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A Note on the Impact of Law Enforcement Design on Legal Compliance and Avoidance*

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Abstract

This exploratory note presents experimental evidence on how the design of law enforcement impacts legal compliance and detection avoidance. The experiment varies the enforcer's identity and the use of fine revenue. The data show that the level of detection avoidance is indeed influenced by the design of law enforcement. There also are observable differences in legal compliance across treatments, but they are not statistically significant.

Keywords: norm compliance, law enforcement, avoidance, experiment.

JEL-Classification: C91, K42

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1 Introduction

The sanctioning of disobedience is usually understood as the price for non-compliance (Cooter 1984). It is widely held that potential offenders do not care about who puts a price on disobedience or why there is a price on it (Polinsky and Shavell 2007). This manifests itself in the literature on corruption where the individual who pays an officer to remain silent about his breaking of the law is indifferent between paying the bribe to the officer and paying the monetary sanction to the law enforcement authorities (Buccirossi and Spagnolo 2006). This reasoning culminates in the argument that corruption is not detrimental to legal compliance as long as the expected bribe does not undercut the expected sanction (Polinsky and Shavell 2001). In the same vein, the calculus of potential offenders is modeled as being unaffected by the government's objective, be it seeking rents or maximizing social welfare (Garoupa and Klerman 2002).

This paper presents evidence to the contrary. In our experiment, participants decide whether or not to steal from others and can invest in detection avoidance. We modify two different law enforcement parameters across treatments. First, the identity of the controlling authority is either a specific person or a neutral random mechanism. Second, the beneficiary of the fine for detected wrongdoing is either the harmed party or the enforcing person. In total, we consider three experimental treatments. In one setting, there are participants who have an influence on the detection process and obtain the fine if a wrongdoer is detected and sanctioned. In another setting, the detection process is random and the fine paid if a wrongdoer is detected and sanctioned goes to the participant harmed by the wrongdoing. Finally, there is an "intermediate" case in which there is a participant influencing the detection process but the fine goes to the participant harmed by the wrongdoing. The way in which we design the treatments is motivated by the very different circumstances referred to above which are nonetheless treated as indistinguishable in the theoretical literature when it comes to a potential offender's incentives.

We find that control by a person reduces investment in avoidance when compared to random control. The use the fine is put to has no impact on avoidance decisions. The difference in the share of non-compliant subjects across treatments is up to 18 percentage points. However, this difference is not statistically significant.

These findings have bearing on the actual design of law enforcement. For instance, Polinsky (1980) and Garoupa (1997) discuss the case of the private enforcement of law where the fine paid by the detected violator is used to remunerate enforcers. Our study unearths potential consequences of such a regime hitherto not taken into consideration. Furthermore, policy makers may utilize our findings by realizing that declaring the purpose to which fine revenue is put may impact the offense rate.

The paper at hand is related to different contributions in the literature. There are many studies focusing on social norm compliance (see, e.g., Fehr and Gächter 2000). Our interest is directed towards compliance with legal norms. Hörisch and Strassmair (2008) seek to test the deterrence hypothesis and find that compliance need not be monotonous in the level of the expected sanction. However, except for different compositions of the expected sanction as regards the level of the fine and the level of the detection probability, they are not interested in the design of law enforcement. Gneezy and Rustichini (2000) find that introducing a monetary fine may increase the occurrence of fined behavior in a field study. In our study, the sanctioning is a given, whereas the organization of law enforcement gains center stage. Tyran and Feld (2006) allow for the endogenous imposition of sanctions and find that this may transmit information about expected behavior. In our setting, law enforcement is exogenously given. We think that this better represents how people usually perceive enforcement systems. Furthermore, we allow violators to invest into detection avoidance. This idea has been analyzed in the theoretical literature (see, e.g., Malik 1990) and implemented in experiments (Bayer and Sutter 2009).

2 The Experiment

2.1 Design

One of three different roles is assigned to participants, A, B, or C. We are interested in player B's decisions. Initially, both player A and B are endowed with 10 points, while player C's endowment is 5 points. Thus, the initial distribution of points within a group of three roles is $(a, b, c) = (10, 10, 5)$. Next, player B decides whether or not to take 5 points from player A. If B decides to steal, the distribution is $(a, b, c) = (5, 15, 5)$. Stealing may be detected and sanctioned. Irrespective of the treatment, the initial detection probability is equal to 25 percent. However, a player B who has decided to steal can reduce the detection probability by investing in detection avoidance. Each point invested reduces the risk of being detected by 10 percentage points. Player B can invest up to 2 points in steps of 0.1 points into cover-up activities. If player B invests the maximum of 2 points, the effective detection probability is equal to five percent. If B steals from A and is dete cted, B pays a fine amounting to 10 points. At the end, all players receive full feedback and there is no repetition.

The payoffs are such that a risk-neutral player B prefers stealing to not stealing and is indifferent regarding the level of detection avoidance. Ignoring detection avoidance for the moment, stealing implies an expected payoff of 12.5 $(3/4 \cdot 15 + 1/4 \cdot 5)$ which is more than the certain payoff of 10 if player B does not steal. After stealing, player B decides about avoidance. Reducing the detection probability by 10 percentage points is equivalent to a reduction of the expected fine by 1 point, which is exactly equal to the price of the reduction of the detection probability.

We test the effect of three different treatments of norm enforcement. Two of these treatments are polar cases in the sense that they are different in two dimensions. In treatment RA, a (R)andom mechanism decides whether player B is controlled or not, and the fine paid by player B is used to (over-)compensate player A, yielding a distribution of points of $(a, b, c) = (15, 5, 5)$. In treatment CC, the fine paid by player B is used to enrich player C, yielding a distribution of points of $(a, b, c) = (5, 5, 15)$, and player C influences whether player B is controlled or not. We implement player C's influence on detection as follows. Player C selects one number out of the set $\{1, 2, 3, 4\}$. The computer randomly generates one number out of the same set where each will be drawn with equal probability of 25 percent. Player B is controlled only if the number selected by C matches the number generated by the computer. The third treatment is an "intermediate" tre atment denominated CA. In this treatment, the fine paid by player B is used to (over-)compensate player A, yielding a distribution of points of $(a, b, c) = (15, 5, 5)$, and player C influences whether player B is controlled or not. We use this treatment to disentangle the effects of our two treatment variables.

2.2 Procedures

The experiment was computerized using z-tree (Fischbacher 2007). Overall, 222 subjects participated in the experiment, 74 of them as player B. Each subject participated in only one of the three treatments. Thus, we receive a total of 74 independent observations, 23 in CA, 25 in CC, and 26 in RA.

Subjects were students within various fields of study at the University of Konstanz, recruited via ORSEE (Greiner 2004). The experiment took place in *Lakelab*, the laboratory for experimental economics at the University of Konstanz. Sessions lasted about 40 minutes. The experimental currency was points, with each point converted into 1 euro after the experiment. On average, participants earned 8.05 euros in the experiment. Before the experiment, subjects received written instructions about the experiment.[1]

3 Behavioral Predictions

Our experiment was motivated by how the theoretical literature treats set-ups comparable to RA, CC and CA, namely as being interchangeable with respect to potential offender's incentives. The design allows us to contrast norm compliance and detection avoidance given very different kinds of law enforcement.

Indeed it is our expectation that the different designs of law enforcement will elicit different kinds of behavior. Regimes RA and CA give more emphasis to the negative consequence of stealing, as they implement a compensation of the victim of detected wrongdoers. This should yield a lower level of stealing than in treatment CC. Moreover, the purpose to which fine revenue is put presumably lends law enforcement in RA and CA more legitimacy. This should influence not only the number of transgressions but also the average level of detection avoidance.

As regards the distinction with respect to the influence on detection, it can be expected that player C's influence on detection, in particular if paired with player C's consuming the

[1] An English translation of the instructions is available from the authors upon request.

fine, will be considered as less legitimate than a purely random procedure. Stated succinctly regarding the polar cases:

Hypothesis 1 *Players B will*
i) choose to steal more often and
ii) invest more in cover-up activities,
if the enforcer C decides on detection and consumes the fine (treatment CC*) than if detection is random and the harmed party benefits from the fine (treatment* RA*). Treatment* CA *will yield intermediate levels of stealing and cover-up activities.*

4 Results

In CC, 68.0 percent of players B decide to steal points from player A, while 60.9 percent of the players B do so in CA and only 50.0 percent in RA. Although the differences in proportions are considerable at face value, they are not statistically significant according to a Fisher Exact Test.[2] Regarding the difference in shares, it is our understanding that players with role B consider the norm not to steal to be more legitimate if they perceive the enforcement system as compensation-oriented (player A gets the fine if B is detected) and as anonymous (random detection).

With regard to detection avoidance, we obtain a different picture. Players B who decided to steal points in RA invest significantly more ($p < 0.1$, Wilcoxon rank-sum test, one-sided) in cover-up activities (1.66 points) than players B in CA (1.29 points) or in CC (1.34 points). Figure 1 shows the cumulative distribution functions of cover-up investments. As a consequence, when considering the polar cases, the differences in detection avoidance run contrary to what a glance at the shares of players B stealing implied. We conjecture about a possible explanation in the conclusion.

[2]The corresponding p-values are: RA vs. CC = 0.2581, RA vs. CA = 0.5675, CA vs. CC = 0.7640.

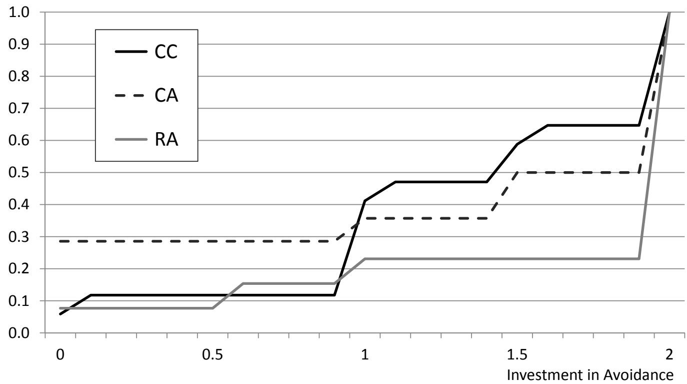

Figure 1: Cumulative Distribution Functions of Investment in Avoidance

5 Conclusion

This note investigated the impact of law enforcement design on legal compliance and detection avoidance. The designs differ in the enforcer's identity and the use to which fine revenue is put. Without yielding results with statistical significance, our data hint towards the notion that people violate the norm less often when detection is anonymous and the fine is used to compensate the harmed party than when detection is influenced by a specific enforcing person who also consumes fine revenue. At the same time, people who actually do violate the norm invest more in detection avoidance, where this difference is at statistically significant levels. The empirical evidence presented is thus in contrast to the non-discriminate treatment of the issue in the theoretical literature thus far.

We interpret the data as follows. People consider norms backed by law enforcement, which may be perceived as facilitating rent-seeking, to be less legitimate. This may explain why the share of non-compliant participants tends to be higher in that regime. Furthermore, we observe less investment in avoidance per offender in this regime. From one point of view, one might interpret this result as an indication for a high legitimation of the rent-seeking enforcement regime, which would be conflicting with our first observation. However, we rather think that this second result regarding detection avoidance reflects an underestimation of the enforcer's ability to successfully detect violations of the norm. The intervention of a person is perceived as allowing for the possibility of human error, implying that the "effective" detection probability falls short of the one with purely random control. Such possible misconception has not been studied yet, but it seems related to concepts of egocentric biases (Fellner et al. 2004).

This study is exploratory in nature. We believe that the data presented highlights that the issue we studied indeed plays a role when it comes to legal compliance and detection avoidance. Furthermore, it goes without saying that optimizing legal compliance is very important for welfare. Accordingly, we contend for more research on this issue.

Appendix: Instructions

Introduction:

Thank you for participating in this experiment.

From now on, please remain seated and stop communicating with other participants. These instructions are identical for all participants. Please read the instructions carefully. If you have any questions, please ask one of the supervisors for help. We will come to your seat to answer your questions in private.

You will be grouped with two other participants. You will not find out who these other participants are, and they will not learn anything about your identity.

(CC) One participant of each group has to make two decisions, another participant one decision. These decisions will influence the expected payoffs of all three group members. The third participant remains inactive. His payoff depends on the choices of participants authorized to make decisions and on a random draw.

(RA) One participant of each group has to make two decisions which will influence the payoff of the other group members. The other two participants remain inactive. Their payoff depends on the choice of the participant authorized to make decisions and on a random draw.

Your payoffs will be stated in points during the experiment. After the experiment, you will be payed 1 Euro in cash for each point you received.

A detailed description of the experiment:

In the experiment, the other participants and you and will take on a role. There are three different roles. These are labeled A, B, and C. Your role will be assigned to you by a random mechanism. You only decide if and what your role is authorized to decide. In the following, the participant who takes on role A will be referred to as participant A.

Participants A and B obtain endowment in the amount of 10 points, participant C in the amount of 5 points.

Participant A	Participant B	Participant C
10	10	5

Table 1: Endowment

Participant B can decide whether he wants to take 5 points from participant A or not. Participant A cannot influence participant B's decision. If participant B takes 5 points from participant A, he holds 15 points and participant A holds 5 points. Otherwise the initial allocation remains.

Participant A	Participant B	Participant C
5	15	5

Table 2: Point allocation if B takes points from A

Participant A	Participant B	Participant C
10	10	5

Table 3: Point allocation if B takes no points from A

(CC) Subsequently participant C decides on an investigation of whether participant B took points from participant A. Here is the precise procedure: Participant C decides for one number from the set $\{1, 2, 3, 4\}$. The computer picks one number from the same set at random. If the number participant C decided for and the number the computer picked match, an investigation takes place. If the two numbers do not match, there will be no investigation. However, participant B can reduce the detection probability, i.e., the chance that an investigation occurs and uncovers B's taking points from A.

(RA) Subsequently, with a 25% probability, an investigation takes place with regard to whether participant B took points from participant A. However, participant B can reduce the detection probability, i.e., the chance that an investigation occurs and uncovers B's taking points from A.

Reducing the detection probability is costly for participant B. In the following, we will refer to these costs as K. In order to decrease the detection probability by 1 percent (for example from the initial 25% to 24%), participant B has to pay 0.1 points from his account. B is allowed to spend at most 2 points from his account to reduce the detection probability. Thus, participant B can reduce the detection probability to 5%.

If the investigation shows that participant B has not taken points from participant A, it will have no effect.

(CC) If the investigation shows that participant B has taken points from participant A, participant B has to hand 10 points over to participant C. In this case, participant A has 5 points, participant B has 5 points minus his costs to reduce the detection probability, and participant C has 15 points.

(RA) If the investigation shows that participant B has taken points from participant A, participant B has to hand 10 points over to participant A. In this case participant A has 15 points and participant B has 5 points minus his costs to reduce the probability of being detected. Otherwise the initial allocation of points applies. Participant C does not make any decisions and will definitely obtain 5 points.

Participant A	Participant B	Participant C
5	15-K	5

Table 4: Point allocation in case B takes points from A but no investigation takes place or the investigation is ineffective because B invested in reducing the probability of being detected

Participant A	Participant B	Participant C
5	5-K	15

Table 5: (CC) Point allocation in case B takes points from A and C detects him doing so

Participant A	Participant B	Participant C
15	5-K	5

Table 6: (RA) Point allocation in case B takes points from A and the investigation uncovers it

Participant A	Participant B	Participant C
10	10	5

Table 7: Point allocation in case B takes no points from A (a potential investigation has no consequence)

(CC) After participants B and C have made their decisions, the experiment is over.

(RA) After participant B has made his decision and, potentially, an inspection took place, the experiment is over.

At the end of the experiment, you will be informed about

- the decision of participant B
- whether there was an investigation and whether it had any effect, and
- the amount of your payoff.

After the experiment, we will ask you to fill in a brief questionnaire. Then your payoff will be payed in cash. The exchange rate is 1 point to 1 Euro.

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