Stronger inspection incentives, less crime? Further experimental evidence on inspection games

Rauhut, Heiko

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Stronger inspection incentives, less crime?
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Heiko Rauhut

University of Zurich, Institute of Sociology
Andreasstrasse 15, 8050 Zurich, Switzerland
heiko.rauhut@uzh.ch

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Abstract

When do more severe punishments not deter crimes and when are stronger incentives for control personnel ineffective to motive control? This contribution shows when incentives for crime control have paradoxical effects. It follows from game theoretical reasoning that the opposed interests between criminals and inspectors lead to strategies, where both seek to outsmart each other. If both do so, ego's incentives only affect alter's behavior. This "strategic incentive effect" implies that higher punishments do not cause less crimes, but less inspections. This was experimentally corroborated by Rauhut (2009). The second implication is that stronger inspection incentives do not cause more inspections, but less crimes. This paper studies the second implication under farsighted strategic actors, shows its robustness by agent-based simulations of backward-looking learning and provides experimental evidence. In the laboratory experiment, 200 subjects were partitioned into "citizens" who could steal money from each other and "inspectors" who could invest in inspection to detect criminal citizens. Results confirm that stronger inspection incentives cause less crime. However, actors are less strategic than predicted: stronger inspection incentives also cause more inspections. This is discussed by differentiating between the "strategic incentive-effect", where ego's incentives only affect alter's behavior and the "own incentive-effect", where ego's incentives also affect ego's behavior. Conclusions discuss alternative models of rationality and heuristics and how the presented findings may be used for constructing novel theories on crime and social norms. Also policy implications are discussed.

Keywords: Crime, punishment, control, social norms, learning, behavioral game theory, subjective probabilities, beliefs, social cognition, heuristics, strategic incentive-effect, own incentive-effect, simulation

A certain proportion of norm violations, uncooperative actions and crimes are undetected. Examples of which are tax evasion, doping in sports, two-timing, moonlighting, fare dodging and many forms of criminal behaviors. These socially undesirable behaviors are often monitored by inspectors such as policemen, conductors, guards, night watchmen, private detectives or doping testers. In these situations, inspectors and norm violators typically have opposite incentive structures. While inspectors are rewarded for successful detections of norm violations, norm violators try to pass undetected.

A crucial problem is to find the right incentives to increase norm compliance. Standard approaches are to increase punishment severity (Becker 1968; Clarke 1995; Friedman 1995; Levitt 2002) or to increase rewards for successful inspectors (Allingham and Sandmo 1972; Andreoni et al. 1998). However, empirical deterrence research has shown that crime and control incentives do not affect respective behavior in such a simple and direct way (Cook 1980; Williams and Hawkins 1986; Nagin 1998; Doob and Webster 2003). It has been shown that punishment severity has relatively little impact on crime and subjective beliefs about the detection likelihood are much more important (Kahan 1997; Lochner 2007). This paper contributes a micro-mechanism showing how beliefs about detection probabilities of criminals and control agents interact dynamically so that they can explain some of the findings in empirical deterrence research.

My argument is based on the fact that criminals and control agents are in complete conflict, where success of one party implies failure for the other. In this "zero-sum game", rational opponents try to outsmart each other. This outsmarting means to choose a probabilistic strategy to commit a crime respectively perform inspections. A game theoretical analysis shows that perfectly farsighted actors choose their strategies such that they take the incentives of their opponents strongly into account. This produces interesting counter-intuitive predictions. More severe punishments do not affect crimes, but cause less controls and stronger inspection incentives do not affect controls but cause less crimes.

This effect that ego's incentives only affect alter's behavior will be called "strategic incentive-effect". The reason is that ego has to keep alter indifferent between her choices so that ego's behavior is only based on alter's payoffs. The effect holds if both parties make farsighted and strategic choices or if both perform at least "rational" updates of their beliefs about the detection probability and maximize their payoffs accordingly. If actors are less strategic, their own payoffs may affect their own behavior, which will be called the "own incentive-effect".[1] Empirical investigations of the inspection game may therefore not only give evidence on crime and control but also on general strategic reasoning of humans and decision-making in complex, cognitively demanding social situations.

The first experiment demonstrating this game theoretical mechanism for the case of punishment severity has been conducted by Rauhut (2009). By

[1] Nosenzo et al. (2012) introduced the term "own payoff-effect". Here, the term own incentive-effect is used and the term strategic incentive-effect has been added here to distinguish between the two.

using laboratory experiments, Rauhut (2009) has confirmed that more severe punishment causes less control. This article explores the mechanism for the case of inspection incentives. Thus, it will be shown that stronger inspection incentives cause less crime. To the best of my knowledge this is the first article testing the mechanism for inspection incentives.[2] My claim here is not to argue that this is the only mechanism at work, however, that it may explain part of what we see in the field.

In what follows, the theoretical and empirical literature about crime, punishment and control is reviewed. Then, the intuition behind the counter-intuitive predictions is explained. Subsequently, the predictions from the formalized mechanism are derived by assuming perfectly farsighted strategic decision makers. In addition, it is shown that the predictions also follow from alternative models of decision making. Here, citizens and inspectors successively update their beliefs about the detection probability and learn how to adjust their behavior to maximize subsequent payoffs. This agent-based learning model converges over time to the same predictions as the game theoretical model of perfect farsighted decision makers. This demonstrates that the predictions are robust with regard to these changes in the assumptions. The next section presents the laboratory experiment and gives empirical support for the mechanism: stronger inspection incentives lead to less crime. Conclusions are drawn for research in behavioral rational-choice and game theory, sociology of crime, and theories of normative behavior.

1 Review of empirical deterrence research

The main argument of this paper is that perceptions of detection likelihood play a major role in explaining criminal and control behavior and that at least part of the mechanisms is based on strategic reasoning. The proposed theoretical mechanism is based on the evidence on deterrence, which shows that subjective perceptions of detection have stronger effects than punishment severity on crime. Most of this empirical research is on punishment effects, which is reviewed below. This is relevant for my study on control incentives, because my study seeks to test a game theoretical mechanism, which can be tested for both sides: punishment severity and control incentives. Punishment severity was tested in Rauhut (2009) and control incentives are tested here.

Empirical deterrence research was pioneered by Gibbs (1968) and Tittle (1969), using aggregated official crime data. They examined whether the crime rates in different geographical areas could be explained by different levels of punishment severity, which was not the case. With a similar design, Sellin (1961)

[2] The paper by Nosenzo et al. (2012) is closely related in investigating rewards in inspection games. However, they investigate rewards for norm compliance and do not investigate rewards for inspectors. Therefore, their investigation is focused on studying payoff effects for criminals and not, as it is the case in my paper, payoff effects for inspectors.

estimated the deterrent effect of capital punishment, comparing murder rates in US states with death penalty with those without, finding no effect. Instead of geographical variation in punishment, Ross (1973, 1975) studied temporal variation in interrupted time-series for the case of the implementation of drunk driving laws. While there was an initial deterrent effect, it declined over time and crime rates increased again to previous levels. Sherman (1990) reviewed a number of interrupted time–series studies, concluding that such returns to initial crime levels are often observed. He termed the decline "initial deterrence decay" and the return "residual deterrence". Also interrupted time–series studies on 'tough' crime intervention policies come to a similar conclusion that there are no long–term effects of increased severity of punishment on crime. MacCoun and Reuter (1998:213), for example, state about drug control that "severity of sanctioning has little or no influence on offending". Zimring et al. (2001:105) conclude for the effects of the Three–Strike–Laws in US that "the decline in crime observed after the effective date of the Three–Strikes law was not the result of the statute".

Doob and Webster (2003) conducted an extensive meta review with similar conclusions:

> "A reasonable assessment of the research to date–with a particular focus on studies conducted in the past decade–is that sentence severity has no effect on the level of crime in society. . . . Particularly given the significant body of literature from which this conclusion is based, the consistency of the findings over time and space, and the multiple measures and methods employed in the research conducted, we would suggest that a stronger conclusion is warranted. More specifically, the null hypothesis that variation in sentence severity does not cause variation in crime rates should be conditionally accepted." (Doob and Webster 2003:p.143, p.187).

This indetermination of empirical results poses the problem to find the relevant factors for crime deterrence. Already Sherman (1993:445) suggested to formulate more specific theories of deterrence: "Widely varying results across a range of sanction studies suggest a far more useful question: under what conditions does each type of criminal sanction reduce, increase, or have no effect on future crimes?" A promising way is to shift the focus of deterrence research from objective to cognitive aspects, or, in other words, from severity to certainty of punishment: "One of the most important issues for further research . . . is the way in which potential criminals acquire information about criminal opportunities and the effectiveness of the criminal justice system." (Cook 1980:211) This *cognitive turn* was motivated by the weak findings of deterrence and by the skepticism regarding official data.

Also official data supported the predominant role of perceptions. Ehrlich (1975) correlated the rate of capital murders with executions in US between 1933 and 1969. He found that execution probability was correlated with murders. Later, Grogger (1991:308) analyzed official arrest records in California and concluded that "the results point to large deterrent effects emanating from increased certainty of punishment, and much smaller, and generally insignificant effects, stemming from increased severity of sanction.

However, analyses with official data rely on the assumption that the relation between the dark figure of undetected crimes and the officially detected crime rate is constant over the units of the analysis. To investigate this assumption about undetected crimes, cross–sectional and longitudinal self–report surveys were conducted. Respondents were asked about their perceptions of certainty and severity of punishments and their prior and prospective offending behavior. The first perceptual deterrence studies appeared in the early seventies (Jensen 1969) and were continued in the eighties (cp. Nagin 1998). For example, Grasmick and Bryjak (1980) conducted a survey of city residents about their risk perceptions of arrest for offenses such as a petty theft, drunk driving, and tax cheating and whether they thought they would commit each of these acts in the future. On one hand, most of these perceptual studies could replicate the findings from official data that severity of punishment has only weak or no effects on crime. On the other hand, it could be shown that certainty and not severity of punishment is an important deterrent of crime, as Paternoster (1987) concluded in the first extensive review of perceptual deterrence research. Kahan (1997:380), ten years later, found the same: "Empirical studies ... conclude that certainty of conviction plays a much bigger role in discouraging all manner of crime than does severity of punishment."

Two years later, Von Hirsch et al. (1999:47) contributed an extensive review on severity and certainty of punishment, reaching a comparable conclusion:

> "There is ... a notable difference between certainty and severity effects. The current research ... indicates that there are consistent and significant negative correlations between likelihood of conviction and crime rates. ... Such a pattern is ... consistent with an hypothesis of ... deterrence with respect to certainty of punishment. ... The evidence concerning the severity of punishment is less impressive. Present association research, mirroring earlier studies, fails ... to disclose significant and consistent negative associations between severity levels (such as ... duration of imprisonment) and crime rates."

Also Braithwaite (1989:69) concluded that "the criminological literature on deterrence ... shows reasonable support for an association between certainty of criminal punishment and offending, but little support for the association between crime and the severity of punishment." Pogarsky and Piquero (2003:97ff.) argued later similarly that "three such perceptions are central to deterrence theory: those of the certainty, severity, and celerity of potential punishment. ... Of the three sanction threat perceptions recognized by deterrence theory, certainty has by far been found to be most influential."

Also perceptual studies on deterrence replicated these patterns. Matsueda et al. (2006) used surveys of self–reports of perpetrators to measure certainty of punishment. They used the Denver Youth Survey (DYS), a longitudinal study of delinquency and drug use in high risk neighborhoods. Two measures of certainty of punishment were used. First, certainty was measured by the ratio of the number of times ever arrested or questioned by the police to the number of all self-reported crimes in the past year. Second, they use unsanctioned offenses, measured by the number of self-reported offenses committed by those who have not been questioned or arrested by the police. They found as well that certainty had greater impact on crime than severity. Lochner (2007) used self-reported beliefs about the probability of one's own arrest from two sources of longitudinal data; the 1997 Cohort of the National Longitudinal Survey of Youth and the National Youth Survey. He concludes that "[t]here is robust evidence in favor of deterrence theory based on an individual's perceived probability of arrest. Estimates suggest that the effects of differences in beliefs about the probability of arrest play an important role in explaining differences in criminal participation." (Lochner 2007:459)

In conclusion, there has been a cognitive turn in the literature on crime and punishment. It is not objective risks which matter, but subjective perceptions. In particular, certainty of punishment matters and, to a lesser extent, subjective perceptions of punishment severity. This résumé is also in line with Wright et al. (2004) who assert that deterrence perceptions have the greatest effect. Furthermore, deterrence may work more likely for planned criminal activities, such as theft, fraud or deception and be less effective for crimes out of passion. The reported laboratory experiments hereafter also represent rather planned criminal activities and have larger external validity for these kinds of norm violations.

2 A game theoretical perspective on crime, control and punishment

2.1 The intuition of the model

The empirical evidence that beliefs about detection probabilities of criminals and control agents are important determinants of crime and control motivate the following game theoretical model. The logic of the so-called "inspection game" (Tsebelis 1989, 1990; Rauhut 2009; Rauhut and Junker 2009) is based on the fact that the payoffs of criminals and control agents are in complete conflict, where success of one party implies failure for the other. Rational and selfish citizens will commit crimes when they believe not to be caught and rational and selfish control personnel will make inspection efforts when they believe criminals will commit crimes. This payoff structure is formally called a "zero-sum game".

The strategic incentive-effect occurs for perfectly farsighted actors right from the start. Farsighted means that actors form a belief about the future behavior of their opponent and perform a payoff-maximizing choice given their belief. This actor type is also called "forward-looking" (Macy and Flache 2009). The opposed incentives imply that only one party can win. Hence, rational opponents will try to outsmart each other. This outsmarting means to choose a probabilistic strategy to commit a crime or to perform inspections with a certain likelihood. Strategic citizens and enforcers try to foresee the others' choices and respond to the believed action in the best way. If both agents are perfectly farsighted and believe their opponents to be so as well, they anticipate the complete course of the dynamics with the implication to take the incentives of their opponents strongly into account. Therefore, both make their behavior only contingent on opponents' incentives, leading to the "strategic incentive effect" that ego's incentives only affect alter's behavior. This has two implications: More severe punishments do not affect crimes, but cause less controls and stronger inspection incentives do not affect controls, but cause less crimes.

The strategic incentive-effect also occurs for actors who are not farsighted but who learn the behavior of their opponent by experience. These "rational learners" form a belief based on their experience and perform a payoff-maximizing choice given their experience. This actor type is also called "backward-looking" (Macy and Flache 2009). The intuition of the game theoretical dynamics can be better understood for backward-looking learning. This is why I will now schematically walk through the learning process and show why ego's incentives only affect alter's behavior.[3]

The stylized dynamics of backward-looking learners is as follows. If punishment severity is increased, criminals will reduce their level of crimes. After a while, the mean crime rate will drop below the threshold where control does not pay off any more for inspectors. At that time, inspectors will reduce their level of control. After a while, the mean inspection rate will drop below the threshold where it becomes again profitable for criminals to start committing more crimes again. After some time, the mean crime rate increases again above the threshold, where control becomes profitable for inspectors and they start controlling again. Consecutively, the control rate increases again up to the point, where it exceeds the threshold where crime pays off for criminals and so on. This process goes on in cycles and it will be shown in the simulation section that the dynamics stabilizes at the same equilibrium as for farsighted actors: more severe punishment has the long-term effect that control is reduced and crime goes back to the initial level.

The same learning dynamics holds for increased control incentives.[4] When

[3] The precise dynamics is presented in the simulation section.

[4] Increased control incentive may be represented in the real world by higher rewards for detection success in terms of higher salaries or more reputation. They may also materialize in less costs, expenditure or efforts for completing the same level of control, for example through a more efficient organization or more technical equipment. All these incentives are captured here in generalized abstract control incentives and costs.

control incentives are increased, inspectors will start controlling more. After some time, the mean inspection rate exceeds the threshold where it does not pay off any more to commit crimes and criminals reduce their level of crime. Consecutively, the crime rate drops until it deceeds the threshold where it is no longer profitable for inspectors to control and they reduce their control level. It can be easily shown that these cycles stabilize at the starting point of the control rate, but at a lower level of crime.

In sum, forward-looking and backward-looking rationality predict equivalent dynamics. (1) More severe punishment does not affect crime but reduces control and (2) stronger inspection incentives do not affect inspections but reduce crimes.[5] The described dynamics — in which individual citizens and enforcers make reasonable decisions given the information they have — predicts the "strategic incentive effect" for strategic, farsighted agents in the first time step and for "unstrategic", but rational learners after some time. Perfectly farsighted agents anticipate the complete course of the dynamics at once and rational learners go through some learning periods after which they show the same prediction in their aggregated mean behavior over time.

The assumption that control personnel receive direct monetary incentives for each successful detection is worth further discussion.[6] While inspectors may often not be directly rewarded for every single inspection, they often receive either indirect or irregular rewards for succesful work. Police officers, public prosecutors, drug inspectors and even professors checking for plagiarism are often motivated by improvements in their long-term career prospects and also by enhanced prestige, reputation or accredited expertise for their inspection success. These examples give evidence for the assumption that inspectors are generally motivated by successful crime detection.

There is another assumption worth to be discussed. It is assumed that there is no policy intervention. The described dynamics holds for the case that criminals and enforcers can freely decide their level of activity and their efforts. This makes sense in order to show the general dynamics of how incentives affect behavior in crime control systems. In reality, it may well be that additional factors come into play. For example, if inspectors control little and "lay back" in regimes with strong punishments, this may be reported to the press and to higher authorities and may lead to negative reviews of the efficiency of the enforcement personnel. These increased public and intra-organizational pressures may motivate inspectors to start controlling more again. Or the negative pub-

[5] Note that this mechanism also holds for decreasing inspection costs. Less inspection costs would imply that criminals anticipate more inspections, commit less crimes, which in turn triggers inspectors to make less effort in catching criminals. Reversely, increasing inspection costs would imply that criminals anticipate less inspections, commit more crimes, which in turn triggers inspectors to make more effort in catching criminals.

[6] In this article, inspection incentives are primarily referred to inspection benefits. The exact incentive structure is defined in the modeling part of the paper. There, incentives are subdivided into inspection rewards for successful inspection and inspection costs for inspection efforts and expenditures.

licity could lead to budget cuts of the police with the consequence of even less controls. Both consequences would be negative for control personnel so that they may anticipate them and be motivated to remain their efforts to catch criminals. However, these arguments imply additional negative payoffs for inspectors: negative press, complaints from their chiefs, and imminent budget cuts. These additional payoffs could either be subsumed in the general, constant payoffs for choosing control or no control. Then the model would hold and just other control payoffs had to be assumed to derive the dynamics. Alternatively, these factors could be taken into account as dynamically changing external payoffs. This would be another complication of the model and go beyond the scope of this paper to show the interplay between constant payoffs and dynamic behavior in crime control systems.

2.2 Incentive structure of citizens and inspectors

The described logic can be formalized as follows. Consider two different groups of actors, where members of one group can decide to commit a crime and members of the other to inspect. The first ones are called *citizens* and the second ones *inspectors*. Citizens (indexed with $i \in I$) earn g for the crime, but face punishment costs p if caught. Inspectors (indexed with $m \in M$) can invest inspection costs k to detect the action of the citizen and earn the reward r for a successful detection.[7]

For the case that none of the two take action, citizens' and inspectors' payoffs are normalized to zero. For citizens, undetected crime is profitable ($g > 0$). This simply means that getting something from crime is better than the status quo, where nobody acts. Punishment costs are higher than profits from crime ($p > g$) so that the ranking $p > g > 0$ holds. This means that payoffs are higher for not committing crimes than to commit a crime and receive a punishment for sure. For example, a bike thief would be better off not to steal a bike than to steal it, keep it and receive a fine. Or a tax payer would be better off not to evade taxes than to make profits from tax evasion and receive a fine. Or a polluter would be better off not to waste the environment than to waste it and receive a fine. Note that the payoffs from crime and punishment are meant to be general and can include material and immaterial payoffs, such as bad conscience for violating norms and positive emotions and reputational gains from norm compliance.

In most cases, this payoff ranking should hold because otherwise, most peo-

[7] Note that this model assumes inspection to be always successful, i.e. inspection yields always reward r if the citizen committed a crime. This is a simplifying assumption which may often not be the case. An additional parameter could be the likelihood that inspection is successful and the criminal is detected. In fact, such a parameter would not change model predictions substantially (see Groeber and Rauhut 2010). Essentially, this likelihood yields a weighted instead of a fixed inspection reward. If actors form false beliefs about detection likelihoods, however, implications do change (see Rauhut 2013; Diekmann et al. forthcoming).

ple would perfrom the criminal action in question.[8] Moreover, if most citizens committed a crime no matter what, all control personell would inspect them to reap off their profits from successful detection. This would have the consequence that we would observe a crime rate of 100 % and an inspection rate of 100 %, which is highly implausible.

For inspectors, inspection is costly and successful detection is rewarded. Rewards are larger than costs so that the ranking $r > k > 0$ holds.[9] This strategic interaction situation is illustrated by the 2×2 matrix in Table 1.

[Table 1 about here.]

Table 1 implies the following. The citizen's best response is to commit a crime if she is not inspected and not to commit a crime if she is inspected. The inspector's best response is to inspect if the citizen is criminal and not to invest inspection costs if there is no crime. There is, however, no pure strategy. This means that there is no stable situation in which both keep the chosen action if both know what the other one is doing. The instability of the system is denoted by the arrows in Table 1, cycling from upper left to lower left to lower right to upper right and again back to upper left.

To clarify why there are no pure strategies in equilibrium, the following consideration may help. A criminal who commits a crime no matter what will be sooner or later sent to prison. On the other hand, a "big-brother-state" who invests in an omnipresent control regime will be highly inefficient because the crime rate will drop and control activities will no longer be worthwhile. Conclusively, both parties will choose a probabilistic instead of a fixed strategy.

2.3 Game theoretical predictions

The game theoretical prediction is that actors choose *mixed* instead of pure strategies. More formally, let s_i denote the probability that citizen i commits the crime and c_m the probability that inspector m will inspect citizen i. A value of zero means no action (no crime and no inspection), a value of one means a

[8] More formally, if punishment would not be greater than the gains from crime, crime would be a dominant choice in a game theoretical sense. This means, citizens would commit a crime regardless of whether they will be detected or not. This follows from the payoff function of the citizen: If $g > p$, then $g - c_m p > 0$ for any inspection probability c_m.

[9] If the reward for successful inspections would not be greater than the inspection costs, it would be a dominant choice for inspectors not to inspect. This means, inspectors would not inspect if citizens commit a crime nor if citizens do not commit a crime. This follows from the payoff function of the inspector: If $k > r$, then $s_i r - k < 0$ for $s_i = 0$ and for $s_i = 1$. This means the inspector receives payoff $-k < 0$ if the citizen does not commit a crime and $r - k < 0$ if the citizen commits a crime. The best response to all actions of the citizen is therefore not to inspect. As a consequence, it would also be a dominant choice for the citizen to commit a crime, regardless what the inspector does. This implies that the crime rate would be 100 % and the inspection rate 0 %. Therefore, it does not make sense to assume that inspection rewards are smaller than inspection costs.

fixed action (crime or inspection) and values between zero and one mean that the actor chooses a probabilistic (mixed) strategy.

This exact definition of strategies allows to define the payoff functions for citizens and inspectors in the following way. The payoff function π for citizen i who plays against inspector m is given by

$$\pi_i(s_i, c_m) = s_i(g - c_m p).$$

The payoff function ϕ for inspector m who plays against citizen i is

$$\phi_m(s_i, c_m) = c_m(s_i r - k).$$

The payoff functions consist of the payoffs from Table 1 and the strategies specified above. For example, if citizen i chooses to commit a crime ($s_i = 1$) and the inspector chooses to inspect citizen i ($c_m = 1$), then the payoff for citizen i is $g - p$ and the payoff for inspector m is $r - k$. Another example is that the citizen chooses a probabilistic strategy of 50 % to commit a crime ($s_i = 0.5$) and the inspector does not inspect ($c_m = 0$). Then, the citizen's payoff is $0.5 \times g$ and the inspector's payoff is 0.

The best response is the best strategy for a given choice of the opponent. Best responses of citizens are calculated by the first partial derivative of the payoff function, i.e. $\frac{\partial \pi_i}{\partial s_i}$:

$$s_i^*(c_m) = \begin{cases} 1 & \text{if } g - c_m p > 0 \\ [0,1] & \text{if } g - c_m p = 0 \\ 0 & \text{if } g - c_m p < 0. \end{cases} \tag{1}$$

Equation 1: Citizen's best crime responses for given inspection decisions

From the first line, it can be seen that the citizen's best response is to commit a crime for sure if the expected payoff is positive, thus if the payoff from crime g is higher than the expected loss from punishment ($c_m \times p$). The expected loss from punishment is simply given by the probability that the inspector chooses to inspect (c_m), which is multiplied with the punishment cost p. From the third line, it can be seen that the citizen's best response is to commit no crime for sure if the expected payoff is negative, thus if the payoff from crime g is lower than the expected loss from punishment ($c_m \times p$). The second line shows that the citizen is indifferent for the case that the payoff from crime g is equal to the expected losses from punishment ($c_m \times p$). Indifference means that any probability to commit a crime yields the same payoffs for the citizen. Thus, the citizen's best response is anything between no crime ($s_i = 0$), crime with some probability ($0 < s_i < 1$) and crime for sure ($s_i = 1$).

Inspector's best responses m are calculated in a similar way, using the first partial derivate of the inspector's payoff function $\frac{\partial \pi_m}{\partial c_m}$. This yields

$$c_m^*(s_i) = \begin{cases} 1 & \text{if } s_i r - k > 0 \\ [0,1] & \text{if } s_i r - k = 0 \\ 0 & \text{if } s_i r - k < 0. \end{cases} \tag{2}$$

Equation 2: Inspector's best inspection responses for given crime decisions

From the first line, it can be seen that the inspector chooses to inspect for sure ($c_m = 1$) if the expected payoff from inspection ($s_i \times r$) is larger than the inspection costs k. The expected payoffs from inspection is simply given by the probability that the citizen chooses to commit a crime (s_i), which is multiplied with the reward for succesful inspection r. From the third line, it can be seen that the inspector's best response is not to inspect for sure if the expected payoffs from inspection ($s_i \times r$) are lower than the inspection costs k. The second line shows that the inspector is indifferent for the case that the payoff from inspection ($s_i \times r$) is equal to the inspection cost k. Thus, any probability to choose inspection yields the same payoffs for the inspector. Thus, the inspector's best response is anything between no inspection ($c_m = 0$), inspection with some probability ($0 < c_m < 1$) and inspection for sure ($c_m = 1$).

The best response analysis reveals that there are no pure strategies in equilibrium. If the citizen chooses to commit a crime for sure ($s_i = 1$), the inspector's best response is to inspect for sure ($c_m = 1$), for which the best response for the citizen is to commit no crime for sure ($s_i = 0$), for which the best response for the inspector is to perform no inspection for sure ($c_m = 0$). Therefore, both have to choose a probabilistic strategy. The only stable strategy combination is that both are indifferent between their choices. The second line of the best response functions in equations 1 and 2 indicate the indifference conditions. The equilibrium for citizens is that they choose crime with probability

$$s_i^* = \frac{k}{r}. \tag{3}$$

Equation 3: Predicted crime rate

This shows that the probability to commit a crime only depends on the inspector's payoffs, thus on the inspection cost k and the inspection reward r. As indicated earlier, this effect will be called the "strategic incentive-effect". This has the counter–intuitive implication that punishment does not affect crime rates. Crime rates are only affected by inspection incentives and inspection costs.

The equilibrium in mixed strategies for inspection is calculated by the indifference condition of the citizen. Thus, the inspector chooses to perform an inspection with probability

$$c_m^* = \frac{g}{p}. \tag{4}$$

Equation 4: Predicted inspection rate

Therefore, the probability to perform an inspection only depends on the citizen's payoffs, thus on the gains from crime g and on the punishment costs p. Hence, the "strategic incentive-effect" also holds for inspections. This has the counter–intuitive implication that inspection incentives do not affect inspection rates. Inspection rates are only affected by criminal gains and punishments.

There are two interesting, counter–intuitive predictions from the game theoretical model. The first one is that punishment does not affect crime. Paradoxically, more severe punishment reduces control activities. This implication has already been experimentally confirmed by Rauhut (2009). The second counter–intuitive prediction is that inspection incentives do not affect inspection behavior. Paradoxically, stronger inspection incentives only reduce criminal behavior. There is no empirical investigation to date to test this implication. This paper is therefore the first to test this implication by laboratory experiments with the following hypotheses.

Hypothesis 1. *The level of inspection incentives has no effect on inspection behavior*

Hypothesis 2. *The stronger the inspection incentives the lower the crime rate*

The logic of mixed strategies may still appear as a complicated reasoning and rely on strong assumptions of rationality. Therefore, the next subsection shows how the same hypotheses can be derived from simple learning models assuming less rationality and strategic reasoning.

3 Simulation of learning dynamics using subjective beliefs about detection probabilities

3.1 Motivation of the learning model

The above described game theoretical reasoning has two critical assumptions. (1) Actors anticipate the behavior of their opponent correctly. (2) Both know the payoffs of their opponents. In this section, it will be shown that model predictions are robust if these assumptions are relaxed. A learning model is introduced, where actors are not perfectly farsighted but learn the detection probability by experience. This relaxes the first assumption about farsighted and correct anticipations of opponents' behaviors. The second assumption is also relaxed such that actors in the learning model do not know the payoffs of their opponent. In the learning model, actors just react on the previous choices of their opponent by a best, payoff-maximizing response. The learning model can be described as backward-looking rationality since actors adapt their behavior with a best response to the past behavior of their opponent.[10]

Besides showing the robustness of the game theoretical reasoning, the second purpose of the learning model is to make the strategic reasoning better understandable by walking through the dynamics of two opposing opponents. This provides a good intuitive understanding of the strategic interaction structure and its implications for the behavioral dynamics.

3.2 Best responses for given subjective beliefs

Let us assume that citizen i has an initial belief about her detection probability ($\hat{c}_i^0$) in period 0. Let us further assume that the citizen calculates her expected payoff from crime using her subjective belief about the detection probability ($g - \hat{c}_i^0 \times p$). This takes into account the gains from crime g and punishment p times the subjective detection probability $\hat{c}_i^0$ in period 0. Finally, let us assume that the citizen commits a crime if her expected payoff from crime is positive ($g - \hat{c}_i^0 \times p > 0$). Note that this is simply the best response given the subjective belief about the detection probability. This takes the citizen's best response from equation 1 and replaces the objective choice of the inspector (c_m) with the citizen's subjective belief about the inspector's choice ($\hat{c}_i$).

Likewise, let us assume that inspector m has an initial belief about her probability to detect a criminal citizen ($\hat{s}_m^0$) in period 0. The inspector calculates her expected payoff from inspection using her subjective belief about the detection probability ($\hat{s}_m^0 r - k$). This takes the inspection cost k into account and the rewards for successful inspection r times the subjective belief that the citizen has committed a crime ($\hat{s}_m^0$) in period 0. The inspector performs an inspection if her expected payoff from inspection is positive ($\hat{s}_m^0 r - k > 0$). Note that this is the best response for her given subjective belief about the detection probability. This uses the inspector's best response from equation 2 and replaces the objective choice of the citizen (s_i) with the inspector's subjective belief about the citizen's choice ($\hat{s}_m$).

[10] This model is also known as fictitious play (Fudenberg and Levine 1998) or Bayesian updating. Note that there are also alternative backward-looking learning models, some of which are described in Macy (1991, 1993) and Macy and Flache (2002).

3.3 Belief updates and learning

Let us assume the following learning dynamics. The citizen observes the inspector's choices and computes the average inspection rate over all past periods. The citizen's belief about the detection probability in the current period t is the average inspection rate until the current period ($\hat{c}_i^t$). The citizen commits a crime if the expected payoff from crime is positive for the current belief about inspections.

The inspector follows the same learning dynamics. The inspector observes the citizen's choices and computes the average crime rate over all periods. The inspector's belief about the detection probability in the current period t is simply the average crime rate until the current period ($\hat{c}_m^t$). The inspector performs an inspection if the expected payoff from inspection is positive for the current belief about the detection probability.

Note that the dynamics does not crucially depend on the specific version of updating. Here, all previous rounds are used with equal weight to compute the current belief about the detection probability. One may argue that humans may remember the most recent interactions very well, but discount those which are long ago. Robustness checks have been done by using alternative weights of previous rounds, such as logarithmic discounting. The results are qualitatively similar. The simulations converge to the same equilibria. For more robustness checks of simulation assumptions in a related inspection game, see also Rauhut and Junker (2009).

3.4 Initial beliefs and payoff parameters

The following initial beliefs are used for the shown simulation runs. The citizen has the (optimistic) initial belief that her detection probability is 0 % ($\hat{c}_i^0 = 0$) with the consequence that the citizen commits a crime in the first period. The inspector has the (optimistic) initial belief that her detection probability is 100 % ($\hat{c}_m^0 = 1$) with the consequence that the inspector performs an inspection in the first period.

Note that the specific implementation of initial beliefs does not affect the qualitative findings nor the equilibria to which the simulations converge. Whereas different initial beliefs change the early dynamics of the simulation, these idiosyncracies level off after some rounds and the system behaves similar, regardless of initial conditions.

[Table 2 about here.]

The following payoff parameters are used for illustration.[11] Simulation runs

[11] Note that these payoff parameters are the same as the payoff parameters in the laboratory experiment described in the next section.

with little inspection incentives ($r = 6$) are compared with those with strong inspection incentives ($r = 25$). All other parameters are hold constant over all simulation runs (see Table 2). The other parameters are chosen such that in the little inspection incentive condition, the inspector inspects if she expects at least a probability of crime of 83 %. In the strong inspection incentive condition, an expected probability of crime of at least 20 % is sufficient for the inspector to perform an inspection. These thresholds are denoted in Table 2 by "threshold for best response". Citizen's payoffs remain unchanged in both simulations. The citizen commits a crime if her subjective expected probability is at most 50 % that the inspector performs an inspection. Citizen's thresholds are denoted in Table 2 by "threshold for best response".

3.5 Simulation results

Figure 1 shows the results of four simulation runs for the given parameters. There is a short (panel A) and a long simulation run (panel C) for strong inspection incentives. Likewise, there is a short (panel B) and a long simulation run (panel D) for little inspection incentives. In all panels, black solid lines refer to decisions of citizens and gray dashed lines to inspectors. The white lines refer to the best response thresholds for citizens and inspectors. In the middle (between A—B and C—D), it is denoted whether the threshold refers to the citizen's or the inspector's best response.

[Figure 1 about here.]

The learning dynamics are described by using the simulation run in panel A as the main example to explain the dynamics. The citizen starts with a believed inspection probability of 0 % and commits a crime. The inspector has a believed crime probability of 100 % and performs an inspection. The citizen is detected, receives a punishment and updates her belief about the inspection probability to 50 %. This is the case, because the average belief of the two periods is 50 % (i.e. $(0 + 1)/2 = 0.5$). Because the citizen only commits a crime if the expected inspection rate is below 50 %, she chooses not to commit a crime in the next period.

The first period for the inspector works as follows. The inspector has a believed crime probability of 100 % and performs an inspection. The inspector detects the citizen. Because the inspector started with an expectation of 100 % crime in the first period and has observed a crime in the first period, her belief about the crime probability remains at 100 %. This is the case, because the average belief about the two periods is 100 % (i.e. $(1 + 1)/2 = 1$). Because the inspector performs an inspection if her expected crime probability is at least 20 %, her expectation is above her threshold and she chooses to perform an inspection in the next period.

From the second period onwards, the inspector inspects and the citizen does not commit crimes. The inspector's believed crime probability decreases and the citizen's believed inspection probability increases accordingly. In the eleventh period, the inspector's believed crime probability drops below the inspector's threshold of 20 %. From then onwards, the inspector does not perform inspections and the citizen does not commit a crime. This leads to a decrease of the citizen's believed inspection probability over time. In the twenty-third period, the citizen's believed inspection probability drops below the threshold of 50 %. From then onwards, the citizen commits crimes. This leads to an increase of the inspector's believed crime probability over time. In the twenty-seventh period, the inspector's believed crime probability rises above the inspector's threshold of 20 %. From then onwards, the inspector performs inspections and the citizen commits crimes. The citizen's believed inspection probability increases. In the thirty-third period, the citizen's believed inspection probability rises above the citizen's threshold and she does not commit a crime anymore. From then onwards, the inspector performs inspections and the citizen does not commit crimes. Accordingly, the inspector's believed crime probability decreases over time.

Panel C in Figure 1 shows the dynamics of panel A over 500 periods. Instead of beliefs, running means of crimes and inspections are shown.[12] The average crime rate converges to the threshold of the inspector and the average inspection rate converges to the threshold of the citizen. Hence, ego's incentives only affect alters's behavior (i.e. the strategic incentive effect). Panels B and D confirm the same logic for little inspection incentives. Little inspection incentives do not affect inspection, but cause higher crime rates (i.e. the strategic incentive effect).

3.6 Comparison of simulated learning dynamics with game theoretical predictions

Referring to the game theoretical predictions, it can be seen that the learning dynamics converge to the same results over time. The equilibria in mixed strategies predict for the case of strong inspection incentives a crime rate of $s_i^* = \frac{k}{r} = 0.2$ and an inspection rate of $c_m^* = \frac{g}{p} = 0.5$. The equilibria in mixed strategies for the case of little inspection incentives predict a crime rate of $s_i^* = \frac{k}{r} = 0.83$ and an inspection rate of $c_m^* = \frac{g}{p} = 0.5$ (see equations 3 and 4). This is exactly where the learning models converges to over time.

It can be shown that this is generally the case. Over time, these learning models generate the same outcomes as the game theoretical equilibria in mixed strategies (Rauhut and Junker 2009). If more than two actors are simulated, the dynamics converges much faster to game theoretical predictions (Rauhut

[12]The running mean for crime is the average crime rate until the current period. The running mean for inspection is computed accordingly.

2009). The simulations, therefore, show that the game theoretical predictions are robust to different assumptions of decision making. Further, studying the dynamics by simulations of simply two players helps understanding the logic of mixed strategies. In a nutshell, the simulation shows how relatively slow rational learners generate similar outcomes compared to perfectly farsighted actors who anticipate the whole 500 periods at once in their first move.

There are additional insights from analyzing random fluctuations and noise in agents' learning and decision making. If there is little noise, oscillations are less pronounced and the system converges notably faster to game theoretical predictions (Rauhut and Junker 2009). If randomness in learning and belief updates is strong, however, predictions subsequently shift from the strategic incentive-effect to the own incentive-effect, the more random agents learn (Rauhut and Junker 2009). In other words, if beliefs about the detection probability are largely guesswork and independent from knowledge or experience, actors make decisions based on their own payoffs and do not take their opponent's payoffs into account. More generally, with decreasing capability to process information and experiences, predictions shift from strongly strategic to less strategic decision making, which only takes own payoffs into account. This randomness in agents' learning can also be called "bounded learning" (Rauhut and Junker 2009).

If even more randomness is considered so that the whole decision making process becomes random, predictions subsequently shift towards the mean value of the random distribution. In the case of a standard uniform distribution, agents subsequently make decisions close to 50 %. These random fluctuations may also be used to explain behavioral choices in inspection games (Rauhut and Junker 2009).

4 Design of the laboratory experiment

4.1 Crime and inspection in the laboratory

The proposed game theoretical mechanism is difficult to test in the field. It is easier for researchers to get information about crime policy than about actual enforcement efforts by control personnel. Relatedly, it is problematic to get precise data on offenders' reactions to actual enforcement levels. Furthermore, the dynamic interplay can hardly be observed in the field. These data limitations in conjunction with the problem of third factors causing spurious correlations show the difficulties of tracking feedback loops between criminal activities and control efforts in the field. There is also an endogeneity problem: do high crime rates affect the level of punishment severity or does punishment severity drive the level of crime? In the laboratory, these methodological concerns can be addressed.[13]

For testing the predictions from the inspection game, the original inspection game from Table 1 was extended to enhance construct validity of crime and inspection in the laboratory.[14] Subjects should associate with the abstract game the interaction between criminals and police officers. Therefore, the original inspection game was extended from two to four actors. There were two citizens, who could both steal money from each other and one "inspector" was allocated to each citizen (see Figure 2). The terms "players" and "inspectors" were used in instructions to avoid value-laden or technical terms.

The allocation of one inspector to one citizen was chosen to foster equal statistical power for citizens and inspectors. Note that in society, there are many citizens and few police officers. In order to increase construct and ecological validity of crime and control in the laboratory, one could think of an implementation that considers an experimental session with 20 subjects, consisting of 19 citizens and 1 inspector. While this may be a scenario somewhat closer to reality, such an experiment would yield considerably less statistical power for inspectors than for citizens. The very first inspection game experiment used such a design (Rauhut 2008). However, the greater ecological validity is clearly bought at the expense of lower statistical power for the behavior of inspectors. For a more extensive discussion of construct and ecological validity concerning inspection game experiments, see Rauhut and Winter (2012).

[Figure 2 about here.]

In the four-subject setup, criminal citizens earned the criminal gain g and their victims suffered the loss l with $(l > g)$. Because victimization losses were higher than criminal gains, this generated a prisoner's dilemma among citizens. This captures the collective inefficiency of most criminal activities. It can be shown that the equilibria in mixed strategies are the same in the simpler and in the more complex model (see the Appendix for details).

4.2 Qualitative post-experimental group interviews

Qualitative interviews were used to test whether subjects actually interpreted the incentive structure as a typical situation between criminals and inspectors. There were five sessions, after which the interviews were conducted. Participation was voluntary. All volunteers of one session were allocated to the same group, yielding five discussion groups. Fourteen persons participated in total; six had the role of citizens and eight the role of inspectors in the preceding

[13]For other laboratory experiments on punishment effects on crime not related to a game theoretical argument, see e.g. Miranne and Gray (1987). For a discussion and review of the usefulness of laboratory experiments to study crime see Horne and Rauhut (2013).

[14]For a thorough discussion of construct validity of laboratory experiments on crime and punishment, see Rauhut and Winter (2012).

inspection game experiment. The interviews were conducted as semi-structured group interviews. They followed a guideline with prepared questions, which initiated the group discussion. The questions asked about understanding of the rules of the game, emotions during and after decision making, reasons for respective strategy choices and associations of everyday situations resembling the experimental incentive structure. The interviews were audio- and video-taped. This material was fully transcribed.

The interviews showed that participants understood the rules and implications of the game well. Subjects' associations were particularly interesting. They were asked to compare the experiment with real life situations. Subjects in the role of citizens thought of fare-dodging, shoplifting, theft, speeding, smuggling, or cheating with scholarships. Inspectors thought of policemen, private control agents, governmental controls, or, more playful, of playing cops and robbers. The statements in the qualitative interviews reflected situations of crime and punishment and provided evidence that the constructs crime and inspection were appropriately operationalized by this design of the inspection game.

4.3 Procedures, information conditions and payoff parameters

The experiment was conducted in a computer laboratory using the software z-Tree (Fischbacher 2007). Observations from 200 subjects were collected, who were randomly drawn from an address pool of 692 students from various fields at the University of Leipzig. Subjects were randomly allocated to one experimental session and participated only once in the experiment. Subjects received a show up fee of 5 Euro, the experiment lasted for about one hour and consisted of three parts.

In the first part of the experiment, subjects earned own money by providing correct answers in a knowledge quiz. The quiz included thirty multiple choice questions about politics, art, geography, science and mathematics with two multiple-choice answer categories. The purpose of the quiz was that the subjects considered the money as own property (for other experiments using other kinds of real effort tasks see Falk and Fischbacher 2002; Winter et al. 2012; Berger et al. 2012).

In the second part of the experiment, subjects received instructions about the rules of the game. Then, they were informed that half of them were assigned to the role of "players" and the others to the role of "inspectors". Then subjects had to learn the rules and the payoffs for both roles, players and inspectors. Then they completed eleven-multiple choice questions about the rules and payoffs of both roles. Then they were assigned their role. The roles were labeled with neutral wording. Citizens were labeled "player" and inspectors were labeled "controller". The word player was used to avoid demand effects such that participants try to behave according the expectations of the experimenter. Two trial periods without payments were played in one of each role. Then, the main experiment started with payment relevant decisions.

[Table 3 about here.]

In the third part, subjects played 30 periods of the inspection game with the following matching rules. In each period, each citizen was randomly allocated to one new citizen and one new inspector (so-called “stranger-matching”). Note that a perfect stranger matching, where every citizen is only matched once with the same inspector and the same other citizen, is only possible for a short number of iterations. For the sake of allowing more iterations, a stranger matching was used, where participants were randomly allocated in each period and did not know with whom they interacted.

Payoff rules and choice alternatives for citizens were as follows. In each period, each citizen was allowed to take 10 experimental tokens from the other citizen's account (10 tokens corresponded to 1 Euro for citizens). While the victims lost 10 tokens, the thief gained 5 tokens, creating the following dilemma. If both did not steal, both kept their money and remained at the status quo. If one player stole, the thief was 15 tokens better off than the victim. If both stole, both citizens lost 5 tokens (50 Eurocent). Both citizens had to decide simultaneously whether to steal money from each other or not.

Inspectors' choice alternatives and payoffs were the following. Inspectors could decide to pay five tokens inspection costs to reveal the decision of their matched player (5 tokens corresponded to 10 Eurocent for inspectors).[15] The inspection cost was gone regardless of whether their matched citizen committed a crime or not. If they chose inspection and their matched citizens chose theft, the inspector received in the little inspection incentive condition 6 tokens and in the high inspection incentive condition 25 tokens. If the citizen committed a theft and was inspected, the citizen received a punishment of 10 tokens (1 Euro) in all experimental conditions. All inspected thieves automatically received the punishment. All payoff parameters are summarized in Table 3.

The following information was given to participants after all decisions were made in the group. Citizens were informed whether their inspector had inspected them. They were also informed whether they were punished (which was the case if they stole and were inspected). They were also informed whether they were victimized by the other citizen.

Inspectors were informed about the decision of their matched citizen. This was the case irrespective of whether the citizen had committed a theft or not. Note that inspectors were not informed whether their matched citizen was victimized from the other citizen, with whom she was matched.

All citizens were also informed about their current income level after each

[15]Note that inspectors have lower exchange rates between tokens and Euros. This was necessary to calibrate similar earnings between citizens and inspectors.

period. All information was common knowledge. All these rules were explicitly stated in the instructions. Control questions about the rules and information conditions in the game were asked for both roles and before participants were assigned to citizens and inspectors. This ensured that all participants understood information conditions for both roles.

4.4 Experimental treatments

There were four experimental treatments. A 2×2 design varied the level of inspection incentives and its order. Twenty subjects took part in each session. There were ten sessions so that the total sample consisted of N=200 subjects. In *experiment 1*, subjects were allocated in period 1 to period 15 to the condition with little inspection incentives. In periods 16 to 30, they were allocated to the condition with strong inspection incentives. Subjects kept their role as citizen or inspector over all 30 periods. In *experiment 2*, treatments were reversed. Subjects were allocated to the condition of strong inspection incentives in periods 1 to 15. In periods 16 to 30, subjects were allocated to the condition with little inspection incentives. They also kept their role over all 30 periods.

4.5 Predictions

The game theoretical predictions can be calculated with equations (3) and (4), using the experimental payoff parameters. Note that the payoffs in the experiment are the same as in the simulation model.

Prediction 1. *The inspection rate is unaffected by inspection incentives. The inspection rate is 50% in the condition with little and 50 % in the condition with strong inspection incentives.*

Prediction 2. *The crime rate is 83 % in the condition with little inspection incentives and 20 % in the condition with strong inspection incentives.*

In what follows, the game theoretical predictions are tested using the experimental data.[16]

5 Empirical results

5.1 Welfare losses from crimes

The income distribution over time illustrates the ineffficy of crimes. On average, citizens start with 22.00 Euros and finish with 9.00 Euros. Inspectors roughly

[16]Note that standard statistical significance thresholds will also be used for predictions of no effects. Hence, if the p-value of the effect of inspection incentives is larger than 5% (i.e. $p > 0.05$), prediction 1 is supported.

stay at their income level and start with 4.40 Euro and finish with 5.20 Euro. citizens and inspectors earned an additional show-up fee of five Euros.

5.2 Results of experiment 1

The bar charts in figure 3 depict crime and inspection rates by sessions. For stronger inspection incentives, there is consistently less criminal *and* more inspection behavior. This pattern replicates in all sessions. On average, the crime rate decreases from 47 % to 38 % for stronger inspection incentives and the inspection rate increases from 39 % to 60 %. This illustrates that the effects of inspection incentives are stronger for inspection behavior (21 %) than for criminal behavior (9 %). Nevertheless, a change of inspection incentivess changes criminal behavior substantially.

[Figure 3 about here.]

A comparison between theoretical predictions and empirical results yields two-fold conclusions. On the one hand, there is strong and consistent empirical support that stronger inspection incentives reduce criminal behavior. One the other hand, the game theoretical argument that inspectors' incentives *only* affect criminals' behavior cannot be supported. While stronger inspection incentives reduce crime rates by about 10 %, a reduction of 60 % was predicted. Furthermore, inspection incentives have a stronger effect on inspection behavior than predicted. Stronger inspection incentives increase the inspection rate by about 20 %, whereas no difference was predicted.

The results show that there is a strategic incentive-effect *and* an own incentive-effect. Inspectors' incentives affect crime (strategic incentive-effect) and they affect inspections (own incentive-effect). This means that people are to some extent strategic in their decision-making; however, less strategic than what game theory predicts.

5.3 Results of experiment 2

Experiment 2 reveals a similar pattern. Lower inspection incentives consistently increase the crime rate. This is the case in all sessions.[17] On average, the crime rate increases from 42 % to 57 % if inspection incentives are reduced and the inspection rate declines from 71 % to 37 %.

[Figure 4 about here.]

[17] Session 10 is an outlier, where crime remains constant for both inspection incentive conditions.

The effect of inspection incentives on inspections is larger than on crimes. On average, the inspection rate declines by 34 % and the crime rate increases by 15 % if inspection incentives are reduced. This confirms the results from experiment 1 that there is a strategic *and* an own incentive-effect. The strategic incentive-effect is shown by the fact that stronger inspection incentives reduce crime (experiment 1) and lower inspection incentives increase crime (experiment 2). The own incentive-effect is shown by the fact that stronger inspection incentives increase inspections (experiments 1) and lower inspection incentives decrease inspections (experiments 2). This shows that strategic decision-making matters for crime and inspection behavior; however, less than predicted by game theoretical models.

5.4 Statistical significance

In what follows, the session data is pooled and significance tests are computed by logistic random intercepts models. Logistic models are used because crime and inspection decisions are dichotomous (yes or no) and random intercept models because thirty decisions are clustered in each subject.[18] Separate models for experiment 1 and 2 are estimated to test for consistency and robustness.

[Table 4 about here.]

Table 4 reports highly significant effects of inspection incentives on both crime and inspection behavior. Firstly, there is a highly significant and consistent effect in both experiments that stronger inspection incentives cause less criminal behavior. Transforming Logit-estimates to probabilities shows that the increase from little to strong inspection incentives causes a decrease in crime from 44 % to 33 % in experiment 1 and from 58 % to 38 % in experiment 2. Secondly, there is a highly significant and consistent effect of inspection incentives on inspection behavior. Calculation of respective probabilities from Logit-estimates shows that an increase from little to strong inspection incentives causes an increase in inspections from 37 % to 61 % in experiment 1 and from 35 % to 73 % in experiment 2. The random part of the model (the standard deviation of intercepts) reveals that subjects vary considerably in their proclivity to commit crimes and perform inspections.

5.5 Dynamics and learning

The preceding "static" statistical analysis looked at pooled choices over periods. However, what about learning? Did subjects improve over time and learn how to

[18] The data is structured as follows. Each experiment consists of 50 citizens and 50 inspectors. Each subject made 30 decisions. This amounts to a total of 1500 decisions. Random intercepts models adjust standard errors for clustered decisions in subjects.

play the game and how to outsmart their opponents? There are two questions, which investigate learning from different perspectives. The first question is: did subjects learn how to play the game? Hence, did they converge towards predictions over time?

The second question is whether subjects adapt to the behavior of their opponents and improve their strategic responses over time. The game was played over thirty periods and subjects received information about their payoffs and the decision of their opponents after each period. Did they use this information to update their beliefs about their opponents' behaviors and did they adapt their own behavior accordingly?

[Figure 5 about here.]

Figure 5 shows the dynamics of crime (panel A) and inspection decisions (panel B) over time. Crime and inspection dynamics are shown for the treatments with fifteen consecutive periods of little inspection incentives (left) and strong inspection incentives (right). The data is pooled with respect to treatment order (first little versus first strong inspection incentives), since the order does not substantively affect the dynamics. Gray lines in each subpanel show the predicted mixed Nash equilibria and error bars denote 95 % confidence intervals of each rate at each period.

Figure 4 shows that crime and inspection rates do not converge towards predictions over time. Crime rates remain roughly stable over time in each of the two treatments. Inspection rates for little inspection incentives are also relatively stable over time. There is some dynamics in inspection rates in the regime with strong inspection incentives; however, inspection rates move away from predictions. The answer to the first question, therefore, is that subjects did not make considerable progress how to play the game in a selfish, payoff-maximizing way and did not improve in outplaying their opponents.

The second questions regarding learning takes a behavioral perspective. Seen from this viewpoint, it can be rational for an actor to respond to out-of-equilibrium behavior of her opponent with adapted out-of-equilibrium behavior. In our case, this can have two implications for inspectors.

The first behavioral implication for inspectors is for the case that they are matched with citizens who consistently commit less crimes than the predicted threshold of the indifference condition. Inspectors could learn from this out-of-equilibrium behavior and adapt by subsequently performing less inspections. This crime behavior is the case in the regime of little inspection incentives (left panel A). Here, citizens commit less crime than the indifference threshold. However, inspectors do not decrease their inspection activities and do not seem to learn from out-of-equilibrium behavior of their opponents (left panel B).

The second behavioral implication for inspector is for the case that citizens commit more crimes than the inspectors' indifference threshold. This is the case in the regime with strong inspection incentives (right panel A). Here, citizens commit "more" crimes than predicted. In this case, inspectors seem to learn. Inspectors perform subsequently more inspections over time (right panel B). Thus, if there are strong incentives, inspectors seem to be more sensitive to out-of-equilibrium behavior of their opponents and seem to adapt such that they make more profits over time.

Taken together, subjects do not learn in the sense that they converge towards mixed Nash predictions. However, there is some indication that subjects learn how to improve their responses to out-of-equilibrium behavior of their opponents, if their incentives are strong enough.

6 Discussion

The question as to whether crime and crime control can be governed by simple incentive schemes has been subject to public and scientific scrutiny. One intuitive way of reasoning is that more severe punishments decrease criminal behaviors such as tax evasion, doping in sports or fare dodging. A second intuitive reasoning is that stronger control incentives increase control activities by policemen, doping testers or conductors. However, many previous empirical deterrence studies have shown that crime and control incentives do not affect behavior in such a simple way. Punishment severity has relatively little impact on crime. Criminals' and control agents' beliefs about their detection likelihood are much more important.

This paper contributes to this debate by demonstrating how a game theoretical mechanism can explain why and how beliefs about detection affect crimes and inspections. In the proposed game theoretical model, criminals and control agents have opposite interests. Due to this "zero-sum" game, incentives work counter-intuitively. Incentives of ego only affect alter's behavior and vice versa. This has two implications. First, more severe punishments reduce control. Rauhut (2009) has confirmed this mechanism for the case of punishment severity, showing that more severe punishment indeed causes less control. The second implication is that stronger control incentives reduce crime. This is the first article to test this second implication.

This article also developed agent-based simulation models of rational and selfish learners. These agents are not perfectly farsighted and do not assume that their opponents are completely farsighted. Instead of foreseeing the complete course of the game, agents are backward looking and learn the behavior of their counterpart by experience. It is shown that this rational learning model (i.e. "fictitious play") has the same predictions as the game theoretical prediction of equilibria in mixed strategies. This demonstrates the robustness of the mechanism for backward-looking and forward-looking rationality.

The first result from the laboratory experiments confirms the proposed mechanism: stronger inspection incentives cause less crime. This effect is robust with respect to order effects, i.e. whether control incentives were increased or decreased. Furthermore, the mechanism is robust and replicable in all ten experimental sessions.

The second result, however, is that stronger inspection incentives also increased control. Both findings were substantively strong and statistically significant and could be replicated in all sessions.[19]

The second result suggests that there is both, a "strategic incentive-effect" and an "own incentive-effect". The strategic incentive-effect means that higher inspection incentives decrease crime (i.e. that ego's incentives affect alter's behavior). The own incentive-effect implies that higher inspection incentives increase inspections (i.e. that ego's incentives affect ego's behavior).

Evidence for an own incentive-effect was also shown in simple zero-sum games (Ochs 1995; Goeree et al. 2003; Goeree and Holt 2001) and in simpler versions of the inspection game (Nosenzo et al. 2012) and it deserves further interpretation. The evidence of an own incentive-effect is not well explainable by subjects who are rational, but slow learners. The simulations of rational learning have shown that backward-looking learners would arrive relatively soon at the same prediction as forward-looking actors. This suggests that humans are even less strategic and rational than what is assumed by slow learners.

The evidence of the own incentive-effect (i.e. that inspection incentives do affect inspection behavior) shows that people are less strategic and less calculating than what is assumed by farsighted, forward-looking rationality and backward-looking rational learning. There are multiple alternatives how to change the model in order to explain the anomalies between theory and data. The smallest change would allow for bounded rationality. In this sense, one could assume that (1) people who make errors in determining their payoff maximizing choice or expect their opponents to make errors. Another kind of bounded rationality (2) would allow for mistakes in learning such that people do not use their experience optimally to increase their payoffs. A more substantial change in the model would go beyond the information processing part of the model. For example, one could assume that the whole decision-making process works differently. One approach in this line of reasoning is that (3) people use heuristics and rules of thumb rather than calculus and (economic) payoff-maximization to make their decisions. In what follows, these three alternatives are discussed.

First, one could explain the own incentive-effect by errors in information processing. People may make errors in their own decisions and may also anticipate errors of their opponents. Therefore, they may form beliefs about the probability of each of their opponents' choice alternatives. This can be modeled by the so-called "quantal response equilibrium" (McKelvey and Palfrey 1995). The intuition behind this model is that errors of the opponent can become very costly if ego does not anticipate these errors and take them into account in

[19]Note the one outlier with respect to crime in session 10.

calculating expected payoffs from choice alternatives. For example, if the punishment is very high, citizens may doubt that inspectors indeed perform only very few controls. If citizens err on this side, they face a very high punishment, which they may try to avoid. Reversely, if the control incentive is very low, inspectors may doubt that criminals perform many crimes. If inspectors err on this side, their control efforts may not amortize so that they may decide to control less if there are only little incentives for control. Nosenzo et al. (2012) support predictions from this so-called "quantal response equilibrium" with data from simpler versions of the inspection game than presented here.

Second, the own incentive-effect could be explained such that people do not learn in a perfectly rational way in inspection games. People may make wrong inferences from the experiences they make and may come up with distorted subjective estimates of the detection likelihood. One way to think about this is that inspectors may only partly learn from experiences of the behavior of criminals and part of their belief comes from randomness. If randomness in learning and belief updates becomes strong, predictions subsequently shift from the strategic incentive-effect to the own incentive-effect (Rauhut and Junker 2009). In the most extreme case, if beliefs about the detection probability becomes guesswork, actors base their decisions subsequently on their own payoffs and do not take their opponent's payoffs into account. In other words, with decreasing capability to process information and experiences, predictions shift from strongly strategic choices to less strategic decision making, which only takes own payoffs into account.

Third, a more substantial change in the model would allow for non-rational decision-making. For example, people may do less sophisticated calculations and less anticipatory reasoning than assumed by game theory. Instead, people may primarily use rules of thumb and "heuristics" in decision-making (Gigerenzer and Goldstein 1996; Todd and Gigerenzer 2000). These heuristics operate easier than complicated calculations of payoff-maximizing strategies for given sophisticated subjective beliefs about the opponents. A simple example of a crime heuristic would be a reversed tit-for-tat strategy: commit a crime if no inspection occured in the last time step and do not commit a crime if there has been an inspection recently. A formal, agent-based learning model of this tit-for-tat heuristic and a respective empirical test in punishment experiments has been recently contributed by Rauhut and Jud (2014).

In addition to the contribution for actor models in the social sciences, the presented findings also have implications for political decision-makers. Deterrence policies are frequently based on too simple mechanisms. Often, politicians restrict their arguments on the "own incentive-effect": Punishment severity is only thought of as a crime deterrence and not as an inspection deterrence. Likewise, inspection rewards are typically created in order to motivate inspections, neglecting their effect on crime. Especially, if crime is on the rise or if single criminal events are widely discussed in the press, politicians come up with the narrow argument that more severe punishment would help to reduce crime.

However, the presented findings show that strategic incentive-effects play a crucial role. More severe punishment can decrease inspections with little impact on crime. Alternatively, it may be cheaper to increase rewards for police and other control agents with the aim to directly deter crime. Utilizing the strategic incentive-effect for the design of crime deterrence policies could give rise to more effective and cheaper deterrence. Deterrence policies should carefully take these considerations into account to be efficient and successful.

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Appendix: Proof that the simple inspection game and the laboratory inspection game experiment have the same equilibria

The simpler model, given in equations (3) and (4) and the extended game result in the same predictions. In the four-player system, citizen i can be inspected by inspector m and victimized by citizen j, so that her payoff function is given by

$$\pi_i(s_i, s_j, c_m, c_n) = s_i(g - c_m p) - s_j l.$$

Likewise, the payoff function ϕ for inspector m who can inspect citizen i is given by

$$\phi_m(s_i, s_j, c_m, c_n) = c_m(s_i r - k).$$

Rearrangement and calculation of the partial derivatives yields the equilibrium in mixed strategies of crime as $s_i^* = \frac{k}{r}$ and of inspection as $c_m^* = \frac{g}{p}$. This demonstrates that derived Nash predictions are robust to the proposed modification. Therefore, the previous predictions remain similar in the case of the experimental design. Stronger inspection incentives result in the same inspection rate, but in lower crime rates.

References

Allingham, Michael G. and Agnar Sandmo. 1972. "Income tax evasion: a theoretical analysis." *Journal of Public Economics* 1:323–338.

Andreoni, James, Brian Erard, and Jonathan Feinstein. 1998. "Tax Compliance." *Journal of Economic Literature* 36:818–860.

Becker, Gary S. 1968. "Crime and Punishment: An Economic Approach." *Journal of Political Economy* 76:169–217.

Berger, Roger, Heiko Rauhut, Simone Prade, and Dirk Helbing. 2012. "Bargaining over waiting time in ultimatum game experiments." *Social Science Research* 41:372–379.

Braithwaite, John. 1989. *Crime, shame and reintegration*. Cambridge: Cambridge University Press.

Clarke, R.V. 1995. "Situational crime prevention." *Crime and justice* pp. 91–150.

Cook, Philip J. 1980. "Research in criminal deterrence: Laying the groundwork for the second decade." *Crime and Justice: An Annual Review of Research* 2.

Diekmann, Andreas, Wojtek Przepiorka, and Heiko Rauhut. forthcoming. "Lifting the veil of ignorance: An experiment on the contagiousness of norm violations." *Rationality and Society* .

Doob, Anthony N. and Cheryl M. Webster. 2003. "Sentence Severity and Crime: Accepting the Null Hypothesis." *Crime and Justice. A Review of Research* 28:143–195.

Ehrlich, Isaac. 1975. "The deterrent effect of capital punishment. A question of life and death." *American Economic Review* 65:397–417.

Falk, Armin and Urs Fischbacher. 2002. "Crime in the Lab. Detecting Social Interaction." *European Economic Review* 46:859–869.

Fischbacher, Urs. 2007. "Z-Tree. Zurich Toolbox for Ready-made Economic Experiments." *Experimental Economics* 10:171–178.

Friedman, David. 1995. "Rational criminals and profit–maximizing police. The economic analysis of law and law enforcement." In *The new economics of behavior*, edited by Mariano Tommasi and Kathryn Ierulli, pp. 43–58. Cambridge: Cambridge University Press.

Fudenberg, Drew and David K. Levine. 1998. *The Theory of Learning in Games*. Cambridge, MA: MIT Press.

Gibbs, Jack P. 1968. “Crime, punishment and deterrence.” *Social Science Quarterly* 58:15–28.

Gigerenzer, Gerd and Daniel G. Goldstein. 1996. “Reasoning the fast and frugal way: Models of bounded rationality.” *Psychological Review* 103:650–669.

Goeree, Jacob K. and Charles A. Holt. 2001. “Ten little treasures of game theory and ten intuitive contradictions.” *American Economic Review* pp. 1402–1422.

Goeree, Jacob K., Charles A. Holt, and Thomas R. Palfrey. 2003. “Risk averse behavior in generalized matching pennies games.” *Games And Economic Behavior* 45:97–113.

Grasmick, Harold G. and George J. Bryjak. 1980. “The Deterrent Effect of Perceived Severity of Punishment.” *Social Forces* 59:471–491.

Groeber, Patrick and Heiko Rauhut. 2010. “Does ignorance promote norm compliance?” *Computational Mathematical Organization Theory* 16:1–28.

Grogger, J. 1991. “Certainty Vs Severity Of Punishment.” *Economic Inquiry* 29:297–309.

Horne, Christine and Heiko Rauhut. 2013. “Using Laboratory Experiments to Study Law and Crime.” *Quality and Quantity* 47:1639–1655.

Jensen, Gary. 1969. “Crime Doesn’t Pay: Correlates of a Shared Misunderstanding.” *Social Problems* 17:189–201.

Kahan, D. M. 1997. “Social influence, social meaning, and deterrence.” *Virginia Law Review* 83:349–395.

Levitt, Steven D. 2002. “Deterrence.” In *Crime: Public Policies for Crime Control*, edited by James Q Wilson and Joan Petersilia, pp. 435–450. Institute for Contemporary Studies Press.

Lochner, Lance. 2007. “Individual perceptions of the criminal justice system.” *American Economic Review* 97:444–460.

MacCoun, Robert and Peter Reuter. 1998. “Drug Control.” In *The Handbook of Crime and Punishment*, edited by Michael Tonry, pp. 207–238. New York: Oxford University Press.

Macy, Michael and Andreas Flache. 2009. “Social dynamics from the bottom up. Agent-based models of social interaction.” In *The Oxford Handbook of Analytical Sociology*. Oxford University Press.

Macy, Michael W. 1991. “Learning to Cooperate: Stochastic and Tacit Collusion in Social Exchange.” *American Journal of Sociology* 97:808–843.

Macy, M. W. 1993. “Backward-Looking Social-Control.” *American Sociological Review* 58:819–836.

Macy, Michael W. and Andreas Flache. 2002. "Learning Dynamics in Social Dilemmas." *Proc Natl Acad Sci USA* 99:7229–7236.

Matsueda, Ross L., Derek A. Kreager, and David Huizinga. 2006. "Deterring Delinquents: A Rational Choice Model of Theft and Violence." *American Sociological Review* 71:95–122.

McKelvey, Richard D. and Thomas R. Palfrey. 1995. "Quantal Response Equilibria for Normal Form Games." *Games and Economic Behavior* 10:6 – 38.

Miranne, Alfred C. and Louis N. Gray. 1987. "Deterrence: A laboratory experiment." *Deviant Behavior* 8:191–203.

Nagin, Daniel S. 1998. "Criminal Deterrence Research at the Outset of the Twenty-First Century." *Crime and Justice. A Review of Research* 23:1–42.

Nosenzo, Daniele, Theo Offerman, Martin Sefton, and Ailko van der Veen. 2012. "Encouraging Compliance: Bonuses versus Fines in Inspection Games." *CeDEx Discussion Paper Series* pp. 1–30.

Ochs, J. 1995. "Games With Unique, Mixed Strategy Equilibria - An Experimental-Study." *Games And Economic Behavior* 10:202–217.

Paternoster, Raymond. 1987. "The deterrent effect of the perceived certainty and severity of punishment: A review of the evidence and issues." *Justice Quarterly* 42:173–217.

Pogarsky, Greg and Alex R. Piquero. 2003. "Can Punishment Encourage Offending? Investigating the Resetting Effect." *Journal of Research in Crime and Delinquency* 40:95–120.

Rauhut, Heiko. 2008. "Höhere Strafen zur Herstellung sozialer Ordnung?" In *Verhandlungsband des 33. Kongresses der Deutschen Gesellschaft für Soziologie in Kassel*, Frankfurt/M. [u.a.]. Campus-Verlag.

Rauhut, Heiko. 2009. "Higher punishment, less control? Experimental evidence on the inspection game." *Rationality and Society* 21:359–392.

Rauhut, Heiko. 2013. "Beliefs about lying and spreading of dishonesty: Undetected lies and their constructive and destructive social dynamics in dice experiments." *PLoS One* 8:1–8.

Rauhut, Heiko and Silvana Jud. 2014. "Avoiding detection or reciprocating norm violations? An experimental comparison of self- and other-regarding mechanisms for norm adherence." *Soziale Welt* 65:153–184.

Rauhut, Heiko and Marcel Junker. 2009. "Punishment deters crime because humans are bounded in their strategic decision-making." *Journal of Artificial Social Systems and Societies (JASSS)* 12.

Rauhut, Heiko and Fabian Winter. 2012. "On the Validity of Laboratory Research in the Political and Social Sciences. The Example of Crime and Punishment." In *Experimental Political Science: Principles and Practices*, edited by Bernhard Kittel, Wolfgang Luhan, and Rebecca Morton, pp. 209–232. Palgrave Research Methods Series.

Ross, H. Laurence. 1973. "Law, Science, and Accidents: The British Road Safety Act of 1967." *Journal ofLegal Studies* 2:1–78.

Ross, H. Laurence. 1975. "The Scandinavian Myth: The Effectiveness of Drinking and Driving Legislation in Sweden and Norway." *Journal ofLegal Studies* 4:285–310.

Sellin, Thorsten. 1961. "Capital punishment." *Federal Probation* 25:3–10.

Sherman, Lawrence. 1990. "Police Crackdowns: Initial and Residual Deterrence." *Crime and Justice: A Review ofResearch* 12.

Sherman, Lawrence W. 1993. "Defiance, Deterrence, and irrelevance: A theory of the criminal sanction." *Journal of Research in Crime and Delinquency* 30:445–473.

Tittle, Charles R. 1969. "Crime rates and legal sanctions." *Social Problems* 16:409–423.

Todd, Peter M. and Gerd Gigerenzer. 2000. "Precis of Simple heuristics that make us smart." *Behavioral And Brain Sciences* 23:727–780.

Tsebelis, George. 1989. "The Abuse of Probability in Political Analysis: The Robinson Crusoe Fallacy." *American Political Science Review* 1:77–91.

Tsebelis, George. 1990. "Penalty Has No Impact on Crime. A Game Theoretic Analysis." *Rationality and Society* 2:255–286.

Von Hirsch, Andrew, Anthony E. Bottoms, Elizabeth Burney, and Wikstrom Per-Olof. 1999. *Criminal Deterrence and Sentence Severity - An analysis of Recent Research*. Oxford: Hart Publishing.

Williams, K. R. and R. Hawkins. 1986. "Perceptual Research On General Deterrence - A Critical-Review." *Law & Society Review* 20:545–572.

Winter, Fabian, Heiko Rauhut, and Dirk Helbing. 2012. "How norms can generate conflict: An experiment on the failure of cooperative micro-motives on the macro-level." *Social Forces* 90:919–948.

Wright, Bradley RE, Avshalom Caspi, Terrie E Moffitt, and Ray Paternoster. 2004. "Does the perceived risk of punishment deter criminally prone individuals? Rational choice, self-control, and crime." *Journal of Research in Crime and Delinquency* 41:180–213.

Zimring, Franklin E., Gordon Hawkins, and Sam Kamin. 2001. *Punishment and Democracy: Three Strikes and You're Out in California*. New York: Oxford University Press.

Figures

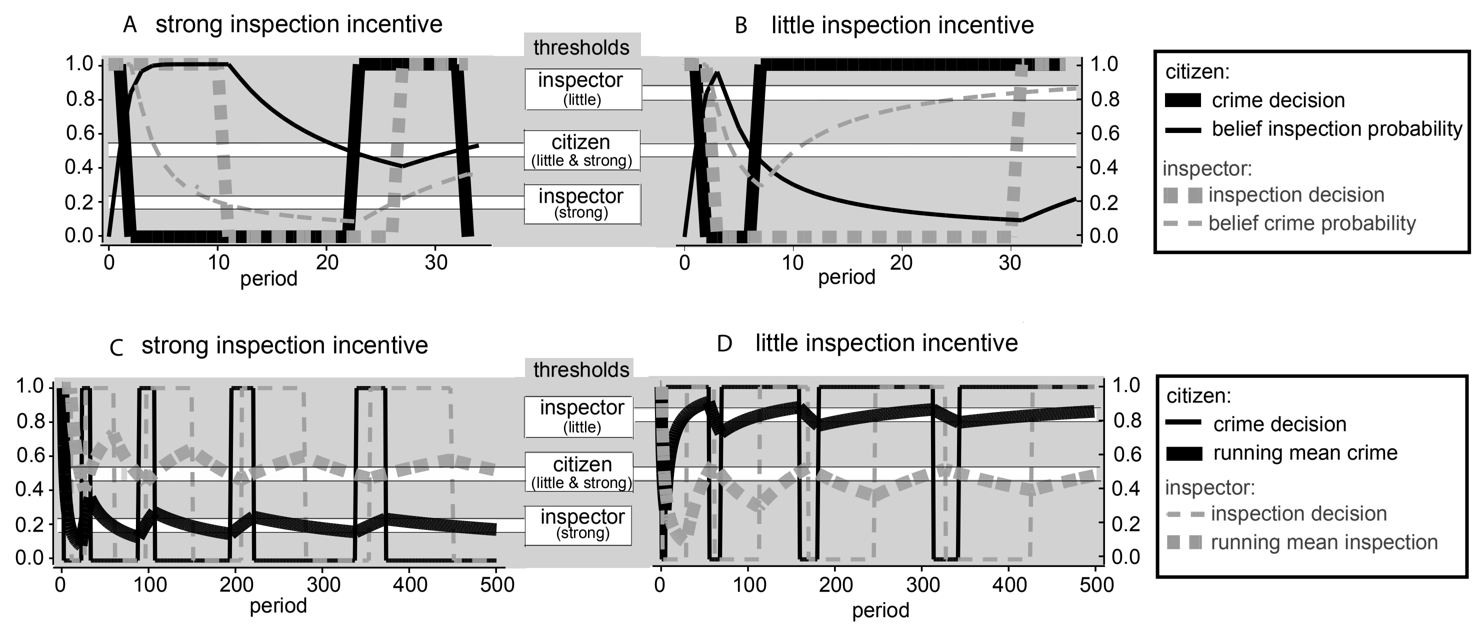

Figure 1. Learning dynamics between one citizen and one inspector. Panel A shows a short exemplary run with 35 periods and strong inspection incentives. Panel C shows a long version of the same simulation with 500 periods. The resulting equilibria are illustrated by running means of inspection and crime rates. Panel B shows a short exemplary run with 35 periods and little inspection incentives. Panel D shows a long version of the same simulation with 500 periods. The resulting equilibria are also illustrated by running means.

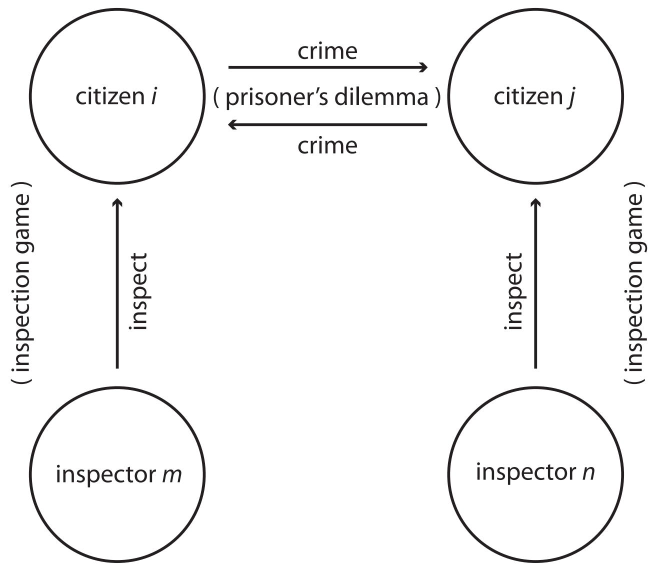

Figure 2. Experimental design for measuring crime and punishment in the laboratory.

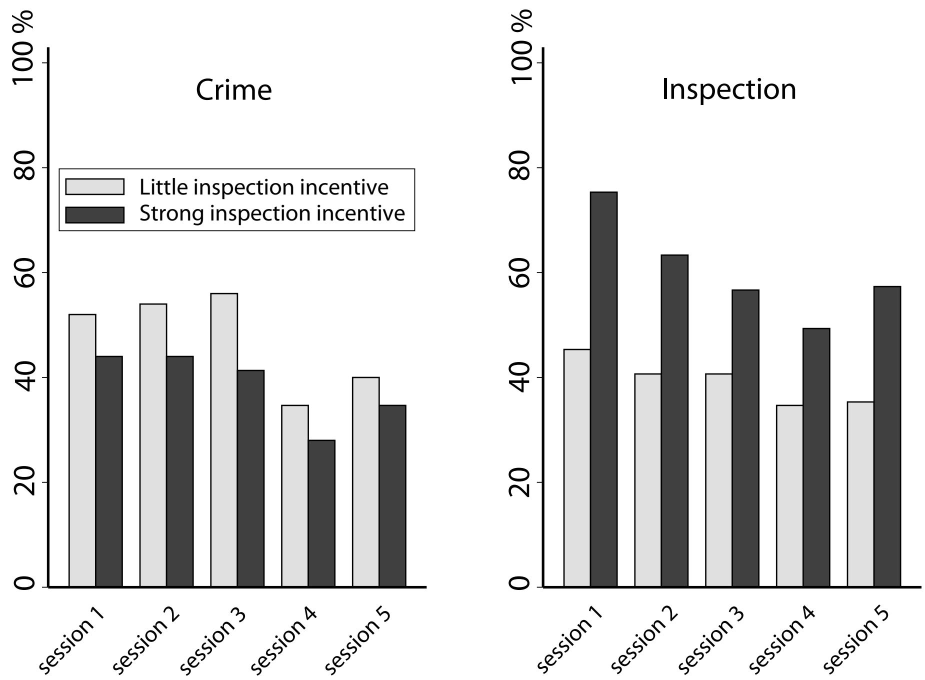

Figure 3. Experiment 1 with an increase from little to strong inspection incentives. Average crime and inspection rates (in percentages). Gray bars denote little and black bars strong inspection incentives. Each bar denotes one session. The left panel denotes crime and the right panel inspection decisions. Each bar represents 150 decisions.

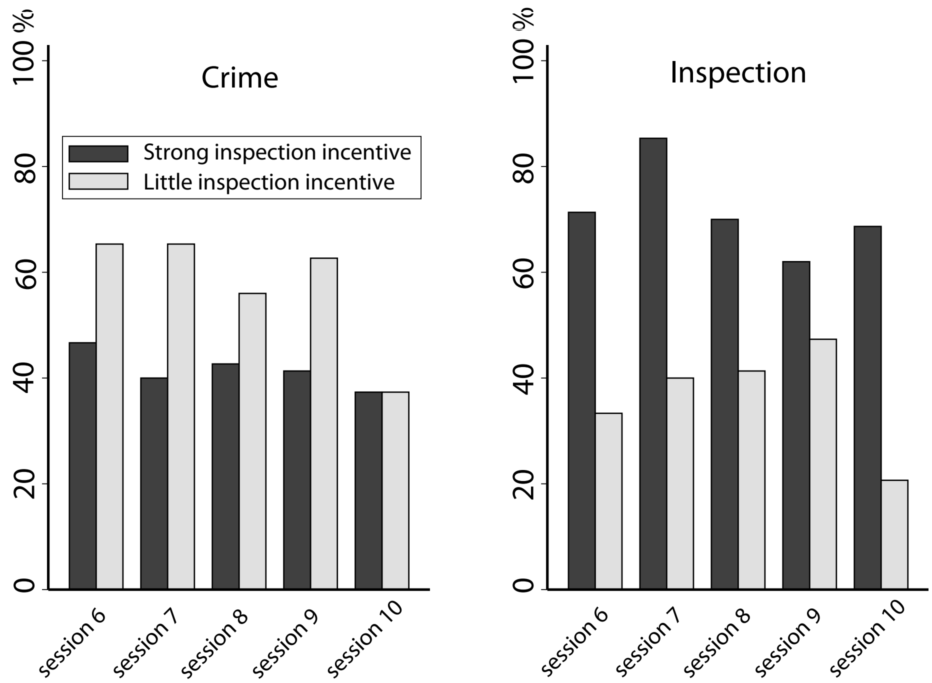

Figure 4. Experiment 2 with a decrease from strong to little inspection incentives. Average crime and inspection rates (in percentages). Black bars denote strong and gray bars little inspection incentives. Each bar denotes one session. The left panel denotes crime and the right panel inspection decisions. Each bar represents 150 decisions.

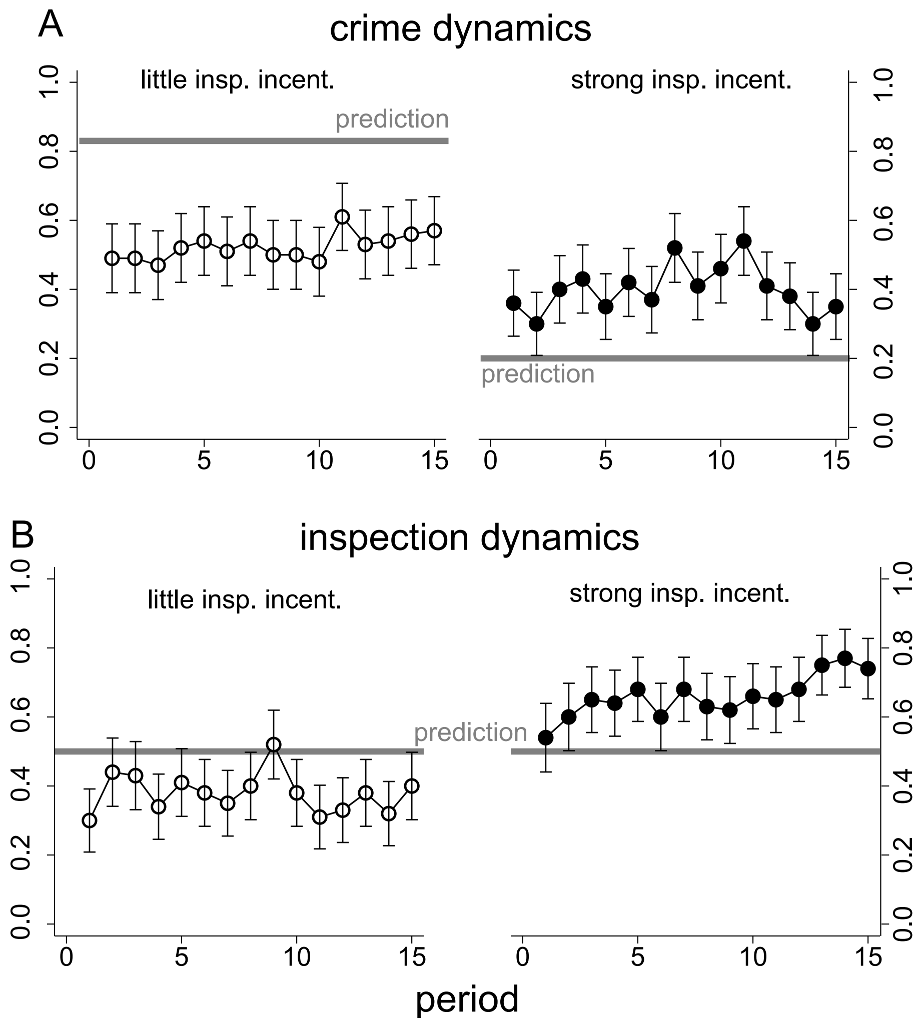

Figure 5. Crime and inspection rates over time. Panel A shows theft rates over 15 periods with little inspection incentives (left) and 15 periods with strong inspection incentives (right). Panel B shows respective inspection rates (left little, right strong inspection incentives). Rates are collapsed over the order of inspection incentive treatments (experiment 1 with little inspection incentives as first condition and experiment 2 with strong inspection incentives first). Gray lines in each subfigure show respective predictions from mixed Nash equilibria. Error bars denote 95% confidence intervals for each rate at each period (consisting of 100 observations each).

Tables

		Inspector m		
		inspect		not inspect
Citizen i	crime	$g-p$, $r-k$	$\Leftarrow$	g , 0
		$\Downarrow$		$\Uparrow$
	no crime	0 , $-k$	$\Rightarrow$	0 , 0

Table 1. The inspection game. Payoffs for citizens are given on the left and for inspectors on the right side of the comma. The payoffs denote g for criminals' gains, p for punishment, k for inspection costs and r for the rewards of successful inspection with $p > g > 0$ and $r > k > 0$.

inspectors		little inspection incentive	strong inspection incentive
k	inspection cost	5	5
r	reward successful inspection	6	25
$\frac{k}{r}$	threshold for best response (minimum crime probability to perform inspection)	0.83	0.2
citizens			
g	gains from crime	5	5
p	severity of punishment	10	10
$\frac{g}{p}$	threshold for best response (maximum inspection probability to commit crime)	0.5	0.5

Table 2. Payoff parameters in the simulation model

inspectors		little inspection incentive	strong inspection incentive
k	inspection cost	5	5
r	reward successful inspection	6	25
$\frac{k}{r}$	threshold for best response	0.83	0.2
	(minimum crime probability to perform inspection)		
$\frac{g}{p}$	predicted inspection rate	0.5	0.5
citizens			
g	gains from crime	5	5
p	severity of punishment	10	10
l	victims' losses	10	10
$\frac{g}{p}$	threshold for best response	0.5	0.5
	(maximum inspection probability to commit crime)		
$\frac{k}{r}$	predicted crime rate	0.83	0.2

Table 3. Payoff parameters in experimental tokens, being transferred to Euros at the end of the experiment

Fixed effects	Experiment 1 Crime	Experiment 1 Inspection	Experiment 2 Crime	Experiment 2 Inspection
Strong inspection incentive	-0.48***	1.00***	-0.81***	1.65***
	(0.12)	(0.12)	(0.12)	(0.12)
Intercept	-0.25	-0.54***	0.33	-0.63***
	(0.25)	(0.16)	(0.19)	(0.14)
Standard deviation intercept	1.65***	0.97***	1.22***	0.79***
	(0.24)	(0.13)	(0.15)	(0.11)
-2LogLikelihood	-873.0	-935.0	-900.3	-896.9
Bic	1767.9	1892.0	1822.5	1815.7
N(decisions)	1500	1500	1500	1500

Table 4. Logistic random intercepts models of inspection incentives on crime and inspection behavior. Each experiment consists of 1500 decisions clustered in 50 citizens and 1500 decisions clustered in 50 inspectors. Standard errors in parentheses. Strong inspection incentive is a dummy variable coded with 0 for little and with 1 for strong inspection incentives. Statistical significance is denoted by $* \, p < 0.05$, $** \, p < 0.01$, $*** \, p < 0.001$.