Certainty and Severity of Punishment in Crime and Corruption Deterrence: An Experimental Study

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Abstract

We investigate experimentally the (relative) effectiveness of certainty (probability) and severity of punishment in deterring corruption and crime jointly and simultaneously in a game developed by Ortner and Chassang (2018). The experimental design features two different policy regimes with the same deterrence power: $\mathcal{HP}$ with high certainty p and low severity $\mathbb{E}(W)$ of punishment and $\mathcal{LP}$ the opposite. Within each regime, we examine whether there is a real deterrent effect by increasing p or $\mathbb{E}(W)$, and which one delivers a greater impact if there is any. The experimental results show that, in regime $\mathcal{LP}$, neither increasing p nor increasing $\mathbb{E}(W)$ deters crime or corruption effectively. In contrast, in regime $\mathcal{HP}$ where the initial p is high enough, increasing p significantly deter crime and corruption, while increasing $\mathbb{E}(W)$ only deters corruption significantly. Furthermore, an increase in p delivers a greater deterrent effect than that in $\mathbb{E}(W)$. In addition, we document the presence of the Cobra Effect in regime $\mathcal{LP}$ when we intend to deter corruption by increasing the expected wage of the monitor. Last but not least, we explore the changes in extensive and intensive margins of crime and corruption, and we find a difference in celerity of deterrent effect between increasing p and $\mathbb{E}(W)$ in regime $\mathcal{HP}$, specifically, subjects are promptly responsive to changes in p while they are inertial to changes in $\mathbb{E}(W)$.

Keywords: Crime Deterrence, Corruption Deterrence, Asymmetric Information, Cobra Effect, Extensive Margin, Intensive Margin.

JEL Codes: D73, D82, K14, K42

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1 Introduction

In the seminal work by Becker (1968), the author suggests that certainty of punishment would have a larger deterrent effect than severity according to the model given the fact that punishment is costly.[1] In addition, since he does not differentiate between crime and corruption as they are both transgressions against laws, his theory applied to both crime deterrence and corruption deterrence. Since then, the certainty and severity of punishment have been the most commonly examined and used instruments to deter crime and corruption.

Since corruption is a special form of crime committed by police or inspectors whose job is to deter crime, the literature examines crime and corruption deterrence separately. Many studies support Becker's prediction and show that certainty of punishment does have a larger deterrent effect than severity of punishment in crime deterrence (see Chauncey, 1975; Grogger, 1991; Mungan, 2017; Witte, 1980, for example) as well as in corruption deterrence (see Barr, Lindelow, & Serneels, 2009, for example). However, some other studies show the opposite: an increase in the severity of punishment is more effective in deterring crime (see Engel & Nagin, 2015; Friesen, 2012, for example) and corruption (see Banerjee & Mitra, 2018; Barr et al., 2009, for example) than an increase in the certainty of punishment. Therefore, the literature is far from conclusive and it requires more exploration in detail to make the jigsaw more complete.

Furthermore, empirical studies usually have several drawbacks in addressing the issue. First, they do not have an accurate measure of the deterrent power of an increase in certainty and severity of punishment, thus the result they have obtained might be due to an incomparable increase in these two policy instruments rather than the difference in these two instruments themselves. Second, it is usually difficult for these studies to separate the effect of certainty and the effect of severity from each other on deterring crime and/or corruption. However, the body of the literature on experimental studies is rather small and the results are still mixed (see Armantier & Boly, 2011; Banerjee & Mitra, 2018; Barr et al., 2009, for example).

One important aspect that is overlooked in the deterrence literature of the relative effectiveness of certainty and severity of punishment is the close relationship between crime and corruption in most scenarios since corruption would not be an issue if crime is completely deterred,[2] therefore,

[1]For more details, see Becker (1968), specifically, starting from page 180.

[2]In our opinion, the ultimate purpose of deterring corruption is to deter crime, so the study of corruption deterrence without bringing crime deterrence into the picture is not complete. One exception is the corruption caused by harassment bribery, which is experimentally studied by Banerjee (2016); Banerjee and Mitra (2018).

the issue of their relative effectiveness in deterring crime and corruption should be re-examined jointly and simultaneously in one framework.

Ortner and Chassang (2018) introduces three-tier hierarchies in a principal-monitor-agent framework which enables us to address crime and corruption deterrence jointly and simultaneously. In the model, the principal pays the monitor to observe the agent's criminal activity and make a report on it, and the agent can propose a bribe τ to the monitor in exchange for a report of innocence while he only knows the monitor's wage distribution and its expectation $\mathbb{E}(w)$. Furthermore, any false report made by the monitor has a chance of p being detected by the principal, and the monitor's wage is deprived. Therefore, the idea is to design a wage structure for a given p such that any bribe $\tau < \pi_A$ is not enough to compensate the monitor's expected cost of corruption, and thus, both crime and corruption are deterred at the same time. With this model, we can study experimentally the relative effectiveness between certainty of punishment by manipulating p and severity of punishment by manipulating $\mathbb{E}(w)$. Therefore, each pair of p and $\mathbb{E}(w)$ is an incentive structure imposed on the monitor, which is also the policy design adopted by the principal fighting against corruption and crime.

Please note that there is a subtle but important difference between crime and corruption deterrence in the model. For corruption deterrence, manipulating p changes the certainty of punishment, and $\mathbb{E}(w)$ changes the severity of punishment on the monitor's side. For crime deterrence, however, manipulating either p or $\mathbb{E}(w)$ or both only affects the certainty of punishment on the agent's side indirectly, and the severity of punishment is a constant k. Therefore, we should expect a weaker deterrent effect against crime (indirect) than against corruption (direct), and an equivalent increase in p or $\mathbb{E}(w)$ should yield an equivalent crime deterrent effect since they both affect the certainty of punishment.

Another feature of our study is that the bribe size is endogenously determined. Previous experimental studies mostly have the bribe size exogenously manipulated and examine how subjects would respond to the changes (see Armantier & Boly, 2011; Schulze & Frank, 2003, for example). In our study, the bribe size is endogenously determined by the interaction between the criminal agent and the monitor. Therefore, we can also examine how the size of bribe changes to the changes in p or $\mathbb{E}(w)$ as a potential mechanism that links crime and corruption together.

Our experimental design is inspired by Nagin (1998) who points out that "for policy makers the issue is not whether the criminal justice system in its totality prevents crime but whether a specific policy, grafted onto the existing structure, will materially add to the preventive effect." In order to examine the deterrent effect of crime and corruption with certainty and severity of punishment as policy instruments, we first initiated two regimes in our experiment: one with a high probability of detection p and a low expected wage $\mathbb{E}(w)$ which is denoted as regime $\mathcal{HP}$ and the other with a low p and high $\mathbb{E}(w)$ which is denoted as regime $\mathcal{LP}$, while maintaining the expected (opportunity) cost of corruption the same. And then within each regime, two treatments are introduced by either increasing p or $\mathbb{E}(w)$ to see which policy intervention has a larger deterrent effect against crime and corruption if there is any. Together with one control in each regime, we have six treatments in total and the only difference is the policy design imposed on the monitor. With those treatments, we can also test Ortner and Chassang (2018)'s model with different parametrizations.

This study provides some novel results on the understanding of crime and corruption deterrence. Our first set of results shows that the relative effectiveness of certainty and severity of punishment in deterring crime and corruption is dependent on the regime. In regime $\mathcal{HP}$, both increasing p and $\mathbb{E}(w)$ would significantly reduce the corruption rate and the magnitude is larger with an increase in p. In contrast, we fail to find any significant deterrent effect with either policy intervention in regime $\mathcal{LP}$. This contributes to the understanding of the whole picture that it requires the certainty of punishment p to be high enough so that either policy intervention would be able to deliver a significant deterrent effect. In the domain of crime deterrence, the difference between these two regimes retains the same pattern though the magnitude is smaller.

In addition, we also document a potential Cobra Effect[3] in regime $\mathcal{LP}$ when we increase the expected wage aiming to deter corruption. The famous Cobra Effect is the most typical representation of the perverse incentive effect where the provided incentive leads to the opposite of the intended outcome. In our experiment, when we increase the expected wage of the monitor, the expected opportunity cost of corruption increases which should lead to a lower corruption rate. However, our data show that, in regime $\mathcal{LP}$, the corruption rate becomes higher when we increase the expected wage. Nonetheless, we do not observe a similar Cobra effect in regime $\mathcal{HP}$. This result suggests that the policy intervention of adopting higher wages to deter corruption

[3]The Cobra Effect refers to the case where the provided incentive to address a problem actually makes it worse. The name is after an anecdote that happened in India: The government offered a bounty for cobra tails to reduce the number of cobras in the town. However, the locals started to breed cobras to claim more bounties in the end which led to an increase in the number of cobras. The story is documented by Lucas and Fuller (2018), and is also discussed in many scenarios. For example, Lueck and Michael (2003) documents that an act that intends to protect the habitat of endangered species leads to a decrease in the area of the habitats. Bajo-Buenestado and Borrella-Mas (2019) show that the effect of tax change on firms beyond borders becomes more prevalent after the authority discourages the residents do not cross the borders to buy.

should be used with caution.

For policy makers, it is also important to investigate whether the policy intervention deters crime/corruption by decreasing the population of those who commit crime/corruption or by decreasing the intensity of committing crime/corruption for those who have committed a crime/corruption. Through analyses of the extensive and intensive margins, we are able to address this concern and show significant and systematic differences between regime $\mathcal{HP}$ and $\mathcal{LP}$. In regime $\mathcal{HP}$, both the extensive and intensive margin of corruption decreases significantly when we increase either p or $\mathbb{E}(w)$ with a stronger effect by increasing p. Furthermore, the two policy interventions also differ in the celerity of deterrent effect. Increasing the certainty of punishment p decreases the extensive margin of corruption immediately. In contrast, the deterrent effect of increasing the severity of punishment $\mathbb{E}(w)$ takes time to build up. In the $\mathcal{LP}$ regime, however, there is no significant change in either the extensive margin or the intensive margin when we increase either the certainty or severity of punishment. For crime deterrence, the pattern of the difference between regime $\mathcal{HP}$ and $\mathcal{LP}$ still holds but the effect is weaker.

The remainder of this paper is organized as follows. section 2 discusses related literature, section 3 presents the basic model that describes the stage game that we use in our experiments, and section 4 shows the experimental design and our hypotheses, followed by results presented in section 5, and section 6 concludes.

2 Related Literature

Becker (1968) builds the foundation of modern economic analysis on efficiently deterring criminal activities. He sets up an economic framework trying to minimize the total social loss from criminal activities by finding the optimal resource allocations, and one of his important findings is that, with the assumption that punishment is costly which is true most of the time, a change in conviction rate should have a larger impact on criminal activities than a change in the magnitude of punishment.

Most empirical studies support Becker's prediction that a change in conviction rate has a larger impact on criminal activities than a change in the magnitude of punishment (see Chauncey, 1975; Grogger, 1991; Witte, 1980, for example). In a review paper, Doob and Webster (2003) conclude that "sentence severity has no effect on the level of crime". On one hand, they examine many studies that fail to support the hypothesis that variations in severity have a deterrent effect against crime with a particular focus on the studies investigating the overall deterrent effect of structural changes in sentencing laws. On the other hand, they also examine the studies that find some evidence on the deterrent effect of increased severity of punishment and they point out that these studies do not arrive at their conclusions in a credible way due to certain serious methodological, statistical, or conceptual problems.[4] Later, Chalfin and McCrary (2017) also summarize that "there is far less evidence that crime responds to the severity of criminal sanctions."

Current experimental studies also investigate crime and corruption deterrence separately and examine the relative effectiveness of certainty and severity of punishment in specific contexts, and the results are also mixed. Some experimental studies also support the above argument. For example, Barr et al. (2009) examine the corruption behavior in service delivery and they show that the corruption rate is lower when the detection probability is high while a higher wage of the service provider has little effect on preventing corruption.[5] In an experiment that involves cheating, Nagin and Pogarsky (2003) show that "the prevalence of cheating was lower when detection was more certain but not when the penalty was more severe."

However, some other experimental studies do not support the argument that certainty of punishment has a greater deterrent effect. For example, Armantier and Boly (2011) study the scenario where subjects have to make two decisions: whether to accept a bribe and whether to pass the briber's exam paper, and the subject can accept the bribe but fail the paper without any consequences.[6] Their results show that both high wages and a high probability of punishment have heterogeneous effects on corruption deterrence.

Some studies even find results that support the opposite argument: severity of punishment has a greater deterrent effect. For example, Friesen (2012) reports that increasing the severity of punishment is more effective in deterring crime than an equivalent increase in the certainty

[4]For example, Kessler and Levitt (1999) suggest that sentence severity produces deterrent effect against crime, however, Doob and Webster (2003) point out that the study suffers from data selection problem. Specifically, Kessler and Levitt (1999) only uses odd-numbered years in their data collection, and no explanation is provided.

[5]We think that the main reason (of the ineffectiveness of higher wages in this study) is that the wage does not stand as an opportunity cost of corruption. The service provider only loses the benefits they keep during the service-providing process if the corruption behavior is detected.

[6]As a result, the definition of corruption behavior is not clear here. It could refer to the bribery accepting behavior, the false grading behavior, or both. In addition, the punishment they investigate is imposed on the accuracy of grading and is not related to the acceptance of bribes. Therefore, the subject should accept the bribery offer all the time irrespective of her own wage, the size of the bribe, and the punishment against false grading behavior.

of punishment.[7] Banerjee and Mitra (2018) examine the harassment bribery game and experimentally show that a low probability of detection with high fines is more effective in reducing both the amount and the likelihood of bribe demand, while a high probability with low fines has no significant effect on bribe demand.[8]

Among all the experimental studies investigating the relative effectiveness of certainty and severity of punishment, Banerjee and Mitra (2018) is the closest to our study. However, there are still several major differences between their study and ours: (i) They only study the deterrence of corruption, while we study the deterrence of crime and corruption jointly and simultaneously; (ii) For corruption deterrence, they study a specific type of corruption that is caused by harassment bribery, while we focus on the corruption where the agents try to bribe the official in exchange for an innocent report and the official cannot demand any bribe from the agent. (iii) The incentive structure against corruption in their control is quite different from that in their treatments, specifically, there's no punishment in their control and thus corruption has no negative consequences. In contrast, the incentive structure in our study is consistent across all the controls and treatments.

Another stream of literature is on the effectiveness of using high wages to deter corruption (or crime). Given the detection probability is usually far less than unity, Becker and Stigler (1974) also asks the question that "How can corrupt enforcement be discouraged when detection is uncertain?" And their suggestion is to "raise the salaries of enforcers above what they could get elsewhere, by an amount that is inversely related to the probability of detection, and directly related to the size of bribers and other benefits from malfeasance." By comparing the benefits of malfeasance against the present value of all future streams of salaries as well as pensions after retirement, they claim that "Malfeasance can be eliminated, therefore, even when the probability of detection is quite low." Niehaus and Sukhtankar (2013) confirms this statement and show that a higher daily wage significantly deters theft behavior in piece-rate projects. Supporting Becker & Stigler's argument from another perspective, Borcan, Lindahl, and Mitrut (2014) show that an

[7] There are three key parameters in the experimental design: the benefit of a crime, probability of detection, and the fine. The experiment lasts for 30 periods and they vary these three parameters from period to period which we consider to be problematic. Such a design is not clean enough to address the issue. In addition, the results are partially driven by the majority of their subjects being risk averse, and the risk preference is a significant predictor of crime rate in their regression results.

[8] However, the control treatment they use as a baseline might suffer some problems from our point of view. Specifically, the chance of corruption being detected and thus punished in the control is zero, therefore, the comparison between the control and the above two policy designs might be problematic since three things are changing at the same time: (i) whether there is a chance that corruption can be punished; (ii) the magnitude of the chance of corruption being punished; (iii) the size of the punishment that will be executed. Nonetheless, they do show that the treatment with a low probability of detection and high punishment yields a significantly lower harassment bribery demand than that with a high probability of detection and low punishment.

unexpected wage cut in the public sector employees will result in an increased level of corruption. Nonetheless, Armantier and Boly (2011) show that high wages have heterogeneous effects on corruption deterrence while there is no chance of being punished in the high wage treatment. Schulze and Frank (2003) reports no significant effect of high wages on corruption deterrence. Furthermore, our study suggests that high wages as a policy instrument against corruption should be used with caution because of a potential Cobra effect.

Our study also relates to the literature on the relationship between risk preference and crime/corruption decisions. Becker (1968) first states that criminals should be risk-loving if they are expected utility maximizers and respond more to certainty than severity of punishment, and risk-averse if they respond more to severity of punishment. Block and Gerety (1995) investigate experimentally how students and prisoners respond to a change in certainty or severity of punishment while measuring their risk attitudes at the same time. Their experimental results show that students are more responsive to severity of punishment while criminals are more responsive to certainty of punishment. Furthermore, the risk preferences elicited by hypothetical questions in a survey show that both students and prisoners are mostly risk averse (roughly 65% 70% of them are risk averse), nonetheless, when they come to actual decisions that had significant financial consequences, the revealed risk preference of prisoners show a strong preference for risky situations. However, since most people are risk averse, many studies try to reconcile the inconsistency between risk aversion and Becker's statement. For example, Neilson and Winter (1997) show that criminals can be both risk averse and more responsive to certainty of punishment if the expected utility hypothesis is weakened.[9] Mungan and Klick (2014, 2015) show that criminals who respond more to certainty than severity of punishment can also be risk averse if they discount future monetary benefits or if the illegal gains can be forfeited.

3 Theoretical Framework

In this paper, we examine the deterrence of crime and corruption jointly by adopting a theoretical framework developed by Ortner and Chassang (2018). There are three players in the game: the principal, the agent, and the monitor. The agent (he hereafter) first chooses whether to commit a crime $c \in \{0, 1\}$ with $c = 1$ implying the agent choosing to commit a crime. He gets a constant positive payoff $\pi_A > 0$ if he chooses $c = 1$ and zero otherwise.

[9] They propose state-dependent utility and rank-dependent utility as alternatives to expected utility hypothesis.

The criminal activity also renders a cost to the principal, and the principal does not observe the agent's action choice so he hires a monitor (her hereafter) to observe and make a report $m \in \{0, 1\}$ on the agent's choice with $m = 1$ (or $m = 0$) implying the agent has chosen $c = 1$ (or $c = 0$).[10] The principal makes a judicial judgment according to this report m and imposes a punishment $k > \pi_A$ on the agent if and only if $m = c = 1$.[11] The monitor can make any report at her will including a false report where $m \neq c$.

The wages of the entire population of monitors follow a statistical distribution with C.D.F. $F(w)$ which is common knowledge. In addition, the agent does not know the exact wage of the monitor (that paired with him),[12] while the monitor knows her wage.[13] The principal also performs an audit on the monitor's report from time to time so that there is a chance $p \in (0, 1)$ that a false report can be detected. This makes the report partially verifiable.[14] Whenever a misreport is detected, the monitor loses her wage as a punishment.[15]

Corruption becomes an issue when the agent can make a bribe $\tau > 0$ to the monitor. As long as the monitor accepts the bribe, she also agrees to destroy any criminal evidence that might be used to convict the agent by reporting $m = 0$ although $c = 1$. Therefore, as long as the monitor reports $m = 0$, the principal can not punish the corresponding criminal agent due to the lack of evidence.

The timing of moves in the game is as follows:[16]

1. The agent decides whether to commit a crime or not $c \in \{0, 1\}$.
2. The agent then decides whether or not to make a take-it-or-leave-it offer $\tau > 0$ to the monitor in exchange for the monitor reporting $m = 0$.
3. The monitor decides whether to accept or reject the offer. Perfect commitment is

[10] The principal does not *observe* the crime actually implies that he does not get the evidence to convict the agent. Surely the principal can infer the agent's decision c by the cost incurred, but he needs the evidence to convict the agent and that's why he hires a monitor who fully *observes* the agent's choice.

[11] This implies that $c = 1$ is only verifiable when the monitor reports $m = 1$, and it is not verifiable when the monitor reports $m = 0$ by destroying all the criminal evidence. This also implies that the monitor cannot make any credible threat ($m = 1$) against the agent when he does not commit a crime ($c = 0$). Therefore, we do not consider the corruption caused by harassment bribery in this paper.

[12] In reality, this can be achieved by staff rotation across cities or states, as what Ortner and Chassang (2018) have discussed in their paper. Abbink (2004) shows that staff rotation reduces corruption in general, however, the mechanism is by reducing the possibility of reciprocity rather than by introducing information asymmetric on the monitor's wage.

[13] Two key assumptions in this model are made here: First, perfect commitment of the principal on the wage distribution, and second, the monitor cannot disclose her wage information to the agent in a credible way.

[14] Ortner and Chassang (2018) argues that partial verifiability can happen in several different ways: for example, "accounting discrepancies, random rechecks, or tips from informed parties", as well as observable consequences from criminal activities.

[15] The principal cannot punish the monitor beyond her wage because of limited liability.

[16] **??** in Section C is a flow chart that shows clearly the structure of the game.

assumed here so that the monitor will report $m = 0$ as long as he accepts the offer made by the agent.

4. When there is no offer made by the agent or the monitor chooses to reject the offer, the monitor makes the report m accordingly.

Ortner and Chassang (2018) show that the government can deter corruption with a lower expected wage cost by introducing asymmetric information on the wages of monitors between the monitor and the (criminal) agent. According to Ortner and Chassang (2018), for any $p \in (0, 1)$, the unique optimal wage distribution $F_p^*(w)$ which just completely deters crime and corruption is characterized as follows:

$$F_p^*(w) = \frac{k - \pi_A}{k - pw}, \quad \forall w \in [0, \pi_A/p]. \tag{1}$$

Let's denote the set of all these optimal wage distributions as $\mathscr{F} = \{F_p^*(w) \mid p \in (0, 1)\}$. For the rest of the paper, we only consider any wage distribution $F_p^*(w) \in \mathscr{F}$, which implies that $(p, F_p^*(w))$ just fully deters crime and corruption.

Each pair of $\{p', F_p^*(w)\}$ specifies a policy design, which is an incentive structure imposed on the monitor, that the principal adopts to fight against corruption and crime. Whether or not it can fully deter crime and corruption is determined by the expected payoff $\mathbb{E}(P_A)$ that an agent can acquire if he commits a crime. Let us use P_A to denote the agent's payoff. With the optimal wage structure characterized by Equation 1, the agent's expected payoff $\mathbb{E}(P_A)$ under $\{p', F_p^*(w)\}$ and a bribe τ becomes:

$$\begin{aligned}
\mathbb{E}(P_A|\pi_A, k, \tau, p, F_p^*(w)) &= \pi_A - \tau F_p^*(\tau/p') - k\left(1 - F_p^*(\tau/p')\right) \\
&= \pi_A - k + (k - \tau)F_p^*(\tau/p') \\
&= (k - \pi_A)\left(\frac{k - \tau}{k - \tau + \tau\left(1 - \dfrac{p}{p'}\right)} - 1\right)
\end{aligned} \tag{2}$$

From Equation 2, we know that, if $\left(1 - \dfrac{p}{p'}\right) < 0$, $\mathbb{E}(P_A) > 0$, which means that the agent can obtain a positive expected payoff from committing a crime and making a bribe offer afterwards, so $\{p', F_p^*(w)\}$ cannot fully deter crime and corruption. Furthermore, the lower the value of $\left(1 - \dfrac{p}{p'}\right)$ is, the higher the expected payoff the agent can obtain from committing a crime.

On the other hand, if $\left(1 - \frac{p}{p'}\right) \geqslant 0$, we have $\mathbb{E}(P_A) \leqslant 0$, thus the agent in expectation cannot gain anything from committing a crime, and the higher the value of $\left(1 - \frac{p}{p'}\right)$ is, the higher the expected loss the agent bears from committing a crime.

Therefore, for any pair of $\{p', F_p^*(w)\}$, we define the Deterring Power against Crime and Corruption (hereafter DPCC) as:[17]

$$\text{DPCC} = \left(1 - \frac{p}{p'}\right) \tag{3}$$

Thus we have (i) if DPCC < 0, $\{p', F_p^*(w)\}$ cannot deter crime and corruption; (ii) if DPCC $= 0$, $\{p', F_p^*(w)\}$ just fully deters crime and corruption; (iii) if DPCC > 0, $\{p', F_p^*(w)\}$ overly deters crime and corruption. And the absolute value of DPCC shows how powerful (when DPCC > 0) or powerless (when DPCC < 0) the pair $\{p', F_p^*(w)\}$ is in deterring crime and corruption.

When DPCC < 0, the agent constantly commits a crime and offers a bribe τ to the monitor. The optimal strategies of both the agent and the monitor are described in the following proposition. The proof is omitted here and relegated in Appendix B.

Proposition 1: *When* DPCC < 0 *under* $\{p', F_p^*(w)\}$, *the agent chooses a bribe* $\tau = p'\pi_A/p$, *and the monitor always accepts the offer.*

4 Experimental Design & Procedures

With a proper measure of DPCC given by Equation 3, we can choose the parameters such that the policy design $\{p', F_p^*(w)\}$ in corresponding treatments has the same DPCC. Therefore, any observed treatment difference in terms of deterring crime and corruption is attributed purely to the structure policy design rather than the difference in DPCC.

4.1 Design of Treatments

Across controls and treatments, we manipulate the policy design (the incentive structure) imposed on the monitor and the rest are exactly the same. We have two policy regimes —

[17] Though it is intuitive to use the opposite of the agent's expected payoff ($-\mathbb{E}(P_A)$) as a measure of DPCC, it is not as clean as this one since $-\mathbb{E}(P_A)$ depends on the agent's offer τ. Alternatively, we can also use the difference between the expected wages $\mathbb{E}(W_p'^*) - \mathbb{E}(W_p^*)$ as a measure of DPCC. Those different measures of DPCC are not going to change the results at all.

$\mathcal{HP}$ and $\mathcal{LP}$ — each with three policy designs under investigation in our experiment. Regime $\mathcal{HP}$ features a high p but low $\mathbb{E}(w)$ while regime $\mathcal{LP}$ features a low p but high $\mathbb{E}(w)$. Within each regime, we have one control group which is denoted as HP or LP respectively, and two treatments which are denoted as HPP and HPW or LPP and LPW respectively. In addition, the DPCC is kept the same between the two controls, so does among the four treatments.

Figure 1 illustrates the philosophy of our experimental design where each regime is enclosed by a dotted circle. The horizontal axis represents the monitor's expected wage $\mathbb{E}_p(w)$ given her wage distribution F_p^*,[18] the vertical axis is the detection probability of a false report p, and each line in the graph is a collection of $(p, \mathbb{E}_p(w))$ that yields the same DPCC.[19] The dashed line is the baseline incentive structure with DPCC $= 0$. Any point on this line generates a policy design where crime and corruption is just fully deterred. We then pick two points on this line, $(p_H, \mathbb{E}_{p_H}(w))$ for regime $\mathcal{HP}$ and $(p_L, \mathbb{E}_{p_L}(w))$ for regime $\mathcal{LP}$, and decrease the corresponding p to obtain two controls HP and LP on the thin solid line with DPCC < 0. Lastly, starting from the controls, we increase either p to obtain two treatments HPP and LPP or $\mathbb{E}(w)$ to obtain two treatments HPW and LPW on the thick solid line with DPCC > 0.

On top of maintaining DPCC the same for parallel treatments, the design has the following considerations. On one hand, for the two controls (HP and LP), we do not want to fully deter crime and corruption such that there are incentives for the agent to commit a crime as well as for the monitor to be corrupted. Equivalently, we want DPCC < 0 for these two control treatments. On the other hand, for the other four treatments (HPP, HPW, LPP, and LPW), we would like crime and corruption to be overly deterred. Equivalently, we want DPCC > 0 for these four treatments. This is to ensure that we should observe some significant differences between the control and the treatments.

The exact parameter values are determined as follows. The baseline policy designs have $p_L = 1/3$ in regime $\mathcal{LP}$ and $p_H = 2/3$ in regime $\mathcal{HP}$.[20] For the wage distributions, we take discrete ones so that it is easier for the experimental subjects to understand. Together with $k = 40$ and

[18] For the implementation of the monitor's random wage, we fix four probability masses (1/2, 1/6, 1/6, 1/6 specifically) and calculate the associated wage levels according to $F_p^*(w)$. When $\mathbb{E}(W_p^*)$ increases, we simply increase the wage level associated with each probability mass. For more details, please see Table 1 presented later.

[19] Each line can be considered as an indifference curve where the agent's willingness to commit a crime is indifferent between any two points on the line. The higher the line, the less willingly the agent commits a crime.

[20] The choice of these two values makes it easy for us to present the numbers to our experimental subjects so that they will not be confused by complicated numbers. More importantly, the resulted probability of detection is 25% in control LP and 50% in control HP, which is in line with the literature. Banerjee and Mitra (2018) uses 20% in the LP and 40% in the HP.

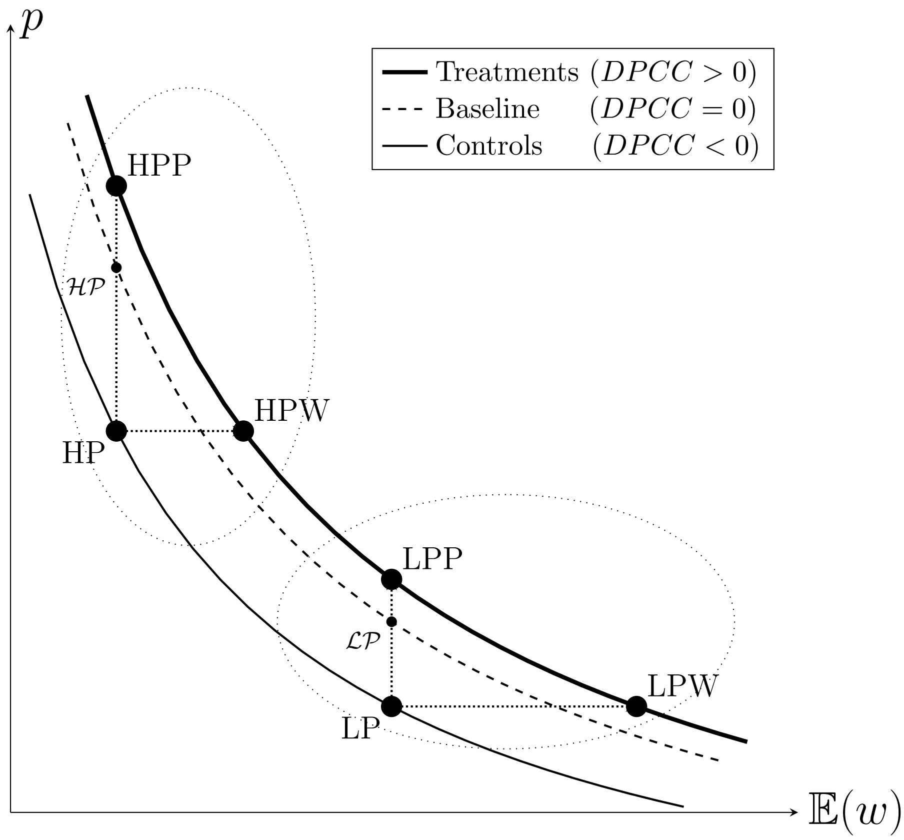


Figure 1: The Philosophy of The Design of Treatments

$\pi_A = 20$, the corresponding optimal wage distributions for the two baselines are presented in Table 1.

Table 1: The Parametrization of All The Treatments

Regime	Treatment	p'	F_p^*	DPCC	Wage Distribution			
					(1/2	1/6	1/6	1/6)
	Baseline	1/3	$F_{1/3}^*$	0	0	30	48	60
	LP	1/4	$F_{1/3}^*$	-1/3	0	30	48	60
$\mathcal{LP}$	LPP	3/8	$F_{1/3}^*$	1/9	0	30	48	60
	LPW	1/4	$F_{2/9}^*$	1/9	0	45	72	90
	Baseline	2/3	$F_{2/3}^*$	0	0	15	24	30
	HP	1/2	$F_{2/3}^*$	-1/3	0	15	24	30
$\mathcal{HP}$	HPP	3/4	$F_{2/3}^*$	1/9	0	15	24	30
	HPW	1/2	$F_{4/9}^*$	1/9	0	22.5	36	45

Note: If DPCC $= 0$, it just fully deters crime and corruption. If DPCC < 0, it does not deter crime and corruption. If DPCC > 0, it overly deters crime and corruption.

From the baselines, we decrease p_L and p_H by 25% to obtain the two controls. And then we increase either the probability of detection or the expected wage in each control by 50% to obtain two treatments in each regime. The specific parametrization of all treatments is shown in Table 1.

In controls HP and LP, the agent's optimal choice is to choose $c = 1$ and $\tau = p'\pi_A/p = 15$ all the time according to Proposition 1, and the monitor always accepts the offer. In all the treatments (HPP, HPW, LPP, and LPW) where DPCC > 0, the agent's expected payoff $\mathbb{E}(P_A)$ is always negative. As a result, the agent will never choose to commit a crime and thus the monitor has no opportunity to be corrupted. This is also consistent with the intention of the design that we should not observe any crime or corruption in those treatments if subjects are risk neutral and expected utility maximizers.

4.2 Hypotheses

Based on the theoretical predictions that we have obtained given the set of parameters, we propose the following hypotheses:

Hypothesis 1A: *In controls LP and HP, crime and corruption are pervasive. Specifically, the agent always chooses to commit a crime $c = 1$ and makes an offer $\tau = 15$. The monitor always accepts the offer and makes a false report $m = 0 \neq c$.*

Hypothesis 1B: *In treatment LPP, LPW, HPP, and HPW, crime and corruption are fully deterred. Specifically, the agent always chooses not to commit a crime $c = 0$ and does not make any offer to the monitor $\tau = 0$. The monitor always report truthfully $m = 0 = c$.*

Hypothesis 1A and 1B are merely direct predictions from the theoretical model. Since $DPCC < 0$ in controls HP and LP while $DPCC > 0$ in treatments LPP, LPW, HPP, and HPW, we should observe a significant decrease in crime and corruption rate in the four treatments than in the two controls. Thus, we have our Hypothesis 2A and 2B.

Hypothesis 2A: *Raising the probability of detection p and raising the monitor's expected wage $\mathbb{E}(W_p^*)$ are both significantly effective in deterring* ***corruption*** *in both regime $\mathcal{HP}$ and $\mathcal{LP}$, i.e., compared against the control LP (HP, respectively), the* ***corruption*** *rate are significantly lower in treatment LPP, LPW (HPP, HPW respectively).*

Hypothesis 2B: *Raising the probability of detection p and raising the monitor's expected wage $\mathbb{E}(W_p^*)$ are both significantly effective in deterring* ***crime*** *in both regime $\mathcal{HP}$ and $\mathcal{LP}$, i.e.,* *compared against the control LP (HP, respectively), the **crime** rate are significantly lower in treatment LPP, LPW (HPP, HPW respectively).*

Note that all the above hypotheses are proposed with the assumption of experimental subjects being risk-neutral and expected utility maximizers. When the assumption is violated, the above hypotheses may not be supported anymore. For example, if most of the experimental subjects are risk averse (which is likely to be the case), the subjects in controls LP and HP may be reluctant to commit crimes or corruption, thus, Hypothesis 1A might not be supported. However, if some subjects are risk loving, they might still choose to commit crimes in the four treatments, as a result, Hypothesis 1B might not be supported.

Risk attitude might also affect our Hypothesis 2A and 2B in various ways. If the subjects are either risk averse enough such that they do not commit crime or corruption in all the controls and treatments or risk loving enough such that they commit crime or corruption all the time irrespective of the controls and treatments, we should not observe any difference in crime and corruption rates between the controls and treatments. Thus, Hypothesis 2A and 2B might not be supported.

The relative deterrent effect between raising p and raising $\mathbb{E}(W_p^*)$ might also depend on risk preference as analyzed by Becker (1968): risk loving subjects respond more to an increase in certainty of punishment, while risk averse subjects respond more to an increase in severity of punishment.[21] Given that a great body of literature has shown transgressors are more responsive to certainty than severity of punishment (see Chalfin & McCrary, 2017; Doob & Webster, 2003, for reviews) and the common assumption of human being generally risk averse, many studies try to reconcile this seeming contradiction by showing that individuals can be both risk averse and more responsive to certainty than severity of punishment (see Mungan & Klick, 2014, 2015; Neilson & Winter, 1997, for example). Therefore, we would like to hypothesize that individuals are also more responsive to certainty than severity of punishment in our framework even if they are risk averse.

There is a subtle but important difference between crime and corruption deterrence that we would like to mention again. For corruption deterrence, raising p leads to an increase in certainty of punishment, and raising $\mathbb{E}(W_p^*)$ leads to an increase in severity of punishment. For crime deterrence, however, raising p and raising $\mathbb{E}(W_p^*)$ both affect the certainty of punishment, so

[21] For more details, see Becker (1968). For example, there is a discussion on this on page 178.

they should deliver equivalent deterrent effects when they lead to an equivalent increase in certainty of punishment even if they might be more responsive to certainty than severity of punishment. Therefore, we have our Hypothesis 3A and 3B stated below.

Hypothesis 3A: *Raising the probability of detection p is <u>more effective</u> than raising the monitor's expected wage $\mathbb{E}(W_p^*)$ in deterring **corruption** in both regime $\mathcal{HP}$ and $\mathcal{LP}$, i.e., the **corruption** rate is significantly lower in treatment HPP (LPP respectively) than HPW (LPW respectively).*

Hypothesis 3B: *Raising the probability of detection p and raising the monitor's expected wage $\mathbb{E}(W_p^*)$ are <u>equivalently effective</u> in deterring **crime** in both regime $\mathcal{HP}$ and $\mathcal{LP}$, i.e., the **crime** rates are not significantly different between treatment HPP (LPP respectively) and HPW (LPW respectively).*

Last but not least, we would like to clarify that the focus of this paper is on Hypothesis 2A, 2B, 3A, and 3B. Whether or not they are supported by our experimental results addresses the research questions that we are interested in. Hypothesis 1A and 1B are basically direct and specific predictions from the theoretical model. We also test it with our experimental results as a test of Ortner and Chassang (2018)'s model.

4.3 Details of Experimental Design and Procedures

At the beginning of the experiment, subjects would be randomly allocated to the role of monitor or agent. In part one, monitors and agents would be randomly paired with one another and play the stage game repeatedly for 24 periods. At the end of each period, one's own decision, as well as his/her payoff, is provided for review, and no other information is provided. The payoffs of two randomly selected periods out of 24 periods become one's payoff in part one. Part two is essentially the same as part one except that the roles are switched, so monitors in part one become agents in part two, and agents in part one become monitors in part two. Part three is a multiple-price-list task originated from Holt and Laury (2002) that measures subjects' risk preferences. A questionnaire is followed to collect subjects' demographics.

The experiment adopts a partner group design and each monitor's wage is randomly determined according to $F_p^*(W)$ at the beginning of each period, and this information is known to the monitor but not to the agent. The rationale for such a design is stated as follows. If we want to follow closely to the theoretical setup, we should have the wage randomly distributed among all the monitors according to $F_p^*(W)$, and then randomly match the agents with the monitors every period. However, such a stranger design creates two problems: (i) The individual data contaminate each other period after period and the entire session becomes one independent observation in the end; (ii) The wages of the monitors would be quite different as they are randomly determined at the beginning of the experiment. As a result, the final payment for the monitors might be quite different and there might be serious complaints. The second problem can be addressed if we randomly assign the wages to monitors according to $F_p^*(W)$ at the beginning of each period. This is equivalent to the case where each monitor's wage is randomly determined according to $F_p^*(W)$ at the beginning of each period, and this, as a result, enables us to use a parter design where the group formation is fixed throughout the experiment once it is randomly determined at the beginning. In this way, each group becomes one independent observation, and the first problem caused by stranger design is addressed.

The experiment was conducted at the CATI lab, School of Social Science, Nanyang Technological University using ztree (Fischbacher, 2007). Participants were recruited from a pool of undergraduate volunteers via email. Upon arrival, the experimenter read the instructions aloud while the subjects were reading their own copies at the same time. Sessions lasted around 60 minutes and participants earned on average S$14 including a show-up fee of S$3. In total, we have 198 undergraduate students participated in our experiment with 102 male students and 96 female students. For each subject, we have collected 48 observations on crime/corruption decisions, and thus we have collected 9504 observations.

Among all the participants, the gender ratio is well balanced, and the average age is around 21∼22 years old. Half of them has gained some knowledge of game theory before they participate in this experiment, and around 80% of them had participated in other experiments before. The detailed demographics across all the treatments are shown in Table 2.

Last but not least, in our experimental instructions, we describe the game in a neutral way without saying anything about crime or corruption in order to eliminate any potential effects caused by the crime or corruption context, although Abbink and Hennig-Schmidt (2006) show that there is no significant difference in results between neutral-context and in-context presentation of experimental tasks in a bribery game. For details on our instructions, please see a sample of our instruction in control LP in Section C in Appendix.

Table 2: Demographics Across All The Treatments

Treatment	No. of Subjects	Male Ratio	Age	Nationality	% Experiment-Exp	% Theory-Exp
HP	28	57.1%	22.4	64.3%	75%	42.9%
HPP	38	47.4%	21.8	34.2%	81.6%	44.7%
HPW	38	63.2%	20.6	15.8%	86.8%	44.7%
LP	22	50.0%	21.8	41.7%	86.1%	38.9%
LPP	38	65.8%	22	42.1%	89.5%	52.6%
LPW	34	47.1%	21.2	41.2%	85.3%	41.2%
Total	198	55.6%	21.6	39.4%	84.3%	42.9%

Nationality represents the percentage of Singaporeans. % Experiment-Exp is the percentage of subjects that have experiences in other experiments before. % Theory-Exp is the percentage of subjects that have learned some knowledge on game theory before.

5 Results

Since the monitor's wage is randomly generated by a computer random device from period to period, it is possible that the realized wage distribution in each treatment is not the same as it should be according to the theoretical distribution. If this is the case, we might fail to observe some treatment differences that should have been observed, or the observed differences cannot be fully attributed to the design of treatments. Therefore, we compare the mean and standard error between the wages according to the theory and the realized wages for each treatment, and we also compare the distributions. The realized wages and their distributions in each treatment are very close to the corresponding theoretical ones. For more details, please see Figure 11 and Table 6 in Appendix.

5.1 Crime & Corruption Rate in General

Table 3 shows the descriptive statistics of the rate of crime and corruption across all the treatments, and the first thing we can notice is that, in all of the treatments, the crime and corruption rates are positive while far less than unity.

On one hand, in controls LP and HP, the results violate our Hypothesis 1A which states that, in these two treatments, a risk neutral individual that maximizes his/her expected utility should always choose to commit a crime as an agent and accept the bribery offer as a monitor. However, there are over 40% of them do not behave as the hypothesis predicted. We should note that the

Table 3: Descriptives of Decisions on Illegal Activity and Corruption

Treatment	Crime			Corruption			Theoretical Prediction
	Mean	SD	SE	Mean	SD	SE	
HP	60.0%	0.490	0.0189	38.2%	0.486	0.0188	1
HPP	48.2%	0.500	0.0166	23.1%	0.422	0.0140	0
HPW	54.5%	0.498	0.0165	28.3%	0.451	0.0149	0
LP	53.4%	0.499	0.0217	31.6%	0.465	0.0203	1
LPP	56.9%	0.495	0.0164	31.6%	0.465	0.0154	0
LPW	58.5%	0.493	0.0173	36.5%	0.482	0.0169	0

theoretical prediction is obtained with the assumption of risk neutral individuals, thus, a risk averse individual would demand some risk premium for him/her to take the risk of committing a crime or accepting an offer. Therefore, they might be reluctant to do so.

In our experiment, we measure subjects' risk preferences using an MPL task originated from Holt and Laury (2002).[22] Figure 2 shows the distribution of risk preferences across all the treatments. The value of 1∼4 indicates that the subject is risk loving, the value of 5 indicates the subject is either risk-neutral or slightly risk averse, and the value of larger than 5 indicates that the subject is risk averse. Therefore, most of the subjects are risk averse across all the treatments, which partially explains the results that crime and corruption rates in LP and HP are less than unity.

On the other hand, in treatments LPP, LPW, HPP, and HPW, the results violate our Hypothesis 1B which states that, in these four treatments, a risk neutral individual that maximizes his/her expected utility should never commit a crime as an agent nor accept an offer as a monitor. However, the results show that at least 20% of them choose to commit a crime as an agent or accept an offer as a monitor. Since most of the subjects in our experiment are risk averse, risk preference should not be the main reason that drives this result[23]. A review study by Doob and Webster (2003) concludes that the literature consistently shows that criminal agents seldom consider the consequences of crimes when they choose to do so. As a result, subjects might be attracted by the immediate benefits of committing a crime or corruption and overlook the coming negative consequences.[24]

[22]For details about the task, please see the experimental instructions in Appendix C.

[23]Block and Gerety (1995) show that, although prisoners are risk averse according to results from a hypothetical survey, their revealed risk preferences are largely risk loving when they come to tasks that have significant financial consequences. This might be the case for some subjects in our study, but we have no grounds to claim this.

[24]There are other similar theories that can contribute to this observation, for example, present-bias preference,

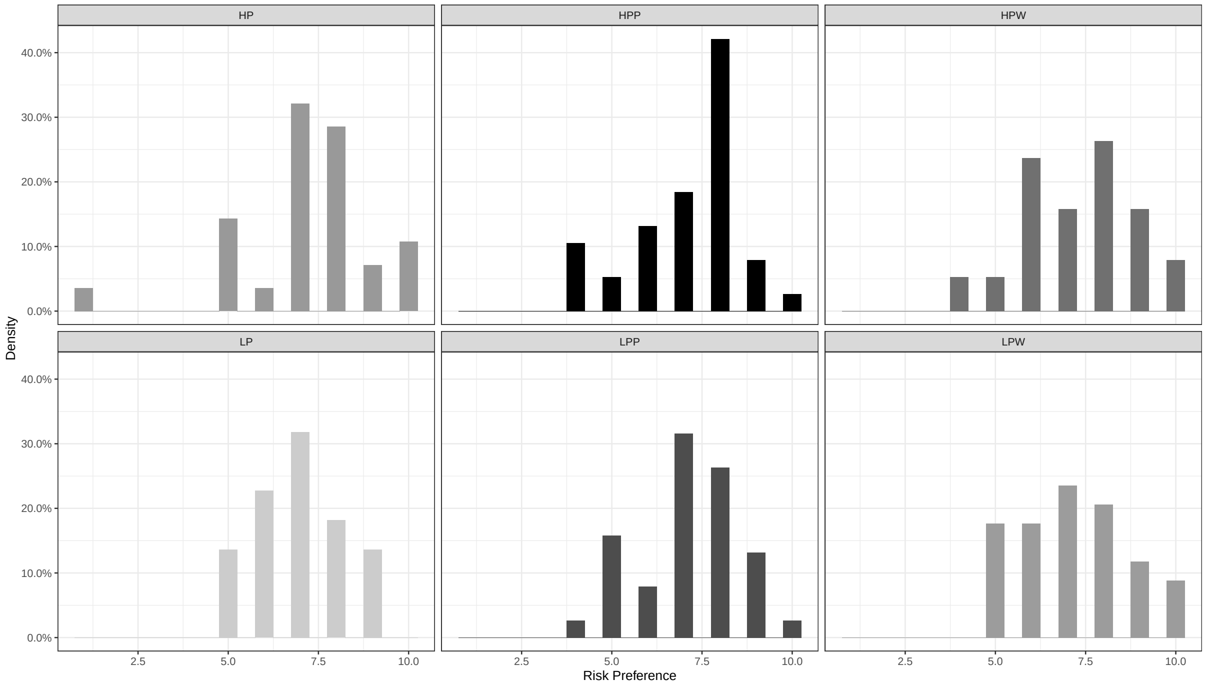


Figure 2: Distribution of Risk Preference Across Treatments

Result 1: *There is consistently a positive proportion of subjects that chooses to commit a crime as an agent or accept the bribery offer as a monitor in all the treatments.*

5.2 Nonparametric Results on Corruption & Crime

In this section, we present the results on the mean of crime and corruption rates across all the experimental treatments. We also test the significance of any differences between treatments using the clustered Wilcoxon Rank-Sum test (denoted as C-WRS test hereafter).[25] Two-sided C-WRS tests are applied unless it is specified otherwise.

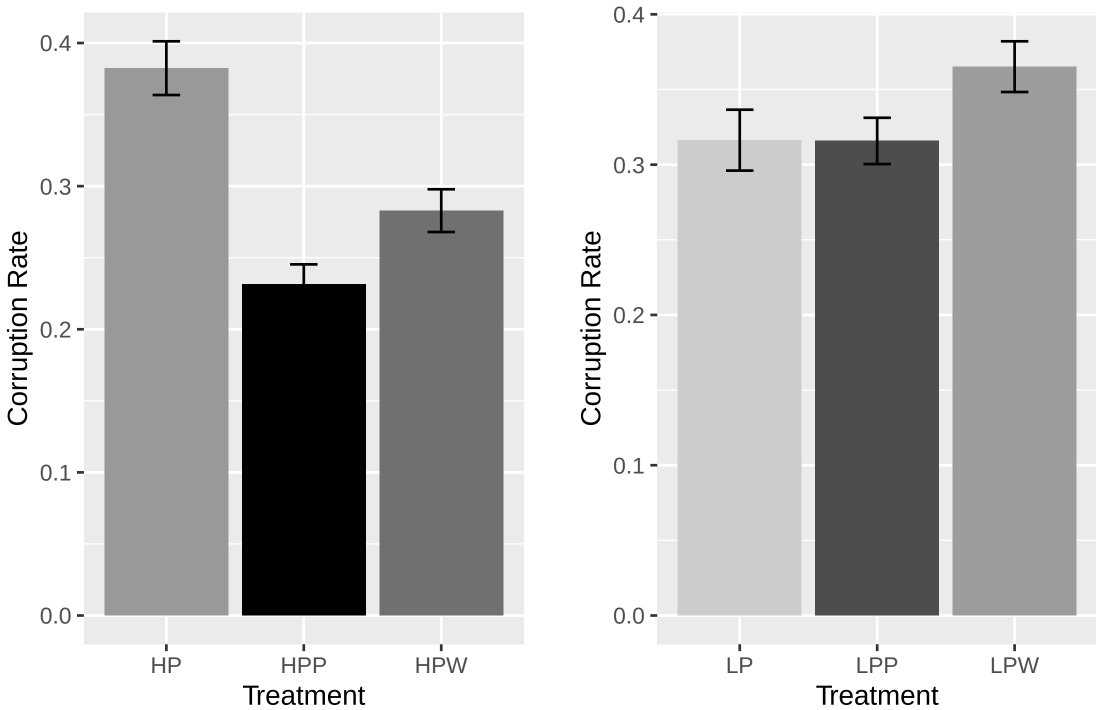
5.2.1 Corruption Deterrence Across Treatments

Figure 3 shows the rate of corruption decisions across all the treatments (as well as the standard error on top of each bar). Compared against control HP, Figure 3(a) shows that the corruption rate decreases evidently when we either raise the detection rate in treatment HPP (from 38.2%

multi-self models, etc. However, since we do not model them in our theory, our experimental design does not allow us to measure them either.

[25] In our experiment, one subject has to play the game for 24 periods for each role, and the payoff is provided at the end of each period. As a result, these 24×2 observations from one subject are not independent of each other, therefore, each subject is taken as a cluster in our data analyses. We perform the clustered rank-sum test with the D-S method proposed by Datta and Satten (2005). We cannot use the commonly used RGL method since it assumes the observations within one cluster are exchangeable which is not the case in our data generating process.

to 23.1%, $p = 0.000$) or raise the expected wage in treatment HPW (from 38.2% to 28.3%, $p = 0.008$) while maintaining the DPCC the same between these two treatments. This strongly supports our Hypothesis 2A.



(a) Corruption Rate in $\mathcal{HP}$ (b) Corruption Rate in $\mathcal{LP}$

Figure 3: Corruption Decision Across Treatments

In addition, the deterrence effect seems to be larger in magnitude in treatment HPP than that in treatment HPW. However, the difference (28.3% vs 23.1%) is only marginally statistically significant ($p = 0.078$). This result lends some support to our Hypothesis 3A.

Result 2: *In regime $\mathcal{HP}$, increasing either the probability of detection or the expected wage is significantly effective in deterring corruption. In addition, the deterrent effect is larger when increasing the probability of detection in treatment HPP.*

In contrast, In regime $\mathcal{LP}$, Figure 3(b) shows us that the corruption rate does not decrease when we either raise the probability of detection in treatment LPP or raise the expected wage in treatment LPW while maintaining the DPCC are the same between these two treatments. Neither the difference between LP and LPP nor that between LP and LPW is statistically significant ($p = 0.990$, and $p = 0.239$ respectively). In addition, the difference between treatment LPP and LPW is also not significant ($p = 0.189$). This indicates that our Hypothesis 2A and 3A are not supported in regime $\mathcal{LP}$, and we have the following result.

However, there is a noticeable increase in corruption rate in treatment LPW where we increase the expected wage of the monitor compared with control LP (from 31.6% to 36.5%). In addition, such an increase is very close to being statistically significant at the 10% level ($p = 0.119$, one-sided C-WRS). This suggests a potential Cobra effect where an incentive leads to the opposite of the intended outcome which will be discussed in detail in Section subsection 5.4.

Result 3: *In regime $\mathcal{LP}$, neither increasing the probability of detection nor the expected wage is effective in deterring corruption, and there is no statistically significant difference between LPP and LPW.*

The above results suggest that the monitors are responsive to increases in either certainty or severity of punishment when the initial certainty of punishment is high enough. In contrast, increases in either certainty or severity of punishment have no significant impact on the monitor's decisions when the initial certainty of punishment is low, as a result, policy interventions in regime $\mathcal{LP}$ are not expected to deliver a significant deterrent effect.

Comparison between regime $\mathcal{HP}$ and $\mathcal{LP}$

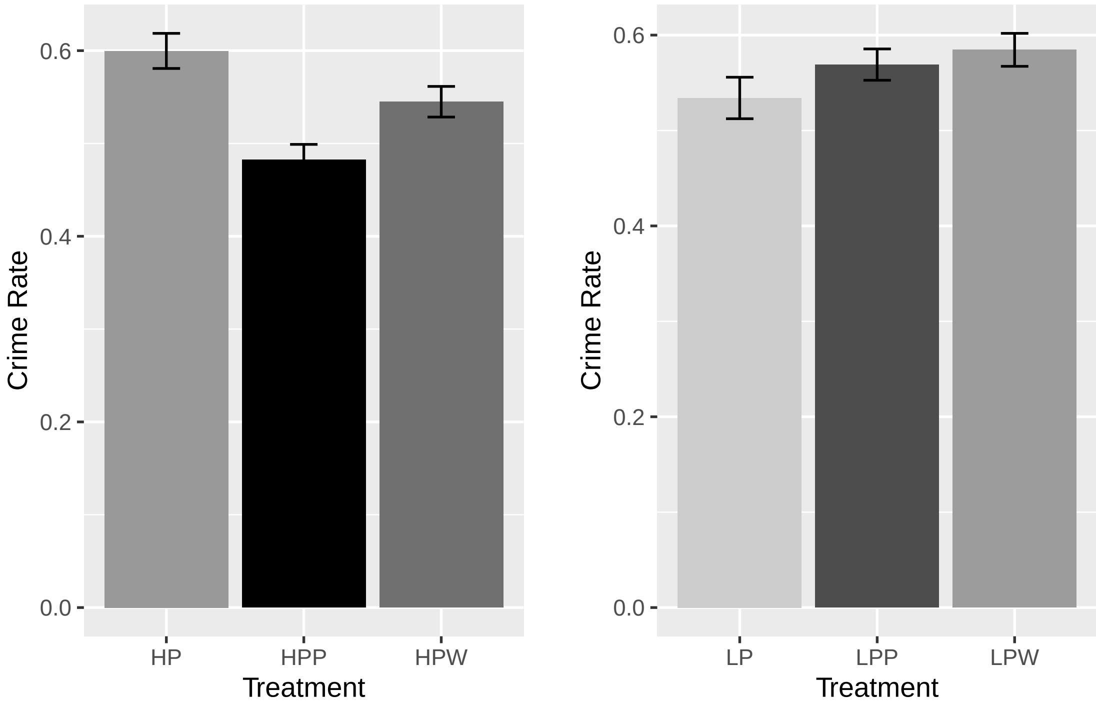
There is a noticeable difference in the corruption rate between the controls HP (38.2%) and LP (31.6%), nevertheless, this difference is not statistically significant ($p = 0.125$). For the other four treatments that share the same DPCC, the corruption rate is lower in treatment HPP (23.1%) than that in treatment LPP (31.6%), and similarly, it is lower in treatment HPW (28.3%) than that in treatment LPW (36.5%). These differences are both statistically significant ($p = 0.011$ and $p = 0.021$ respectively). This result further shows the superiority of regime $\mathcal{HP}$ over regime $\mathcal{LP}$ in corruption deterrence, and it violates Hypothesis 2A partially since the corruption deterrent effect should be homogeneous between the two regimes according to the hypothesis.

Result 4: *Between regime $\mathcal{HP}$ and $\mathcal{LP}$, the corruption rate is not significantly different between controls HP and LP, however, the difference is significant between treatments. Specifically, policy interventions in regime $\mathcal{HP}$ deliver a large deterrent effect against corruption than that in regime $\mathcal{LP}$.*

5.2.2 Crime Deterrence Across Treatments

Figure 4 shows the rate of crime decisions across all the treatments (as well as the standard error on top of each bar). In regime $\mathcal{HP}$ with a high detection probability and low expected wage,

Figure 4(a) shows that, compared to the control HP, the corruption rate decreases significantly when we raise the detection rate in treatment HPP (from 60% to 48.2%), and the difference is marginally statistically significant ($p = 0.072$). However, although there is a decrease in the crime rate in treatment HPW (from 60% to 54.5%), the difference is not statistically significant ($p = 0.418$). This result only partially supports our Hypothesis 2B.



(a) Crime Rate in $\mathcal{HP}$

(b) Crime Rate in $\mathcal{LP}$

Figure 4: Crime Decision Across Treatments

The difference in crime rate between treatment HPP and HPW (48.2% vs 54.5%) is not statistically significant ($p = 0.364$), which supports our Hypothesis 3B. However, this is not so meaningful since treatment HPW does not deliver a significant deterrent effect against crime.

Result 5: *In regime $\mathcal{HP}$, the crime rate decreases significantly in treatment HPP when we increase p. In contrast, although there is a decrease in the crime rate in treatment HPW when we increase $\mathbb{E}(w)$, the difference is not statistically significant.*

Crime deterrence in regime $\mathcal{LP}$

In regime $\mathcal{LP}$ with a low detection probability of false report and high expected wage, Figure 4(b) shows that there is no evident difference of the crime rate between treatment LPP and LP or between treatment LPW and LP, and these differences are not statistically significant ($p = 0.698$, and $p = 0.574$ respectively). Neither does the difference between LPP and LPW is significant ($p = 0.835$). This greatly violates our Hypothesis 2B in regime $\mathcal{LP}$, and, we have our Result 6.

Result 6: *In regime $\mathcal{LP}$, the crime rate does not decrease in either the LPP treatment or the LPW treatment, and any difference is not statistically significant.*

The above results show that, for crime deterrence, our Hypothesis 2B is only supported by treatment HPP when we increase p in the regime, while it is not generally supported in other scenarios. Although there is no significant difference in the deterrent effect between increasing p and increasing $\mathbb{E}(w)$ in both regimes which supports our Hypothesis 3B, it is meaningless since most of them do not yield any deterrent effect. This is largely due to the fact that the deterrent effect is originated from an incentive structure that is imposed on the monitor, so the agent is indirectly affected, therefore, the deterrent effect against crime is not as strong as that against corruption. Next, we show some regression results to check how the results obtained via non-parametric tests would change when we control for the important covariate.

5.3 Regression Results on Crime & Corruption

In this section, we present logit regression results in each regime with several different model specifications. Robust standard errors that are clustered at the subject level are used to compute test statistics as well as the p-values. Let us use Y to denote the crime or corruption decision, then our econometric model specification can be described as follows:[26]

$$P(\boldsymbol{Y} = \mathbf{1}|\beta_0, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\alpha}, \boldsymbol{T}, \boldsymbol{S}, \boldsymbol{A}, \boldsymbol{c}) = \Lambda(\beta_0 + \boldsymbol{\beta T} + \boldsymbol{\gamma S} + \boldsymbol{\alpha A} + \boldsymbol{c}) \tag{4}$$

where $\Lambda(x) = e^x/(1 + e^x)$ is the C.D.F. of a standard logitstic distribution. $\boldsymbol{T}$ is a vector of treatment dummies which will be (HPP, HPW)$'$ in regime $\mathcal{HP}$ and (LPP, LPW)$'$ in regime $\mathcal{LP}$. $\boldsymbol{S}$ represents a particular specification of a logit regression model on corruption or crime, i.e., $\boldsymbol{S}$ would be different for different regressions on corruption or crime which will be discussed in detail later on. $\boldsymbol{A}$ is a vector of control variables that are the same across different model specifications. Particularly, $\boldsymbol{A}$ includes six continuous variables (Age, Grade, Nationality, Risk Preference, Experimental Experience, Theory Experience)[27] and two binary variables (Gender that equals 1 for males and 0 for females, and Role_Exp that equals 1 if subjects have played the other role before and 0 otherwise). $\boldsymbol{c}$ is a vector of period fixed effects.

[26] This specification is equivalent as $\text{logit}(P(\boldsymbol{Y} = \mathbf{1}|...)) = \beta_0 + \boldsymbol{\beta T} + \boldsymbol{\gamma S} + \boldsymbol{\alpha A} + \boldsymbol{c}$ where $\text{logit}(x) = \log\left(\frac{x}{1-x}\right)$.

[27] Nationality is the percentage of Singaporeans in one treatment. Experimental Experience is the percentage of subjects that have experiences in other experiments before. % Theory Experience is the percentage of subjects that have learned some knowledge on game theory before.

5.3.1 Regression Results on Corruption Decisions

For corruption deterrence, when the monitor accepted a bribe and was detected, her corruption decision in the following period is likely to be affected. In addition, we also suspect that the frequency of corruption decisions in all previous periods probably affects the likelihood of her being corrupted in the current period. Furthermore, the amount of bribes she receives in the current period is likely to be a strong predictor of her corruption decision in the current period. Therefore, we have three specifications for $\boldsymbol{S}$: $\boldsymbol{S_1}$ is simply an empty vector. $\boldsymbol{S_2}$ includes three variables: a binary variable `Corruption_lag1` which equals 1 if she committed corruption in the previous period and 0 otherwise, a binary variable `Detection_lag1` which equals 1 if her false report was detected in the previous period and 0 otherwise, and a continuous variable `Cum_Corruption` which is the frequency that she commits a corruption in all previous periods. $\boldsymbol{S_3}$ includes another continuous variable on top of $\boldsymbol{S_2}$: `Offer` which is the amount of bribe she receives in the current period. Please note that those lagged variables that we add in regressions are endogenous variables, so they can only give us some correlations but not causations.

Table 4 shows the Logit regression results on corruption choices in both regimes. Columns (1)∼(3) show regression results in regime $\mathcal{HP}$, and (4)∼(6) show regression results in regime $\mathcal{LP}$. The specifications within each regime includes either $\boldsymbol{S_1}$ or $\boldsymbol{S_2}$ or $\boldsymbol{S_3}$.

Regression results in column (1) show a significant decrease in the odds of being corrupted in treatment HPP compared with the control HP. The coefficient of -0.824 translates to an odds ratio of 0.439 which suggests that the odds of being corrupted in treatment HPP is 56.1% lower than that in control HP, fixing other covariates at the same level. In addition, the odds of being corrupted are also significantly lower in treatment HPW. Specifically, the coefficient of -0.579 translates to an odds ratio of 0.560 which implies that the odds of being corrupted in treatment HPW is 44% lower than that in control HP, fixing other covariates the same. This implies that, in regime $\mathcal{HP}$, raising p significantly lowers the odds of being corrupted. Thus, raising the expected wage of the monitor in HPW is also significantly effective in deterring corruption, though the magnitude is smaller compared to the HPP treatment. This strongly support our Result 2 obtained via non-parametric tests. In contrast, column (4) shows that in regime $\mathcal{LP}$, there is not a significant decrease in the odds of being corrupted in LPP or LPW, which confirms our Result 3.

Columns (2) and (5) show that, in both regimes, `Cum_Corruption` is significantly and positively

Table 4: Logit Regression on Corruption in Both Regimes

	Regime $\mathcal{HP}$			Regime $\mathcal{LP}$		
	(1)	(2)	(3)	(4)	(5)	(6)
HPP	-0.824^{***}	-0.123	-0.215			
	(0.147)	(0.098)	(0.193)			
HPW	-0.579^{***}	-0.205^{**}	-0.000			
	(0.164)	(0.098)	(0.167)			
LPP				-0.123	-0.102	-0.235
				(0.169)	(0.109)	(0.170)
LPW				0.145	-0.093	-0.355^{**}
				(0.157)	(0.107)	(0.178)
Cum_Corruption		0.421^{***}	0.413^{***}		0.395^{***}	0.344^{***}
		(0.034)	(0.035)		(0.038)	(0.041)
Corruption_lag1		-0.378^{**}	-0.551^{**}		-0.390^{***}	-0.494^{***}
		(0.182)	(0.245)		(0.120)	(0.149)
Detection_lag1		0.040	-0.154		-0.114	-0.038
		(0.130)	(0.195)		(0.152)	(0.170)
Offer			0.333^{***}			0.262^{***}
			(0.015)			(0.016)
Covariate	Yes	Yes	Yes	Yes	Yes	Yes
Period F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	2496	2392	2392	2256	2162	2162
Log Likelihood	-1457.800	-1266.898	-787.764	-1397.474	-1210.233	-888.798
Pseudo R^2	0.009	0.097	0.428	0.004	0.093	0.326
Chi-sq Test	0.113	0.315	0.185	0.077	0.921	0.454

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Robust standard errors clustered at individual level are presented in parenthesis. *Covariate* includes age, grade, nationality, gender, risk preference, past experience of participating in lab experiments, past experience with game theory, and `Role_Exp` (equals 1 if one has experiences of the other role and 0 otherwise) as control variables. A `Period` fixed effect is also included in all regressions. `Corruption_lag1` equals 1 if the monitor accepted a bribe in the last period and 0 otherwise, `Detection_lag1` equals 1 if the false report was detected and 0 otherwise, `Cum_Corruption` shows the accumulated incidences of corruption decisions that the monitor have committed in all previous periods, and `Offer` is the amount of bribe she receives in the current period. *Chi-sq Test* reports the p-value of the test of equality of coefficients between HPP and HPW (LPP and LPW respectively).

correlated with likelihood of being corrupted in the current period. This suggests that corruption decisions exhibit the feature of path dependence, which will be discussed in detail in section 5.3.3. The coefficient of `Corruption_lag1` is significantly negative which is counterintuitive. This largely dues to the fact that the monitor might not be offered a bribe in the previous period. The same argument goes for the insignificance of `Detection_lag1` which suggests that the monitor seems not responsive to whether her false report was detected in the previous period.[28]

Columns (3) and (6) show that, in both regimes, how much bribe the monitor is offered significantly affects the odds of her committing corruption in the current period. In addition, column (6) shows that the odds of being corrupted in treatment LPW is significantly lower than that in the control which is surprising given the results in Figure 3b. Note that the deterrent effect in treatment LPW is not significant in columns (4) and (5), and it only becomes significant when we control for the size of bribe offer in column (6). This implies that the increase in corruption rate in LPW that we observe in Figure 3b is mainly due to an increase in the bribe offered by the agent, and when we control for the bribe size, the corruption rate in LPW actually decreases. This suggests the underlying channel for the observed Cobra effect and will be discussed in more detail later.

Last but not least, in columns (2) and (3), the deterrent effect from treatment HPP and HPW disappears when we include the variable `Cum_Corruption`. This suggests that treatment HPP and HPW deter corruption by decreasing the intensity of the monitor committing corruption, and once we control for that, the treatment effect disappears. This will be further discussed in detail in Section 5.5.

5.3.2 Regression Results on Crime Decisions

For crime deterrence, when the agent committed a crime and made a bribery offer in the previous period, his crime decision in the current period is likely to be affected. In addition, whether the bribe was accepted or rejected might have an impact on his current crime decision. Furthermore, we also suspect that the frequency of crime decisions in all previous periods probably affects

[28]When we run regression model (2) and (4) only with the observations where the monitor receives a positive bribe, `Corruption_lag1` is not significant anymore, and `Detection_lag1` becomes a marginally significant predictor. In addition, the results in regression (1) persist with some small changes in the coefficients. However, we still run regressions with all the observations since the bribe offer is endogenously determined in our framework, so the difference in the status and size of the bribe is part of the difference between treatments.

the likelihood of him committing a crime in the current period. Therefore, we make three specifications for $\boldsymbol{S}$ in the domain of crime deterrence: $\boldsymbol{S_1}$ is again an empty vector. $\boldsymbol{S_2}$ includes two binary variables: `OfferStatus_lag1` which equals 1 if he offered a bribe in the previous period and 0 otherwise,[29] and `OfferAccept_lag1` which equals 1 if his bribe was accepted in the previous period and 0 otherwise. $\boldsymbol{S_3}$ includes a continuous variable on top of $\boldsymbol{S_2}$: `Cum_Crime` which is the frequency that he commits a corruption in all previous periods.

Table 5 shows the Logit regression results on crime choices in both regimes. Results in column (1) and (4) basically supports our Result 5 and 6 obtained via nonparametric tests. In column (1), the coefficient of -0.804 translates to an odds ratio of 0.448 which suggests that the odds of committing a crime in treatment HPP is 55.2% lower than that in control HP, fixing other covariates at the same level. In contrast, no significant deterrence effect is observed in regime $\mathcal{LP}$.

Columns (2) and (4) show that, if an agent made a bribe in the previous period, the odds of him committing a crime are significantly higher than that if he did not make a bribe (143% higher in $\mathcal{HP}$ and 271% higher in $\mathcal{LP}$). However, this effect disappears when we include the intensity of crime in columns (3) and (6) which suggests that the agent's crime intensity in past periods is more significantly correlated with his crime decision in the current period. This shows some evidence of path dependence on crime decisions.

One consistent result across columns (2), (3), (5), and (6) is that the agent's odds of committing a crime in the current period significantly increase if his bribe was accepted in the previous period (ranges from 107% higher to 261% higher). This result implies that crime can be effectively deterred if the monitor is hard to be corrupted which suggests that we should put more emphasis on corruption deterrence. Operation Ampscam quoted by Ortner and Chassang (2018) also serves as an example here. Undercover police inspectors in this operation are the hard-to-be-corrupted monitors, so they reject the bribery offers and arrest the contractors trying to get approval for low-quality work.

[29] This variable should be equivalent to crime status in the previous period since one would only make an offer when he commits a crime. However, sometimes the agent makes an offer without committing a crime in the current period. This can also be observed in realities where the potential criminal agent intends to see how likely the official can be corrupted. In order to capture this, we use `OfferStatus_lag1` instead of `Crime_lag1` in all regressions. No matter which variable we choose to include between the two in those regressions, the main results are the same with some changes in magnitude.

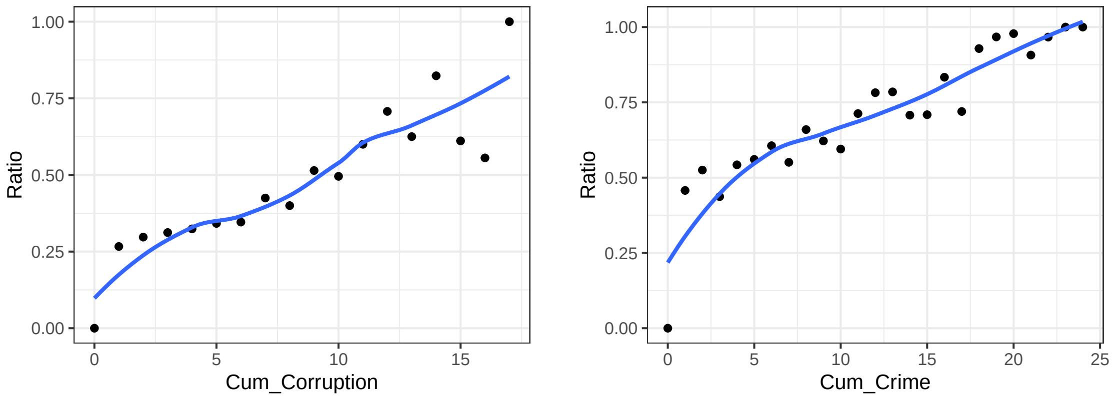
Table 5: Logit Regression on Crime in Both Regimes

	Regime $\mathcal{HP}$			Regime $\mathcal{LP}$		
	(1)	(2)	(3)	(4)	(5)	(6)
HPP	-0.804^{***}	-0.529^{**}	-0.195			
	(0.287)	(0.224)	(0.152)			
HPW	-0.682^{**}	-0.484^{*}	-0.402^{**}			
	(0.327)	(0.253)	(0.172)			
LPP				0.048	0.039	-0.136
				(0.404)	(0.324)	(0.202)
LPW				0.206	0.159	-0.282
				(0.368)	(0.288)	(0.208)
OfferStatus_lag1		0.889^{***}	-0.301		1.311^{***}	-0.506^{**}
		(0.215)	(0.217)		(0.243)	(0.231)
OfferAccept_lag1		0.887^{***}	1.024^{***}		0.726^{***}	1.283^{***}
		(0.199)	(0.203)		(0.213)	(0.224)
Cum_Crime			0.396^{***}			0.524^{***}
			(0.035)			(0.044)
Covariate	Yes	Yes	Yes	Yes	Yes	Yes
Period F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	2496	2392	2392	2256	2162	2162
Log Likelihood	-1617.317	-1408.963	-1156.060	-1475.659	-1234.099	-893.557
Pseudo R^2	0.042	0.126	0.279	0.023	0.142	0.372
Chi-sq Test	0.655	0.837	0.175	0.624	0.638	0.331

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Robust standard errors clustered at individual level are presented in parenthesis. *Covariate* includes age, grade, nationality, gender, risk preference, past experience of participating in lab experiments, past experience with game theory, and `Role_Exp` (equals 1 if one has experiences of the other role and 0 otherwise) as control variables. A `Period` fixed effect is also included in all regressions. `OfferStatus_lag1` is a binary variable that equals 1 if the agent made an offer in the last period and 0 otherwise, `OfferAccept_lag1` equals 1 if the offer was accepted and 0 otherwise, and `Cum_Crime` shows the accumulated incidences of crime decisions that the agent have made in all previous periods. *Chi-sq Test* reports the p-value of the test of equality of coefficients between HPP and HPW (LPP and LPW respectively).

5.3.3 Path Dependence of Crime and Corruptions

First of all, we show visually in Figure 5 the path dependence of crime and corruption. In each subfigure, the horizontal axis is the cumulative frequency of crime or corruption decisions, and the vertical axis is the ratio of committing crime or corruption for a given cumulative frequency. The figure is a strong demonstration of the path dependence of crime and corruption.



(a) Path Dependence of Corruption

(b) Path Dependence of Crime

Figure 5: Path Dependence of Crime & Corruption

The regression results in Table 4 and 5 show some support on path dependence of crime and corruption. However, the treatment dummy variables are very likely to be correlated with the variables related to previous decisions, and thus the magnitude, as well as the significance of those variables, might be affected. Therefore, in order to get a cleaner evidence, we run regressions for crime and corruption decisions within each treatment. The regression results across treatments consistently show that the intensity of crime or corruption in previous periods is a significant predictor of crime or corruption decisions. Specifically, the odds of being corrupted in the current period are at least 45.3% higher if the monitor commits one more corruption in the past, and the odds of committing a crime in the current period are at least 46.8% higher if the agent commits one more crime in the past. For more details on the regression results, please see Table 7 and 8 in Appendix A.

Result 7: *Both crime and corruption display a strong feature of path dependence. The more one has committed a crime (corruption) in the past, the more likely he is going to commit a crime (corruption) this time. According to our experimental data, the odds of committing a crime (corruption) increases by 67.5% (53.8%) on average per extra crime (corruption) incident in the past.*

Result 7 is related to our Hypothesis 2A and 2B since crime and corruption deterrence might take effect partially by reducing the intensity of crime and corruption which also leads to a weaker path dependence.

Since each subject in our experiment plays both roles, so they have to make crime and corruption decisions. Therefore, one might also suspect that those who commit crimes (corruptions) frequently would also commit corruptions (crimes) frequently which is another form of path dependence. We test this by showing the relationship between each subject's crime (corruption) incidents in stage 1 and corruption (crime) incidents in stage 2 for those who are the agent (monitors) in stage 1, and the fitted lines in both graphs are rather flat which implies that there is not such a correlation between high crime and high corruption according to our experimental data. Please see Figure 12 in Appendix for more details.

5.4 The Cobra Effect in Regime LP and HP

The famous Cobra Effect is about the misuse of incentives where some unintended consequences lead to the opposite of the "should have been induced" outcomes by the provided incentive. This is the thing that we should be very careful about and try our best to avoid when we use incentives to achieve some purpose because it does not only waste the resources that we have but also makes our situations even worse.

Cobra Effect may be present in our experiment. We have two policy instruments at hand to modify in order to deter crime and corruption, and one of them is the expected wage of the monitor. We presuppose that an increase in the expected wage of the monitor would make the expected (opportunity) cost of accepting a bribery offer higher than before, and thus the likelihood of the monitor accepting a bribery offer becomes lower. Anticipating this, the agent would be less likely to make an offer and thus less likely to commit a crime. Therefore, increasing the expected wage deters crime and corruption effectively. However, the agent might respond to an increase in the expected wage by increasing his bribery offer such that the effect dominates that of the increase in the expected wage, and thus the monitor takes the offer more likely. Figure 6 illustrates this potential Cobra Effect.

An increase in the corruption rate in LPW shown in Figure 3b and the regression results of column (6) in Table 4 suggest that such an increase is probably driven by an increase in the bribe offered by the agent in treatment LPW which is consistent with the above conjecture.

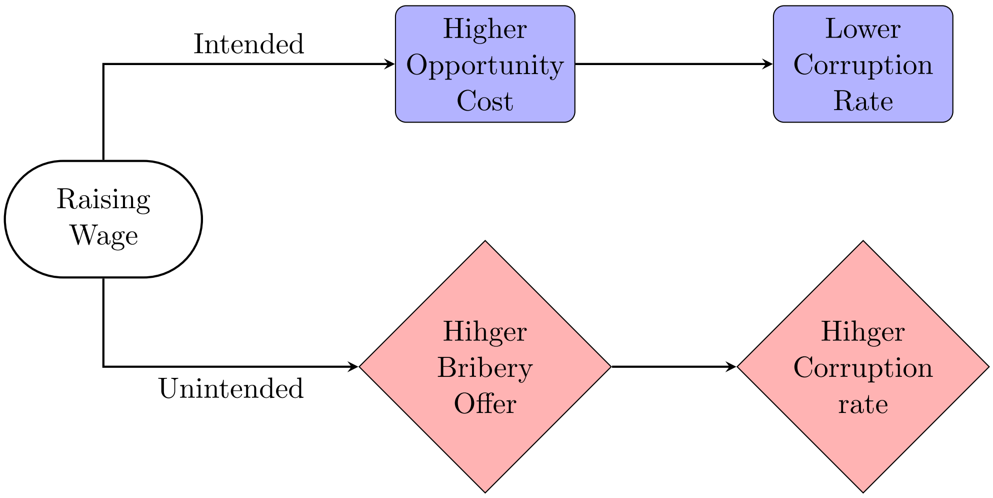
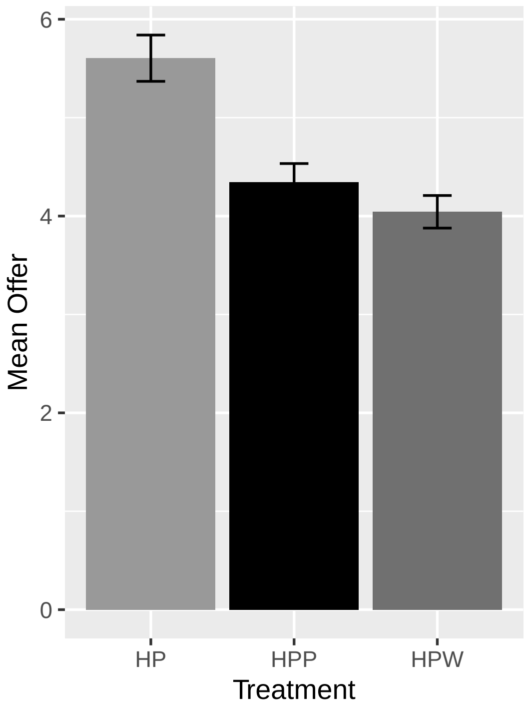
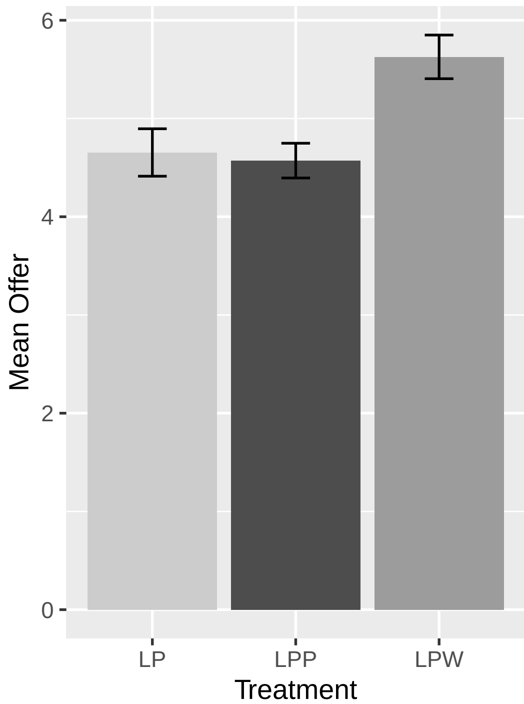


Figure 6: Illustration of Potential Cobra Effect

Figure 7b shows the mean offer across all the treatments in regime $\mathcal{LP}$ which confirms the above conjecture. The mean offer in treatment LPW (5.63) is (21.1%) higher than that in control LP (4.65).



(a) Mean Offer in $\mathcal{HP}$



(b) Mean Offer in $\mathcal{LP}$

Figure 7: Mean Offer Across Treatments

However, the validity of the suggested mechanism of the Cobra effect requires further decomposition of the increase in the mean offer: such an increase should be driven by an increase in the bribe size made by the agents instead of by an increase in the population of bribers. This will be further discussed in Section 5.5.

Is there a similar Cobra Effect when we raise the expected wage of the monitor in regime $\mathcal{HP}$? The answer is no. Figure 7a shows that there is an evident decrease in the mean offer in treatment HPW compared to that in control HP. This rules out the underlying mechanism of the Cobra Effect observed in regime $\mathcal{LP}$. Furthermore, Figure 3 and Result 2 tell us that the corruption rate in treatment HPW is significantly lower than that in control HP, which completely negates the presence of Cobra Effect in regime $\mathcal{HP}$.

Given the above results, it seems that the presence of the Cobra Effect in our study is regime dependent. In regime $\mathcal{LP}$ with a low probability of detection(25% in LP), the increase in the expected wage of the monitor only increases the DPCC on paper, and in effect, it leads to an increase in corruption rate since it induces the agent to make a higher bribe. In contrast, in regime $\mathcal{HP}$ with a high probability of detection (50% in HP), the increase in the expected wage of the monitor results in an increase in the DPCC in effect as intended, and the agents are discouraged to make bribes.

Why do the agents respond so differently to an increase in the expected wage of the monitor between regime $\mathcal{HP}$ and $\mathcal{LP}$? We suggest that this is because of the difference in the perception of detection probabilities. In regime $\mathcal{LP}$ where the detection probability is low (25% in LP), the agents are not responsive to changes in the probability of detection (up to a 50% increase). In addition, the agents would consider the monitor to be easily corruptible, and she will take his offer as long as the offer is attractive. As a result, a higher expected wage level of the monitor induces a higher level of bribery offers and thus a higher corruption rate. On the contrary, in regime $\mathcal{HP}$ where the detection probability is high (50% in HP), the agents would take it seriously and consider the monitor to be hardly corruptible. As a result, a higher expected wage level of the monitor in treatment HPW together with the high detection probability induce the agents to believe that the monitor is even harder to be corrupted. As a result, the average level of bribery offers decreases, and the corruption rate decreases consequently.[30]

Result 8: *As a policy instrument against crime and corruption, raising the (expected) wage of the monitor induces the Cobra Effect in regime $\mathcal{LP}$ where the probability of detection is low (25% in LP). However, such a perversive incentive effect is not present in regime $\mathcal{HP}$ where the detection probability is high (50% in HP).*

[30] The decrease in the mean offer level in treatment HPW shown in Figure 7 is mainly driven by the fact that fewer subjects in treatment HPW make a bribery offer than in HP treatment. Conditional on an offer is being made, the mean offer level is roughly the same. This is shown clearly in Section 5.5.

This result does not support our Hypothesis 2A which states that treatment LPW should also deter corruption effectively. However, this result further lends strong support to regime $\mathcal{HP}$ over regime $\mathcal{LP}$ since the former would not suffer from the Cobra Effect whereas the latter would. Not only does regime $\mathcal{LP}$ fail to deter crime and corruption effectively, but it might also induce a higher corruption rate if raising the expected wage is taken as the policy intervention. The regression results in Table 7 show that when the amount of the offer increases by 1 unit (Experimental Currency), the odds of the monitor being corrupted in the current period increases by 38.1% on average (ranges from 27.9% to 47.8% across all the treatments). This clearly demonstrates the detrimental effect of the presence of the Cobra Effect, which further invalidates the use of higher (expected) wages as a policy intervention to deter corruption when the detection probability is low.

The literature also suggests the existence of such a Cobra Effect in theory. Kugler, Verdier, and Zenou (2005) show in a theoretical model that, when bribing costs are low and rents are sufficiently high, increasing policing as well as sanctions can generate higher crime rates. Increases in intended expected punishment lead to extended corruption rings, which further results in a fall in actual expected punishment and thus yields more crime. Basu, Basu, and Cordella (2016) develop a theoretical model and they notice that, in many cases, a rise in the expected punishment (either by increasing the probability of detection or magnitude of the punishment) will lead to an adjustment of the bribe size to compensate the increased expected punishment which is merely a reallocation of surplus. Our study shows empirically that this is true when the probability of detection is low and thus induces the Cobra Effect, however, when the probability of detection is high, an increase in the expected punishment delivers real deterrence power against crime and corruption in effect.

5.5 Analyses on Intensive-Extensive Margins

Previously we have shown that there are some significant changes in the means of crime rate, corruption rate, and bribery offers across all the treatments. For example, Figure 4 shows that there's a noticeable decrease in the crime rate when we raise the detection probability in treatment HPP compared to that in control HP. However, we do not know where this decrease should be attributed to. Is it a result of fewer agents committing a crime? Or is it a result of each agent committing crimes less frequently? The same concern remains for the significant decrease in the corruption rate in both treatment HPP and HPW compared to that in control

HP. To uncover the veil, it is necessary for us to perform an analysis of the changes in extensive and intensive margins of crime and corruption.

In addition, the presence of the Cobra Effect in treatment LPW requires us to perform such an analysis to further validate its underlying mechanism. Specifically, Figure 7 shows that there is a visibly significant increase in the mean bribery offer in treatment LPW compared to that in control LP. The question is where this increase should be attributed to. Is it due to an increase in the number of agents that makes a positive bribery offer in treatment LPW? Or is it due to an increase in the bribery offer made by each agent? The argument for the underlying mechanism of the Cobra Effect requires that the increase in the mean bribery offer is caused by an increase in the intensive margin of the bribery offer, rather than the other possibility.

For crime choices, we define the extensive margin as the percentage of individuals that commits a crime in each period, and the intensive margin as the mean intensity of crime choices over the 24 periods conditional on an agent does commit a crime. The definitions of the ex- and intensive margins of corruption and offer choices are pretty much the same.

5.5.1 Ex- & Intensive Margin of Crime Decisions

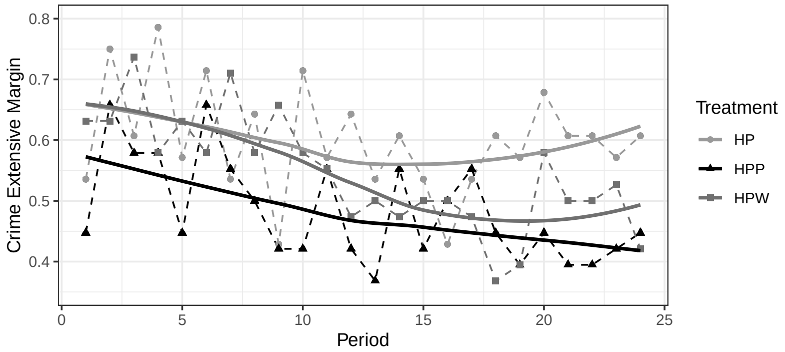
In order to measure the intensive margin of crime choices, we calculate the frequency of committing a crime choice over the entire 24 periods for each individual as his crime intensity, and then take the mean within each treatment conditional on he does commit a crime, i.e., his intensive margin is positive.

For the measure of extensive margins, we first calculate the percentage of agents that commit a crime in each period as the extensive margin in that period and then show the dynamic changes of the extensive margin over the entire 24 periods.

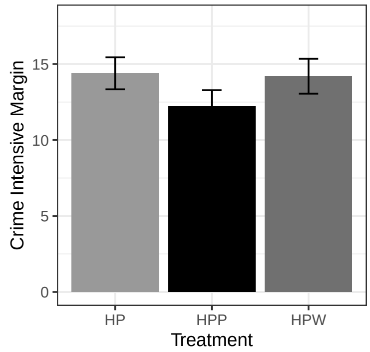
Figure 8(a) shows the dynamics of the extensive margin of crime over time in regime $\mathcal{HP}$. The extensive margin in treatment HPP is consistently lower than that in control HP.[31] The interesting part is the dynamics of the extensive margins in treatment HPW. It is almost the same as that in control HP in early periods. However, the agent gradually realizes that it is hard to corrupt the monitor, therefore, the number of agents that chooses to commit a crime decreases over time, and the extensive margin becomes closer to that in treatment HPP in the

[31] The fitted line is drawn with LOESS (locally estimated scatterplot smoothing) method.

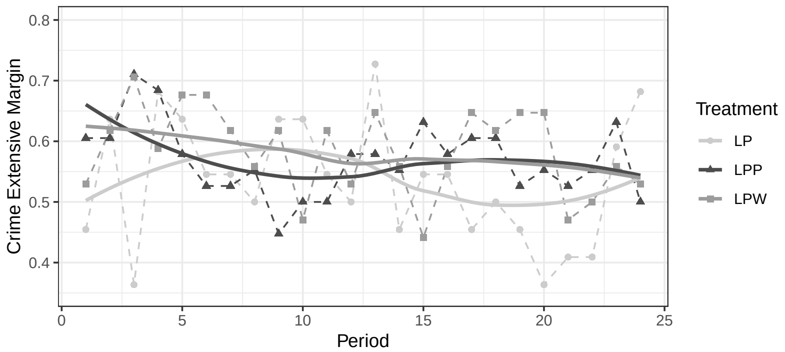
end (recall that by design the DPCC is the same in treatment HPP and HPW).



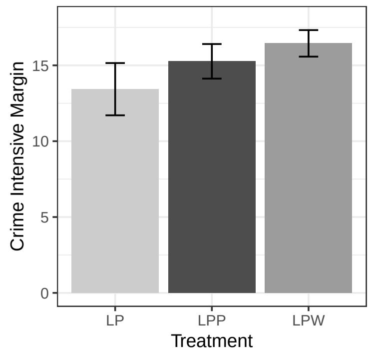
(a) Extensive Margin in $\mathcal{HP}$



(b) Intensive Margin in $\mathcal{HP}$



(c) Extensive Margin in $\mathcal{LP}$



(d) Intensive Margin in $\mathcal{LP}$

Figure 8: Ex- & Intensive Margin of Crime Across Treatments

This result suggests that the extensive margins are more sensitive to a change in the probability of detection rather than an expected wage change. As long as the detection probability increases in regime $\mathcal{HP}$, they would take a prompt response to decrease their likelihood of committing a crime, which leads to a lower extensive margin immediately from the very beginning in treatment HPP. In contrast, the agents are slow in response to an expected wage increase when the detection probability remains the same in treatment HPW. Actually, the agents, in general, cannot differentiate between treatment HPW and control HP in the beginning periods. The deterrent effect due to a decrease in the extensive margin of crime requires some time to take effect in treatment HPW when we use a higher expected wage as a policy intervention.

This suggests a difference in the celerity of deterrent effect against crime between an increase in certainty and an increase in severity of punishment: increasing the probability of detection deters crime immediately by decreasing the extensive margin immediately while increasing the expected wage takes some time to produce a decrease in the extensive margin.

Figure 8(b) shows the intensive margin of these treatments in the regime $\mathcal{HP}$. Compared to control HP, there is a moderate significant decrease in the intensive margin in treatment HPP ($p = 0.066$, one-sided C-WRS test), while there is not a noticeable change in treatment HPW.

Result 9a: *In regime $\mathcal{HP}$, there is a significant decrease in the extensive margin of crime and a marginally significant decrease in the intensive margin of crime in treatment HPP when p increases (from 50% to 75%). There is not a significant decrease in the intensive margin in treatment HPW when the expected wage is raised, and the extensive margin lies decreases gradually over time which lies between the extensive margin in treatment HPP and HP.*

Result 9b: *The agents are more sensitive to a probability change in detection than a change in the expected wage when making crime decisions.*

Result 9a supports our Hypothesis 2B by showing the underlying mechanism of crime deterrence: increasing p deters crime by decreasing both the extensive and intensive margin of crime. However, Result 9b violates our Hypothesis 3B that an increase in p delivers a larger deterrent effect than an increase in $\mathbb{E}(w)$.

Figure 8(c) displays the dynamics of the extensive margin of crime over time in regime $\mathcal{LP}$. The extensive margins in treatments LP, LPP, and LPW are intertwined with each other and it is hard to say which one is higher or lower than the other. This suggests that, when the detection probability is low (25% in LP), neither increasing the detection probability (from 25% to 37.5%) nor raising the expected wage would have an impact on the extensive margins of crime choices, i.e., both policy interventions won't lower the population of criminals in regime $\mathcal{LP}$.

In addition, Figure 8(d) shows the intensive margins in these three treatments. Although there are some differences in the mean values, none of them is close to statistical significance.

Result 10: *In regime $\mathcal{LP}$, there is no significant difference in either the extensive margin or the intensive margin of crime by increasing either the probability of detection or the expected wage.*

This result stands in contrast to the significant differences in the extensive margins among treatments in regime $\mathcal{HP}$, and it fails to support Hypothesis 2B. It further validates the idea that both Hypothesis 2B and Hypothesis 3B are regime dependent. The detection probability has to be high enough (as it is in regime $\mathcal{HP}$) so that both increasing the detection probability and increasing the expected wage would have an impact on the extensive margins of crime, and increasing the probability of detection produces a more prompt decrease in the extensive margin. In addition, increasing the probability of detection in regime $\mathcal{HP}$ also produces a significant decrease in the intensive margin of crime.

5.5.2 Ex- & Intensive Margin of Offer & Corruption Decisions

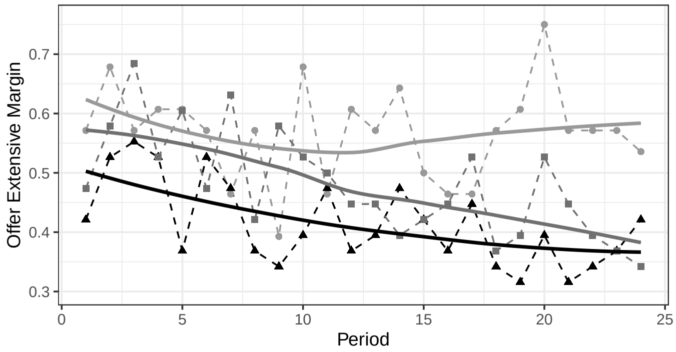
The ex- and intensive margins of offer and corruption across all the treatments are displayed in Figure 9 and Figure 10 respectively.

For the dynamics of the extensive margins of offer and corruption over time across all the treatments, the characteristics are very similar to that of the extensive margins of crime. On one hand, the extensive margins of both offer and corruption in the $\mathcal{HP}$ regime show a significant difference between treatment HPP and control HP, and the extensive margins in treatment HPW lie in between them. On the other hand, the extensive margins of both offer and corruption in the $\mathcal{LP}$ regime are intertwined with each other which implies insignificant differences among the treatments in the $\mathcal{LP}$ regime.

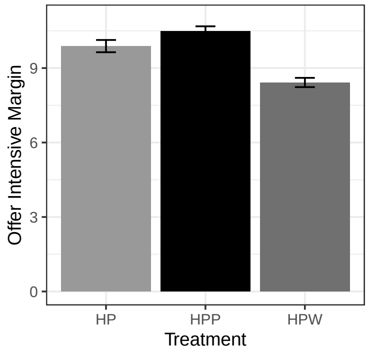
It is quite intuitive and easy to understand the resemblance among the extensive margins of crime, offer, and corruption. As the agent chooses to commit a crime, he will make an offer to the monitor, and more offer implies more opportunity to be corrupted for the monitor, therefore, the extensive margins of crime, offer, and corruption goes hand in hand with each other. For example in control HP, the extensive margin of crime and offer is around 15 at the beginning, and the extensive margin of corruption is around 10 at the beginning which is 5 less than the bribery offer. The pattern of the dynamics of extensive margin over time are very similar among crime, offer, and corruption.

Similar to the results of the extensive margin of crime in regime $\mathcal{HP}$, this suggests a difference in the celerity of deterrent effect against corruption between an increase in certainty and an increase in severity of punishment, which is probably the reason that we observe a larger deterrent effect against corruption in treatment HPP than that in treatment HPW.

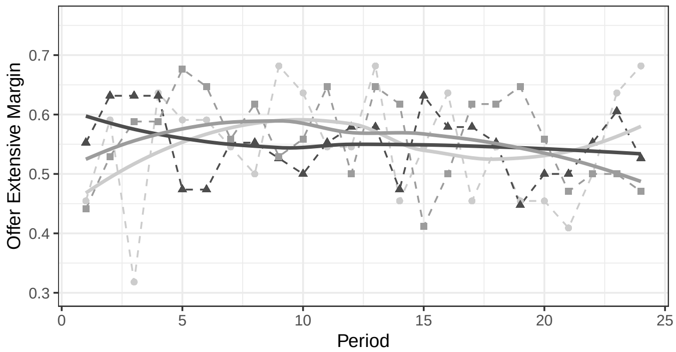
It is a different story for the intensive margins of offer and corruption. Figure 9(b) shows the intensive margins of bribery offers in the $\mathcal{HP}$ regime. Compared to control HP, there is a minor increase in treatment HPP and a slight decrease in treatment HPW, but none of them is statistically significant.



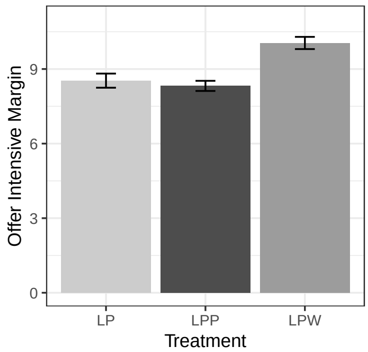
(a) Extensive Margin in $\mathcal{HP}$



(b) Intensive Margin in $\mathcal{HP}$

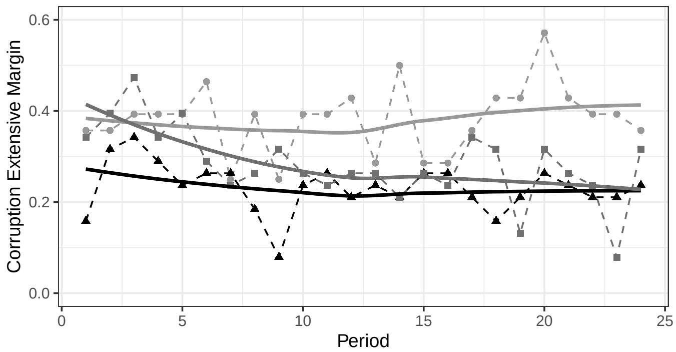


(c) Extensive Margin in $\mathcal{LP}$

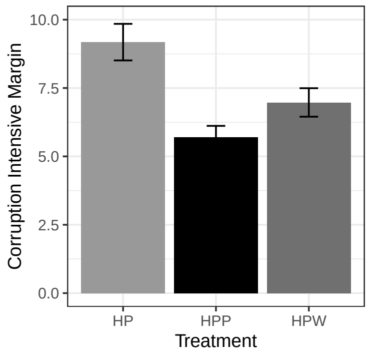


(d) Intensive Margin in $\mathcal{LP}$

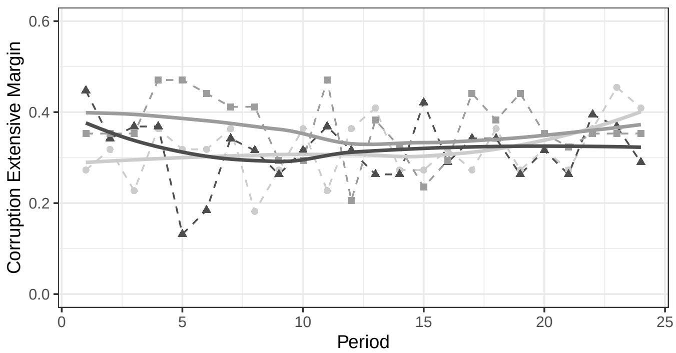
Figure 9: Ex- & Intensive Margin of Offer Across Treatments



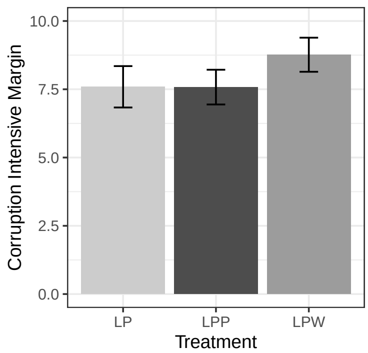
(a) Extensive Margin in $\mathcal{HP}$



(b) Intensive Margin in $\mathcal{HP}$



(c) Extensive Margin in $\mathcal{LP}$



(d) Intensive Margin in $\mathcal{LP}$

Figure 10: Ex- & Intensive Margin of Corruption Across Treatments

Nonetheless, Figure 10(b) shows an evident decrease in the intensive margins of corruption in both treatment HPP and HPW compared against that in control HP, and these differences are both statistically significant ($p = 0.000$ and $p = 0.007$ respectively, one-sided C-WRS test). This sharp contrast with Figure 9(b) implies a real deterrence power against corruption in both treatment HPP and HPW, especially for the case of treatment HPP - Despite a slightly higher intensive margin of the bribery offer, the intensive margin of corruption in treatment HPP is significantly lower than that in control HP.

However, in the $\mathcal{LP}$ regime, Figure 9(c) and Figure 10(c) show that the extensive margins of both bribery offer and corruption are very close among LP, LPP, and LPW. In addition, the intensive margins of bribery offers and corruption respectively shown in Figure 9(d) and Figure 10(d) closely resemble each other. When the intensive margin of the bribery offer is higher in treatment LPW, the intensive margin of corruption is also higher. Together with the pattern of extensive margins being roughly the same across treatments, we know that the increase in the mean bribery offer in treatment LPW (compared to that in LP) is mainly due to an increase in the intensive margin of the bribery offers, namely, the agents on average make higher offers to the monitor which is driven by a higher expected wage of the monitor. This completes the demonstration of the underlying mechanism of the observed Cobra Effect in LPW treatment.

Result 11: *In regime $\mathcal{HP}$, there is a significant decrease in both the extensive and intensive margin of corruption in both treatment HPP and HPW with treatment HPP yielding a larger decrease in intensive margin and an instant decrease in extensive margin. In regime $\mathcal{LP}$, however, there is no significant difference in either the extensive margin or the intensive margin of corruption by increasing either the probability of detection or the expected wage.*

6 Conclusion and Discussion

Given the fact that complete elimination of crime and corruption is impossible due to the extremely high marginal cost of increasing the certainty of punishment when it is already very high, the issue is more about how to control the crime and corruption at an acceptable level or the desired level.[32] The authority should have effective policy instruments at hand such that they

[32] There are some concerns on the welfare effect of corruption deterrence since it might consume too many resources and thus the costs exceed the benefits. In addition, the relationship between corruption and economic growth is still unclear. For example, Ang (2020) points out that China has achieved a fast economic growth

can effectively achieve the desired corruption level by manipulating these policy instruments.

Following the long debate on the effectiveness of crime and corruption deterrence between certainty and severity of punishment, this study investigates that, grafted onto the existing policy design concerning crime and corruption deterrence, whether there is a real deterrent effect by increasing the certainty or severity of punishment, and which one delivers a greater impact if there is any.

In this study, we document a novel take-off effect in crime and corruption deterrence when one compares the effectiveness between certainty and severity of punishment. In regime $\mathcal{HP}$ where the probability of detection is high enough (50% in control HP), both increasing the certainty and increasing the severity of punishment have a significant noticeable deterrent effect against crime and corruption, and the magnitude of deterrence is greater when the effect is due to an increase in the probability of detection. This suggests that both policy interventions would be able to deliver significant corruption and crime deterrence as long as the certainty of punishment is high enough. However, in the $\mathcal{LP}$ regime where the probability of detection is low (25% in control LP), neither increasing the certainty nor increasing the severity of punishment would deter crime or corruption. This might provide an explanation for many empirical studies that fail to find any significant deterrent effect of increased severity of punishment against crime and/or corruption.

We suggest that the above result relates to the difference in risk perception in different regimes.[33] In regime $\mathcal{LP}$, the agents do not take the possibility of the public officials being detected seriously and believe that the officials are easy to be corrupted as long as the bribery offer is high enough. However, when the probability of detection is high, the agents consider the public officials to be hard to be corrupted and thus either policy intervention can produce a significant deterrent effect. Nagin (1998, 2013) repeatedly states a research gap on the relationship between risk perceptions and policy regimes regarding crime and corruption deterrence. Our result might shed some light on this issue.

The sharp contrast between the $\mathcal{HP}$ and $\mathcal{LP}$ regimes persists when we talk about the potential Cobra Effect. When the authority increases the expected wage of the monitor expecting a lower

while corruption is prevalent since China's Reform and Opening in 1978, and the US in the late 19^{th} century experienced a very similar process. Therefore, it is very important to make the level of corruption under control.

[33]Probability weighting might be another possible explanation. However, Mungan (2019) examines how attaching higher probability weights to more salient outcomes would account for the stylized fact that people are more responsive to certainty than severity of punishment, however, they show that this probability weighting in salience theory does not contribute to the stylized fact.

corruption rate due to a higher opportunity cost, the criminal agent can anticipate this and might compensate the monitors with a higher bribery offer which leads to a higher corruption rate instead. This is indeed what happened in LPW treatment. However, in the $\mathcal{HP}$ regime, since the probability of detection is high enough, an increase in the expected wage in HPW treatment yields a significant deterrent effect against corruption.

Furthermore, we perform analyses on changes in extensive and intensive margins of crime and corruption across treatments within each regime, therefore, we are able to identify where the deterrent effect against crime or corruption is attributed if there is any. Specifically, we investigate whether the policy intervention deters crime (corruption) by decreasing the population of those who commit a crime (corruption) or by decreasing the intensity of those who have committed a crime (corruption). Our results show that the changes in extensive margins of crime and corruption are pretty consistent within each regime. In the $\mathcal{LP}$ regime, there is no significant difference among the three treatments. However, in the $\mathcal{HP}$ regime, the extensive margin of crime (corruption) in HPP treatment is significantly lower than that in control HP from the very beginning. In contrast, the extensive margin of crime (corruption) in HPW treatment is roughly the same as that in control HP in the beginning periods but it gradually decreases over time. This implies that an increase in the certainty of punishment in the $\mathcal{HP}$ regime can decrease the crime (corruption) population immediately while an increase in the severity will only have a similar impact after a certain period. One major difference in the relative effectiveness between certainty and severity of punishment lies in the celerity of their deterrent effect.

The intensive margins of crime and corruption do not differ significantly across treatments within the $\mathcal{LP}$ regime. The story goes differently for crime and corruption in the $\mathcal{HP}$ regime. The intensive margin of crime is not significantly different across treatments within the $\mathcal{HP}$ regime, while the intensive margin of corruption significantly decreases when we increase the probability of detection. We consider that the difference in the pattern of intensive margins between crime and corruption is due to the fact that the policy interventions are on the monitor's side, so they are more prompt and sensitive to the changes.

We do not allow any form of communication in the game. If we allow the monitor to send wage-relevant information to the agent, the babbling equilibrium would be the only equilibrium in theory since the monitor has incentives to deviate when she does not send the highest wage according to any other messaging strategy. As a result, the presence of a signaling mechanism makes no difference assuming risk neutrality and expected utility maximization. Nevertheless, subjects might not behave accordingly and thus the results might be different. For example, if subjects are not expected utility maximizers or if they are not risk neutral, there might be credible information transmission. Therefore, it might be worthwhile to investigate how information transmission would affect crime and corruption deterrence in the future.

Future studies can also aim to identify the true take-off threshold beyond which certainty and severity are both effective deterrent instruments. It might be different for different types of crime or corruption, and it requires a suitable data set to deliver credible results. It might also be affected by culture, religion, etc., so, the take-off threshold might also be an interval. Another direction is to allow the monitor to demand bribery offers from the agent when the agent is innocent. The harassment bribery game might be the ideal stage game to address this issue and investigate how corruption and crime would be affected and how the extensive and intensive margins would change accordingly.

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Appendix A Extra Tables & Figures

Table 6: Wage Comparison Between Observations and Theory

Treatment	Mean		SD		SE	
	Observed	Theory	Observed	Theory	Observed	Theory
LP	22.2	23	24.3	26.9	1.06	NA*
LPP	23.0	23	24.6	26.9	0.814	NA
LPW	36.7	34.5	36.9	40.4	1.29	NA
HP	11.1	11.5	12.0	13.5	0.464	NA
HPP	11.9	11.5	12.5	13.5	0.414	NA
HPW	16.8	17.2	18.3	20.2	0.607	NA

* Standard error is only available for sampling distributions.

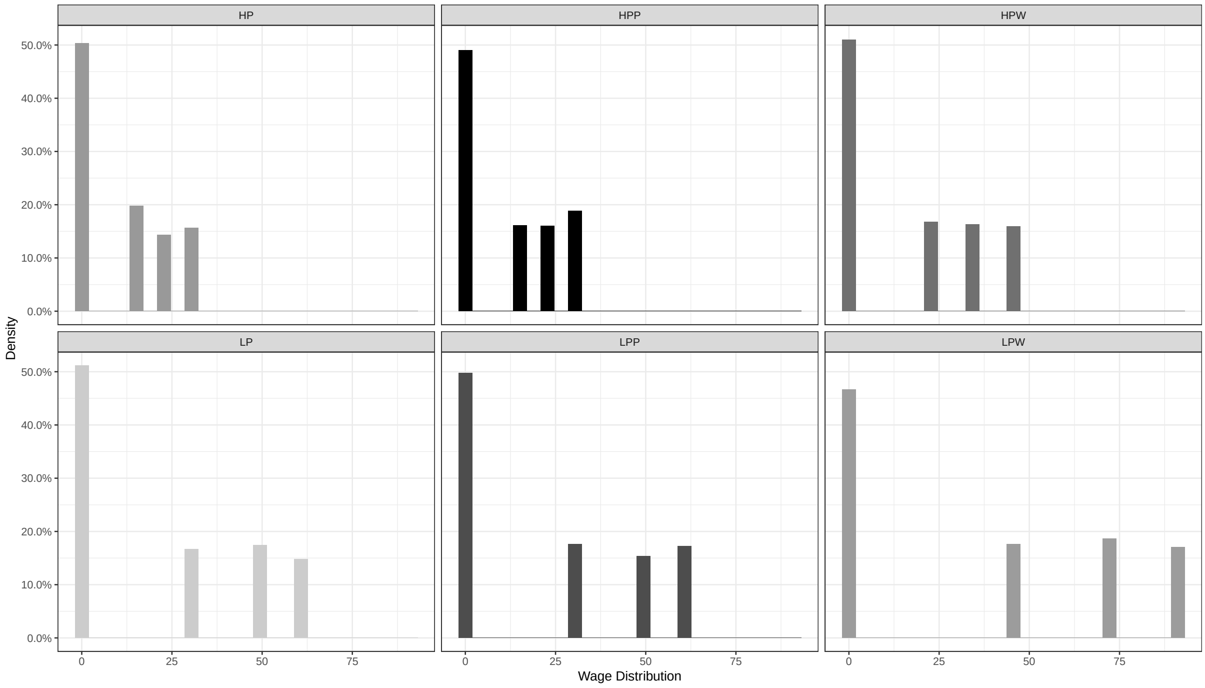
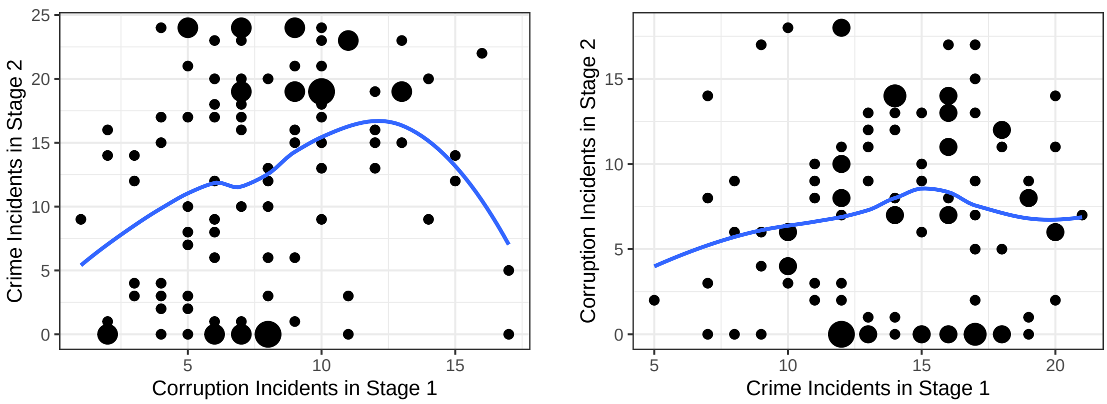


Figure 11: Wage Distribution For Each Treatment

Table 7: Logit Regression on Corruption Within Each Treatment

	Dependent variable: Corruption					
	(1)	(2)	(3)	(4)	(5)	(6)
	HP	HPP	HPW	LP	LPP	LPW
Offer	0.391***	0.331***	0.347***	0.344***	0.246***	0.271***
	(0.030)	(0.027)	(0.029)	(0.050)	(0.024)	(0.028)
Cum_Corruption	0.424***	0.439***	0.473***	0.374***	0.489***	0.380***
	(0.076)	(0.099)	(0.066)	(0.067)	(0.087)	(0.079)
Corruption_lag1	−0.370	−0.837	−0.651	−0.434*	−0.837**	−0.366*
	(0.401)	(0.537)	(0.423)	(0.261)	(0.331)	(0.206)
Detection_lag1	0.132	−0.540	0.009	0.227	−0.357	0.097
	(0.447)	(0.405)	(0.276)	(0.483)	(0.264)	(0.278)
Covariate	Yes	Yes	Yes	Yes	Yes	Yes
Period F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	644	874	874	506	874	782
Log Likelihood	−209.586	−256.240	−287.554	−190.441	−345.381	−317.176
Pseudo R^2	0.429	0.387	0.377	0.287	0.297	0.314

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Robust standard errors clustered at individual level are presented in parenthesis. *Covariate* includes age, grade, nationality, gender, risk preference, past experience of participating in lab experiments, past experience with game theory, and *Role_Exp* (equals 1 if one has experiences of the other role and 0 otherwise) as control variables. A *Period* fixed effect is also included in all regressions. *FalseReport_lag1* equals 1 if the monitor made a false report in the last period and 0 otherwise, *Detection_lag1* equals 1 if the false report was detected and 0 otherwise, and *Cum_Corruption* shows the accumulated incidences of corruption decisions that the monitor have committed in all previous periods.



(a) Correlation for Monitors in Stage 1 (b) Correlation for Agents in Stage 1

Figure 12: Correlation Between Crime and Corruption Incidents

Table 8: Logit Regression on Crime Within Each Treatment

	Dependent variable: Crime					
	(1)	(2)	(3)	(4)	(5)	(6)
	HP	HPP	HPW	LP	LPP	LPW
Cum_Crime	0.450^{***}	0.384^{***}	0.414^{***}	0.618^{***}	0.683^{***}	0.511^{***}
	(0.053)	(0.057)	(0.072)	(0.105)	(0.081)	(0.071)
OfferStatus_lag1	-0.796^{***}	-0.374	0.059	0.058	-0.928^{**}	-0.726^{**}
	(0.263)	(0.365)	(0.439)	(0.503)	(0.374)	(0.362)
OfferAccept_lag1	1.068^{***}	1.133^{***}	1.031^{***}	0.953^{**}	0.706^{**}	2.176^{***}
	(0.398)	(0.316)	(0.385)	(0.388)	(0.358)	(0.412)
Covariate	Yes	Yes	Yes	Yes	Yes	Yes
Period F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	644	874	874	506	874	782
Log Likelihood	-319.686	-425.125	-365.637	-175.675	-342.966	-313.085
Pseudo R^2	0.185	0.243	0.338	0.401	0.370	0.347

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Robust standard errors clustered at individual level are presented in parenthesis. *Covariate* includes age, grade, nationality, gender, risk preference, past experience of participating in lab experiments, past experience with game theory, and *Role_Exp* (equals 1 if one has experiences of the other role and 0 otherwise) as control variables. *OfferStatus_lag1* is a binary variable that equals 1 if the agent made an offer in the last period and 0 otherwise, *OfferAccept_lag1* equals 1 if the offer was accepted and 0 otherwise, and *Cum_Crime* shows the accumulated incidences of crime decisions that the agent have made in all previous periods.

Appendix B The Proof

Proposition: When DPCC < 0 under $\{p', F_p^*(w)\}$, the agent chooses a bribe $\tau = p'\pi_A/p$, and the monitor always accepts the offer.

Proof: The agent's expected payoff $\mathbb{E}(P_A)$ shown in Equation 2 can further be rearranged as follows:

$$\mathbb{E}(P_A) = (k - \pi_A)\left(1 - \frac{p'}{p}\right)\left(\frac{k}{k - \tau p/p'} - 1\right) \tag{5}$$

When DPCC < 0 under $\{p', F_p^*(w)\}$, Equation 5 shows that $\mathbb{E}(P_A)$ is positive and monotonically increasing in τ. However, this formulation of $\mathbb{E}(P_A)$ is derived under the assumption that there is a chance that the monitor will reject the offer, so τ is bounded. Specifically, since the monitor's highest possible wage is π_A/p given $F_p^*(w)$, so we must have $\tau < p'\pi_A/p$.

When $\tau \geqslant p'\pi_A/p$, the monitor is going to accept the bribe all the time, and thus, the agent would pay the least amount of bribe, which is $p'\pi_A/p$, to maximize his payoff.

Q.E.D.

Appendix C A Sample Experimental Instruction: Treatment LP

General Instruction

You are now taking part in an interactive study on decision making. **Please pay attention to the information provided here and make your decisions carefully. If at any time you have questions to ask, please raise your hand and we will attend to you in private.**

Please note that unauthorized communication is prohibited. Failure to adhere to this rule would force us to stop the experiment and you may be held liable for the cost incurred in this experiment. You have the right to withdraw from the experiment at any point, and if you decide to do so your payoff earned during this study will be forfeited.

Your **anonymity will be preserved** for the study. You will **never be aware of** the personal identities of other players **during or after** the study. Similarly, other players will also **never be aware of** your personal identities **during or after** the study. You will only be identified by your subject ID in our data collection. All information collected will **strictly be kept confidential** for the sole purpose of this study.

By participating in this study, you will be able to earn a considerable amount of money. The amount depends on the decisions you and others make. Your earnings in the experiment are denominated by "**Experimental Currency Unit(s)**" or "**ECU(s)**". At the end of the experiment, they will be converted into Singapore Dollars at the rate of

1 ECU = 0.05 SGD.

The real-dollar equivalent of your final earnings will be added to your **show-up fee** as your final payoff and paid to you privately in cash at the end of the experiment. It would be contained in an envelope indicated with your unique subject ID. You will need to sign a receipt form to acknowledge that you have been given the correct amount.

Specific Instructions

You will participate in **three** parts of our experiment, the specific instructions will be given to you at the beginning of each part. The following is the specific instruction for part one.

Part One

In this part of the experiment, you will play a game repeatedly for several periods. There are two roles in this game, **Monitor** and **Employee**. At the beginning of Part One, you will get **50 ECUs** as your initial wealth, and your role will be **randomly determined** which will **remain the same** throughout Part One of the experiment.

At the beginning of each period, each Monitor and each Employee will **be randomly paired**, so the **group formation changes from period to period**. The Employee can **choose a production method, either A or B**.

The Monitor is hired by an authority to **watch over the employee and report the**

production method chosen by the Employee. The wage the Monitor is going to receive in each period **is determined randomly by a computer program**. Specifically, with 1/2 of the chance, the wage is going to be 0 ECUs; With 1/6 of the chance, the wage is 30 ECUs; With 1/6 of the chance, the wage is 48 ECUs; With 1/6 of the chance, the wage is 60 ECUs. The wage structure can be summarized as follows:

Table 9: Monitor's Wage Structure

Chance	1/2	1/6	1/6	1/6
Wage (ECUs)	0	30	48	60

Once the wage is determined at the beginning of each period, the **Monitor will get to know his wage**, while the **Employee will not know the Monitor's wage**. The sequence of decisions for the Employee and the Monitor is described in detail as follows:

Step 1 Employee's production decision: The Employee can **choose a production method, either A or B**. Method A yields **10** ECUs, while method B yields **30** ECUs which is 20 ECUs more than method A. Once the Employee has made the production method choice, the Monitor will observe the choice.

If the Employee chooses production method A, **he will get 10** ECUs regardless of what report the Monitor makes.

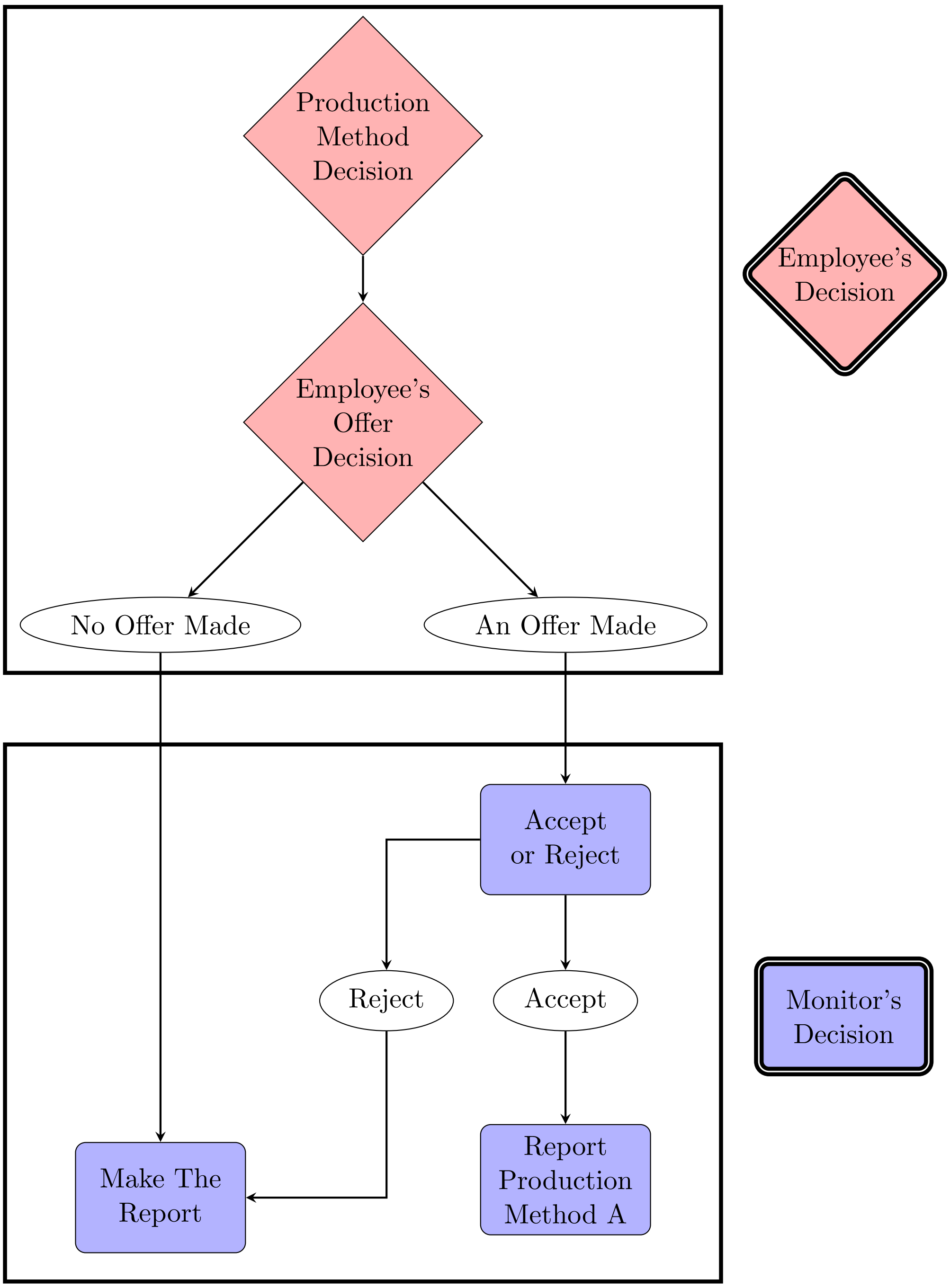
If the Employee chooses production method B, there might be a fine of 40 ECUs imposed on the Employee which depends on the Monitor's report. If the Monitor reports to the corresponding authority that the chosen method is B, the Employee will be fined for 40 ECUs. However, **if the Monitor reports that the chosen method is A**, **no fine will be imposed** even if the authority later on finds out that the Employee's chosen production method is B.

Step 2 Employee's offer decision: The Employee can **make an offer to the Monitor**, so that, upon acceptance of the offer, the Monitor will report that the chosen production method is A regardless of the Employee's actual choice of production method. If the offer is rejected, the Monitor can make the report that s/he would like to make. The offer can be any amount of ECUs that the Employee thinks it is worth to make.

Step 3 Monitor's report decision: No matter whether the Employee makes an offer or not, the Monitor needs to decide what report to make about the Employee's choice of production method. If the reported choice of production method is different from the Employee's actual choice, **the authority will detect it with a 25% chance** and **the monitor's wage is going to be deducted** in this period.

When there is an offer from the Employee, the Monitor first decides whether to accept the offer or not. **If s/he accepts the offer, s/he automatically agree to report that the Employee chosen production method is A regardless of the actual choice**. In addition, if the reported choice of production method is different from the Employee's actual choice and the authority detects it (with a 25% chance), **the monitor's wage is going to be deducted but the monitor can keep the offer received**.

The following chart shows the structure of the game.



As a Monitor, there are three different scenarios that you should consider:

(M_1) The Employee did not make an offer. Suppose the Employee chose production method A (B), you keep your wage for sure if you report A (B), while you keep your wage W with 75% and lose it with 25% if you report B (A).

(M_2) The Employee did make an offer, for example 50 ECUs, and you choose to accept the offer. Thus, you agree to report A. Suppose the Employee chose production method A, you keep your wage W for sure as well as the offer, and you get $W + 50$ in this period. Suppose the Employee chose production method B, you keep your wage W with 75% and lose it with 25%. Together with the offer, you get $W + 50$ ECUs with 75% and 50 ECUs with 25%.

(M_3) The Employee did make an offer, for example 50 ECUs, and you choose to reject the offer. It becomes the same as scenario (M_1) from now on.

As an employee, there are four different scenarios that you should consider:

(E_1) You choose production method A, and you choose do not make any offer. Then, you will get 10 ECUs in this period no matter whether the Monitor reports A or B.

(E_2) You choose production method A, and you choose to make an offer, say 50 ECUs. Then, you will get $10 - 50 = -40$ ECUs if the Monitor accepts the offer, and 10 ECUs if the Monitor rejects the offfer.

(E_3) You choose production method B and get 30 ECUs from it. You further choose not to make any offer. Suppose the Monitor reports A, no fine will be imposed on you and thus you get 30 ECUs in this period (Keep in mind that, by reporting A which is different from your actual choice B, the Monitor suffers a risk of losing his/her wage with a 25% chance). Suppose the monitor reports B, you will be imposed a fine of 40 ECUs and get $30 - 40 = -10$ ECUs.

(E_4) You choose production method B and get 30 ECUs from it. You further choose to make an offer, for example 50 ECUs. Suppose the Monitor accepts the offer, s/he agrees to report A and thus you are not imposed of any fine, and you receive $30 - 50 = -20$ ECUs. Suppose the Monitor rejects the offer, it becomes the same as scenario (E_3) from now on.

There are a few test questions before Part One actually starts. You have to answer all of them correctly in order to proceed. Please raise your hand if you have any questions.

At the end of each period, **your decisions as well as your earnings in this period will be displayed on your screen.** The game will be played repeatedly for 24 periods.

At the end of the experiment, **two out of 24 periods** in this part will be randomly selected and **the sum of your earnings in these two periods as well as the initial wealth (50 ECUs) will be your total earnings in Part One**, which will be added to your final earnings from this experiment when the experiment is completed. Then you will be shown on your screen **your earnings** in each period in Part One as well as the two periods that are selected. Since you do not know which periods are going to be selected, **the best strategy is to take each period equally important.**

Part Two

In Part Two, you are going to play the same game as you've played in Part One for another 24 periods with only one change: the roles are exchanged in this part. **The monitor in Part One becomes the Employee in Part Two, and the Employee in Part One becomes the Monitor in Part Two.** Everything else remains the same, and you can refer to Part One instruction for details.

At the end of each period, **your decisions as well as your earnings in this period will be displayed on your screen.** The game will be played repeatedly for 24 periods.

At the end of the experiment, **two out of 24 periods** in this part will be randomly selected and **the sum of your earnings in these periods as well as the initial wealth (50 ECUs) will be your total earnings in Part Two**, which will be added to your final earnings from this experiment when the experiment is completed. Then you will be shown on your screen **your earnings** in each period in Part Two as well as the two periods that are selected. Since you do not know which periods are going to be selected, **the best strategy is to take each period equally important.**

Part Three

In Part Three, you will be asked to make a series of choices. How much you receive will depend partly on chance and partly on your own choices. The decision problems are not designed to test you. What we want to know is **what choices you would make** in them. The only right answer is what you really would choose.

For each of the ten lines in the table on the computer screen, please state whether you prefer **Option L** or **Option R**. Table 1 below is an example of what you will see on your computer screen later on. Both **Option L** and **Option R** give you either a high amount of ECUs or a low amount of ECUs with different chances in different lines. In **Option L**, the difference between the high amount and the low amount is relatively small, which is $40 - 32 = 8$ (ECUs). By contrast, in **Option R**, the difference between the high amount and the low amount is relatively large, which is $77 - 2 = 75$ (ECUs).

Let's first look at Line 1. **Option L** gives you 40 ECUs with a 10% chance and 32 ECUs with a 90% chance. In other words, you will get 40 ECUs in 1 out of 10 cases and 32 ECUs in 9 out of 10 cases. By contrast, **Option R** gives you 77 ECUs with a 10% chance and 2 ECUs with a 90% chance. Therefore, if you want to stay on the safe side and get either 40 ECUs or 32 ECUs, you can choose **Option L** in Line 1. However, if you want to take the risk and try to get the 77 ECUs with a 10% chance, you would choose **Option R** in Line 1.

When you move from Line 1 to Line 2, the high amount and low amount are the same for each option, but the chances are different. In Line 2, compared against Line 1, the chance of getting the high amount increases by 10%, and the chance of getting the low amount decreases by 10%. Similarly, whenever you go down the table by one line, the chance of getting the high amount increases by 10%, and the chance of getting the low amount decreases by 10%, with Line 10 gives you the high amount with 100% chance and the low amount with 0% chance.

Notice that there are a total of ten lines in the table but **just one line** will be randomly selected for your earning. Since you do not know which line will be paid when you make your choices, **you**

Table 10: Option Task

Line	Option L (ECUs)	Option R (ECUs)	Your Choice
1	(40 with 10% chance, 32 with 90% chance)	(77 with 10% chance, 2 with 90% chance)	
2	(40 with 20% chance, 32 with 80% chance)	(77 with 20% chance, 2 with 80% chance)	
3	(40 with 30% chance, 32 with 70% chance)	(77 with 30% chance, 2 with 70% chance)	
4	(40 with 40% chance, 32 with 60% chance)	(77 with 40% chance, 2 with 60% chance)	
5	(40 with 50% chance, 32 with 50% chance)	(77 with 50% chance, 2 with 50% chance)	
6	(40 with 60% chance, 32 with 40% chance)	(77 with 60% chance, 2 with 40% chance)	
7	(40 with 70% chance, 32 with 30% chance)	(77 with 70% chance, 2 with 30% chance)	
8	(40 with 80% chance, 32 with 20% chance)	(77 with 80% chance, 2 with 20% chance)	
9	(40 with 90% chance, 32 with 10% chance)	(77 with 90% chance, 2 with 10% chance)	
10	(40 with 100% chance, 32 with 0% chance)	(77 with 100% chance, 2 with 0% chance)	

should pay attention to the choice you make in every line. After you have completed all your choices, the computer will randomly choose a line to be paid with equal chance of 1/10 for each line.

Your earning for the selected line depends on which option you chose: If you chose **Option L** in that line, you will receive **either 40 ECUs or 32 ECUs** with the **chances stated in Option L in that line**, which will be executed by a computer program. If you chose **Option R** in that line, you will receive **either 77 ECUs or 2 ECUs** with the **chances stated in Option R**, which will also be executed by a computer program.

Your earning in Part Three will be added to your final earnings from this experiment when the experiment is completed.

This is the end of the specific instructions for each part.

Final Payoff

For your reference, your **total earnings** in this experiment would be the sum of the following parts:

1. Total earnings of **Two randomly chosen binding periods** and the **initial wealth** in Part One.
2. Total earnings of **Two randomly chosen binding periods initial wealth** in Part Two.
3. Earning in Part Three.

Your total earnings will then be converted to S$ and added to your **show-up fee as your final payoff** in this experiment. You will be paid privately according to your unique subject ID.

Thank you again for your participation!