

Economic Experiments to Compare the Effectiveness of Punishment Severity and Risk of Apprehension in Deterring Dishonest Behavior

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ABSTRACT

For many types of wrongdoings, deterrent may be the more desirable goal than punishment due to the damage these wrongdoings already cause and the strain on the resources of enforcement authorities. This paper uses economic experiments to offer insights into the relative effectiveness of monitoring (increasing the risk of apprehension) and punishment severity in deterring dishonest behavior. Experimental results show that varying the degree of punishment severity does not alter self-reported scores on a 5-minute quiz, an indicator of dishonest behavior, given a low risk of apprehension. On the other hand, at a seemingly light punishment level (no gain received), higher risks of apprehension are associated with lower levels of dishonest behavior as seen from lower self-reported quiz scores. These results suggest that current approach to deterring wrongdoings that usually involve threats of more severe punishment may not be achieving the desired outcome.

1. Introduction

One of the most important issues facing many societies today is how to reduce negative behaviors like crime and corruption. The central focus, perhaps, is how to deter people from participating in this kind of activity. Deterrence is important because society does not have to deal with the direct consequences of the crime itself, and we do not have to identify, capture, prosecute, and deliver the punishment to the culprit. All of these indirect activities are costly. For this reason, deterrence would be more efficient compared to incapacitation (Chalfin and McCrary, 2017).

Deterrence has been mentioned and discussed since the time of Adam Smith (1776) and Jeremy Bentham (1789). The core concept of the theories of deterrence focuses on the responses of individuals to changes in certainty, severity, and celerity of punishment. In the modern period, the standard economic model of criminal behavior was developed by Becker (1968) where the main assumption centers on a rational agent facing the choice of whether to commit a crime. He can choose either to commit an illegal activity and receive a benefit or not to commit it. The former could associate him with risk of apprehension and punishment. The latter will yield no criminal benefit but is risk free for him. The deterrence depends on the probability of apprehension and punishment. The important question for policy is whether to deter criminal activity by increasing the probability of apprehension or to increase the severity of the punishment once apprehended.

Becker's model theoretically predicts that if individuals are risk preferring, risk of apprehension would be more effective to deter them from committing crime. If individuals, however, were risk averse, then increasing in punishment would be more effective than increasing probability of apprehension. Both punishment and risk of apprehension would have

the same impact on crime decision if individuals were risk neutral. However, research findings in behavioral decision making suggests that events that will or may happen in the future would hold less sway on decisions in the present than they rationally should (Darley and Alter, 2013). This suggests that people would be more sensitive to changes in risk of apprehension, which affect utility immediately, than by changes in punishment, which mostly affect utility in the far future. Furthermore, other studies in behavioral economics point out that people tend to overestimate the likelihood of rare events and underestimate the likelihood of common events. This implies that people may overly respond to changes in probability of apprehension especially when the perceived probability of detection is very low (Durlauf and Nagin, 2011).

The empirical evidence of crime responsiveness to probability of apprehension and punishment is mixed. While some studies find that deterrence is effective when increases in punishment and sanction are imposed (e.g. Helland and Tabarrok, 2007; Machin, 2014), others find no impact of punishment on crime deterrence (e.g. Hjalmarsson, 2009; Fagan and Johnson, 2010). The similar story also happens for risk of apprehension where the evidence of risk of apprehension effectiveness is mixed (e.g. Levitt, 1997; Lin, 2009; DeAngelo and Hansen, 2014). Many previous studies, however, suffer from data and technical limitations, especially the difficulty of causal effect clarification under treatment of policy endogeneity as changes in deterrence levels are generally not random (Donohue and Wolfers, 2009; Chalfin and McCrary, 2017).

Our study therefore uses the experimental technique to clarify causation, and importantly to elicit the effects of changes in risk of apprehension and punishment on the negative behavior of cheating. In addition, our experimental design was set up to immediately generate the impacts of cheating, in both positive and negative directions (benefit of not being caught and punishment

of being caught, respectively). This allows us to clean out the impact of preference being time dependent. We could therefore compare the effectiveness between the risk of apprehension and punishment in deterring cheating behavior, given that the benefit and punishment of cheating can happen in the same time.

Using self-reported scores on a 5-minute quiz as an indicator of cheating behavior, the experimental results suggest that risk of apprehension are more effective in deterring cheating behavior. Though the results are not monotonic, higher levels of apprehension risk bring cheating behavior closer to the full monitoring case where the researchers recheck each reported score. The results are not as promising for punishment severity. At a low level of monitoring (1%), varying punishment severity does not seem to alter cheating behavior. Even in cases where subjects can lose *their own* money, we can still observe similar levels of dishonest behavior. When trying to deter dishonest behavior, increasing monitoring effort seems to be the appropriate way.

Friesen (2012) conducted an experiment study investigating the same question with students at the University of Queensland, Australia. In that experiment, the author finds that increasing punishment severity is the more effective way to deter wrongdoing. In particular, an increase in punishment severity reduces incidence of non-compliance more than an equivalent increase in punishment probability, where equivalence is defined as changing expected penalty equally. In our study, we consider situations where expected payoff cannot be known beforehand, e.g. different people stand to gain differently from cheating. We instead vary punishment risk and punishment severity separately and examine how each changes cheating behavior.

The rest of the article is presented in 5 sections. The next section describes the model of decision making when people face choices of whether to cheat or not cheat. We then describe our experimental design and its implementation in section 3. Section 4 presents the empirical analysis and interpretation. We conclude our findings and discuss results in section 5.

2. A Theoretical Model of Risk and Consequences

We need a theoretical model to understand the interplay among the determinants and deterrents of cheating. The model will also help us make sense of the experiments' results. We use the expected utility model as our starting point. The decision is whether to cheat or not. Cheating provides either a gain relative to not cheating if it is not caught and punished, or a loss if it is caught and punished. For simplicity and without any loss, we can take the non-cheating outcome as the status quo or the reference point in the language of prospect theory (Kahneman and Tversky, 2013; Koszegi and Rabin, 2006). To cheat is thus a gamble that one chooses to accept or not accept.

The following model is adapted from Becker (1968) model of the "supply of offenses," which relates the number of crimes committed to the probability of conviction and the severity of punishment. Let v denote the one-time payoff from cheating and not getting caught, relative to the reference utility point of not cheating, and $-e$ denote the one-time punishment incurred if caught cheating. The punishment is denoted as a negative value to be explicit that it represents a loss. For concreteness both the payoff and the punishment are in terms of one common currency, say money. Then finally let p represent the *subjective* probability of getting caught cheating, as decisions are based on subjective and not objective probability. We take the view that the individual's subjective probability of getting caught is manipulated by the enforcer, and is thus an external variable.

Recall that both possible outcomes from cheating, getting caught or not, are relative to the status quo of not cheating where payoff is 0. Given the agents are making a comparison between cheating and not cheating, and not cheating is viewed as status quo, the two possibilities are viewed as a gain or a loss relative to the status quo. Let $U(.)$ denote the utility function.

Following the tradition of prospect theory where agents are loss averse around the reference point, loss utility is given by $-\lambda U(\cdot)$, or differs from a gain by the loss aversion parameter λ and the negative sign. We can thus write the expected prospect value as

$$(1 - p)U(v) - p\lambda U(e)$$

To cheat, which is to accept the gamble, means

$$(1 - p)U(v) - p\lambda U(e) > 0$$

The condition for cheating thus depends on a three-way interaction among the external parameters v , e , and p (external to the individual, manipulable by the enforcer or a policymaker).

To better understand the role of each external parameter it is useful to write the condition as the relationship between each pair of parameters while holding the third constant. This gives rise to 3 non-trivial bi-variate relationships, each pair illustrating how one controllable depends on the other two controllables. These relationships can tell us the “threshold” level of each controllable that will deter cheating in an individual, depending on the values of the other 2. Once the thresholds are derived, we can combine them with the distributions of these thresholds to find the deterrent effect of varying the sizes of p , v , and e . We start by the discussion of the individual thresholds of the three external variables, followed by their combination with the distribution of individual thresholds to determine the marginal deterrent effect of each external parameter.

First, consider the threshold p , subjective probability of getting caught that would deter cheating under different circumstances we can write the condition for not cheating as

$$p \geq \frac{U(v)}{U(v) + \lambda U(e)}$$

This relationship shows that the subjective probability p that would deter cheating has to be at least the proportion of the gain utility, $U(v)$ relative to the entire range of possible utilities from cheating $U(v) + \lambda U(e)$. The threshold p depends positively on v and negatively on e . A larger loss-aversion parameter reduces the threshold subjective probability. To explore the relationship between p and e , holding v constant, we can write

$$p \geq \frac{U(\bar{v})}{U(\bar{v}) + \lambda U(e)}$$

With the overbars ($\bar{\cdot}$) denote a constant value. Similarly, we can write the relationship below to highlight the relationship between the threshold p and the reward v , holding the punishment e constant, as well as all the remaining pairs of relationships. For conciseness we show only the equations that show how e and v depend on the other parameters.

The threshold punishment or the smallest e that would deter cheating is given by

$$e \geq U^{-1}\left(\frac{1}{\lambda}\left(\frac{1-p}{p}\right)U(v)\right)$$

The intuition here is that if the odds of not getting caught is large (note the odds ratio) you need a larger punishment to deter cheating. Also, higher loss aversion reduces the punishment threshold.

Finally, the threshold reward, or the largest v that deters cheating is given by

$$v \leq U^{-1}\left(\lambda\left(\frac{p}{1-p}\right)U(e)\right)$$

Higher odds of getting caught ($\frac{p}{1-p}$) increases the threshold reward that deters cheating (a higher reward is needed to justify cheating). Higher punishment (e) and higher loss aversion (λ) is also shown to increase the threshold.

The effectiveness of a deterrent mechanism is measured by the number of cheating incidents prevented. The number of incidents is just the number of individuals who finds that the value of one of p , v , or e in the mechanism is beyond their threshold, and depends on the distribution of the threshold external parameter in the population.

Let us assume that all the threshold parameters are normally distributed, and are independent from one another. For example, consider the subjective probability of getting caught p . The proportion of individuals in the population that would cheat, given the subjective probability \bar{p} is given by $1 - cdf(\bar{p})$. If we know, or have a good estimate of the size of the population, we can compute estimate the number of cheaters. We can also compute the resulting change from a given increase in the subjective probability. This is also true of the remaining parameters v and e .

In practice, however, the only manipulable variable (among p , v , e) that law enforcement or the justice system can feasibly influence is p , the subjective probability of getting caught. This is done by either committing to an actual monitoring effort, or by leading observers to believe a certain level of monitoring is in place. For example, more frequent auditing can be used, or an announcement of random auditing can be made. With the variable v , the reward of cheating, it is difficult to know how individuals are rewarded and therefore would require further work to intervene with this reward. Finally, the punishment e is made mostly with moral considerations and not deterrent considerations. The punishment has to fit the crime, and it is hard to imagine passing a law that punishes a jaywalker with a prison sentence or a large fine. Finally, changing the written law is a cumbersome process, especially in less developed countries where established order is not very strong.

The experiments that follow are designed to empirically examine the relative importance of 2 manipulable variables, the chance of getting caught (p) and the magnitude of the punishment (e). These results will help in the design of deterrent mechanisms, specifically the choice between increasing the chance of getting caught (via more monitoring or surveillance) or changing the punishment code.

3. Experimental Design and Implementation

Overall Design:

To determine the relative importance of the possibility of getting caught, p , and the severity of punishment, e , we carry out an experiment involving a quiz of general knowledge with monetary reward according to the number of questions answered correctly. Different groups of subjects get the same quiz questions with different cheating deterrent mechanisms. Scores across groups are then compared with two extreme control groups. These are 1) complete deterrence where the administrators check the answers, and 2) zero deterrence where participants simply report their own scores. Higher mean scores are taken as indicative of more cheating.

Subjects are divided into 3 groups of experiments. Group 1 is the control group consisting of 2 subgroups—complete deterrence and zero deterrence. The outcomes of the subgroups serve as references for no cheating and complete freedom to cheat, respectively. Group 2 consists of 5 subgroups with varying degrees of risk and a constant monetary punishment if caught cheating. These will help to identify the effect of the risk of getting caught. Group 3 consists of 6 subgroups with varying levels of punishment and a constant risk of getting caught cheating. The experiments in this group are meant to identify the effect of punishment severity. The same set of questions is given to all the groups.

The experiments are conducted with Khon Kaen University students. We believe there are no systematic differences across the experiment groups because the sample consists of students in similar ages, and different majors are randomly assigned to different experiment groups.

Summary statistics of experimental subjects are given below in table xxx below.

[Insert Table XXX]

Each subject is given a 10-question multiple choice quiz with 5 minutes to complete. The participant receives 30 THB (slightly less than 1 USD as of 2016) for each question correctly answered. The questions are not field-specific in order to avoid any possible bias. Two example questions are given below.

Example Question 1:

“The 6th ASEM Meeting was held on 10 – 11 September 2006 in Helsinki. What does ASEM stand for?”

Example Question 2:

“Given this sequence 4, 3, 3, 36, 6, 3, 5, 90, 8, 3, 7, ..., what is the number in the blank?”

Implementation

Group 1—the control group

The experiments in this group consists of 2 subgroups—complete surveillance and complete freedom to cheat. See the first column of figure 1. In subgroup 1, complete surveillance, each subject turns in their quiz to be graded by the administrator and monetary reward is given accordingly. In subgroup 2, complete freedom, each subject grades their own quiz with answers

provided by the administrators, and reports the score. Money reward is given without verification. For this subgroup, the administrators either walk away or do other activities during the 5 minutes of the quiz.

[Insert figure 1]

Group 2—constant punishment severity and varying degrees of risk

There are 5 sub experiments in this group, each with varying levels of risk of getting caught (punishment risk henceforth) and a constant punishment severity. See the second column of figure 1. For every subgroup, participants complete the 10-question quiz in 5 minutes, grade their own quiz, and then report the score to the administrators to receive money reward. If they are found to over-report, they receive no money reward. The punishment is that the cheater would have wasted 5 minutes plus grading time and receive nothing in return, and possibly some degree of shame.

To represent punishment risk, we have the administrators randomly verify the participants' answers at 5 different levels of probability. And since we are interested in how agents make actual decisions based on perceived risk, or the subjective probability, we tell subjects in this group beforehand the level of verification probability they face. The different levels of verification probability are 1%, 5%, 50%, 70%, and 90%.

To implement the verification probability, say at 5%, a participant is asked to think of a number between 1 and 20, then a number is drawn from a hat containing numbers from 1 – 20. If the participant's chosen number is not drawn, they receive the money award according to the number of questions they claim to have answered correctly. If their number is drawn, the

administrators check their answers. The participant receives money award if their reported score is the true score, and receives no money if the reported score is incorrect.

Group 3—constant risk and varying punishment severity

The experiments in this group are aimed at testing the importance of punishment severity.

Subjects are assigned to one of the 6 sub experiments with constant subjective punishment risk and varying punishment severity. **See the third column of figure 1.** Again, participants complete a 10-question quiz in 5 minutes, grade their own quiz, and report the score to receive money reward. However, instead of being verified randomly at varying probabilities, scores are verified at 1% probability for everyone in this group using the same mechanism as for group 2. If they are found to over-report, they face varying levels of sanctions announced beforehand.

Of the 6 sub groups, the first three are given probable sanctions in the form of a forgone gain. If caught over reporting, they receive money reward based on the number of actual correctly answered questions minus 30%, 70%, or 100% of that amount. The other three are given probable sanctions in the form of a loss. In addition to receiving no money reward, they are fined 30%, 70%, or 100% of the reward based on their reported score. Thus there are 6 levels of punishment severity, ranging from a reduced gain of 30% of the deserved reward (based on correctly answered questions) to a fine equal to 100% of the undeserved reward (based on over-reporting).

4. Experiment Results

Given rather similar participants in all the groups, we should expect the average scores on the quiz to be similar across all groups. Because of this we view differences in average scores to

be indicative of systematic differences in participants' over-reporting the scores under different deterrent regimes. **Table 1** shows the average scores under all deterrent regimes.

[insert Table 1]

There are visible differences across different regimes. For example, in the design where researchers check the questions themselves and there is no chance to over-report, the average score is the lowest. This is as expected. Also, the highest scores are for cases where random checks occur at a lowest percentage (0%, 1% or 5%), and there seems to be decreasing average scores with increasing chance of a random check. However, there is little detectable pattern related to the size of monetary sanctions. In fact, among the groups with varying sanction sizes, the average score is the highest with the largest sanction (a loss of 100% reward from over-reported score).

We next perform linear regression to statistically test for the effect of different deterrent regimes. The first regression tests for significant differences in the mean scores across groups whose deterrent regimes vary by punishment risk but face the same punishment severity. The dependent variable is the score of a participant, while the dependent variables are group dummy variables indicating punishment risk levels. The reference group is 100% surveillance, where researchers check the scores of all participants. **Table 2** presents the results.

[insert Table 2: Constant punishment severity and varying punishment risks]

Consistent with the comparison of means across groups, the coefficients of all group dummies are positive indicating that the scores of all treatment groups are higher than in the control group. In particular, statistically significantly higher scores are observed for groups with 0%, 1%, and 5% verification probabilities (punishment risks). No-risk group score 1.3 points above the

reference while the 1% risk group scores 2.2 points higher than the reference group. The 5% risk group score 1.7 points higher than the difference. The scores across these 3 high-punishment-risk groups are not significantly different from one another. Groups with higher levels of risk have scores no different from the reference group. It seems that a punishment of 50% is sufficient to deter cheating in this sample.

The second regression tests for the effect of varying levels of punishment severity holding punishment risk constant. Again the dependent variable is the test score. The independent variables are group dummy variables indicating punishment severity levels. The reference group for the second regression is where the participants check their own scores. Lower mean scores in the control groups occur when coefficient on the dummy group variable is negative and significant. Table 3 reports the results.

[insert Table 3: Constant punishment risk and varying punishment severity]

In all variations of punishment severity, the mean scores are not significantly different from the full-cheating scenario with participants grading and reporting their own scores. This is true even in the most severe punishment scenario—a loss of 100% of reward from over-reporting. In fact, the coefficient on this variable does not even have a negative sign as others despite having the more severe punishment than the rest. The results here show that at least for this sample, punishment severity play little role in deterring cheating.

5. Discussion of Results

The empirical results when combined with our theoretical model provide us with useful insights. Certainly the lack of any deterrent effect from increasing the severity of punishment, and the

visible deterrent effect from increasing punishment risk, are both informative in their own right. However, some discussion on the applicability and limitations of the results is in order.

Our experimental design allows for studying the effect of varying punishment severity and probability of getting caught, or enforcement intensity, independent of relevant confounding factors. The control and treatment situations are similar in all aspects other than these two dimensions, enabling us to make *ceteris paribus* conclusions about the deterrent effect of punishment severity and punishment risk. At the same time, our experiment subjects consist of college students, who are certainly not representative of the adult population in Thailand. While our results are conclusive in this sample, we cannot completely apply our findings to the general population.

The experimental results we obtain are both similar to and different from another experimental study by Friesen (2012). In both that work and ours, we find that “inspection rate” reduces cheating behavior. However, we find a larger effect from increasing inspection rate than from increasing punishment severity, while Friesen (2012) find the opposite. In that work, both inspection rate and punishment severity significantly deter cheating, but a stronger effect comes from increasing punishment severity. We attribute part of the difference to the actual magnitudes of punishment severity and inspection rates used in each experiment. In addition, the anonymity in the Friesen (2012) study may allow subjects to approach the problem in a more traditional way, which is to attempt to maximize total payoff. In our case, monitoring involves face-to-face interaction and thus adds to the “pain” of getting caught.

Our experiment design varies the punishment risks and punishment severity to examine how each affects cheating behavior. While the range of values for punishment risk, i.e. inspection

rate, can only take a value between 1 and 100, reasonable punishment severity varies across offenses. Our chosen punishment severity values reflect this consideration, and it is arguable that these values are too small to affect decisions. At any rate, we still observe a higher degree of effectiveness coming from punishment risk, even with what one might argue to be a punishment that is too light to deter cheating. We take these observations as further evidence of a higher relative effectiveness of punishment risk in deterring crimes where reasonable punishment severity is low.

We can glean a few insights from our results by comparing them to the theoretical framework.

The theoretical model posits that the threshold punishment risk is determined by punishment severity (e) and value of cheating reward without getting caught (v). Recall that the threshold punishment level is given by

$$p \geq \frac{U(v)}{U(v) + \lambda U(e)}$$

In the experiments we have identified this threshold given both these parameters (e , v) to be between 10% and 50% punishment risk. The 10% is the highest punishment risk that fails to deter cheating, and comes from results of the second control group where deterrent is not observed at any level of punishment severity at this level of punishment risk. The 50% is the lowest punishment risk that deters cheating, and comes from the first control group's results where punishment risk varies while punishment severity remains constant.

It is worth mentioning again that the so-called “punishment” in the first group of controlled experiments is only “not receiving” the reward from cheating—there is no loss involved. The results then are indicative of some risk aversion at play. Assuming no loss aversion such that $\lambda =$

1 the results straight-forwardly provide evidence against “risk-neutral” or “expected value” decision making. Expected value would simplify the threshold p to be $v/(v + e)$. Given that our $e = 0$ in the experiments, it is clear that only a punishment risk of 100% would deter cheating. There appears to be some risk aversion involved when participants make their decisions in our experiments, consistent with expected utility theory. At any rate, given our parameters, which in our judgment are suitable for what is at stake and the severity of the crime, punishment risk seems to be effective in deterring undesirable behavior.

On the other hand, punishment severity (e) does not hold that promise. Theoretically, threshold punishment severity is determined by punishment risk (p) and cheating reward (v). Higher punishment risk (p) would lower threshold punishment severity while higher cheating reward (v) would increase this threshold. From the theoretical section this threshold is given by

$$e \geq U^{-1} \left(\frac{1}{\lambda} \left(\frac{1-p}{p} \right) U(v) \right)$$

In the experiments to explore the effect of punishment severity given constant punishment risk, participants seem willing to even risk a loss in order to try to get a high reward. In particular, given the punishment risk at 10% ($p = 10\%$) participants are not deterred even when $e = v$, the punishment is the same size as the cheating reward. Risk aversion would certainly not have predicted this outcome. For illustration, risk-neutral utility function (with no loss aversion) would simplify the threshold punishment to

$$e \geq \left(\frac{1-p}{p} \right) v$$

which would put the deterrent threshold at 9 times the reward when $p = 0.1$. The punishment severity of only 1 time the cheating reward is well below this amount, so the results do not contradict commonly observed human preference. Overall, one lesson can be learned from the results exploring punishment severity: no reasonable levels of punishment severity that fit our crime can deter cheating.

The empirical results regarding punishment severity and punishment risk should at least bring attention to our design of various rules and laws. We sometimes hear governments discuss versions of “getting tough on crime,” followed by descriptions of how harsh the new punishments will be. In light of what we observe here about the relative importance of punishment risk and punishment severity, these declarations do not seem assuring in terms of deterring certain crimes.

Instead of announcing new harsher punishments, and possibly unjustifiable given the crimes, more productive efforts could be directed toward increasing enforcement or the perception thereof. In fact, the Thai police force had a creative idea to set up policeman mannequins at intersections to reduce traffic violations, and most would agree that they are quite effective. Further examples include putting parked cars with locked wheels (locked by police as punishment of parking violations) to bring attention to drivers who are considering parking at an illegal spot, or putting fake cameras along with real ones to increase “perceived risk” beyond the actual risk.

There are also practical arguments for increasing punishment risks over punishment severity. In most societies, Thailand certainly included, crime punishment severity is almost always determined by society’s sense of what is fair. Different values toward the same crime will carry

different punishment severity across countries. For example, as of this writing certain states in the USA allow recreational use of marijuana, whereas possession of any of it in Thailand carries a hefty sentence. The justice system will have a hard time convincing the public of a new law that puts people in prison for failing to use the pedestrian bridge to cross a road. Furthermore, any change in the written law is a cumbersome process and immediate change is not possible.

The experimental design here allows for straightforward comparison of cost and benefit of cheating because the reward and punishment are denominated in monetary terms. Useful insights emerge, but are limited as real world situations sometimes involve non-monetary costs and benefits, and costs and benefits are not measured in the same units. For example, in the case of cheating within an organization or engaging in corruption, a worker may see a reward in the form of increased sense of belonging if everyone else engages in the same behavior. In this situation, *not* being corrupt incurs a personal cost in the form of weakened ties with coworkers. The insights from these experimental results are not readily adaptable to non-monetary gains and losses, or to situations where gains and losses are denominated differently. Nonetheless, we can have this simple model in the back of our minds when thinking about how to forcefully, via laws and enforcement, to reduce or prevent undesirable behavior.

Finally, the cost and benefit analysis considered in this experiment is only taken from the perspective of individuals. We take for granted that any reduction in undesirable behavior is justifiable in terms of its costs. For example, we make a case of increasing monitoring or surveillance in order to deter the undesirable behavior, without making any statement about how undesirable these behaviors actually are for society. A complete picture of an optimal deterrent mechanism design should further consider social costs and benefits of increasing monitoring

efforts, and an optimal design would be where the social deterrent costs do not outweigh the social benefits.

6. Conclusions and Directions for Future Work

As societies become ever more complex, occurrences of transgressions are sure to increase. Without the internal motivation to avoid doing harm to others, relegating all peacekeeping responsibilities to law enforcement will only stretch their resources thinner and thinner over time. Crime deterrence therefore becomes increasingly important as resources are struggling to keep up with enforcement responsibilities. This study uses economic experiments to explore two broad alternatives to deterring potential wrongdoing—risk of apprehension and severity of punishment. The results are somewhat comforting, that increasing the risk of apprehension, i.e. monitoring effort, seems more effective than increasing the severity of punishment.

Increasing punishment severity is undesirable from both the economic and moral standpoints. From the economic standpoint, severe punishments are typically associated with higher costs of implementing, such as longer sentences or lengthy processes due to the convicted expending more effort to avoid a stronger punishment than more lenient ones. From the moral standpoint, most societies do not want to punish someone more harshly than the crime warrants. To increase the severity of punishment will likely push the punishment above the appropriate threshold, and most societies prefer to avoid that.

The experimental results, though convincing in many respects, are still subject to a few shortcomings worth mentioning. First, the subjects in this study are university students, a special group of young people in Thailand given that this group make up of about ¼ of the country's current working age population. The behavior in this sample may not be representative of much

of the population. Another issue is the size of the sample, which some may argue does not provide sufficient statistical power. Furthermore, and possibly the most serious, the results do not generalize to all wrongdoings. In this experiment, the offense does not involve much emotion in the decision making process typical in many violent crimes, for example. Finally, different rewards sizes may produce different results than those we have here.

Future studies may explore other types of wrongdoings, alter the amounts or types of punishment and reward, increase the sample size, and/or experiment with different subsets of the population. They may also address different types of offenses that are motivated by different factors other than monetary gains. The experiments in this study address only the “sticks” side of the motivation to avoid wrongdoing, and future work may explore “carrot” type of options. It is expected that not only different types of “sticks” will generate different deterrent effects, but also that “carrots” will deliver different results than “sticks.” Furthermore, the types of offenses may require different types of different mechanisms. It is up to each society to decide how much resources they are willing to commit to learn about the appropriate deterrent schemes for myriad types of wrongdoings they most want to prevent.

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Tables and Figures

Figure 1: Experiment Groups

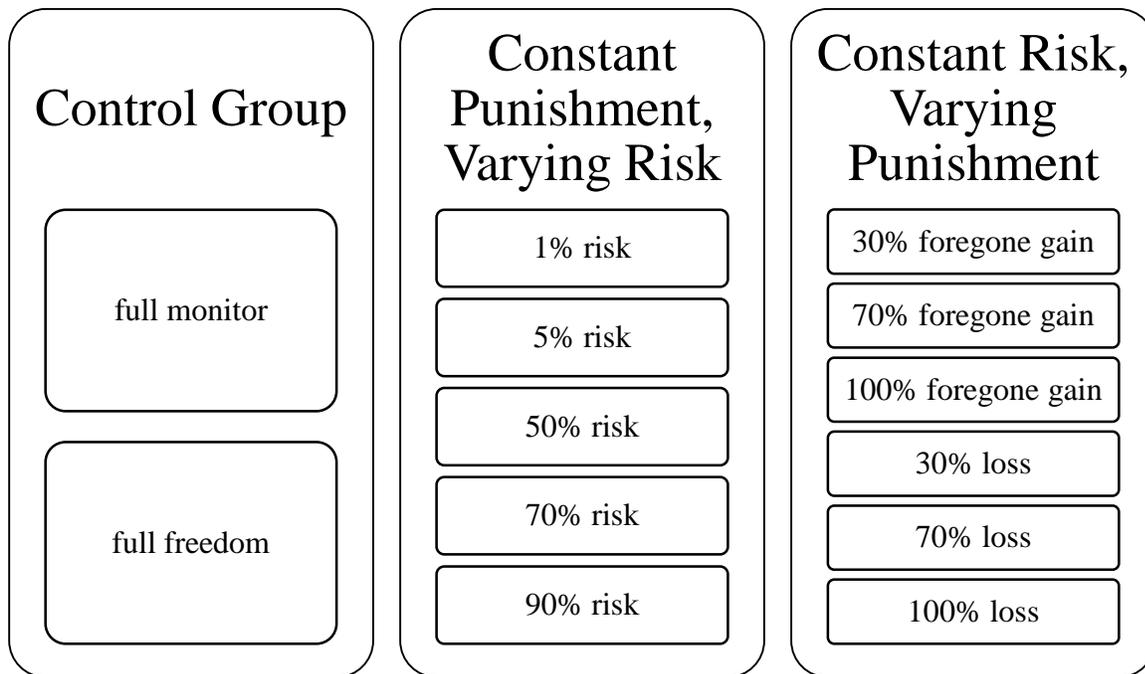


Table 1: Average Scores under all Regimes

Group	Average
Full Monitor	3.00
Full Freedom	4.30
Constant Punishment, 1% risk	4.90
Constant Punishment, 5% risk	4.70
Constant Punishment, 50% risk	3.90
Constant Punishment, 70% risk	4.00
Constant Punishment, 90% risk	3.30
Constant Risk, Forgone gain 30%	4.10
Constant Risk, Forgone gain 70%	3.60
Constant Risk, Forgone gain 100%	3.90
Constant Risk, Loss 30%	4.10
Constant Risk, Loss 70%	4.20
Constant Risk, Loss 100%	4.30

Table 2: Regression result for constant punishment severity and varying punishment risks

Variable	Net Total Cheating
Constant (full monitor)	3.000 (6.344)
Full Freedom	1.300* (1.994)
Constant Punishment, 1% risk	2.200* (3.375)
Constant Punishment, 5% risk	1.700* (2.608)
Constant Punishment, 50% risk	0.900 (1.381)
Constant Punishment, 70% risk	1.000 (1.534)
Constant Punishment, 90% risk	0.300 (0.460)
R^2	0.213
Number of Observations	69

Table 3 Regression result for constant punishment risk and varying punishment severity

Variable	Net Total Cheating
Constant (full freedom)	4.300 (10.014)
Full Monitor	-1.300*** (-2.084)
Constant Risk, Forgone gain 30%	-.200 (-0.329)
Constant Risk, Forgone gain 70%	-.700 (-1.153)
Constant Risk, Forgone gain 100%	-.400 (-0.659)
Constant Risk, Loss 30%	-.200 (-0.329)
Constant Risk, Loss 70%	-.100 (-0.165)
Constant Risk, Loss 100%	0 (0)
R ²	0.090
Number of Observations	79