

# Penalty Lottery\*

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## Abstract

I propose a new institution, penalty lottery, to control sequential public bad productions under imperfect monitoring for punishment: A violator (a citizen who produced a public bad and got monitored) hands over the fine to the next potential violator with some probability, and pays all the accumulated fines with the complementary probability. The penalty lottery is different from imposing a larger fixed fine in the long run for complete deterrence, as that absorbing state would not practically be reached when heterogeneities in citizen's attributes including risk preferences are considered. The penalty lottery *self-selects* those who are more willing to produce a public bad, and hence endogenously imposes the larger expected fines to them. The penalty lottery has advantages over the day fine system in which the fine payment depends on the offender's daily personal income, as it can endogenously implement the day fine system. From lab experiments with abstract framing, I find strong support of the theoretical predictions.

**Keywords:** Institutional change, Public bads, Misdemeanors, Imperfect monitoring, Laboratory experiments

## 1 Introduction

Tickets issued for misdemeanors are a multi-billion industry. 10,803,028 citations for parking violations had been issued during the fiscal year 2017 in New York City.<sup>1</sup> The minimum fine is \$35, so the parking tickets alone are at least a 378-million-dollar deal. If

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<sup>1</sup>Source: [NYC Open Data](#)

that number represents the social costs incurred by the negative externalities of wrongdoing, it is natural to consider what the proper way to minimize misdemeanors is. A day fine system in which a unit of fine payment is based on the offender's daily personal income is employed in some countries, and it has been considered as an alternative to the fixed fine (Hillsman, 1990). However, it is still debatable whether the wealth level—a factor not directly related to the offending action—justifies the different fines for the same wrongdoing, and whether it would prevent misdemeanors of the poor.<sup>2</sup> Spending more resources to enhance public monitoring, such as hiring more police officers, is not always implementable. Increasing the fine may not be justifiable. If the fine is precisely determined at the level to correct the negative externality of wrongdoing (Becker, 1968), there is no ground for increasing the fine. Even so, if the local government enforces exceptionally severe penalties to eradicate all public bad productions, that leads to distorted incentives on the margin (Stigler, 1970). If, for example, every misdemeanor results in a substantial fine so the punishment for littering is almost the same as for burglary, then a person willing to litter might also be willing to break into a structure.

Given that the fundamental reason of prohibiting misdemeanors is that it produces a public bad in the course of doing so, a broader goal is to seek efficient ways to reduce individual's sequential public bad production under imperfect monitoring. The primary purpose of this paper is to propose a simple institutional change that helps to attain the goal, which I call a *penalty lottery*. A violator, a citizen who produced a public bad for his own sake and got monitored, hands over and accumulates the fine for the next violator with some probability  $q$ , and he pays all the accumulated fines with probability  $1 - q$ . The standard rule of the game is nested as a particular case with  $q = 0$ . This institutional change does involve neither a change of a public monitoring capacity nor an increase of the nominal fines, but it could reduce the number of public bad producers in the long run. Even in a situation where public bad production is beneficial to every citizen initially, this penalty lottery asymptotically prevents every citizen from producing a public bad after some finite time periods. However, the existence of the 'steady state,' where a sufficiently large number of fines are accumulated, and no one violates the law, is neither the main advantage of the penalty lottery nor the main claim that I want to raise. Although the prediction of asymptotic convergence to the steady state is robust to heterogeneities in citizens' risk preferences and social preferences, it can take substantially longer periods to reach such steady state when a minuscule fraction of the population brings an additional heterogeneity.

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<sup>2</sup>Another practical issue is how the income level can be transparently measured: The fact that a day fine system is currently employed in countries where the degree public tax transparency is high suggests that establishing a high level of public tax transparency may be the first-order requirement for the implementation of the day fine system.

The merit of the penalty lottery is that it endogenously imposes the larger expected fines to those who are more likely to produce a public bad. This is because those who are more likely to produce a public bad *self-select* to take larger accumulated fines. If people subjectively evaluate the fine relative to their income, then the penalty lottery could endogenously build up the day fine system. If individual's risk preferences are different, then risk seekers are willing to produce a public bad when the size of accumulated fines is relatively larger than what the risk-averse can afford, which makes them share the burden of the large accumulated fines. This implies that when the penalty lottery is introduced, the expected benefit of risk seekers might be not larger than that of the risk-averse.

I claim that the penalty lottery, or random handover of the penalty, would work in various situations in which the primary challenge is to minimize the production of public bads with imperfect monitoring capacity, such as reducing carbon dioxide emissions of firms and controlling individual spending of the common goods. In particular, this institution would work as a mechanism to offer different fines based on the offender's willingness to commit misdemeanors. A citizen decides whether to violate the law for his own sake, with knowing that his action bears a small chance to pay all the accumulated fines. This does not mean that the system unilaterally imposes every citizen unjustly added penalties. Those who find the accumulated fines are large enough will stay out of committing misdemeanors and therefore have to pay no penalties. Only those who are willing to take the risk of paying all the accumulated fines will commit misdemeanors. In this regard, the penalty lottery has significant advantages over the day fine system. Under the penalty lottery, a unit of (ex-ante) fine payment is based on the offender's willingness to commit misdemeanors, so it endogenously implements the day fine system currently employed in some developed countries. At the very best, the day fine system can be justified when the personal daily income works as a proxy for how strongly the offender minds paying the fine. The penalty lottery makes them directly reveal their true willingness.

Testing the new institution and citizens' responses to it in real-world jurisdictions is extremely challenging especially when we do not know whether there are unexpected negative outcomes from the institutional change. In particular, behavioral responses to the payment of the other's fines have not been reported, so we are unsure how people would behave under this new institution. This is the main reason why I propose to use laboratory experiments as a testbed.

I consider two treatments in each of them differs in the probability ( $q \in \{0.1, 0.5\}$ ) of accumulating the fine rather than paying it. The treatment with  $q = 0.1$  works as a baseline experiment, which mimics the current rule of the game. The experiment is

designed to minimize the framing effects: I use neutral terms so that any of their actions are not labeled as bad behaviors. During the experiment, one subject per each round either choose a red ball or a blue ball, with knowing how many black stickers are in the common pool that is shared by the group members. When the subject chose a red ball, he keeps the ball, and nothing further happens. When he chose a blue ball, a black sticker is attached to the blue ball with a 30% chance. In the case of drawing a blue ball with a black sticker, the black sticker is accumulated to the common pool with probability  $q$ , but with the other probability  $1 - q$ , he will keep the black sticker as well as all the stickers that were in the common pool. A red ball is worth  $-1$  token, where a token is a currency unit of the experiment, a blue ball is worth  $+5$  tokens, and a black sticker is worth  $-8$  tokens. Subjects get paid based on the number of red balls, blue balls, and black stickers that they have kept during the experiment. After the main experiment, subjects' risk preferences were measured by the Bomb Risk Elicitation Task (Crosetto and Filippin, 2013).

The experimental evidence is largely consistent with the theoretical predictions. First, as more black stickers are accumulated into the common pool, fewer subjects chose the blue ball. Although the treatment with  $q = 0.5$  gives more incentives for them to choose the blue ball as the joint probability of getting the stickers is low, the accumulation of the black stickers leads them to choose the red ball about two times more than those in the treatment with  $q = 0.1$ .<sup>3</sup> Second, risk-seeking behavior does not pay under the treatment with  $q = 0.5$ . When  $q = 0.1$ , taking risks of getting the black stickers is beneficial so there is a significant negative relationship between the risk averseness and the earnings from the main experiment. When  $q = 0.5$ , however, the negative relationship is completely nullified.

The rest of the paper is organized as follows. In the following subsection, we discuss the related literature. Section 2 describes the model and provides the main theoretical implications. In Section 3 we describe the experiments and Section 4 reports experimental findings. Section 5 discusses the objective of the local government, and Section 6 concludes. Proofs of some of the lemmas and propositions that appear in the main text are provided in the Appendix.

## 1.1 Related Literature

This study is inspired by Gerardi et al. (2016), Duffy and Matros (2014), and Bhattacharya et al. (2014) who study how an institutional change affects voter turnout. Gerardi et al. (2016) compare the lottery (of giving a prize to one of turnout) with the fine

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<sup>3</sup>This result communicates to Drago et al. (2009) who examine the behavioral responses to (exogenously determined) heavier penalty on recidivism by using a natural field experiment.

(to those who do not turn out to vote), and [Duffy and Matros \(2014\)](#) consider a combined mechanism in which the fines imposed on non-participants are used to finance the prize of the lottery winner. In a similar vein, [Bhattacharya et al. \(2014\)](#) compare the compulsory voting with the voluntary voting. In a broader sense that we examine how an institutional change drives citizens to behave more desirably, this paper contributes to the literature on the impact of institutional changes.

This study is also related to imperfect public monitoring of the behavior of producing public bads. [Ambrus and Greiner \(2012\)](#) report how imperfect monitoring, compared with perfect monitoring, changes the contribution behavior in the public good contribution games with a costly punishment option. Their experimental evidence shows that access to a standard punishment technology significantly decreases net payoffs even in the long run, and access to a severe punishment technology leads to roughly the same payoffs as with no punishment option. This implies that how hard to make the individuals act in a socially desirable way, even if a severe punishment is adopted. The main advantage of the penalty lottery over a simple severe punishment is that it works well under imperfect monitoring.

Using lotteries in a non-standard setting is not a new idea. [Kearney et al. \(2010\)](#) overview prize-linked savings (PLS) accounts which essentially provide ‘no-lose’ lottery tickets to savors and [Filiz-Ozbay et al. \(2015\)](#) examine its validity using lab experiments.<sup>4</sup> [Morgan \(2000\)](#) theoretically shows that funding public goods utilizing lotteries outperform voluntary contributions in that lotteries increase the provision of the public good close to the first-best level, and the theoretical predictions are consistent with experimental findings in [Morgan and Sefton \(2000\)](#). The penalty lottery may seem as odd as it gets, but turnout lotteries, voluntary contribution lotteries, and savings lotteries had also been odd before we started discussing them.

## 2 Theoretical Framework and Implications

Although the model can be applied to general situations of sequential public bad production under imperfect monitoring for punishment, we consider a problem of conducting a misdemeanor for clearer illustration. Violating the law for one’s own sake can be read as producing a public bad.

Consider a society with a continuum of citizens indexed by  $i$ . A random citizen sequentially<sup>5</sup> faces a problem of wrongdoing for his/her own benefit at a discrete time

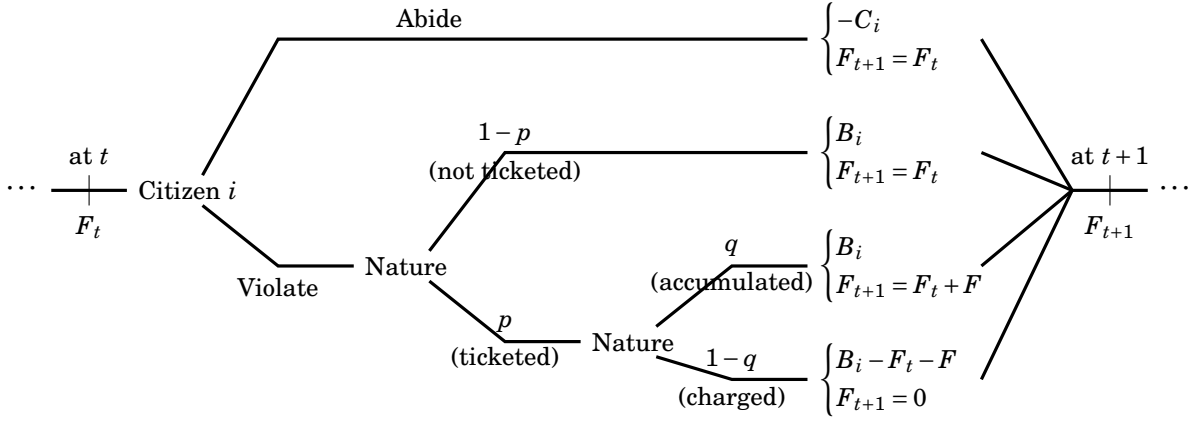
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<sup>4</sup>Texas Proposition 7: Financial Institutions to Offer Prizes to Promote Savings Amendment, was approved on November 7, 2017. This proposition allows banks and credit unions in Texas to offer PLS accounts as a savings option.

<sup>5</sup>Their decisions are independent to what others are doing. This can also be interpreted that each

$t \in \mathbb{N}_+$ .<sup>6</sup> For terminological clarity, I call those who violate the law as “wrongdoers”, and some wrongdoers who got caught by a police officer as “violators”. Let  $B_i$  denote the units of benefit from wrongdoing,  $C_i$  denote the units of cost to abide by the law, and  $F$  denote the amount of the fine. To make the problem nontrivial, assume that  $F > 0$ ,  $B_i > C_i > 0$ , and  $(1-p)u_i(B_i) + pu_i(B_i - F) > u_i(-C_i)$ , where  $p \in (0, 1)$  is the common probability of getting monitored (hence ticketed), and  $u_i(\cdot)$  is an increasing concave utility function of citizen  $i$ . That is, the expected utility of wrongdoing is greater than that of paying the cost of abiding by the law for all  $i$ . In this scenario, every citizen is better off by wrongdoing.

Figure 1: Timing of events



Now I consider one additional state variable. A violator is asked to pay the fine with probability  $1-q$ . With probability  $q$ , the violator hands over the fine to a (potential) next violator and the fine is accumulated to a public account. Let  $F_t$  denote the accumulated fines at time  $t$ , with  $F_0 = 0$ . That is, at time  $t$ , a citizen faces a problem of choosing either  $B_i$  or  $C_i$  with knowing that the probability of paying the fine,  $F_t + F$ , is  $p(1-q)$ . The timing of event is described in Figure 1. Note that the typical rule of the game is nested in this institution as a special case with  $q = 0$ . I assume here that the local government’s goal is to minimize infractions and misdemeanors.<sup>7</sup>

For any  $q \in [0, 1)$ , a finite number of citizens would violate the law as the probability to pay the fine,  $p(1-q)$ , is lower than  $p$ . However, once the fines are sufficiently accumu-

citizen does not encounter others in the situation where wrongdoing is considered.

<sup>6</sup>Alternatively we can consider  $n$  citizens and each citizen sequentially arrives at  $t = (\tau - 1)n + i, \tau \in \mathbb{N}_+$ , where the finite number of citizens and the circular time index are used for lab experiments. It does not mean that the model should assume that every citizen makes a decision in a circular queue.

<sup>7</sup>Considering that the state court system’s budget typically relies on funding from traffic citations as a source of revenue, this may not be a trivial assumption. I discuss this further in Section 5.

lated, the expected benefit of wrongdoing becomes no longer greater than the cost of abiding by the law. Specifically, for any  $\tau$  such that  $(1-p+pq)u_i(B_i)+p(1-q)u_i(B-(F_\tau+F)) \leq u_i(-C)$ , citizen  $i$  will not violate the law. For risk neutral citizen  $i$ , there exists  $k_i \in \mathbb{N}_+$  such that  $k_i = \left\lceil \frac{B_i+C_i}{p(1-q)F} \right\rceil - 1$ , where  $\lceil x \rceil$  is the smallest integer larger than  $x$ , if there are  $k_i$  consecutive violators who have not paid the fines, citizen  $i$  will not violate the law afterwards. Since  $k_i$  is a cutoff level of fine accumulation for a risk-neutral citizen,  $k_i$  can be understood as the upper bound<sup>8</sup> of cutoffs for any degree of risk aversion. Although this model deals with three types of heterogeneities, all the other various dimensions of individual heterogeneities can also be summarized by  $k_i$ , and  $k_i$  is interpreted as a degree of willingness to violate the law. Let  $\bar{k}$  denote  $\max_i k_i$ , and  $G(k)$  denote the cumulative distribution of  $k_i$ . The actual number of wrongdoers varies by how many violators happened to pay the fines before reaching  $F_t = \bar{k}F$ . However, the probability of  $\bar{k}$  consecutive accumulations approaches 1 as time goes by. Let  $P(V|t;p)$  be the ex-ante probability that a violation is observed after  $t$  periods when the probability being monitored is  $p \in (0, 1)$ . I use  $P(V|t)$  whenever  $p$  is not of interest.

**Proposition 1.** *For  $q \in (0, 1)$ ,  $P(V|t)$  is monotone decreasing in  $t$ . The expected time to reach  $P(V|t) = 0$  is finite. If  $q = 0$ ,  $P(V|t) = 1$  for any  $t$ .*

**Proof:** See Appendix.

Proposition 1 becomes more intuitive if we consider a homogeneous economy where  $u_i = u$ ,  $B_i = B$ , and  $C_i = C$  for all  $i$ . Then  $P(V|t;p)$  approximates to the probability that a success run of at least length  $k$  for an event with a probability of  $q$  occurs at least once within  $pt$ <sup>9</sup> number of trials. The nondecreasing probability of success run in the number of trials implies that in a longer period it is more likely to reach the threshold  $kF$  and no one will violate the law with a higher probability. For example, if  $\{B, C, F, p, q\} = \{5, 1, 8, 0.4, 0.5\}$ ,  $k = 3 (= \lceil \frac{5+1}{0.4 \cdot 0.5 \cdot 8} \rceil - 1)$ , and the probability of at least 3 consecutive accumulations in 100 periods is 95.66%. That is, the probability that there is still a wrongdoer after 100 periods is less than 5%. Such a probability monotone decreases in  $t$ .

It is worth noting that  $q$  must be intermediate—neither too close to 0 nor to 1—for this institution to work in shorter time periods. If it were to be near 0, the threshold of the accumulated fines is not likely to be achieved. If it were to be near 1, no one would actually pay the accumulated fines as  $\frac{B+C}{p(1-q)F}$  is convex increasing in  $q$ . If  $\{B, C, F, p\} =$

<sup>8</sup>The assumption of weak concavity of the utility function applies here. If some citizens have a convex utility function, which implies that they enjoy taking risks, then they may have a higher cutoff threshold than  $k_i$ .

<sup>9</sup>Since we consider an imperfect monitoring and only  $p$  proportion of the whole wrongdoings are monitored, only  $tp$  periods out of  $t$  can be considered as Bernoulli trials, on average.



$\{5, 1, 8, 0.3\}$ , for example, the probability that there is a wrongdoer after 50 periods is near 0% with  $q = 0.5$ , while the probability is 41.18% with  $q = 0.1$  and 25.21% with  $q = 0.9$ .

In sum, after the society consecutively accumulates  $k$  fines, it reaches a ‘steady state’ where no one violates the law. Although we figured out that the penalty lottery may lead to complete elimination of sequential public bad production in the long run, it is also important to understand what happens before reaching the steady state, because it takes substantially longer time when individuals are more heterogeneous: Even a minuscule fraction of the population with a larger  $k_i$  being added to the society leads to a substantial delay to reach the steady state.

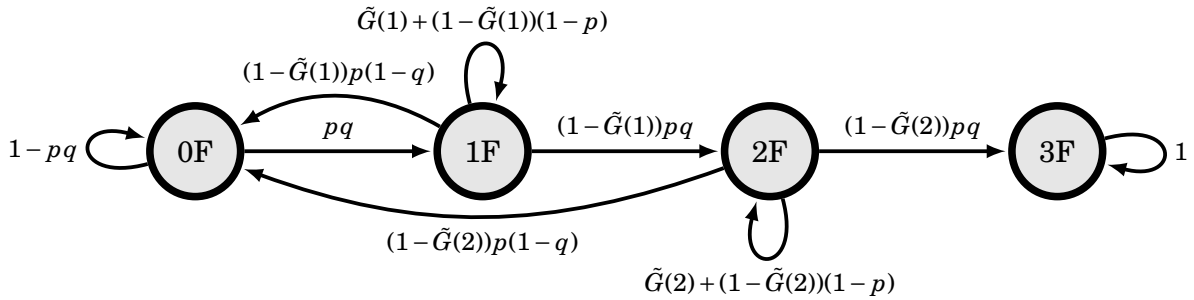
**Proposition 2.** *The expected number of time periods reaching the steady state starting from zero fine accumulations is*

$$\frac{1}{pq} \sum_{i=0}^{\bar{k}-1} \frac{1}{(1-G(i))q^i},$$

which leads to two observations. (a) Given the class of the distributions with the same mean,  $P(V|t)$  is decreasing in  $g(\bar{k}) = 1 - G(\bar{k} - 1)$ . (b) If  $\tilde{G}(k)$  is the mean-preserving spread of  $G(k)$  with a larger  $\bar{k}$ , and  $\tilde{P}(V|t)$  be the ex-ante probability under  $\tilde{G}(k)$ ,  $\tilde{P}(V|t) \geq P(V|t)$ .

**Proof:** See Appendix.

Figure 2: Finite-State Absorbing Markov Chain and Transition Probability Matrices



$$T_G = \begin{bmatrix} 1-pq & pq & 0 \\ p(1-q) & 1-p & pq \\ 0 & 0 & 1 \end{bmatrix} \quad T_{\tilde{G}} = \begin{bmatrix} 1-pq & pq & 0 & 0 \\ (p-pq)/2 & (2-p)/2 & pq/2 & 0 \\ (p-pq)/2 & 0 & (2-p)/2 & pq/2 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Consider  $\tilde{G}(k)$ , a mean-preserving spread of a degenerate distribution at 2, where  $g(1) = g(3) = 0.5$ . The probability of reaching the final node from the initial node after  $t$  periods,  $(T_{\tilde{G}}^t)_{1,k_h+1}$ , is smaller than  $(T_G^t)_{1,k+1}$ .

For illustration of Proposition 2, consider a society where a half of the citizens have



$k_l = 1$  and the other half have  $k_h = 3$ . Then, until  $k_l$  fines are consecutively accumulated everyone will violate the law, and for any given time  $t$ ,  $pt$  violations on average will be monitored. However, when  $k_l$  fines are consecutively accumulated, only the half of the population would still violate the law, and for any given additional time  $\tau$ ,  $\frac{1}{2}p\tau$  violations on average will be monitored. Two additional fines need to be consecutively accumulated with a smaller number ( $\frac{1}{2}p\tau$  instead of  $p\tau$ ) of probabilistic trials, so it must take longer time to reach the steady state, compared with a homogeneous society where  $k_i = 2$  for all  $i$ . Worse yet, if someone with  $k_h = 3$  pays all the accumulated fines before reaching  $F_t = k_h F$ , then the entire population starts violating the law again. Figure 2 illustrates the Markov chain and the corresponding transition probability matrices for the aforementioned example. The probability of observing a violation after  $t$  periods is the first element of the last column in  $T^t$ , where  $T$  is the transition probability matrix. Although the above example considered drastically different distributions, a minuscule change can lead to a significant delay. When the society consists of homogeneous citizens with  $k_i = 2$ , the probability that a violation is observed after 100 periods is 0.32% (with  $p = 0.3$ ,  $q = 0.5$ ), while if 1% of the population has  $k_i = 3$  instead, such a probability skyrockets to 88.95% (Observation (b) in Proposition 2). More interestingly, compared with a society with 99% of  $k_i = 2$  citizens and 1% of  $k_i = 3$  citizens, if 99.9% of citizens are of  $k_i = 2$  and 0.1% of them are of  $k_i = 3$ , such a probability is 98.81%, even larger than 88.95% (Observation (a) in Proposition 2).

A naturally followed question is whether the penalty lottery is desirable for a substantively longer before-the-steady-state periods. The answer is yes, as it endogenously imposes the larger expected fines to those who are more likely to violate the law.

**Corollary 1.** *Let  $\phi(k_i)$  be the ex-ante expected fines for an individual with  $k_i$ .  $\phi(k_i)$  is increasing.*

**Proof:**  $\phi(k_i) = \sum_{\kappa=0}^{k_i} p(\kappa)(\kappa + 1)$  is the ex-ante expected fines, where  $p(\kappa)$  is the ex-ante probability that  $\kappa$  fines have been accumulated.  $\square$

Among the various dimensions of individual heterogeneities lead to different  $k_i$ , I focus on a few crucial dimensions: risk aversions, heterogeneous benefits,  $B_i$ , and some social preferences. Corollary 1 implies that those who have more benefits from wrongdoing and those who are more risk-seeking are *self-selecting* to pay the higher ex-ante expected fines. The risk-averse citizens have a small  $k_i$ : As the fine gets accumulated more, the possible payoffs become more volatile. Thus, their expected benefit of wrongdoing decreases with risk averseness. A similar logic applies to those who have a larger  $B_i$ . As the fine gets accumulated more, the smaller fraction of citizens with higher  $B_i$

would remain to be wrongdoers. Interpreting  $\frac{B_i}{F}$  as a subjective value of the fine,<sup>10</sup> the higher ex-ante expected fines for those with a higher  $B_i$  would naturally implement a day fine system. Lying-averse citizens or sincere citizens can be understood as those with  $B_i = 0$ . Therefore, lying-averse citizens would not be wrongdoers no matter what  $q$  is, and the institutional change does not affect their decisions. If citizens have heterogeneous other-regarding preferences, especially inequity aversions, then those with a higher inequity aversion would have a lower  $k_i$ . When  $F_t > 0$ , a wrongdoer is voluntarily taking the possibility of paying previous violators' fines, which exacerbate the inequity between him and the previous violators (who did the same action). All in all, the effect of the institutional change would be significant and is robust to heterogeneities in individual characteristics.

### 3 Experimental Design and Procedure

To the best of my knowledge, behavioral responses to the (potential) payment of the other's penalties have not been reported, so it is unclear whether the institutional change would work in the desired direction. This is why the controlled lab experiments are used as a testbed.

Having abstract framing<sup>11</sup> in mind, I consider two experimental treatments which differ in the probability of penalty accumulation ( $q$ ). For notational simplicity, the treatment with  $q = 0.1$  is called Lq (Low  $q$ ), and the other treatment with  $q = 0.5$  is called Mq (Middle  $q$ ). Table 1 summarizes the design of the experiments.

The basic procedure of an experimental session is as follows: Each subject is endowed with 100 tokens (the experimental currency units) in his/her account. Each subject is randomly grouped with three other subjects and sequentially decides within the group. The experiment consists of 60 decision-making rounds, so each subject made 15 decisions.<sup>12</sup> When a subject is on her turn, she is asked to choose either a red ball or a blue

<sup>10</sup>More often than not, the benefits of wrongdoing are not measurable, while the fine, especially if it is a monetary penalty, is. From the perspective of the rich,  $F$  could be relatively minor compared with their wealth. In this case, a higher  $\frac{B_i}{F}$  could mean that citizen  $i$  subjectively undervalues the fine.

<sup>11</sup>Although the design of experiments to test the effect of the institutional change might be straightforward, one of the critical challenges in this particular context is to maintain abstract framing. I avoid using terms such as "wrongdoing," "violations," "fines," and "misdemeanors": Otherwise interpretations of the experimental results could be confounded as there could exist an experimenter-demand effect (Zizzo, 2010). It is also known that subjects are heterogeneous regarding internalizing the social norms (Kimbrough and Vostroknutov, 2016), so the statistical analysis would have less power to conclude when the particular frame of violating a law is considered.

<sup>12</sup>There are two reasons why a subject makes 15 separate decisions rather than 15 consecutive decisions as a single player. First, if 15 consecutive decisions were to be made, then the state variable of the next round (the number of black stickers in the common pool) is endogenously affected by the previous decision while having three decisions between a single subject's actions dilutes such endogeneity. Second, although

Table 1: Experimental Design and Summary of Hypotheses

Treatment	$p$	$q$	$p(1 - q)$	$k$	$P(V t = 60)$
Mq	0.3	0.5	0.15	4	56.19%
Lq	0.3	0.1	0.27	2	85.44%

Each session consists of 60 consecutive rounds. In each round, one subject among a group of four chooses either a red ball or a blue ball. A red ball has a value of  $-1$ . A blue ball has a value of  $5$  but with probability  $p$  a black sticker of which value is  $-8$  is attached to the blue ball. The black sticker is collected to the common pool with probability  $q$ .

ball, with knowing that how many black stickers are accumulated in the common pool shared by the group members. In the beginning, there are no black stickers in the common pool. Keeping a red ball ends her turn. When choosing a blue ball, with probability  $0.3$  a black sticker is attached to the blue ball, and with the complementary probability  $0.7$ , no black sticker is followed. If a black sticker is attached, the computer determines where the black sticker goes. With probability  $q$ , the black sticker is removed from the blue ball and added to the common pool. With probability  $1 - q$ , the subject keeps the black sticker as well as all the black stickers from the common pool. In each turn, a subject does not know which balls other subjects have chosen but know how many black stickers are accumulated in the common pool. At the end of the session, the total payoff of a subject who has  $x$  red balls,  $y$  blue balls, and  $z$  black stickers is  $100 - x + 5y - 8z$ . That is, each red ball (the cost of abiding by the law) is worth  $-1$  token, each blue ball (the benefits of wrongdoing) is worth  $+5$  tokens, and each black sticker (the fine) is worth  $-8$  tokens.

Two treatments which I do not conduct may be worth mentioning. First, when a subject makes a decision, how other subjects had acted is not informed. Although I believe that knowing other subjects' decisions would affect the subject to some degree and it would be interesting to know to what extent an indirect social pressure impacts, the main purpose of the experiments is not on examining such an impact. Second, instead of having  $q = 0$ , I consider treatments with  $q = 0.1$  as a baseline experiment. Several studies including [Tversky and Kahneman \(1981\)](#) and [Martinez-Marquina et al. \(2018\)](#) have reported that individual's behavior under zero probability (or certainty) is distinctively different to that under near-zero probability (or near-certainty), and it is also known that people tend to treat complex lotteries different to simple lotteries even though those two lotteries are equivalent ([Huck and Weizsäcker, 1999](#)). Thus I believe that individual decisions on probabilistic events should be compared with those on other probabilistic

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it would be ideal if the size of the group is larger, with considering the typical capacity of a laboratory, the group size of four was practically optimal as it is large enough for diluting endogeneity as well as small enough for collecting many observations within a limited time.

events, not deterministic events.<sup>13</sup>

Experiments were conducted at the Mannheim Laboratory for Experimental Economics (mLab) from February to April 2018. I ran three sessions for each treatment, with 20 to 24 subjects (or 5 to 6 independent groups of four) each. A total of 128 subjects participated in one of the sessions. The participants were drawn from the mLab subject pool. Python and its application Pygame were used to computerize the games and to establish a server–client platform. All experimental sessions were organized along the same procedure: After the subjects were randomly assigned to separate desks equipped with a computer interface, they were asked to carefully read the instructions (see Appendix B) for the experiment. After reading the instructions, subjects took a quiz to prove their understanding of the experiment. Those who failed the quiz were asked to read the instructions and to retake the quiz until they passed. An instructor answered all questions until every participant thoroughly understood the experiment. Although each of the subjects belonged to a group of four, there was no physical reallocation of the subjects, and they only knew that they were randomly grouped. They were not allowed to communicate with other participants during the experiment, nor allowed to head up to look around the room. It was also emphasized to participants that their decisions would be anonymous and no deception is employed. At the end of the experiment, they were asked to fill out a survey asking their gender and age. The subjects’ risk preferences were also measured by an additionally paid Bomb Risk Elicitation Task (BRET) (Crosetto and Filippin, 2013). BRET is known to be a parsimonious but accurate way to elicit one’s risk preference: One box among 36 boxes hides a bomb, and a subject collects as many as boxes she wants without knowing where the bomb is hidden. If the bomb was in one of the collected boxes, she earns zero. If the bomb was not in the collected boxes, she earns €0.11 for each chosen box. The total amount of tokens that each subject earned during the main session was converted into Euro at the rate of €0.08/token.<sup>14</sup> Payments (€11.94 on average, including the earnings from BRET) were made in private at the end of the session, and subjects were asked not to share their payment information. Each session lasted approximately 1 hour.

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<sup>13</sup>Given that  $q$  must not be zero in the baseline, another practical reason for considering  $q = 0.1$ , not lower than 0.1, is that subjects may find the joint probability complicated than the  $Mq$  treatment. During the pilot session,  $q = 0.05$  was used, and many subjects struggled to instantly figure out the joint probability  $p(1 - q) = 0.285$ .

<sup>14</sup>I instructed subjects that the currency exchange should not be a concern as the server computer would handle it. The exchange rate €0.08/token is chosen to make the average earning to be close to the desired size of payments.

## 4 Experimental Results

To summarize first, I found that the experimental evidence is largely consistent with the theoretical predictions. First, the proportion of wrongdoers approaches 0 as the size of the accumulated fines increases. Second, risk-seekers are not better off than the risk-averse agents in the  $Mq$  treatment, while risk-seekers are better off in the  $Lq$  treatment.

Table 2: Data Summary

Treatment	Number of Subjects	Red Balls (%)	Blue Balls (%)		
			w/o Sticker	Common	Subject
$Mq$	64	18.33	58.75	10.21	12.71
$Lq$	64	8.85	64.17	3.02	23.96

Table 2 summarizes the data. In the total of 128 subjects (64 in each treatment) have participated in one of the sessions. Red Balls refer to the percentage of the actual choices of red balls. The number of black stickers in the common pool affects subjects' choices, which will be examined shortly. There are three cases when a subject chose a blue ball. Blue Balls w/o Sticker refers to the case where the subject chose a blue ball, and it came without a black sticker. Blue Balls Common refers to the case where the subject chose a blue ball, it came with a black sticker, and the sticker is added to the common pool. Blue Balls Subject refers to the case where the subject chose a blue ball, it came with a black sticker, and the sticker, as well as all the stickers in the common pool, are added to the subject's account. The results are well randomized. In the  $Lq$  treatment, for example, given that a blue ball was chosen for 91.15% of the whole decision-making rounds, the fraction of those three cases would be close to 63.81% ( $=0.7*91.15$ ), 2.73% ( $=0.3*91.15*0.1$ ), and 24.61% ( $=0.3*91.15*0.9$ ), respectively. Also, it seems that abstract framing worked properly: For 96.25% of the whole decision-making rounds in the  $Mq$  treatment, choosing a blue ball maximizes the subject's (risk neutral) expected payoff, and about 83.12% of the cases the blue ball was chosen. Similarly, among 96.88% of the decision-making rounds in the  $Lq$  treatment, 93.01% of the cases the blue ball was chosen. If subjects viewed the problems faced during the experiment as a situation of violating the law for the sake of their benefits, the fraction of the blue ball choices might have been much lower.

### 4.1 Responses to Penalty Accumulations

One desirable observation is that subjects respond to the number of the black stickers in the common pool. Figure 3 shows how many red balls were chosen at different

numbers of black stickers in the common pool. In both treatments it is upward sloping, which implies that the more fines are accumulated, the fewer subjects choose to produce a public bad. In the  $Mq$  treatment, if the number of accumulated black stickers in the common pool exceeds 4, it is indeed not beneficial for risk neutral subjects to choose a blue ball. Except for one subject who consistently chose a blue ball when five stickers are in the common pool and another subject who did so in the final round, everyone else chose a red ball. Unlike realistic situations, the experiment has the last round, and subjects may choose a riskier option in their last round. Such a “last round effect” is observed (see the blue lines in Figure 3), but it is statistically insignificant. From now on, I examine all the decisions from the whole rounds unless otherwise stated.

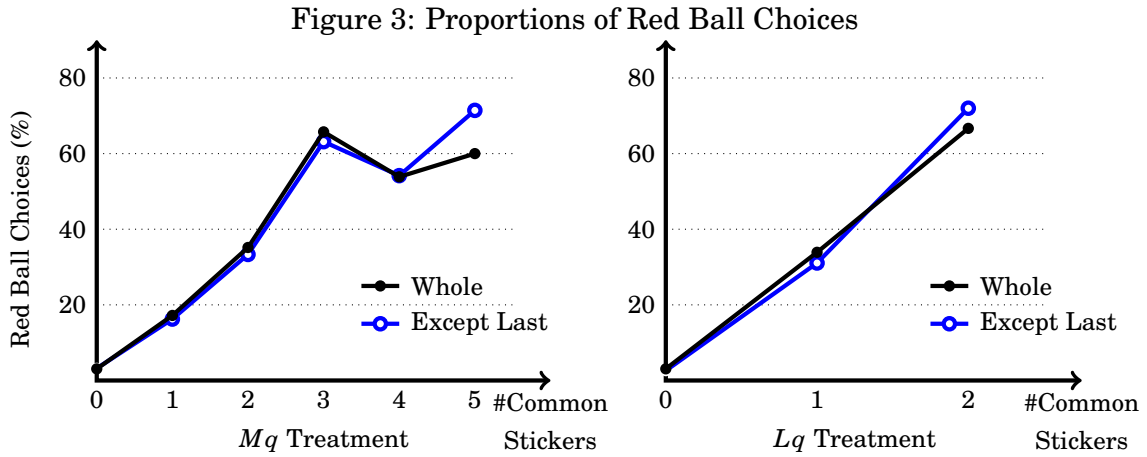


Table 3 summarizes some regression results. Throughout all the regression models being considered, two explanatory variables are statistically significant at the 1% level: the number of black stickers in the common pool (ComBlack) and the subject’s previous action of choosing a red ball (prevRed). Consistent with the theoretical prediction and the trend shown in Figure 3, subjects actively respond to the number of the black stickers in the common pool after controlling for other explanations. It is also reasonable that subjects respond more vigilantly under the  $Lq$  treatment, which is captured by negative estimates of the coefficient of  $\text{ComBlack} \times Mq$ , where  $Mq$  is a binary variable indicating whether the treatment of the session was  $Mq$ . This is because  $k$ , the theoretical threshold for a risk-neutral agent to start choosing red balls, is 4 in the  $Mq$  treatment, while it is 2 in the  $Lq$  treatment. The positive relationship between a previous red ball choice and a current red ball choice implies that some subjects consistently chose red balls: Perhaps they are more risk-averse, more reluctant to take an action that has a potential to negatively impact the other members’ payoffs, or more inequity averse.

The previous realization of a probabilistic event also affects subjects’ decisions in the

Table 3: Red Ball Choices

	LPM			Logit	
	(1)	(2)	(3)	(4)	(5)
ComBlack	0.3147*** (0.0414)	0.3138*** (0.0423)	0.2336*** (0.0394)	2.4332*** (0.3221)	2.0148*** (0.3238)
SubjBlack	-0.0051 (0.0065)	-0.0045 (0.0066)	-0.0031 (0.0056)	-0.0479 (0.0724)	-0.0386 (0.0639)
Mq	-0.0036 (0.0257)	0.0009 (0.0262)	-0.0040 (0.0183)	0.5006 (0.4620)	0.4388 (0.3469)
ComBlack×Mq	-0.1516*** (0.0465)	-0.1516*** (0.0475)	-0.1063** (0.0405)	-1.3710*** (0.3798)	-1.1504*** (0.3498)
prevRed			0.3378*** (0.0602)		2.0001*** (0.3494)
prevBCom			0.0336 (0.0410)		0.4037 (0.3092)
prevBSubj			-0.0059 (0.0132)		-0.4198 (0.3579)
cons.	0.0408** (0.0167)	-0.1045 (0.1491)	-0.0361 (0.1043)	-4.9428*** (1.7655)	-4.4831*** (1.3146)
Indiv.Chars.	Excluded	Included	Included	Included	Included
$R^2$	0.2580	0.2734	0.3597	0.2872	0.3598
$N$	1,920	1,920	1,664	1,920	1,664

The dependent variable is the choice of a red ball. ComBlack is the number of black stickers in the common pool, and SubjBlack is the number of black stickers that the subject has kept.  $Mq$  is a binary variable indicating whether the treatment of the session was  $Mq$ . prevRed, prevBCom, and prevBSubj are binary variables respectively indicating whether the subject chose a red ball in the previous turn, whether she chose a blue ball followed by a black sticker added to the common pool, and whether she chose a blue ball followed by a sticker and kept all the stickers including ones in the common pool, respectively. Heteroskedasticity-robust standard errors clustered by subject id are in parenthesis. \*, \*\*, and \*\*\* indicate statistical significances at the 10% level, 5% level, and 1% level, respectively.



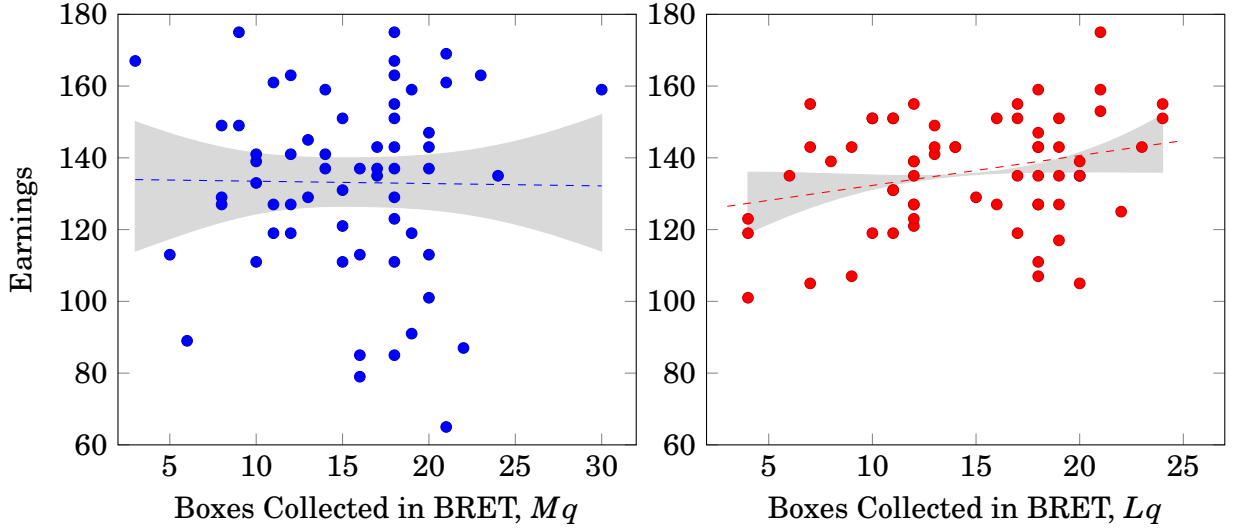
following round especially when the realization is a loss, as many previous experimental studies regarding decision making under uncertainty report so (Imas, 2016). When a subject chose a blue ball in the previous round, and it led him to keep the black stickers including ones in the common pool (labeled as *prevBSubj* in the regression table), he tends to choose a blue ball again in the following round. However, this risk-taking behavior after a loss is not as significant as the effect of the number of black stickers in the common pool. Also, some individual characteristics collected by the after-experiment survey—gender, age, self-confidence in their performance of the experiment, and familiarity with this type of experiment—were insignificant.

## 4.2 Risk Seeking does not Pay

Another crucial theoretical prediction is regarding self-selection: Those who are more risk-seeking are self-selecting to pay the higher ex-ante expected fines. This implies that risk-taking actions will be paid less under the penalty lottery. The experimental evidence supports this claim. Figure 4 shows scatter plots and fitted lines of earnings (from the main experiment) on the number of boxes collected in BRET. A subject’s risk preference is elicited by the number of the collected boxes in BRET: As she collects more boxes, both the probability that the bomb is included in one of the collected boxes and the payoff when the bomb is not included in one of them increase. Thus a natural interpretation is that those who collect more boxes in BRET are more risk seeking. In *Lq* treatment, those who are more risk-seeking are paid more: Those who collect one more box in BRET earns on average 0.83 tokens ( $p = 0.032$ ). In *Mq* treatment, however, there is no linear relationship ( $p = 0.918$ ) between earnings and the number of boxes collected in BRET. The two-sample Kolmogorov-Smirnov test does not reject the hypothesis that the distributions of the two sample data on the collected boxes are different ( $D = 0.1235$ ,  $p = 0.737$ ), so it can be regarded that risk-taking behaviors per se are similar in both treatments.

This result, the null relationship between risk preferences and earnings under the penalty lottery, must require careful interpretation. Choosing a risky option (a blue ball) can increase the expected payoff when the expected loss (the number of black stickers in the common pool) is not large. That is, even with the penalty lottery, still some risk takers would be better off than the risk-averse. In this regard, a more accurate but verbose title for this subsection should be “risk seeking pays less than what it used to pay without the penalty lottery.” What we should look further is the variance of the earnings. Table 4 shows the F-test results of equality of variances. In the *Mq* treatment, the variance of the earnings of the subjects whose risk preferences are in the top half is significantly larger than the variance of those in the bottom half. In the *Lq* treatment,

Figure 4: Risk Preferences and Earnings



This figure shows scatter plots and fitted lines of earnings on the number of boxes collected in BRET. In  $Mq$  treatment, there is no linear relationship between earnings and the number of boxes collected in BRET. In  $Lq$  treatment, however, those who are more risk-seeking are paid more.

such a difference in variances is not found. This demonstrates how the penalty lottery works in a way to prevent risk takers to earn more: Although it is, in general, correct that a high risk yields a high return, with the penalty lottery, a high risk brings higher volatility in payoffs.

Table 4: F-test of Equality of Variances

$Mq$		$Lq$	
St.dev.(Earnings   $B_i < \text{Med}(B_j)$ )	St.dev.(Earnings   $B_i > \text{Med}(B_j)$ )	St.dev.(Earnings   $B_i < \text{Med}(B_j)$ )	St.dev.(Earnings   $B_i > \text{Med}(B_j)$ )
19.49	28.33	15.22	16.60
$F_{29,28}(2.1117) = 0.0256^{**}$		$F_{31,29}(1.1888) = 0.3211$	

## 5 Discussions

### 5.1 The purpose of the local government

Although I claim that the penalty lottery would work in general situations of sequential public bad production under imperfect monitoring for punishment, I should admit

that reducing misdemeanors is one of the most relevant cases. If we narrow down our focus to the elimination of misdemeanors, the primary objective of the local government would matter because it affects the size of the fine and therefore the validity of the penalty lottery.

The primary purpose of this study is not on investigating the optimal size of the fine. This is because I assume that a policymaker deliberately measures the negative externality of wrongdoing, so the fine is given at an appropriate level (Becker, 1968). That is, I assume that the fine is equal to a Pigouvian tax to correct the negative externality incurred by the wrongdoing<sup>15</sup> plus the cost of executions. If the local government has a balanced budget on misdemeanors, having no revenues with few violations, in the end, is as good as having full (budget balanced) revenues with everyone's violation. It is a plus that in the course of attaining the steady state of no violations, the revenues are almost the same while imposing larger fines to those who are more willing to violate the law.

However, from many anecdotal pieces of evidence and some rigorous reports,<sup>16</sup> we know that the fundamental goal of the municipalities may not be on eliminating infractions and misdemeanors: Speeding and parking tickets to drivers could be considered as an essential revenue source of the local government. If the government's purpose is not to maximize the social welfare, but to maximize the revenue accrued from the fines, minimizing misdemeanors is not of their interests at all. In this case, still, we can exploit the idea of the penalty lottery by introducing a nonlinear penalty accumulation. If  $q$  can be dependent to the current level of accumulated fines, the policymaker of the local municipality may want to set  $q(F)$  to maximize the tax revenue from the fines.

A novel type of time inconsistency problem may arise under the penalty lottery if the government maximizes the tax revenue from the fines. Since the citizens self-select the expected fines, the government will gradually know the type of each citizen better. In particular, when a citizen produces a public bad and gets monitored when  $F_\tau$  is accumulated, the lower bound of the willingness to produce a public bad is for sure  $F_\tau$ . Then the government may want to use this information to design a "personalized" penalty system based on the revealed willingness in later periods. However, this personalized penalty may be problematic in the sense that this system does not charge the same fine for those with the same willingness to produce a public bad.

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<sup>15</sup>In this regard of interpreting the fines as indirect taxes, it makes more sense that speeding tickets are more issued to drivers who are not local constituents, as Makowsky and Stratmann (2009) find: This is a way to increase tax revenues from the outside effectively.

<sup>16</sup>Garrett and Wagner (2009) find that significantly more tickets are issued in the year following a decline in revenue, but an increase in revenue does not lead to the smaller issuance of tickets. Makowsky and Stratmann (2011) also find that budgetary shortfalls lead to the more frequent issuance of tickets to drivers.

## 5.2 Sincere vs. rational non-violators

So far I have assumed that  $B_i > C_i > 0$  and  $(1-p)u_i(B_i) + pu_i(B_i - F) \geq u_i(-C_i)$  for all  $i$ , to start from a benchmark case where everyone is better off by producing a public bad. If we relax these assumptions, there could be some citizens who will not produce a public bad under the standard rule of the game. In the context of conducting misdemeanors, I call citizen  $i$  with  $u_i(B_i) \leq u_i(-C_i)$  as a *sincere* non-violator because he does not violate the law regardless of  $p$ , and citizen  $j$  whose utility function satisfies  $u_j(B_j) > u_j(-C_j)$  and  $(1-p)u_j(B_j) + pu_j(B_j - F) \leq u_j(-C_j)$  as a *rational* non-violator. That is, while the penalty lottery does not give an incentive to sincere non-violators to violate the law, it does give an incentive to some rational non-violators if  $q$  is too large. For a rational non-violator  $j$ , there exists  $q_j \in (0, 1)$  such that for all  $q \geq q_j$ ,  $(1-p+pq)u_j(B_j) + p(1-q)u_j(B_j - F) \geq u_j(-C_j)$ .

Even when a large fraction of the population is the rational non-violators, the penalty lottery will work unless  $q$  is not too high. Consider a ‘marginal’ citizen among rational non-violators such that  $(1-p)u_j(B_j) + pu_j(B_j - F) = u_j(-C_j)$ . This citizen is called marginal because he is indifferent between violating and not violating the law when  $q = 0$ , but for all  $q > 0$  he violates the law if  $F_t = 0$ . Even if the marginal citizen is risk neutral, he will again abide by the law immediately after  $\lceil q/(1-q) \rceil$  fines are accumulated. Thus, if  $q \leq 0.5$ , then all the rational non-violators will not violate the law when one fine is accumulated in the public account.

Also, I claim it is not a bad idea to distinguish sincere non-violators from those who strategically choose not to violate the law. Indeed, their violations can be increased without the introduction of the penalty lottery: For example, if the monitoring capacity were to be  $p(1-q)$  instead of  $p$ , they would have violated the law.

## 6 Concluding Remarks

I propose using lotteries to control public bad production under imperfect monitoring for punishment. The fundamental idea is to randomly accumulate the penalties to the public account, rather than to ask each violator to pay the penalty. The penalty lottery has many advantages over both the fixed fine system and the day fine system. With the penalty lottery, the society approaches zero public bad production in the long run, without increasing the monitoring capacity or the size of the penalty. With an appropriate level of probability of accumulating the penalties, the steady state (of zero public bad production) can be reached faster. Even if it takes a long time to reach the steady state, the penalty lottery is desirable because it endogenously imposes larger expected fines to those who are more willing to produce a public bad. It is particularly important if

people believe the current system, often cynically described as “evil pays better,” needs to be changed. The experimental evidence broadly supports the theoretical predictions. In particular, evil does not pay better in the sense that producing more public bads does not yield larger payoffs.

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## Appendix A. Proofs

### Approximation of $k$ Consecutive Accumulations

First I introduce the method for calculating the probability that a success run of at least length  $k$  for an event with a probability of  $q$  occurs at least once within  $n$  trials. Regarding a success run of length  $\kappa \in \{0, 1, \dots, k\}$  as a state, we can construct the following transition probability matrix,  $T$  of order  $k + 1$ .

$$T = \begin{bmatrix} 1-q & q & 0 & \cdots & 0 \\ 1-q & 0 & q & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1-q & 0 & 0 & \cdots & q \\ 0 & 0 & 0 & \cdots & 1 \end{bmatrix},$$

where the probability of moving from state  $i$  to state  $j$  in one time period is  $Pr(j|i) = T_{i+1,j+1}$ . For example,  $T_{23} = q$  is the probability of moving from a success run of length 1 to a success run of length 2. Then the entities of  $T^n$  are the probabilities of transitioning from one given state to another state in  $n$  Bernoulli trials. We call a Markov chain absorbing if there is at least one state such that the chain can never leave that state once entered. That is,  $k$  is an absorbing state. A stationary probability vector  $\pi$ , which does not change under application of the transition matrix, is  $(0, 0, \dots, 1)$ . That is,  $\pi T = \pi$  and  $\lim_{n \rightarrow \infty} (T^n)_{1,k+1} = 1$ .

Although this is the exact method to find the probability, [Feller \(2008\)](#) provides the approximation of the probability that a success run of at least length  $k$  for an event with a probability of  $q$  occurs at least once within  $n$  trials:

$$q_n \sim 1 - \frac{1 - qx}{(k + 1 - kx)(1 - q)} \frac{1}{x^{n+1}},$$

where  $q_n$  is the probability of a success run of at least length  $k$  in  $n$  trials, and  $x$  is the root of

$$Q(x) = 1 - x + (1 - q)q^k x^{k+1} = 0,$$

other than  $x = \frac{1}{q}$ . The other root is smaller than  $\frac{1}{q}$  if  $(1 - q)(k + 1) > 1$ . To check this, we need to show

$$x^* = \arg \min_x Q(x) < \frac{1}{q}$$

because for any  $x > \frac{1}{q}$ ,  $Q(x)$  is increasing.  $x^* = \left( \frac{1}{(1-q)q^k(k+1)} \right)^{1/k}$ , and this is strictly smaller than  $\frac{1}{q}$  if and only if  $\frac{1}{(1-q)(k+1)} < 1$ . When  $(1 - q)(k + 1) > 1$ , the other root must be greater than 1 because  $Q(1) = (1 - q)q^k$ , but it is typically close to 1.  $Q(1) = (1 - q)q^k$  tends to be



small for a large  $k$ . This approximation renders an easier way to illustrate the theoretical predictions when citizens are homogeneous.

**Proof of Proposition 1:**

We apply the approximation of  $k$  consecutive accumulations to the relevant situations that we have in mind: a sequential public bad production in a society of risk-neutral homogeneous citizens. Suppose  $n$  violators (among  $n/p$  wrongdoers) sequentially arrive, and each of the violators hands over his/her fine to the next violator with probability  $q$  and pays all the accumulated fines with probability  $1 - q$ . The probability that the fines are accumulated at least for  $k$  consecutive times is approximately  $1 - \frac{1-qx}{(k+1-kx)(1-q)} \frac{1}{x^{n+1}}$ . Since every citizen violates the law whenever it is beneficial to do so, the probability that a wrongdoer exists after  $n/p$  periods is

$$P(V|t = n/p) = \frac{1 - qx}{(k + 1 - kx)(1 - q)} \frac{1}{x^{n+1}}.$$

For the cases where we consider, the condition  $(1 - q)(k + 1) > 1$  always holds because

$$k = \left\lceil \frac{B + C}{Fp(1 - q)} \right\rceil - 1 \geq \frac{B + C}{Fp(1 - q)} - 1 \Leftrightarrow (1 - q)(k + 1) \geq \frac{B + C}{Fp} > 1.$$

Note  $B + C > Fp$ , or  $(1 - p)B + p(B - F) > -C$  must hold, otherwise the assumption  $(1 - p)u_i(B) + pu_i(B - F) > u_i(-C)$  is violated. Since  $x$  is greater than 1,  $P(V|n/p)$  decreases as  $n$  gets larger. However, if  $q = 0$ ,  $Q(x) = 1 - x$ , so  $x = 1$ . If  $x = 1$ ,  $P(V|t)$  is always 1 for any  $t$ .

Now we consider heterogeneous citizens.  $k_i$  is the smallest integer such that

$$(1 - p + pq)u_i(B_i) - p(1 - q)u_i(k_i F + F) \leq u_i(-C).$$

Since  $u_i(\cdot)$  is weakly concave, the upper bound of such  $k_i$  is  $\left\lceil \frac{B_i + C_i}{p(1 - q)F} \right\rceil - 1$ . Thus  $\bar{k} = \max_i k_i$  is finite for any  $q \in [0, 1)$ . Let  $G(k)$  denote the cumulative density function of  $k = 0, \dots, \bar{k}$ , and  $g(k) = G(k) - G(k - 1)$ ,  $k = 1, \dots, \bar{k}$  is the probability mass of the citizens with  $k_i = k$ . By the assumption of the initial incentive of public bad production,  $g(0) = G(0) = 0$ .

The transition probability matrix with the density function  $G$ ,  $T_G$  is a square matrix of order  $\bar{k} + 1$ . For notational simplicity, denote  $l = \bar{k} + 1$ .  $T_G$  is characterized as follows:

- $(T_G)_{1,1} = 1 - pq$ .
- $(T_G)_{i,1} = (1 - G(i - 1))p(1 - q)$  for  $i = 2, \dots, l$ .
- $(T_G)_{i,i} = G(i - 1) + (1 - G(i - 1))(1 - p)$  for  $i = 2, \dots, l$ .

- $(T_G)_{i,i+1} = (1 - G(i - 1))pq$  for  $i = 1, \dots, l - 1$ .
- All the other entities are zero.

Note that  $G(l) = 1$  and  $l$  is an absorbing state, so the last row of  $T_G$  is a standard unit vector whose last entity is 1. Since  $T_{1,l}^t$  is the probability of transitioning from state 0 to state  $\bar{k}$  in  $t$  trials,  $P(V|t) = 1 - T_{1,l}^t$ . The stationary probability vector  $\pi$  is  $(0, 0, \dots, 1)$ . That is,  $\lim_{n \rightarrow \infty} (T_G^t)_{1,l} = 1$ , or  $\lim_{t \rightarrow \infty} P(V|t) = 0$ . Next we want to show the monotonicity:  $(T_G^{t+1})_{1,l} \geq (T_G^t)_{1,l}$  for any  $t$ . Since  $(T_G^{t+1})_{1,l} = (T_G^t)_{1,l-1}(T_G)_{l-1,l} + (T_G^t)_{1,l}(T_G)_{l,l} = (T_G^t)_{1,l-1}g(\bar{k})pq + (T_G^t)_{1,l}$ ,  $(T_G^{t+1})_{1,l} \geq (T_G^t)_{1,l}$  if and only if  $(T_G^t)_{1,l-1}g(\bar{k})pq \geq 0$ .

Last, we show that the expected time to reach the absorbing state is finite. Let

$$T_G = \begin{bmatrix} \mathbf{Q} & \mathbf{R} \\ \mathbf{0} & 1 \end{bmatrix},$$

where  $\mathbf{Q}$  is a  $\bar{k}$ -by- $\bar{k}$  matrix,  $\mathbf{R} = [0, \dots, 0, g(\bar{k})pq]'$  is a  $\bar{k}$ -by-1 vector, and  $\mathbf{0}$  is an 1-by- $\bar{k}$  zero vector. Thus,  $\mathbf{Q}$  describes the probability of transitioning from some transient state to another, and  $\mathbf{R}$  describes the probability of transitioning from some transient state to the absorbing state. Since state  $\bar{k} - 1$  is the only state that has a positive probability of transitioning to the absorbing state, all the other entities in  $\mathbf{R}$  except for the last one are zeros.

The expected number of visits to a transient state  $j$  starting from a transient state  $i$  before being absorbed is described by the so-called fundamental matrix, denoted by  $\mathbf{N}$ .

$$\mathbf{N} = \sum_{k=0}^{\infty} \mathbf{Q}^k = (\mathbf{I}_{\bar{k}} - \mathbf{Q})^{-1},$$

where  $(\mathbf{Q}^k)_{i,j}$  is the probability of transitioning from state  $i$  to  $j$  in exactly  $k$  periods, and  $\mathbf{I}_{\bar{k}}$  is the  $\bar{k}$ -by- $\bar{k}$  identity matrix. Summing this for all  $k$  yields the expected number of visits to transient states. Since the determinant of  $(\mathbf{I}_{\bar{k}} - \mathbf{Q})$  is nonzero,  $\mathbf{N}$  is well-defined. The expected number of periods being absorbed when starting in state 0 is the first entry of the vector  $\mathbf{t} = \mathbf{N}\mathbf{J}$ , where  $\mathbf{J}$  is a  $\bar{k}$ -by-1 vector of which entities are all 1, that is,  $\sum_{i=1}^{\bar{k}} \mathbf{N}_{1,i}$ , which is finite.  $\square$

### Proof of Proposition 2:

Our goal is to characterize the first row of  $\mathbf{N}$  in terms of  $G(k)$ ,  $p$  and  $q$ . Since the sum of the first row of  $\mathbf{N}$  yields the expected number of time periods to reach the absorbing state, and we showed the monotonicity in Proposition 1, characterizing  $\mathbf{N}$  is the key to describe  $P(V|t)$ . One property of the absorbing Markov chain is the probability of being

absorbed in the absorbing state is captured by

$$\mathbf{B} = \mathbf{NR},$$

where  $\mathbf{B}_i$  is the probability of being absorbed when starting from transient state  $i$ . Since there is only one absorbing state,  $\mathbf{B}$ 's entries are all 1. Also, since  $\mathbf{R} = [0, \dots, 0, g(\bar{k})pq]'$ , the last column of  $\mathbf{N}$  is  $[\frac{1}{(1-G(\bar{k}-1))pq}, \dots, \frac{1}{(1-G(\bar{k}-1))pq}]'$ . Another important feature of the transition probability matrix considered in this paper is that state  $i-1$  is the only transient state to reach state  $i$  in the next period,  $i = 1, \dots, \bar{k}-1$ . Therefore we can recursively calculate  $\mathbf{N}_{1,i}$  from  $\mathbf{N}_{1,\bar{k}}$ . For example, the expected number of visits to state  $\bar{k}-2$ ,  $\mathbf{N}_{1,\bar{k}-1}$  must be equal to  $\mathbf{N}_{1,\bar{k}}(1-G(\bar{k}-1))\frac{1}{(1-G(\bar{k}-2))q}$ , which is  $\frac{1}{1-G(\bar{k}-2)pq^2}$ . Thus, we have

$$\mathbf{N}_{1,i} = \frac{1}{(1-G(i-1))pq^{\bar{k}-(i-1)}}, \quad \text{for } i = 1, \dots, \bar{k}.$$

$N_{1,1} = \frac{1}{pq^{\bar{k}}}$  is intuitive because  $\frac{1}{q}$  is the inverse of the probability of transitioning from the other  $\bar{k}-1$  transient state to another state than state 0, and  $\frac{1}{pq}$  is the inverse of the probability of leaving state 0. Therefore the expected number of time periods being absorbed when starting in state 0 is

$$\sum_{k=1}^{\bar{k}} \mathbf{N}_{1,k} = \frac{1}{pq} \sum_{i=0}^{\bar{k}-1} \frac{1}{(1-G(i))q^i}.$$

Now we preform two exercises regarding a mean-preserving spread (MPS) of  $G(k)$ : (1) a MPS with the same support, and (2) a MPS with a larger support. If  $\tilde{G}(k)$  is a MPS of  $G(k)$  with the same support, it must imply that  $\tilde{G}(k)$  has fatter tails. That is, there exists  $i \in [0, \bar{k}]$  such that  $\tilde{G}(i) \leq G(i)$  for  $k \geq i$ . Since the expected number of time periods depends on  $\frac{1}{(1-G(i))q^i}$ , having a larger  $1-\tilde{G}(i)$  for some large  $i$  decreases the expected number of time periods. When it comes to a MPS with a larger support, Without loss of generality, we can construct  $\tilde{G}(k)$  by

$$\{(\tilde{g}(1), \dots, \tilde{g}(\bar{k}), \tilde{g}(\bar{k}+1)) \in \Delta | \tilde{g}(i) = g(i) - \varepsilon_i \text{ for } i \leq \bar{k}, \tilde{g}(\bar{k}+1) = \frac{1}{\bar{k}+1} \sum_{i=1}^{\bar{k}} i\varepsilon_i\},$$

where  $\varepsilon_i \geq 0$ . Then  $1-\tilde{G}(i)$  is slightly larger than  $1-G(i)$  for  $i = 1, \dots, \bar{k}$ , so  $\sum_{i=0}^{\bar{k}-1} \frac{1}{(1-\tilde{G}(i))q^i} < \sum_{i=0}^{\bar{k}-1} \frac{1}{(1-G(i))q^i}$ , but  $\frac{1}{g(\bar{k}+1)q^{\bar{k}+1}}$  is substantially larger than  $\sum_{i=0}^{\bar{k}-1} \left[ \frac{1}{(1-G(i))q^i} - \frac{1}{(1-\tilde{G}(i))q^i} \right]$  due to Jensen's inequality.  $\square$

## Appendix B.

### B.1. Sample Instructions, $M_q$ Treatment

This is an experiment in group decision making. Please pay attention to the instructions. You may earn a considerable amount of money which will be paid in cash at the end of the experiment. The currency in this experiment is called ‘tokens’. In the beginning, you are endowed with 100 tokens.

There will be a quiz after the instructions, to ensure you understand the experiment.

#### **Overview:**

The experiment consists of 60 group decision-making ‘rounds’. In each round, one of the group members decides (while others wait) to choose either a red ball or a blue ball, with knowing how many black stickers are in the common pool. The details follow.

#### **How the groups are formed:**

All subjects will be randomly assigned to groups of four. For example, if there are 20 subjects in this lab, there will be five groups of four subjects. You will belong to the same group throughout the whole experiment. There will be neither physical reallocation nor interactions. Only the server computer knows who are grouped with whom, and you input your choices to your computer interface. That is, you will not know who your group members are, and your group members will not know you either.

#### **The balls:**

In each round, one of the group members will choose either a red ball or a blue ball, while other members will see ‘Please Wait’ screen. What happens in your turn are as follows:

When you choose a red ball, nothing will happen further. You keep it and your group moves on to the next round.

When you choose a blue ball, nothing will happen with probability 0.7. With the other probability 0.3, a black sticker will be attached to the blue ball. If you have a black sticker, the computer will determine where black stickers go. With probability 0.5, the black sticker is removed from your blue ball, and added to the common pool shared by group members. With the other probability 0.5, you will keep your black sticker as well as all the black stickers from the common pool. That is, if you choose a blue ball, the probability that you will have black sticker(s) is 0.15 ( $= 0.3 \cdot 0.5$ ). Then your group moves on to the next round.

The balls and the sticker have different values. 1 token per each red ball will be deducted from your account, 5 tokens per each blue ball will be added to your account,

and 8 tokens per each black sticker will be deducted from your account at the end of the session.

[Example] Suppose there are no black stickers in the common pool. If you choose a red ball in your turn, you lose 1 token. If you choose a blue ball and it does not have a black sticker, you earn 5 tokens. If the blue ball has a black sticker, then with probability 0.5 you earn 5 tokens and the sticker is added to the common pool. (Now 1 sticker is in the common pool.) With the other probability 0.5, you lose 3 tokens (earn 5 tokens from the blue ball, but lose 8 tokens from the black sticker).

### **Information in your turn:**

When it is your turn, you will receive the following information:

- The number of black stickers in the common pool
- The numbers of red balls, blue balls, and black stickers you have kept

It will not be informed what other participants have done. If there are no black stickers in the common pool, it could mean either that no one has added black stickers to the common pool, or that someone ahead of you kept all the stickers from the common pool.

### **Final Earnings:**

You are endowed with 100 tokens. If you have  $x$  red balls,  $y$  blue balls, and  $z$  black stickers at the end of the session, your total payoff is  $100 - x + 5y - 8z$ . Your earning will be converted into Euros at the rate of 8 eurocents per token. At the end of the main session, there might be an additional task of which result would be paid. The server computer will calculate the final payment. Please don't worry about this conversion.

### **Summary of the process:**

1. The experiment will consist of 60 rounds. Everyone is endowed with 100 tokens.
2. In the beginning, all subjects will be randomly assigned to groups of four members. One of the group members will make a decision in each round.
3. When it is your turn, you will choose either a red ball or a blue ball, with knowing how many black stickers are in the common pool.
4. If you choose a red ball, your turn ends. If you choose a blue ball, with probability 0.3 a black sticker is followed. When a black sticker is followed by the blue ball, the black sticker will be detached from your blue ball and added to the common

pool with probability 0.5. With the other probability 0.5, you will keep all the black stickers including those in the common pool.

5. A red ball is worth -1 token. A blue ball is worth +5 tokens. A black sticker is worth -8 tokens.

### Quiz

- Q1. Suppose 1 black sticker is in the common pool in your turn. You choose a red ball. Which of the followings is correct? (a) With some probability, it will come with a black sticker. (b) I keep the red ball. It will add 1 token to my account. (c) I keep the red ball. It will deduct 1 token from my account. (d) I keep the red ball and the black sticker in the common pool.
- Q2. Suppose 2 black stickers are in the common pool in your turn. You choose a blue ball, and it does not come with a black sticker. Which of the followings is correct? (a) I keep the blue ball and one black sticker from the common pool. (b) I can decide how many black stickers I can add to the common pool. (c) I keep the blue ball. It will add 5 tokens to my account. (d) I keep the blue ball. It will deduct 8 tokens from my account.
- Q3. Suppose 2 black stickers are in the common pool in your turn. You choose a blue ball, and it comes with a black sticker. Which of the followings is NOT correct? (a) With probability 0.5, I can change my choice. (b) With probability 0.5, I keep the blue ball, and the black sticker goes to the common pool. (c) With probability 0.5, I keep the blue ball and all the black stickers. (d) If the black sticker goes to the common pool, there are 3 stickers in the common pool.
- Q4. If you choose a blue ball, what's the probability of keeping black sticker(s) in your account?
- Q5. Suppose that you keep 10 blue balls and 2 black stickers at the end of the session. During the session, how many tokens have you gained/lost in total? (Don't count the endowment.)