instructions, neither normative nor judgmental descriptions were used. Considering that subjects might have some baseline utilities on good citizenry, my finding could be the lower bound of the estimate.

$m > 0$ is the base payoff to guarantee the participant's minimum earnings to be positive. Choosing the white ball earns m. On top of that, one of the group members who chose the white ball is randomly selected to get an additional payoff of kF, where k is the number of the members who got the red ball within the group of n.

Round	1	2	3	4	5	6	7	8	9	10	11	12
n (when $N = 18$)	6	9	18	3	9	6	18	3	9	6	3	18
n (when $N = 20$)	5	10	20	2	10	5	20	2	10	5	2	20
Choosing a box $\Rightarrow$ Red ball with prob p; Blue ball with prob $1-p$.												
Choosing a white ball $\Rightarrow$ Randomly selected one additionally earns kF.												
$p = 0.3$ or $p = 0.5$												

Table 1: Experimental Design, $n = 18$

Table 1 summarizes the experimental design. Each round comes with a different group size in the mixed order as shown in Table 1. The participants were told that they would know how many subjects form a group at the beginning of each round, without knowing the group sizes of the following rounds. To control for the potential order effect, the same mixed order is used for all sessions. For example, in the first round of every session with 18 participants, they were told that the group size is 6. Between subjects, there are two treatments in terms of the monitoring capacity p. I call the treatment with $p = 0.3$ as P03, and P05 is denoted accordingly. After completing the 12 rounds, risk preferences and subjective probability weighting tendencies are elicited via a simple survey.[10] Post-experimental survey include some individual characteristics, which would be used as control variables later. Finally, one of the 12 rounds is randomly selected to be paid.

I set the parameters to be tightly aligned with the theoretical predictions in section 3, and to guarantee the theoretical minimum payment to be reasonably close to a typical show-up payment. The experiment currency unit used in this experiment is tokens, and I set the exchange rate at 1 token to 100KRW (about 0.07USD), the base payoff m to be 100 tokens, and B and F to be 140 and 200 tokens, respectively. This means, when a subject chooses a box, it comes with $240(= 140+100)$ tokens with probability $1-p$, or with $40(= 140-200+100)$ tokens with probability p. Choosing a white ball comes with a payoff of 100 tokens, and in case of the lottery winner, $200 * k$ tokens are added, where k is the number of the red balls appeared in the group. Given those parameters, $b = \frac{B}{pF} - 1 = \frac{7}{3}$ for $p = 0.3$ and 1 for $p = 0.5$,

[10]a long description about non-incentivized elicitation

which means that in P03, the proportion of white ball choices would increase to converge to $0.3(=\frac{1}{7/3+1})$, while in P05, it would be rather stable around $0.5(=\frac{1}{1+1})$.

4.2 Hypotheses

Corresponding to the propositions and claims summarized in section 3, I primarily investigate the following four testable hypotheses. For notational consistency, I call the action of choosing a white ball in the experiment as playing S.

Hypothesis 1. *In P03, the fraction of subjects playing S is increasing with the group size. In P05, the fraction of subjects playing S is relatively stable with the group size.*

Hypothesis 2. *The fraction of subjects playing S is greater in P05 than in P03.*

Hypothesis 3. *For the group sizes considered in the experiment, risk aversion does not affect the choices.*

Hypothesis 4. *The subjects with a stronger tendency of overestimating small probabilities would prefer to play S.*

A few remarks on the null hypotheses are worth mentioning. These null hypotheses are not meant to be normative: I do not claim that the experimental findings must be consistent with what theory says. Instead, those must be considered as theoretical benchmarks. We can learn more from what is different from theory, not from what is as predicted. For example, the relationship between risk preferences and likelihood of playing S is theoretically ambiguous, so I set the null hypothesis of no relationship between them to learn what the experimental findings guide us.

4.3 Experimental Procedure

All sessions were conducted via the real-time online mode using Zoom. Upon arrival at the designated Zoom meeting, subjects' sign-up information were checked, and then they were instructed to rename their display name with two random alphabet letters. Profile images were disabled so that the Zoom meeting environment does not make any one of the participants distinctive. Each received a web link to the standalone experimental pages created by LIONESS (Live Interactive ONline Experimental Server Software). To induce public knowledge on the information contained in the instructions, the same instructions were presented on the participants' display, and the experimenter read them aloud. After all questions were addressed in Zoom, the participants answered comprehension check quizzes, and they started the session only when every participant passed the quizzes. The experiment was conducted at Sungkyunkwan University in South Korea and the original instructions were conveyed in Korean,[11] with a total of 8 sessions (4 sessions for each of P03 and P05) with 150 participants. To minimize any dynamic effects from the previous decision rounds, the participants were told that at the beginning of every round, the entire subjects in the session were randomly shuffled and regrouped. The subjects earned on average 18,800KRW (about 14USD) with the minimum earnings of 5,000KRW and the maximum of 75,000KRW. Due to administrative restrictions regarding the cash payments to the subjects, a Starbucks e-gift card whose balance corresponds to the subject's earning was sent mobile.

5 Results

This section presents the experimental findings corresponding to the hypotheses presented in the previous section. The first set of findings regards the changes in the proportion of those who play S, or choose a white ball, when the size of the group or the monitoring capacity changes.

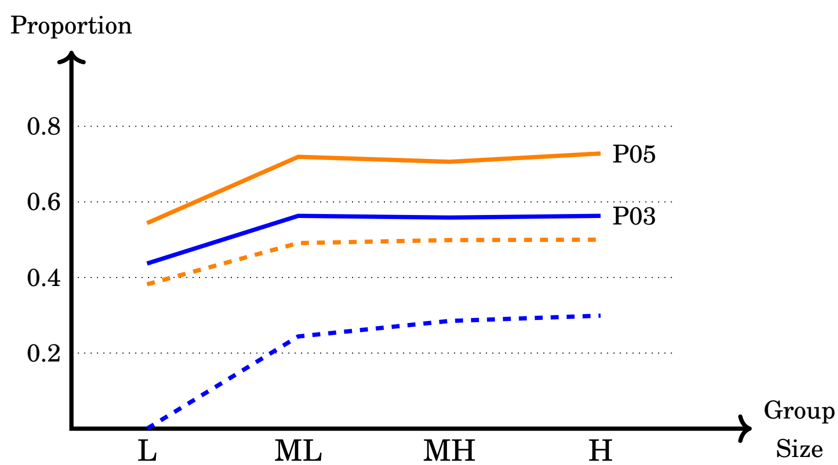


Figure 3: Proportion of playing S

Figure 3 presents several findings. The x-axis represents the size of the group. For

[11]The instructions translated in English are available in the Appendix B. The original Korean version is available upon request

illustrative simplicity, I collectively label the group size of 3 in the session of 18 and size of 2 in the session of 20 as L. The larger group sizes are labeled as ML, MH, and H in the same manner.[12] The y-axis represents the proportion of the subjects who played action S or chose a white ball. Solid lines are what I observed from the experimental data, and dashed lines with corresponding colors are theoretical predictions when the size of the session is 18.

In P03, where the theory predicts that the proportion of playing S would increase from 0 to near 0.3, the proportion of subjects playing S is nearly close to 50%, far greater than 0.3 (p <0.001)[13]. Another observation from both P03 and P05 is that the proportions of playing S have similar patterns of the theoretical predictions, making the solid lines look like parallel shifts from the corresponding dashed lines. Meanwhile, in P05, the proportion weakly increases in the size of the group (p = 0.031), but the increasing pattern is not statistically significant in P03. These findings support some of Hypothesis 1.

Result 1. *In P05, the fraction of subjects playing S weakly increases with the group size. In P03, the significant fraction of subjects play S.*

Hypothesis 2 regards how subjects would respond to the changes in monitoring capacity. The proportion of playing S in P05 is significantly larger than that in P03 (p <0.001), supporting Hypothesis 2.

Result 2. *The fraction of subjects playing S is greater in P05 than in P03.*

Note that with the between-subject design, each subject only faces either $p = 0.3$ or $p = 0.5$, so it is innocuous to claim Result 2 is not the outcome of the experimenter demand effect. Then what could the observations of larger proportions of S than the theoretical predictions explain?

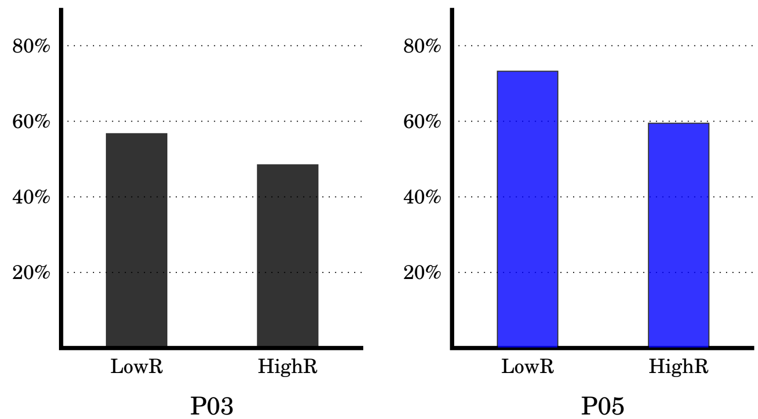
Figure 4 shows the tendency of playing S in terms of the risk preferences. Although subjects with a higher risk-taking tendency play S less in both treatments, the difference is not statistically significant. This finding corresponds to Hypothesis 3.

Result 3. *Subjects with more risk aversion tend to play S more, but the difference is statistically insignificant.*

If risk aversion is positively associated with aversion to strategic uncertainty, then action S could have been less frequent for subjects with a lower risk-taking tendency. This

[12]This labeling is considered only for illustrative simplicity. All regression results reported here takes the group size as a continuous variable.

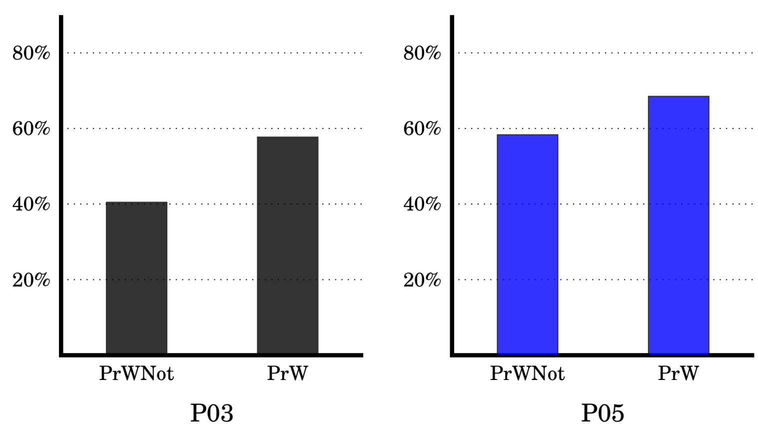
[13]Unless otherwise noted, I report the p-value from the linear regression with the standard errors clustered at the individual level.



* HighR: high risk-taking tendency.

Figure 4: Proportion of Ball Choices By Risk Preference

is because while action V does not involve any uncertainty associated with other subjects' strategies, action S highly depends on the belief on how other subjects behave. Result 3 corroborates that the concern for strategic uncertainty matters in a less significant manner.[14]



* PrW: exhibiting a tendency of probability weighting.

Figure 5: Proportion of Ball Choices By Probability Weighting Tendency

Last, but not least interesting observation is that the choice of action S is highly associated with the tendency of subjectively overestimating small probabilities, supporting Hypothesis 4.

[14]Regarding the strategic uncertainty, it would be also possible if p is uninformed to the citizens, ambiguity-averse citizens would prefer S to avoid ambiguous outcomes from V. This speculation is beyond the scope of the current paper, but it is certainly worth of further investigation.

Result 4. *Subjects with a stronger tendency of overestimating small probabilities play S more.*

Figure 5 shows the proportions of playing S in terms of the subject's tendency of overestimating small probabilities. I divided the subjects into two groups based on their self-reported willingness to pay for fictitious lotteries for gains and insurances for losses using the questions suggested by Rieger et al. (2017). The three questions involve the willingness to pay for a lottery with possible gains, and another three questions ask about their willingness to pay to avoid a lottery with possible losses. For instance, if a subject answered that he is willing to pay \$10 for purchasing a lottery that pays \$100 with a 5% chance and \$20 for a lottery paying \$100 with a 15% chance, then the subject's willingness to pay (and hence subjective probability to the event) is relatively larger for a small chance of winning.

Result 4 is particularly interesting because it raises a possibility of applying the citizen lottery in a large scale. Standard theory clearly predicts that the fraction of good-citizen behaviors would decrease if every citizen is objective in appreciating small probabilities.

6 Discussions

In this section, I address some issues not discussed in the main body of the paper.

6.1 Supplementary Evidence from an Online Experiment

A common concern regarding laboratory experiments is that the group size, intended to represent a community or local society, is often too small. In the laboratory experiment, the largest group size was 20. Although this group size is sufficiently large for the equilibrium probability of choosing S to approximate the equilibrium in the infinite population limit, some may question whether the non-decreasing pattern observed in the lab is merely an artifact of the small scale. To address this concern and test the asymptotic stability predicted by the theoretical model, I conducted an additional online experiment on Prolific in February 2025 using significantly larger groups.[15]

The online experiment followed a similar procedure to the P03 treatment of the laboratory study, with three key differences: (1) decisions were made asynchronously, (2) participants were recruited from a representative sample of the United States, and (3) most

[15]This experiment was pre-registered on AsPredicted.org (registration #208968) under the same title, 'Good-Citizen Lottery'. Since the online experiment was conducted after the laboratory data had been collected, I explicitly stated that it serves as an extension of the laboratory findings.

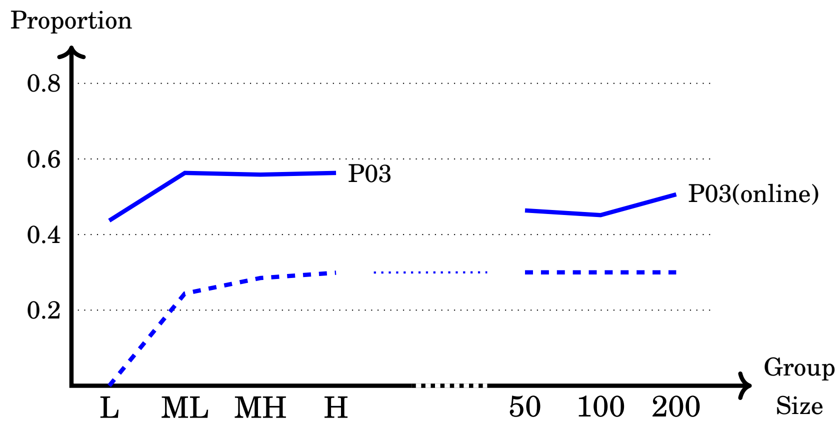


Figure 6: Proportion of playing S: Laboratory vs. Online Extension

importantly, the group sizes were 50, 100, and 200. After consenting to participate, subjects read the same instructions as in the laboratory experiment—choosing either a box or a white ball in each period, with varying payoffs associated with each decision. Participants were informed that their actual payment would be determined only after all group members had completed the study. At the start of each period, participants were randomly assigned to one of the group sizes: 50, 100, or 200. The order of group sizes was randomized. Following their decision-making, participants completed post-experiment survey questions. A total of 401 subjects participated.

Figure 6 presents the results, with a portion of Figure 3 from P03 included for direct comparison. The smallest group size in the online experiment (50) is at least 2.5 times larger than the largest group size in the laboratory experiment (18 or 20). Notably, the results confirm the theoretical prediction of stability: there were no significant decreases in the proportion of participants choosing the good-citizen action as group size increased. This finding suggests that the citizen lottery remains an effective deterrent against socially costly behaviors, even in much larger populations.

6.2 Assumptions

This subsection addresses two assumptions made throughout the paper: the desirability of bad-citizen behavior and citizen homogeneity.

I assumed that $B_i - pF > 0$ for every citizen i. This assumption was made to simplify the analysis and to ensure that the theoretical predictions without the citizen lottery are straightforward (i.e., universal non-compliance). It is, of course, possible to assume that citizens are distributed over an interval $[\underline{B},\overline{B}]$, with a value $B^* \in [\underline{B},\overline{B}]$ such that citizens with $B_i \leq B^*$ are innately good (finding $B_i - pF \leq 0$). Introducing such innately good citizens would lower the incentives for strategic individuals to act as good citizens, as the presence of "innate" winners dilutes the lottery probability. However, this would not alter the qualitative predictions of the model regarding stability. Strategic citizens ($B_i > B^*$) would still face a prize pool that scales with the number of violators, preserving the mechanism's robustness.

The assumption of citizen homogeneity is another important consideration. In assuming that there are no innately good citizens, I set $B_i = B$ for all i. However, other factors—particularly wealth and household income—may influence decision-making. It is well documented that lower-income households often spend a larger proportion of their income on lottery tickets. While the citizen lottery is distinct from a typical lottery (as there is no purchase fee), if the behavioral response to the "lottery" framing mimics that of commercial lotteries, the mechanism might exert a stronger deterrent effect on lower-income households. Although this potential unintended consequence—shifting the burden of good citizenship onto poorer individuals—is purely theoretical and has not been substantiated in this study, it remains an important consideration for welfare analysis.

7 Conclusions

This study bridges theoretical predictions with experimental findings to examine citizen behaviors in a "Good-Citizen Lottery" framework. Unlike standard voluntary contribution mechanisms where cooperation decays in large groups, our game-theoretic model predicts that the good-citizen lottery leads to asymptotically stable good-citizen behaviors: because the prize pool is funded by violators, the reward for good citizenship scales endogenously with the population size, offsetting the dilution of winning probabilities.

The experimental findings strongly support this prediction. Across both laboratory settings ($N \leq 20$) and a large-scale online extension ($N = 200$), the proportion of good behavior remained stable as group size increased, confirming the mechanism's scalability. Furthermore, we observe that the *level* of good-citizen behavior consistently exceeds the risk-neutral theoretical benchmark. This "level shift" is driven by a behavioral channel: individuals who subjectively overestimate small winning probabilities find the uncertain reward relatively more appealing. These insights imply that the citizen lottery is doubly effective: its institutional structure ensures stability against group size, while natural psychological biases (probability weighting) enhance the overall compliance rate.

From a policy perspective, the budget-neutral nature of this mechanism is particularly appealing. It offers a way to minimize public bads without requiring external subsidies or expensive increases in monitoring capacity. Speculatively, if the tendency to overestimate small probabilities is correlated with risk-taking behaviors that exacerbate public bads (e.g., speeding or tax evasion), the citizen lottery could serve as a targeted counterweight. This interplay between behavioral tendencies and institutional design opens promising avenues for future research on the production of public goods and bads.

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A Appendix: Proofs

Proof of Lemma 1: The most important task is to show $R(\delta,n) = \sum_{k=1}^{n}(1-\delta)^k$. First, we simplify the term $\binom{n}{i}\frac{i}{n+1-i}$.

$$\begin{aligned}\binom{n}{i}\frac{i}{n+1-i} &= \frac{n!}{i!(n-i)!}\frac{i}{n+1-i} = \frac{n+1}{n+1}\frac{n!}{i!(n-i)!}\frac{i}{n+1-i} = \frac{i}{n+1}\frac{(n+1)!}{i!(n+1-i)!}\\ &= \frac{i}{n+1}\binom{n+1}{i}\end{aligned}$$

Substituting this back into the original expression for $R(\delta,n)$:

$$R(\delta,n) = \sum_{i=1}^{n}\frac{i}{n+1}\binom{n+1}{i}\delta^{n-i}(1-\delta)^i$$

To relate this to the expectation of a binomial distribution, add and subtract a term for $i = n+1$.

$$\begin{aligned}R(\delta,n) &= \sum_{i=1}^{n+1}\frac{i}{n+1}\binom{n+1}{i}\delta^{n-i}(1-\delta)^i - \frac{n+1}{n+1}\binom{n+1}{n+1}\delta^{n-(n+1)}(1-\delta)^{n+1}\\ &= \frac{1}{(n+1)\delta}\underbrace{\sum_{i=1}^{n+1}i\binom{n+1}{i}\delta^{n+1-i}(1-\delta)^i}_{=(n+1)(1-\delta)} - \delta^{-1}(1-\delta)^{n+1}\\ &= \frac{1-\delta}{\delta} - \frac{(1-\delta)^{n+1}}{\delta} = \frac{1-\delta}{\delta}(1-(1-\delta)^n),\end{aligned}$$

where the sum $\sum_{i=1}^{n+1} i\binom{n+1}{i}\delta^{n+1-i}(1-\delta)^i$ represents the expected value of a random variable $X \sim \text{Binomial}(n+1, 1-\delta)$, which is $(n+1)(1-\delta)$. Finally, let $x = 1-\delta$. Since $\delta \in (0,1)$, $x \in (0,1)$. Substituting $\delta = 1-x$ yields

$$R(d,n) = \frac{x}{1-x}(1-x^n) = x\frac{1-x^n}{1-x} = x\sum_{k=0}^{n-1}x^k = \sum_{k=1}^{n}x^k,$$

where the geometric series sum formula $\sum_{k=0}^{n-1}x^k = \frac{1-x^n}{1-x}$ was applied. Therefore, $R(\delta,n)$ is simplified as $\sum_{k=1}^{n}(1-\delta)^k$. It is immediate that $R(0,n) = \sum_{k=1}^{n}1^k = n$, and $R(1,n) = \sum_{k=1}^{n}0^k = 0$. Since each term in the summation form, $(1-\delta)^k$, is decreasing in δ, $R(\delta,n)$ is a monotone decreasing function in δ. $\square$

Proof of Proposition 1: It is straightforward to show that the solution to $b = \sum_{k=1}^{n}(1-\delta)^k$ is unique for $b \in [0,n]$. Since $\sum_{k=1}^{n}(1-\delta)^k$ is monotone decreasing from n to 0 (Lemma 1) and b is constant in terms of δ, there must be a unique δ^* that equates both hands.

Let $\delta^*(n)$ denote the solution for a given n, such that $b = R(\delta^*(n), n)$. Consider the case for $n+1$. The summation on the right-hand side can be decomposed as:

$$R(\delta, n+1) = \sum_{k=1}^{n+1}(1-\delta)^k = R(\delta, n) + (1-\delta)^{n+1}.$$

Evaluate this function at $\delta = \delta^*(n)$, the solution for n:

$$R(\delta^*(n), n+1) = R(\delta^*(n), n) + (1-\delta^*(n))^{n+1} = b + (1-\delta^*(n))^{n+1}$$

Since $\delta^*(n) \in (0,1)$, the term $(1-d_n^*)^{n+1}$ is strictly positive. Therefore, $R(\delta^*(n), n+1) > b$. By definition, $\delta^*(n+1)$ is the unique value that satisfies $b = R(d^*(n+1), n+1)$. Substituting b, we have

$$R(\delta^*(n), n+1) > R(\delta^*(n+1), n+1).$$

Since $R(\cdot, n+1)$ is a strictly decreasing function in δ, the inequality in function values implies the reverse inequality in the arguments:

$$\delta^*(n) < \delta^*(n+1).$$

Thus, d^* is strictly increasing in n. □

Proof of Proposition 2: In Proposition 1, we established that $\delta^*(n)$ is strictly increasing in n. As $n \to \infty$, the geometric sum converges to $\frac{1-\delta}{\delta}$. Setting $b = \frac{1-\delta}{\delta}$ yields the limit $\lim_{n\to\infty} \delta^*(n) = \frac{1}{1+b}$. Since the sequence is bounded and monotone, it converges. Next, consider the defining equations for population size n and $n+1$:

$$\sum_{k=1}^{n+1}(1-\delta^*(n+1))^k = b = \sum_{k=1}^{n}(1-\delta^*(n))^k.$$

Rearranging the terms:

$$\sum_{k=1}^{n}\left[(1-\delta^*(n+1))^k - (1-\delta^*(n))^k\right] + (1-\delta^*(n+1))^{n+1} = 0.$$

Let $\Delta = \delta^*(n+1) - \delta^*(n)$. Using the Mean Value Theorem on $R(\delta) = \sum_{k=1}^{n}(1-\delta)^k$, there exists

$c \in (\delta^*(n), \delta^*(n+1))$ such that $R(\delta^*(n+1)) - R(\delta^*(n)) = R'(c)\Delta$. Substituting this back gives:

$$R'(c)\Delta + (1-\delta^*(n+1))^{n+1} = 0 \implies \Delta = \frac{(1-\delta^*(n+1))^{n+1}}{-R'(c)}$$

The derivative of $R(\delta)$ with respect to δ at $\delta = c$ is $R'(c) = -\sum_{k=1}^{n} k(1-c)^{k-1}$. Since $c \in (0,1)$, the first term of the sum (where $k = 1$) is -1, and all subsequent terms are negative. Thus, $|R'(c)| > 1$, which provides the inequality:

$$\Delta < (1-\delta^*(n+1))^{n+1}.$$

Since $\delta^*(n)$ is increasing, $\delta^*(n+1) > \delta^*(1)$. For $b \in (0,1)$, the solution for $n = 1$ exists and is given by $(1-\delta^*(1))^1 = b \implies \delta^*(1) = 1-b$. Thus, $1-\delta^*(n+1) < 1-\delta^*(1) = b$. Substituting this into the inequality above yields the proposed bound:

$$\delta^*(n+1) - \delta^*(n) < b^{n+1}$$

This confirms that for $b \in (0,1)$, the sequence stabilizes exponentially fast. □

B Appendix: Experimental Instructions

Welcome

Before you read this instruction, please make sure that you do not force-close this webpage. If you close the webpage, you may not log in to the same experiment again, which may make us unable to calculate your earnings from your participation.

If you have questions or need clarifications, please ask the experimenter via the concurrent Zoom meeting.

Instructions

Thank you for participating in this experiment. Please read carefully the following experiment instructions. At the end of the instructions are quizzes to check your understanding.

Your earnings from this experiment are determined by your choices, other participants' choices, and luck. The monetary unit used in this experiment is called a "token."

Overview

In this experiment, you and many other participants form a group and make simultaneous decisions for 12 times (rounds). In each round, the conditions for your decision would vary, so please be careful in checking the changes. Details follow.

Main task: Choosing a box or a white ball

Participants are randomly assigned to a new group of N people at the beginning of each session.
[Note: The number of group members (N) may vary from round to round, so please make sure to check.]

Participants then simultaneously choose either **a box** or **a white ball**.

- If you choose the box, there is a 70% chance of a blue ball inside the box and a 30% chance of a red ball. You earn 240 tokens with the blue ball, and 40 tokens with the red ball.
- If you choose the white ball, you get 100 tokens. In addition, one randomly selected group member who chose the white ball will receive additional

$$\text{total number of red balls in the group} * 200 \text{ tokens.}$$

Example: Suppose that in a group of four people, two people chose the box and the other two chose the white ball.

- If both of the box choosers get blue balls, no additional earnings go for any of the two white ball choosers.
- If one of the two box choosers gets a red ball, then one of the two white ball choosers receives additional 200 tokens.
- If both box choosers get red balls, one of the two white ball choosers receives additional 400 tokens (=2 red balls*200 tokens).

Feedback at the end of each round

At the end of each round, participants are only told what choices they made in that round. They won't be informed about who the members were or what choices they made during the experiment.

Payments

After the 12 rounds, the server computer will randomly select one round, and the tokens earned by the participant in that round will be converted to cash(*) and paid out.

(*) To be precise, the tokens will be converted into Starbucks e-Gift gift certificates.

Each round has an equal chance of being selected, so it is of your benefits to play all rounds carefully. The earnings for the selected round will be converted at the rate of 1 token = 100 Korean Won.

Comprehension Check Quiz

You must answer all quizzes correctly to move to the next stage. If necessary, please double-check the instructions above.

Q1 Suppose you belong to a group of 12 people. Which of the following earnings are you *unlikely* to get if you choose the box? (A) 40 tokens (B) 100 tokens (C) 240 tokens

Q2 Suppose you belong to a group of 4 people. Which of the following earnings are you *unlikely* to get if you choose the white ball? (A) 240 tokens (B) 100 tokens (C) 500 tokens

Q3 In a group of 4 people, suppose that members 1 and 2 chose a box and got a blue ball, member 3 chose a box and got a red ball, and member 4 chose a white ball. How much will member 4 earn? [Hint: If only one person chose the white ball, that person will be the one who receives the extra tokens (since one person is randomly selected from a group of one person).] (A) 100 tokens (B) 240 tokens (C) 300 tokens

Q4 Which of the following is a correct description of how the experiment goes? (A) Once the group members are initially determined, the experiment will continue with those members until the end of the experiment. (B) If the box is checked, there is a 60% chance of a red ball. (C) The maximum number of tokens that can be earned by checking the box is 240 tokens.

[After the participant passing the quiz]

You are waiting for all participants to finish reading the instructions and solving the comprehension check quiz. While you are waiting, please review the summary of the experimental procedure below.

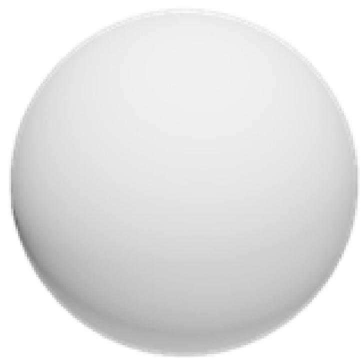
1. The experiment consists of 12 rounds of decision-making.
2. In each round, all participants are randomly assigned to a new group of N people.
3. Each participant simultaneously chooses either a box or a white ball.

- The box contains a blue ball worth 240 tokens with a 70% probability and a red ball worth 40 tokens with a 30% probability.
- If you choose the white ball, you receive 100 tokens. In addition, one randomly selected person among those who chose the white ball receives an additional reward equal to [the number of red balls in the group * 200 tokens].

[Repeat the following for 12 times, with varying N]

In this round, you belong to a group of **6** participants.

Please choose either a box or a white ball. Your choice cannot be undone, so please be careful.



- Choosing the white ball, you receive 100 tokens. In addition, one of those who chose the white ball receives an additional reward equal to [the number of red balls in the group * 200 tokens].
- Choosing the box, you receive 240 tokens if a blue ball is drawn with a 70% chance, or 40 tokens if a red ball is drawn with a 30% chance.

[After the 12 rounds]

The main part of the experiment is complete. Once you fill out the following questionnaire, you will receive the results of your experiment and your earnings.

[After the post-experiment survey]

The results: Round *%R%* was selected as the payout round.

- (When the box was chosen) In this round, you chose the box and got a blue (red) ball. Your reward for this is 240 (40) tokens. The number of red balls that came out of this group is $\%TotalRed\%$. One of the group members who chose the white ball received additional $\%200 * TotalRed\%$ tokens.

- (When a white ball was chosen and the subject was not the winner of the citizen lottery) In this round, you chose the white ball, and your reward for this is 100 tokens. The number of red balls that came out of this group is $\%TotalRed\%$. Unfortunately, you are not one of the members who receive additional $\%200 * TotalRed\%$ tokens.

- (When a white ball was chosen and the subject was the winner of the citizen lottery) In this round, you chose the white ball, and your reward for this is 100 tokens. The number of red balls that came out of this group is $\%TotalRed\%$. You are the one who receives additional $\%200 * TotalRed\%$ tokens.

Your total earning is $\%TotalEarning\%$ tokens or $\%TotalEarning * 100\%$ Korean Won. A Starbucks e-Gift card worth $\%TotalEarning * 100\%$ will be sent to your registered mobile number. You will receive further instructions from Zoom regarding the payment procedure.