Avoiding Detection or Reciprocating Norm Violations?

An Experimental Comparison of Self- and Other-Regarding Mechanisms for Norm Adherence

By Heiko Rauhut and Silvana Jud*

Abstract: There is a growing body of research showing that people altruistically enforce cooperation norms in social dilemmas. Most of this research analyzes situations where norm violators are known and group members enforce cooperation among each other. However, in many situations norm violators are unknown and detection and punishment is enforced by third parties, such as in plagiarism, tax evasion, doping or even two-timing. Our contribution is threefold. Conceptually, we show the usefulness of inspection game experiments for studying normative behavior in these situations. Methodologically, we present a novel measurement of strategic norm adherence and enforcement, asking for continuous, "frequentistic" choice probabilities. Substantively, we demonstrate that norm adherence in these situations is best understood by coexisting distinct actor types. Self-regarding types learn the inspection rate and calibrate their norm violations to maximize own payoffs. Other-regarding types reciprocate experienced victimizations by stealing from other unknown group members; even at additional costs. We specify both mechanisms by agent-based simulation models and compare their relative explanatory strength by behavioral and attitudinal data in inspection game experiments (N = 220). Our results suggest a modern sociological perspective, which combines homo oeconomicus with homo sociologicus. Further, our findings contribute to understanding conditional norm compliance in „broken windows" dynamics, since we show under controlled conditions that such dynamics may result jointly from self- and other regarding mechanisms.

1 Introduction

The discussion of reciprocity as a mechanism for cooperation is becoming increasingly important in sociology, economics, anthropology and psychology (see e.g. Axelrod / Hamilton 1981; Fehr / Gächter 1998; Hoffman et al. 1998; Nowak / Sigmund 1998; Milinski et al. 2002). Already in his classical essay on *The Gift*, Marcel Mauss (1954, p. 5) calls reciprocity „one of the human foundations on which societies are built". Doing favours for others and feeling in debt after having received favours are crucial mechanisms for social order in our society.

In recent years, research in behavioral game theory has shown that the *homo oeconomicus* model of purely self-regarding actors is not sufficient to explain reciprocal behavior. Experimental results of dictator and ultimatum games, for example, are hardly explainable without other-regarding motives such as altruism, fairness or reciprocity (Komorita et al. 1992; Ashton et al. 1998; Fehr / Gächter 2000; Perugini / Gallucci 2001; Diekmann 2004; Berger et al. 2012; Berger / Rauhut 2014; Winter et al. 2012).

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To whom correspondence should be addressed: Heiko Rauhut, University of Zurich, Institute of Sociology, and Swiss Federal Institute of Technology Zurich, heiko.rauhut@uzh.ch.

Our contribution shows that reciprocity is a powerful mechanism for norm adherence and social order. The first novelty of our contribution is substantive in demonstrating that the specific kind of generalized negative reciprocity has an important role for understanding normative behavior. While the existing literature has often studied direct positive reciprocity, little is known about the causes and consequences of generalized negative reciprocity. Our work analyzes generalized negative reciprocity in victims who return experienced thefts by own thefts from third party players who are not known to be the perpetrators.

The second novelty of our contribution is conceptual. Our article illustrates the usefulness of inspection games for studying adherence and enforcement of norms. While the existing literature mostly considers norm enforcement, where norm violators are known, the inspection game offers the possibility to test the likewise often occurring case, where norm violators are unknown and have to be detected to be punished. More specifically, our inspection game models target actors of the norm who can commit thefts from each other. On the other hand, there are norm enforcers, who invest in controlling the target actors. If the target actors are detected violating a norm, enforcers receive a reward and targets a punishment. The exchanges are modeled by abstract monetary payoffs. The strategic setting is implemented in a laboratory experiment, using a student population from the University of Leipzig (N = 220).

The third novelty of our contribution concerns measurement. We introduce a new, more fine-grained design for inspection game experiments. The problem with previous experimental designs of the inspection game is the measurement of a probabilistic strategy. Our design allows people to make continuous choices in frequentistic probability formats. For example, actors can specify to commit a norm violation in two out of ten cases. This allows a more fine-grained, continuous measure of probabilistic strategies and higher construct validity due to the better comprehensibility of the probability statements in frequentistic terms compared to probabilistic formats.

Our contribution is structured as follows. We first introduce our novel perspective of detection problems (section 2) by defining social norms and discussing existing literature (2.1). Then we introduce other-regarding reciprocity and specify our version of generalized negative reciprocity (2.2). After that, we introduce the inspection game as a parsimonious model for detection problems (section 3). In the next section (4) we derive hypotheses for the frequentistic inspection game, starting with the baseline model of perfectly farsighted, self-regarding actors (4.1). This is used to develop a self-regarding learning model, where target actors learn the empirically occurring inspection rate to commit as many norm violations as they maximize own payoffs (4.3). This is confronted with other-regarding learning, where target actors reciprocate victimizations by thefts (4.4). Then, we present the experimental design (section 5) and results (section 6). We conclude by relating our findings to sociological theory about actor conceptions and to the sociology of norms and deviance (section 7).

2 A novel perspective: detection of norm violators

2.1 Social norms and control

A social norm is a commonly held expectation of how actors ought to behave, which is enforced by sanctions in case of violations (see Winter et al. 2012: 921). Examples range from coordinated behavior such as dress codes, eating habits or dialects through cooperative behavior such as contributions to environmentally friendly behavior, maintaining trust in business relationships or compliance with the criminal law.

Social norms can be enforced by informal or formal punishment. Informal punishment refers to peer punishment, where the punishers have to bear the costs for detection and punishment. Formal punishment is enforced by actors who have incentives for detection or punishment. In most cases, formal punishment refers to state-driven enforcement of legal norms.

There is much research on the emergence of informal norms and the effects of informal punishment. It has become an interdisciplinary topic of wide interest. A typical setup in this line of research is the analysis of public good provisions, where peers can punish each other for free-riding. In this context, the level of everybody's public good provision is known to every group member. Most setups consider a two-step setup, separating norm adherence from norm enforcement. Group members can choose the level of public good provisions in the first step and, after hearing about the contributions of all others in the group, they can assign the level of punishment to the other group members.

One of the earliest experimental investigations in this line of research was done in social psychology by Yamagishi (1986), it was continued in sociology by a theoretical investigation by Heckathorn (1989), experimentally tested in a political science setup by Ostrom et al. (1992) and became most well-known by the study by Fehr / Gächter (2000) in economics.

The most important finding in this research is that a substantial fraction of actors are willing to bear the costs to punish free-riders. This so-called „altruistic punishment" (Fehr / Gächter 2002) leads to the emergence of cooperation norms, which can prevail in punishment regimes. Without punishment, however, cooperation typically declines up to a point where almost nobody cooperates anymore (Ledyard 1995). People can also learn that regimes with altruistic punishment yield higher profits over the long run than regimes without punishment so that they progressively self-select into regimes which allow for peer punishment (Gürerk et al. 2006; Gächter et al. 2008). In the meanwhile, there exists a number of studies, documenting that altruistic punishment is a powerful mechanism for the emergence of cooperation norms. Some of these studies are reviewed by Fehr / Gintis (2007), who link this line of research to fundamental sociological topics of social order and the emergence of institutions. See also more interdisciplinary reviews, where the relevance of these findings is discussed for economics, biology and game theory (Camerer / Fehr 2006; Nowak 2006; Sigmund 2007).

However, the approach of altruistic punishment fails to explain many forms of cooperation norms. Firstly, victims of free-riding and norm violations frequently do not know their perpetrators. There are many dilemmas like doping in sports, non-environmentally friendly behavior, overfishing, theft or burglary, where the main problem is not to punish defectors. In these situations, the main problem is to *detect* the norm violators. Secondly, actors often do not have the resources for costly altruistic punishment. This may be especially the case, when suckers loose many resources. In the case of criminal behavior, victims may face considerable losses, disabling them to strike back with punishment. Then, third parties often administer punishment of norm violators.

Yet, there are only few investigations of the adherence of norms, where norm violators are not known and have to be detected to be punished. Likewise, there is a lack of research of formal punishment, where third party actors receive incentives for successful detection and punishment of norm violators. The study by Falk / Fischbacher (2002) is an exception, which goes in a similar direction as our study. They studied reciprocity in „criminal" decision-making. In their setup, subjects could steal their earned property from their fellows. They could condition their theft decisions on the level of theft of the other group members.

The authors concluded that crime is reciprocal, because individuals stole more in groups with higher theft rates. However, their design did not allow for punishment of thieves. Fehr / Fischbacher (2004) is another exception, which is related to our investigation. They investigated third party punishment. In their setup, an uninvolved actor could observe payoff divisions between a dictator and a receiver. They could show that even these uninvolved actors were willing to altruistically punish „unfair“ dictators, i.e. those who split the money unequally. Remarkably, uninvolved actors even punished despite that they had to pay substantial costs. Yet, although this design considered third-party punishment, the violators of an equality norm were known to everybody in the setup.

Consequently, we propose to draw more attention to investigating norm adherence under conditions, where it is not known who violated the norms and where efforts and costs have to be taken to detect the norm violators. A good and simple representation of this situation is the inspection game. The inspection game was introduced by Tsebelis (1989) and first experimentally tested by Rauhut (2009). It has been developed to analyze the effects of formal punishment on norm violations and crimes.[1]

2.2 Generalized negative reciprocity and control

For our substantive argument of reciprocity, it is important to classify different types of reciprocity to understand our contribution. All types of reciprocity can be defined as mutual conditional exchange of resources (Gouldner 1960: 164). The resources can comprise of material goods; but also work performance, time, control, expectations or social approval are exchangeable. Different types of reciprocity can be classified by three dimensions: the motivation, the form and the recipient of reciprocal actions (Berger / Rauhut 2014). First, the motivation can either be strategic (self-regarding) or altruistic (other-regarding). Second, the form can be positive in returning favors by friendly responses and negative by returning disfavors by unfriendly responses. Finally, the recipient can reciprocate directly to the sender (specific) or indirectly to a third party (generalized). Taken together, we understand generalized negative reciprocity as retaliation behavior, where an unfavorable gift is returned by punishment of an uninvolved actor who is not the sender (or at least unknown to be the sender) of the „rotten gift“. The form of generalized negative reciprocity in our contribution considers other-regarding (altruistic) reciprocity. Hence, we consider retaliations, which are or can become costly to the retaliator. In particular, the retaliation cannot be used to attain long-term profits by forcing others to cooperate in order to profit from the same actors' cooperative behaviors in the long run.

Consider the two illustrating examples of generalized negative reciprocity. First, a woman finds a trashed beer can on her front lawn. She could either put it in the garbage bin or just throw it on the pavement outside of her lawn. When she throws it on the pavement, her behavior can be regarded as generalized negative reciprocity. She returns the unfavorable gift of her trashed territory by trashing the pavement. In this way, not the sender but other, third parties suffer from her punishment. The second example is bike theft, where the victim steals someone else's bike. This behavior reflects generalized negative reciprocity, because the retaliation does not hurt the thief but a third, uninvolved actor. Both examples reflect other-regarding reciprocity, because both retaliations could be punished with costly consequences. Reciprocal littering and reciprocal theft can be fined by the police.

The examples above illustrate that two conditions are important for studying generalized negative reciprocity. First, the situation involves some kind of wrongdoing to a person, who reacts with emotional distress and anger, leading to retaliation behavior. Secondly, there is

1 The inspection game is also discussed in applied game theory (Avenhaus et al. 2001).

an inspection institution with the power to punish the retaliator. In our contribution, we use the inspection game. This is an ideal strategic setting, which fulfills these two conditions and is therefore a good model for studying generalized negative reciprocity.

3 Theoretical mechanisms of norm adherence in the inspection game

3.1 Norm adherence and enforcement in the inspection game

The inspection game was introduced by Tsebelis (1989, 1990) and first experimentally tested by Rauhut (2009). The simple version of the model considers two opposing parties: target actors of the norm and norm enforcers. Target actors can either adhere to a norm or violate it.[2]

Norm enforcers can either inspect or not inspect the target actors. The two players have exactly conflicting incentives. Target actors receive the highest payoffs for violating a norm without being detected and norm enforcers for detecting norm violators.

Target actors can decide to commit a norm violation and earn the deviance reward $r > 0$. Norm enforcers can decide to spend the inspection cost $c > 0$ to detect the norm violators. If they detect them, norm enforcers receive inspection rewards $s > c$. Detected norm violators receive the punishment $\omega > r$. The incentive structure of this simple inspection game is displayed by the 2×2 game matrix in Table 1.

The model has the implication that rational and selfish target actors commit a norm violation if not inspected and adhere to the norm if inspected. In contrast, norm enforcers perform inspections if target actors violate the norm and do not inspect if target actors adhere to the norm. This has the consequence that there is no dominant strategy. This is illustrated by the circling arrows in Table 1. This can be demonstrated when starting in the upper left corner of Table 1. If the norm enforcer inspects and the target actor violates the norm, the target actor receives a punishment which exceeds the reward from the norm violation. This strategy combination is, therefore, not in equilibrium. Let us assume, the target actor decides to change her strategy and commits no norm violation. In this case, the target actor pays inspection costs c without receiving the reward s. Hence, the norm enforcer may decide not to inspect. In this case, however, the target actor receives an incentive to commit a norm violation, because she would receive the reward r, which is higher than receiving no payoff. This strategy combination, however, gives the norm enforcer an incentive to change her strategy to inspection, yielding the payoff $s - c$, which is higher than nothing. Yet, this strategy combination has been the starting point of our analysis and had no equilibrium in pure strategies either.

Table 1: The simple inspection game

		norm enforcer *i*		
		inspect		not inspect
target actor *h*	norm violation	$r - \omega,\ s - c$	$\Leftarrow$	$r,\ 0$
		$\Downarrow$		$\Uparrow$
	norm adherence	$0, -c$	$\Rightarrow$	$0,\ 0$

Notes: The payoffs denote r = rewards for the norm violation, ω = punishment, c = inspection cost, s = rewards for successful inspection with $\omega > r > 0, s > c > 0$.

2 The term “target actor“ stems from Coleman (1990).

This demonstration shows that there is no combination of pure strategies, where both actors have no incentive to unilaterally change their strategy. In this case without dominant strategies, actors can „mix“ their strategies. This means that players choose a certain probability to perform one of their alternatives. The idea is that the actors try to outsmart their opponents. Outsmarting only works if target actors choose the probability of committing a norm violation at the indifference point of norm enforcers and norm enforcers choose the probability of inspection at the indifference point of target actors.

The intuition for this logic of outsmarting the opponent may be illustrated by the following consideration: A target actor who commits norm violations no matter what will sooner or later receive many punishments in a row. On the other hand, a „big-brother“ control regime, where the norm enforcer invests in omnipresent inspection will be highly inefficient because norm violations will decrease up to a minimum and control activities will no longer amortize. As a consequence, both parties will choose a mixed strategy instead of a fixed one.

This strategic incentive structure has the interesting, counter-intuitive implication that more severe punishments do not decrease the rate of norm violations. This effect can be derived with equilibria in „mixed“ strategies. A mix of strategies is only in equilibrium if both actors make their opponent indifferent between the two alternatives. If one actor is not indifferent, she will take advantage and exploit the other which gives an incentive for the other to change her strategy. Mixing means to play a strategy with a certain probability.

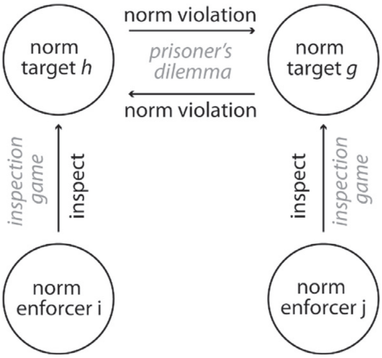
To derive this effect, we denote p_h as the probability that target actor h violates the norm and q_i as the probability that norm enforcer *i* inspects norm target h. The norm enforcer is indifferent if her expectation value of inspection minus her inspection cost equals zero. Her expectation value of inspection is simply the probability p_h that the target actor violates the norm times the inspection reward s. The inspection costs are given by c. Thus, the norm enforcer is indifferent if $p_h s - c = 0$. Solving for p_h shows that the target actor will violate the norm with the probability $p_s^* = c \big/ s$. This shows that norm violations in this model do not depend on the level of punishment. In contrast, the level of norm violations depends on inspection costs and inspection rewards.

The same counter-intuitive logic holds for the behavior of the norm enforcers. Norm enforcers will try to make the target actors indifferent. The target actor is indifferent if the reward of the norm violation *r* minus the expectation value of punishment equals zero. The expected punishment cost $q_i \omega$ is simply the probability q_i that the norm enforcer inspects times the punishment level ω. Hence, the norm enforcer chooses her inspection probability q_i such that the target actor is indifferent, i.e. such that $r - q_i \omega = 0$. Solving for q_i shows that the target actor will violate the norm with the probability $q_i^* = r \big/ \omega$. This shows that inspections in this model do not depend on the level of inspection rewards. In contrast, the level of inspections depend on the gains from norm violations and punishment severity of the target actors. A more precise and formal derivation of these effects can be found in Rauhut (2009). In summary, the analysis shows that more severe punishments reduce the inspection rate and do not affect norm violations. Vice versa, higher inspection rewards reduce the rate of norm violations and do not affect inspections.

3.2 From simple games to laboratory tests of theories

Simple game theoretical models such as the described version of the inspection game above highlight a particular strategic structure of a social situation, be it voting, environmental protection or, as in our case, norm violations. In order to design a laboratory test of a simple game model, it is often necessary to incorporate more elements into the incentive structure.[3] Sometimes, only this extension allows valid inferences to the constructs of the theory. The inspection game is a parsimonious model of how norm violators and enforcers react to severity of punishment and material (or immaterial) inspection rewards. The inspection game highlights the strategic interaction between target actors and norm enforcers in these situations. The original structure of the inspection game in Table 1 in fact only models a pure „discoordination" situation. One party is interested in a mismatch (that is, committing a norm violation if there is no control) while the other party is interested in a match (that is, performing control if there is a norm violation). However, the logic of discoordination games also applies to other settings. By labeling the decision alternatives differently, it would also be possible to interpret the game in terms of penalty kicks in football or serves in tennis. Taking the example of penalty kicks in football, the shooter tries to shoot in a different corner than the one in which he expects the goal-keeper to jump, whereas the goal-keeper tries to jump in the same corner (For empirical investigations of mixed strategy predictions in penalty kicks in football, see Chiappori et al. 2002; Palacios-Huerta 2003; Moschini 2004; Berger / Hammer 2007).

Figure 1: The extended inspection game



Notes: See Rauhut (2009); Rauhut / Winter (2012).

We argue that inspection of norm violations may be different from penalty kicks in football because norm violations typically cause negative externalities to third parties, i.e. to the victims. Optimizing norm violations and inspection expenditures may not only be motivated by optimal responses between target actors and inspectors, but also by moral concerns, reciprocity or social norms with respect to the harm done to the victims. Such considerations are unlikely to play a role in football, where externalities are excluded by the commonly accepted rules of the game.

In order to represent the constructs norm violations and inspection accurately, we include externalities to third parties in the game theoretical model as well as in the experiment. This modification of the game yields higher construct validity by creating a specific discoordination situation which resembles the one between target actors and norm enforcers.

The social interactions between target actors and norm enforcers are modeled in the extended inspection game by target actors who can steal money from each other. This is implemented by combining the simple inspection game with the prisoners' dilemma. The prisoners' dilemma of mutual theft can be modeled such that two target actors can perpetrate each

3 For an extended discussion of this argument see Rauhut and Winter (2012).

other with a norm violation. If ego violates the norm, alter suffers from it as a victim and vice versa. If both violate the norm, both are worse off compared to if both adhere to the norm. This models norm violations as inefficient payoff transfers between norm violator and victim. Taking the example of theft, the payoffs are such that theft is more damaging for the victim than rewarding for the thief.

The complete interaction structure between target actors and norm enforcers can be modeled by a four-player system (see Figure 1 and for more extensive discussion Rauhut 2009). There are two target actors, who can commit a norm violation and harm each other with the payoffs of the prisoner's dilemma. In addition, however, there is one norm enforcer for each target actor. The strategic interaction between the norm enforcer and the target actor is an inspection game with the payoffs of Table 1.

The incorporation of victims into the inspection game significantly enriches the theoretical model of norm violations: it captures the interaction between target actors and norm enforcers and it includes welfare losses which often go along with norm violations. The game theoretical predictions are equivalent in the simple and in the extended inspection game. For a proof and more details see Rauhut (2009) and Rauhut / Winter (2012).

3.3 The frequentistic inspection game

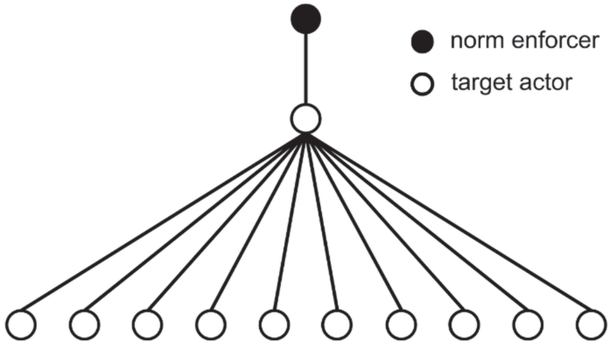
The above discussed extended inspection game has been tested in previous articles (Rauhut 2009, 2014). In this contribution, we present a novel setup, which allows a more fine-grained measure of mixed strategies in inspection games. The limitation of the original inspection game (Table 1) and of the extended version (Figure 1) is that players can only make dichotomous choices. This means that mixed strategies can only be measured indirectly in two ways. Either the strategy mix is measured inter-individually over the rate of choices of a population of many actors or it is measured intra-individually over the rate of one actor's choices over several periods. Both measures are indirect and relatively rough-grained.

The idea of our new measurement is to let people make continuous choices. This has two advantages. First, this yields a more fine-grained measure of actors' proclivity for norm violations and inspections, respectively. Second, it also yields a measure with better construct validity. This is the case because the novel measure reflects psychological literature on probabilistic decision making, which shows that people have problems with stating, estimating and acting according to probabilities (Gigerenzer / Hoffrage, 1995).

The extent to which people can understand and communicate probabilities depends on the format in which the probabilities are presented. The standard way of presenting probabilities is the so-called „probabilistic" format, where either percentages or probabilities with „*p*-values" between 0 and 1 are stated. However, research shows that people can operate and communicate better with probabilities if they are framed in the so-called „frequentistic" format (Gigerenzer / Hoffrage 1995; Hoffrage et al. 2000; Siegrist 1997). An example of a frequentistic probability statement is „two out of ten" or „twenty out of one hundred", which corresponds to the „probabilistic" statement of twenty percent (or $p = 0.2$). Although both versions are formally equivalent, fundamental and applied research in a variety of areas has shown that people make more accurate statements if they are confronted with and can express probabilities in frequentistic rather than probabilistic terms (for a review see Gigerenzer 2002).

The strategy mix in this design can be expressed in frequentistic terms. For example, the target actor can state to commit two out of ten possible norm violations. This is equivalent to a strategy mix of committing norm violations with probability 20%. Note that our design goes beyond just framing the decision in different words. Our proposed design directly implements a frequentistic choice. The target actors can make a continuous choice of *how many* other norm targets they want to victimize. Likewise, the norm enforcers can also make a continuous choice by stating *how many* choices of their target actor they want to inspect. Hence, our design extends the 1 - 1 - 1 design of one norm enforcer who is matched with one target actor who is matched with one other target actor (Figure 1) to a 1 - 1 - n setup (Figure 2). In this setup, there is still one norm enforcer matched with one target actor. However, the target actor is matched with n other target actors.

Figure 2: The frequentistic inspection game (one of ten identical sub-networks)



Notes: One norm enforcer (black) is matched with one target actor (white), who is matched with ten other target actors (white). The target actor decides *how many* out of the ten others to victimize, the norm enforcer, *how many* out of the ten interactions to inspect.

In our specific implementation, there are eleven target actors, who can steal money from each other (see Figure 2). This means that each target actor is matched with ten other target actors and can make the decision how many out of ten she wants to victimize. Each target actors is matched with one norm enforcer (i.e. partner matching). The norm enforcer has the power to inspect the interactions between the target actors. The decision is implemented in the same way so that the enforcer can make the decision how many out of ten actions of her target actor she wants to inspect. Thus, both actor types make a frequentistic decision of choosing n out of ten. It is determined randomly, which specific n actors are victimized and which specific actions are inspected. In the experiment, this is done by a computer program. The interaction structure is visualized in Figure 2.

4 Hypotheses and predictions

4.1 Predictions for self-regarding, farsighted actors

In what follows, we present the baseline predictions in the frequentistic inspection game. These predictions consider actors who are (1) self-regarding, (2) risk-neutral and (3) farsighted inasmuch as they foresee the complete course of the game and also expect the opponent to foresee the complete course of the game. The respective predictions in Nash equilibria are substantially equivalent in the simple inspection game (Table 1), in the extended inspection game (Figure 1), and in the frequentistic inspection game (Figure 2). The mixed strategies in the simple and extended game are stated in probability mixtures with likelihood $l \in [0,1]$ that the target actor commits one norm violation or that the norm enforcer inspects the action of the target actor. In the extended inspection game, however, the same probability is stated in frequentistic terms in a pure strategy (p out of m). Equivalent in this context means that the frequentistic statement is substantially similar to the probabilistic statement (i.e. $p / m = l$). For example, if the predictions for self-regarding players in the simple inspection game is given by the likelihood $l = 0.2$ (i.e. 20 %), the prediction in a formally equivalent frequentistic inspection game is 2 out of 10 (i.e. 2/10 = 0.2).

Table 2: Expected number of detected norm violations d for given numbers of all norm violations (column) and all numbers of inspections (row)

		inspections										
	d	0	1	2	3	4	5	6	7	8	9	10
norm violations	0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	1	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
	2	0.0	0.2	0.4	0.6	0.8	1.0	1.2	1.4	1.6	1.8	2.0
	3	0.0	0.3	0.6	0.9	1.2	1.5	1.8	2.1	2.4	2.7	3.0
	4	0.0	0.4	0.8	1.2	1.6	2.0	2.4	2.8	3.2	3.6	4.0
	5	0.0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	4.5	5.0
	6	0.0	0.6	1.2	1.8	2.4	3.0	3.6	4.2	4.8	5.4	6.0
	7	0.0	0.7	1.4	2.1	2.8	3.5	4.2	4.9	5.6	6.3	7.0
	8	0.0	0.8	1.6	2.4	3.2	4.0	4.8	5.6	6.4	7.2	8.0
	9	0.0	0.9	1.8	2.7	3.6	4.5	5.4	6.3	7.2	8.1	9.0
	10	0.0	1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0	10.0

The predictions for self-regarding players in the extended inspection game are derived by calculating the detection rate for a given number of norm violations and inspections. In order to compute the best response for any combination of given possibilities let l be the likelihood that n out of p thefts are detected. This is given by

$$l(p, q) = \frac{\binom{p}{n}\binom{10-p}{q-n}}{\binom{10}{q}} \quad (1)$$

when the inspectee chooses p thefts and the inspector chooses q inspections in the range between 0 and 10 where $n \in [0, q]$. The expectation value d of detected thefts is computed by summing up the likelihood l that a given amount of n thefts are detected over all possible n (Rauhut 2012):

$$d(p, q) = \sum_{n=0}^{p} nl = \sum_{n=0}^{p} n \frac{\binom{p}{n}\binom{10-p}{q-n}}{\binom{10}{q}} \quad (2)$$

Table 2 shows the number of detected norm violations d as a function of the number of norm violations p and the number of inspections q, which are computed by equation 2. The increase of the detection probability with higher numbers of inspections and norm violations is reflected in the expected payoffs for both inspector and inspectee. The expected utility h for target actors is a function of the payoffs, namely reward r and punishment ω, the number of committed norm violations p and the expectation value of the number of detected norm violations d for a given number of inspections q. This yields the expected utility for norm violations h as

$$h(p, q) = p \cdot r + d(p, q) \cdot \omega. \quad (3)$$

The expected utility i for norm enforcers is a function of the payoffs, namely inspection cost c and reward for successful inspection s, the number of performed inspections q and the expectation value of the number of detected norm violations d for a given number of performed norm violations p. This yields the expected utility for inspections i as

$$i(p, q) = q \cdot c + d(p, q) \cdot s. \tag{4}$$

We illustrate the game dynamics by using exemplary payoffs for target actors and norm enforcers for two different punishment scenarios (mild and severe punishment). The exemplary payoffs here correspond to the monetary payoffs in the laboratory experiment. The payoffs are displayed in Table 3.

Table 3: Payoffs for illustration of the game dynamics (also used in the experiment)

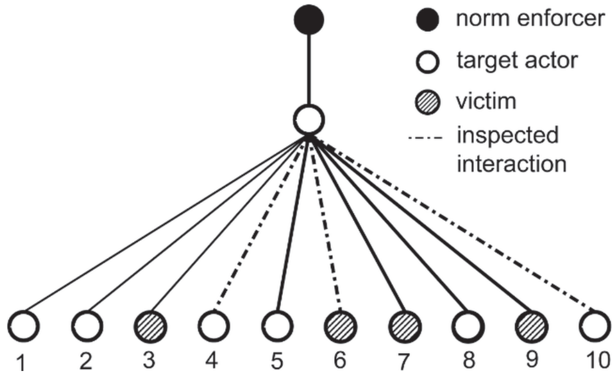
	target actor *h*		
	reward r	punishment ω	victimization v
mild punishment	+8 cents	-10 cents	-20 cents
severe punishment	+8 cents	-40 cents	-20 cents

	norm enforcer *i*	
	inspection cost c	reward for successful inspection s
mild punishment	-10 cents	+20 cents
severe punishment	-10 cents	+20 cents

For illustration of the rules of the game and the corresponding payoffs, consider the following example (Figure 3). The depicted target actor steals from four other target actors. The four victims are randomly selected (shaded circles 3, 6, 7 and 9 in Figure 3). Simultaneously, the norm enforcer decides to inspect three of the target actor's interactions, which are also randomly selected (dashed lines 4, 6 and 10 in Figure 3). In this example, the norm enforcer pays 30 Cents for three inspections and gains 20 Cents for one successful inspection (interaction number 6). This adds up to a loss of 10 Cents. The target actor would earn 22 Cents in the mild punishment and lose 8 Cents in the severe punishment condition.[4] This is true if she has not been victimized. Each victimization would yield an additional loss of twenty Cents.

4 The gain of 22 Cents in mild punishment comes from 4 thefts times eight Cents (i.e. 32 Cents) minus 10 cents punishment. For severe punishment, the gain of 32 Cents is reduced by 40 Cents punishment, yielding a loss of 8 Cents.

Figure 3: Randomization example of the number of detected norm violations for a given number of all committed norm violations and all inspections in the frequentistic inspection game



Notes: The target actor commits four norm violations (shaded circles 3, 6, 7, 9), the norm enforcer performs three inspections (dashed lines 4, 6, 10) and one norm violation is detected (number 6).

Using the payoffs from Table 3, we can compute expected utilities for all combinations of the number of norm violations and inspections (Tables 4 and 5) under risk neutrality. The table shows payoffs for target actors on the left side of the comma and for norm enforcers on the right side. The expected utilities can be used to compute best responses for both players (gray areas) and corresponding equilibria (overlapping gray areas).

For the target actor, expected utilities are generally higher in the mild punishment condition than in the severe punishment condition. This supports the intuition that target actors receive higher payoffs for lower punishment. Up to a certain point, target actors receive higher payoffs for more norm violations. This is true up to the „indifference point" of target actors (gray column), where payoffs are zero no matter how many norm violations are committed. The indifference point for the target actor is exactly at eight inspections in the mild punishment scenario (Table 4) and at two inspections in the severe punishment scenario (Table 5). When the target actor commits more norm violations than at the indifference point, payoffs become negative and subsequently decrease for more norm violations.

Table 4: Game matrix of expected utilities in normal form (mild punishment)

		inspections										
		0	1	2	3	4	5	6	7	8	9	10
norm violations	0	0,0	0,-10	0,-20	0,-30	0,-40	0,-50	0,-60	0,-70	**0**,-80	0,-90	0,-100
	1	8,0	7,-8	6,-16	5,-24	4,-32	3,-40	2,-48	1,-56	**0**,-64	-1,-72	-2,-80
	2	16,0	14,-6	12,-12	10,-18	8,-24	6,-30	4,-36	2,-42	**0**,-48	-2,-54	-4,-60
	3	24,0	21,-4	18,-8	15,-12	12,-16	9,-20	6,-24	3,-28	**0**,-32	-3,-36	-6,-40
	4	32,0	28,-2	24,-4	20,-6	16,-8	12,-10	8,-12	4,-14	**0**,-16	-4,-18	-8,-20
	5	40,**0**	35,**0**	30,**0**	25,**0**	20,**0**	15,**0**	10,**0**	5,**0**	**0,0**	-5,**0**	-10,**0**
	6	48,0	42,2	36,4	30,6	24,8	18,10	12,12	6,14	**0**,16	-6,18	-12,20
	7	56,0	49,4	42,8	35,12	28,16	21,20	14,24	7,28	**0**,32	-7,36	-14,40
	8	64,0	56,6	48,12	40,18	32,24	24,30	16,36	8,42	**0**,48	-8,54	-16,60
	9	72,0	63,8	54,16	45,24	36,32	27,40	18,48	9,56	**0**,64	-9,72	-18,80
	10	80,0	70,10	60,20	50,30	40,40	30,50	20,60	10,70	**0**,80	-10,90	-20,100

Table 5: Game matrix of expected utilities in normal form (severe punishment)

		inspections										
		0	1	2	3	4	5	6	7	8	9	10
norm violations	0	0,0	0,-10	**0**,-20	0,-30	0,-40	0,-50	0,-60	0,-70	0,-80	0,-90	0,-100
	1	8,0	4,-8	**0**,-16	-4,-24	-8,-32	-12,-40	-16,-48	-20,-56	-24,-64	-28,-72	-32,-80
	2	16,0	8,-6	**0**,-12	-8,-18	-16,-24	-24,-30	-32,-36	-40,-42	-48,-48	-56,-54	-64,-60
	3	24,0	12,-4	**0**,-8	-12,-12	-24,-16	-36,-20	-48,-24	-60,-28	-72,-32	-84,-36	-96,-40
	4	32,0	16,-2	**0**,-4	-16,-6	-32,-8	-48,-10	-64,-12	-80,-14	-96,-16	-112,-18	-128,-20
	5	40,**0**	20,**0**	**0**,**0**	-20,**0**	-40,**0**	-60,**0**	-80,**0**	-100,**0**	-120,**0**	-140,**0**	-160,**0**
	6	48,0	24,2	**0**,4	-24,6	-48,8	-72,10	-96,12	-120,14	-144,16	-168,18	-192,20
	7	56,0	28,4	**0**,8	-28,12	-56,16	-84,20	-112,24	-140,28	-168,32	-196,36	-224,40
	8	64,0	32,6	**0**,12	-32,18	-64,24	-96,30	-128,36	-160,42	-192,48	-224,54	-256,60
	9	72,0	36,8	**0**,16	-36,24	-72,32	-108,40	-144,48	-180,56	-216,64	-252,72	-288,80
	10	80,0	40,10	**0**,20	-40,30	-80,40	-120,50	-160,60	-200,70	-240,80	-280,90	-320,100

For the norm enforcer, the exact opposite structure holds. The inspector's expected utilities are similar for mild and severe punishment for given norm violations of the target actor. This reflects the intuition that payoffs of the target actor do not directly affect expected utilities of the norm enforcer. If there are at least five norm violations, the inspector's expected utility is positive and becomes higher, the more inspections she performs. If there are less than five norm violations, however, her expected utility is negative and becomes smaller the more inspections she performs. If there are exactly five norm violations, the inspector is indifferent and every number of inspections returns the same expected utility. These dynamics are true for both scenarios; mild and severe punishment.

From the considerations above about how expected utilities increase or decrease if a certain strategy is intensified and the opponent's strategy is hold constant, best responses can be derived as follows. Target actors in the mild punishment scenario commit the maximum number of ten norm violations if norm enforcers inspect between 0 and 8 of their actions. If norm enforcers inspect more than eight actions, target actors do not commit any norm violation at all. They are indifferent if norm enforcers inspect exactly eight actions. For the case of severe punishment, target actors commit the maximum number of ten norm violations if norm enforcers inspect between 0 and 2 actions. If norm enforcers inspect more than two actions, target actors do not commit any norm violation at all. They are indifferent if norm enforcers choose exactly two inspections.

Norm enforcers' best responses are derived similarly. Norm enforcers perform no inspections if target actors commit between 0 and 5 norm violations. They are indifferent if target actors commit exactly five norm violations. Norm enforcers perform the maximum of ten inspections if target actors commit more than five norm violations.

The combination of best responses is given by the combination of gray areas in Tables 4 and 5. This combination is also the Nash equilibrium. It can be seen that there is only one Nash equilibrium in pure strategies for each punishment scenario. In the mild punishment scenario, target actors commit five norm violations and norm enforcers perform eight inspections. In the severe punishment scenario, target actors commit as well five norm violations and inspectors perform two inspections.

The assumed underlying logic is that both players make their opponent indifferent. In the case of dichotomous choices, this works with mixed strategies. In the case of choosing a number of norm violations and inspections between 0 and 10, this works with pure strategies. Yet, the predictions in both game designs is equivalent. Target actors choose their norm violations based on the payoffs of norm enforcers and norm enforcers choose their inspections based on payoffs of the target actor. In short, the theoretical prediction is that more severe punishments do not affect the level of norm violations. In contrast, more severe punishment causes less inspections.

4.2 Learning models of self- and other-regarding actors

In what follows, we use the model of perfectly farsighted, self-regarding target actors as baseline model to develop a self-regarding learning model. Here target actors learn the empirically occurring inspection rate to commit as many norm violations as they maximize own payoffs. This is a more behavioral and data-driven approach, which considers best responses of target actors for their specific situation which they actually experience. We develop these models as agent based simulations. Simulations are used because analytical calculations of these more complicated behavioral types become too complex. We contrast the self-regarding model with an other-regarding model of negative reciprocity of a tit-for-tat kind.

Both models of our comparison represent backward-looking learning. They are both implemented in a simple and a complex structure. In the simple models, actors learn only from the last time step. Here, the time lag from the previous period explains the behavior in the current period. In the complex models, actors learn from all previous time steps and update every period. Here, all preceding actions are taken into account and learning includes the whole time series up to time $t - 1$.

4.3 Self-regarding learners

The self-regarding learning model depicts target actors who try to outplay the norm enforcer. They try to learn the strategy of the norm enforcer and give a best response for a given expected behavior of the norm enforcer. We call this model *self-regarding learning* of target actors. Here, target actors try to avoid detection, but try to commit as many norm violations as possible if undetected. In this way, target actors commit many norm violations if they expect few inspections (and therefore few punishments), and they commit few norm violations if they expect many inspections (and therefore many punishments).

This model considers target actors who act purely self-regarding. They try to learn the strategy of the norm enforcer to optimally outplay her. Outplaying is performed such that own expected utility is maximized. Therefore, the actions of other target actors and any experienced victimizations do not matter for this type.

Short-term self-regarding learning

Self-regarding actors condition on the last action of the norm enforcer. The inspection rate k from the last period $t - 1$ predicts the current number of norm violations at the current period t:[5]

$$p_t = k_{t-1} \tag{5}$$

5 For the first period no prediction is modeled, since no previous observations of inspections are available.

Long-term self-regarding learning

The long-term self-regarding learning model is more elaborate. In every period, the best response is calculated from all previously experienced interactions. All target actors simultaneously update in every period. Target actors calculate the expected inspection probability c in the current period from all previously experienced inspections. If the expected inspection probability exceeds the threshold where the expected utility for norm violations becomes negative, no norm violations are committed. If the expected inspection probability is lower than this threshold, the maximum number of norm violations are committed.[6]

More formally, target actors update the expectation value of inspections based on all previous periods. Target actor h therefore sums up all previous inspections k up to time $t - 1$ and computes the average by dividing by $t - 1$.

$$\bar{k}_{h,t-1} = \frac{\sum_{\tilde{t}=1}^{t-1} k_{h,\tilde{t}}}{t - 1} \tag{6}$$

The expectation value of inspection c consists of the mean of all previous inspections up to time $t - 1$ plus the previous expectation value of getting inspected divided by two. The second operation generates an average between the current and the previous expectation value of getting inspected.[7]

$$c_{h,t} = \frac{\bar{k}_{h,t-1} + c_{h,t-1}}{2} \tag{7}$$

The number of committed norm violations p_t at the current period depends on the expectation value of getting inspected $c_{h,t}$ and the punishment level. Considering the payoffs from Table 3, the threshold of committing norm violations in the mild punishment scenario is at the indifference point eight (as marked in Table 4). This means, that there are no norm violations if the target actor expects more than eight inspections. There are ten norm violations if the target actor expects less than eight inspections. There are 5 norm violations (the middle value) if the target actor expects exactly eight inspections:

$$p_{t,mild} = \begin{cases} 0 \ \ if \, c_{h,t} > 8 \\ 5 \ \ if \, c_{h,t} = 8 \\ 10 \ \ if \, c_{h,t} < 8 \end{cases} \tag{8}$$

Analogously, the threshold is at the indifference point two for severe punishments s (see Table 5). There are no norm violations for more than two expected inspections, ten norm

6 Note that this model corresponds to the game theoretical learning model fictitious play. The first experimental test of this learning model in inspections games has been contributed by Rauhut (2009) and Rauhut and Junker (2009). There exists a number of theoretical explorations for other games, for example by Fudenberg and Levine (1998) and Berger (2005). The name fictitious play comes from Brown (1951).

7 Note that this update method discounts time by taking the average of the expectation value at t and at $t - 1$. In this way, the last period carries more weight compared to a model without this adaption. This adjustment addresses the concern that weighing all periods equally would demand unrealistically high cognitive abilities. This adaption, therefore, makes the last experience more important than what happened before. See Kuroczka (2009) for further discussion of this adaption and an experimental test in inspection games.

violations for less than two expected inspections and 5 norm violations (the middle value) for exactly two expected inspections:

$$p_{t,severe} = \begin{cases} 0 \ \mathit{if}\, c_{h,t} > 2 \\ 5 \ \mathit{if}\, c_{h,t} = 2 \\ 10 \ \mathit{if}\, c_{h,t} < 2 \end{cases} \tag{9}$$

The initial belief at time t_0 is assumed such that it fits an expected utility maximization in the first period. This allows more fine-grained computations of expectation values in subsequent periods.[8]

4.4 Other-regarding reciprocators

The basic idea of this simulation is to model the other-regarding orientation of generalized negative reciprocity. It models an orientation of the kind *I will do to any others what happened to me*. This means in the inspection game that experienced victimizations v are reciprocated by norm violations p which affect any others. Note that our version of reciprocity of responding on victimizations with thefts reflects the well-known reciprocal strategy „tit-for-tat". In our context, we call the actor type who follows a tit-for-tat strategy „reciprocator". We implement a short-term and a long-term version of reciprocity. Short-term reciprocators only care about the last period. Long-term reciprocators consider the complete experience over all previous periods. This can be formalized as follows.

Short-term reciprocator

Target actors reciprocate the number of experienced victimizations from the last round by the same number of own norm violations in the next round.[9] Formally, victimization v at time t predicts norm violations at time $t + 1$. For a sequence of 50 time steps, it holds for each time step $t \in [2{,}50]$ that

$$p_t = v_{t-1.} \tag{10}$$

Long-term reciprocator

A long-term reciprocity strategy considers all previous periods. The model uses the average number of victimizations up to time t - 1. The average of all previously experienced victimizations predicts the rate of norm violations p at the current period t:

$$p_t = \frac{\sum_{\tilde{t}=1}^{t-1} v_{\tilde{t}}}{t-1}. \tag{11}$$

8 More precisely, the initial belief b is implemented in the mild punishment condition with $b_m = [0{,}8]$ if $p \geq 1$ and $b_m = [8{,}10]$ if $p = 0$. For severe punishment, $b_s = [0{,}2]$ if $p \geq 1$ and $b_s = [2{,}10]$ if $p = 0$. Specific values within the intervals were set randomly.

9 At time t_1 no value is set because no previous victimizations occurred.

4.5 Comparability of the models

The short-term models of self-regarding and other-regarding types are constructed equivalently by using only one variable: prior inspections versus prior victimizations of the last period. The long-term models are conceptually equivalent, but differ in their construction. The long-term reciprocity model only considers one variable: prior victimizations. The long-term self-regarding learning model considers two variables: prior inspections and punishment severity.

The difference in the long-term models is required for the following reasons. The long-term learning model considers updates of the inspection probability, which are used for calculating the current payoff maximizing decision. This reflects a perfect selfish response for a current subjective estimate of the inspection probability, which is calculated over the complete course of the game. The long-term reciprocity model is equivalent in its sophistication, because it also reflects a perfect response for a given current estimate of the number of all prior norm violations of others, which is also calculated over the complete course of the game. Since reciprocity to other target actors does not require taking punishment severity into account, the long-term other-regarding model only requires conditioning on one variable, whereas the long-term self-regarding model requires conditioning on two variables.

5 Experimental design

5.1 Procedures, rules and participants

The experiment was conducted at the University of Leipzig, Germany. Students from various disciplines ($N = 220$) participated in the experiment. The experiment consisted of paper- and computer-based instructions, comprehension questions for both roles in the game, a knowledge quiz, the inspection game experiment and a reciprocity questionnaire. The experiment was conducted using z-tree (Fischbacher 2007).

In the knowledge quiz, participants answered questions about general topics. Participants earned money for each correct answer. As a consequence, the start-off money for every participant in the experiment varied depending on the quality of answers in the quiz.

There were ten experimental sessions. Twenty-two participants took part in each session. They were randomly divided into *target actors* and *norm enforcers*, using neutral wording. This yielded $N = 220$ participants divided into 110 target actors and 110 norm enforcers. Target actors and norm enforcers were paired in partner matching. Instructions were common knowledge for both roles.

Each session comprised of 50 periods, yielding a total of 11.000 observed decisions. These decisions are split between 5.500 decisions of target actors and 5.500 decisions of norm enforcers, which are made half in mild and half in severe punishment scenarios.

Each target actor was matched with ten other target actors from whom she could steal the fixed amount of 20 Euro-Cent (see Figure 2). Each theft earned eight Cents for the perpetrator. The asymmetry between payoffs of perpetrators and victims yielded collective welfare losses for each theft. The norm enforcers could inspect any number of interactions of her paired target actor at own costs. The computer randomly allocated the exact persons from whom money was stolen and whose interactions were inspected. Hence, it was impossible for the target actor to identify from whom she stole money or by whom she was victimized. This was common knowledge. This feature allowed to test generalized reciprocity, because actions and reactions were not identifiable. Detected thefts were automatically punished.

The severe punishment condition considered 40 Cents and the mild punishment condition eight Cents of punishment. Table 3 lists all payoffs.

The norm enforcer could decide the number of inspections of her target actor's actions. The specific interactions were randomly selected by the computer. Each inspection costs ten Cents and every successful detection of a theft earned 20 Cents (see Table 3). Fifty periods were played in total. They were split into 25 periods of mild and 25 of severe punishment. One treatment condition considered a sequence of 25 periods of mild punishment and then a sequence of 25 periods severe punishment. The second treatment condition reversed the order and implemented severe and then mild punishment. Norm enforcers were matched with the same target actor over the complete course of all 50 periods (partner matching).

5.2 Attitudinal measure of negative reciprocity

The above discussed learning models yield a behavioral measure of reciprocity in terms of responding to victimizations by thefts. This allows computing optimal reciprocity strategies for given experienced victimization levels for each actor, yielding individual behavioral reciprocity predictors for thefts. This enables testing how accurately people follow the strategy to give back as they were given.

In addition to this behavioral reciprocity measure, we also include an attitudinal measure of reciprocity. This allows statistical separation between the explanatory power of a reciprocal attitude of generally approving reciprocity in a „cost-free“ statement and a costly reciprocal strategy to pay victimizations back with thefts, „whatever the costs“.

We use the reciprocity questionnaire „Personal Norm of Reciprocity“ (Perugini et al. 2003) as attitudinal measure. The questionnaire conceptualizes three dimensions of reciprocity: beliefs in reciprocity, positive reciprocity and negative reciprocity. Each dimension is measured by nine questions, using a seven-point Likert scale (1 = not true for me, 7 = very true for me). We only utilize the negative reciprocity dimension in this investigation. The items of negative reciprocity capture the extent to which people are sensitive to negative actions of others and approve negative reactions. Table 6 lists the nine items.

We confirmed the validity of the scale by factor analyses, corroborating that the three subdimensions (beliefs, positive and negative reciprocity) clearly discriminate and that all items load consistently on one dimension. Our validity analysis generally replicates the scores of Perugini et al. (2003); our full analysis is available on request. Table 6 shows exclusively factor loadings for negative reciprocity items, since this is our theoretical focus and we only use this sub-dimension for subsequent analyses.[10]

10 Note that the factor loadings in Table 6 are computed from factor analyses including negative and positive reciprocity items, following the suggestion by Perugini et al. (2003).

Table 6: Items of negative reciprocity attitude and corresponding factor loadings

item	statement	loading
1	If somebody puts me in a difficult position, I will do the same to him/her.	0.71
2	If somebody offends me, I will offend him/her back.	0.67
3	If I suffer a serious wrong, I will take my revenge as soon as possible, no matter what the costs.	0.64
4	I am kind and nice if others behave well with me, otherwise it's tit-for-tat.	0.59
5	If somebody is impolite to me, I become impolite.	0.58
6	If someone is unfair to me, I prefer to give him/her what s/he deserves instead of accepting his/her apologies.	0.55
7	I am willing to invest time and effort to reciprocate an unfair action.	0.52
8	The way I treat others depends much on how they treat me.	0.50
9	I would not do a favor for somebody who behaved badly with me, even if it meant forgoing some personal gains.	0.47

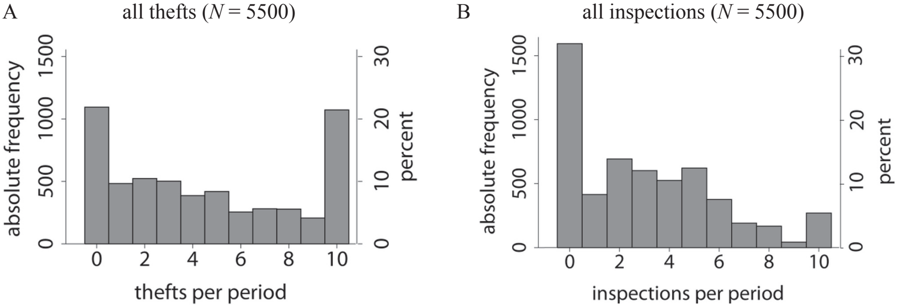
Notes: Statements are rated on 7-point Likert scales (ranging from „not true for me" to „very true for me"). Items are ordered from highest to lowest loadings, reflecting their relative importance in the factor score of negative reciprocity. The factor analysis is computed over all subjects; target actors and norm enforcers ($N = 220$).

6 Results

6.1 Measurement validation of the frequentistic inspection game

In the first step of our empirical analysis, we present descriptive statistics, demonstrating the usefulness of the novel „frequentistic inspection game". The main motivation of the frequentistic inspection game was twofold: allowing people to make more fine-grained, continuous choices and enabling them to express their choice probabilities in frequentistic terms. However, do people actually take advantage of the more fine-grained scale? Do people graduate their level of norm violations and inspections along the continuum between no and full action?

Figure 4: Distribution of the number of committed thefts and performed inspections per period, added up over all periods



Notes: Each subfigure shows on the left y-axis absolute and on the right y-axis relative frequencies.

Figure 4A shows how many times target actors commit how many thefts per period. It reveals three patterns. First, target actors graduate their level of norm adherence. There are many decisions in between the extremes of behaving as „saints" or „devils". About half of the decisions are graduated in the middle. This demonstrates the usefulness of our more fine-grained measure of norm adherence and our novel way of measuring mixed strategies compared to previous designs with dichotomous choices. The second observation is that about the other half of theft decisions peak at the extremes of the minimum or the maximum number of thefts. This dichotomy of either playing extremes or graduating thefts may already indicate a dichotomy of types in the population: self-regarding target actors who play the extremes as best response to norm enforcers and other-regarding target actors who graduate their thefts as responses to victimizations from other target actors. The third observation is the sheer number of measured decisions, which come with the design. The left y-axis shows that absolute frequencies of thefts goes into thousands, demonstrating the richness of the data obtained from frequentistic inspection game experiments.

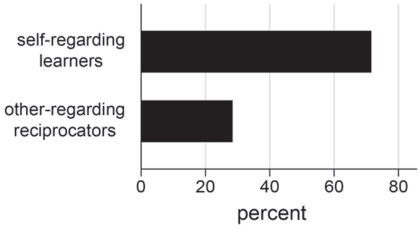
Figure 4B shows how many times norm enforcers perform inspections per period. The three patterns for thefts (4A) roughly replicate for inspections (4B). First, norm enforcers also graduate their behavior. About two thirds of all inspection decisions are graduated in the middle of both extremes of a „laissez-faire“ or a „big-brother“ control regime. This also confirms the usefulness of the fine-grained measures from the frequentistic inspection game. The second observation is that about one third of the inspection decisions peak at the extremes of inspecting nothing or everything. In contrast to similar peaks in thefts, there are more minimum than maximum inspections. Third, also inspection decisions (left y-axis) are very rich in absolute numbers.

6.2 Fragmentation between self-regarding learners and other-regarding reciprocators

In the second step of our empirical analysis, we investigate the existence and proportion of different types in the population. Self-regarding learners are target actors who commit as many thefts as they pay off for a given inspection rate of the norm enforcer. Other-regarding reciprocators respond to victimizations of other target actors with thefts. We also show here that reciprocity is other-regarding in the sense that reciprocators pay additional costs for paying back victimizations by thefts.

We use the described typology in section 4.2 for investigating the relative proportion of these two types in our population. More specifically, we compute for every target actor in each period the strategy for a perfect self-regarding learner and for a perfect other-regarding reciprocator. Since there are 110 target actors and 50 periods, we compute for each of the two models 5.500 predictions for the number of committed thefts. These predictions are compared with the actually committed number of thefts in each period by taking the differences between model and data. For each target actor, this yields 110 differences for both models, which are summed up, yielding a measure of accuracy. We classify each target actor to the respective type with the smallest difference between model and data. Target actors with equal accuracy for both models are disregarded and coded as missing for this analysis. We use our so-called „short-term“ learning models for the classification.

Figure 5: Distribution of self-regarding learners and other-regarding reciprocators



Notes: Types are categorized by the smallest difference between model predictions and actual theft behaviors.

Figure 5 shows the distribution of types. About two thirds of target actors are classified as self-regarding and one third as other-regarding. Although the larger group is self-regarding, there is a substantial part of the population following a tit-for-tat strategy and respond stronger to victimizations than to inspections and punishments.

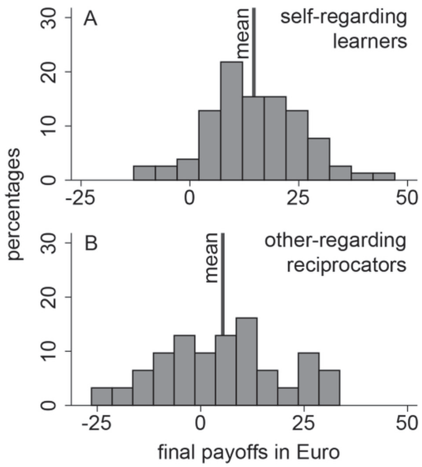
In addition, we investigate whether reciprocity is indeed „other-regarding“. Thus, we measure the price for paying victimizations back with thefts. This is done by comparing the final profits for self-regarding learners and other-regarding reciprocators. Figure 6 shows that self-regarding learners (panel A) receive indeed more payouts than other-regarding reciprocators (panel B). The average final payout for self-regarding learners is about three times as high (15 Euro) as for other-regarding reciprocators (5 Euro).[11] On average, this justifies the categorization of reciprocators as „other-regarding“.

6.3 Explanatory power of self-regarding learning and other-regarding reciprocity

In the third step of our empirical analysis, we investigate the explanatory power of self- and other-regarding motives for norm violations. Are norm violations mainly driven by selfish, strategic outplaying of norm enforcers to reap as many gains from norm violations as possible with the least possible detection rate? Or are norm violations rather driven by reciprocating experienced victimizations from others by own norm violations?

11 Note that the standard bankruptcy rule has been applied that no negative payouts were demanded from subjects so that negative earnings yielded zero actual earnings. If mean final earnings are computed under this rule, there are still substantial differences: self-regarding learners earned 15 Euros and other-regarding reciprocators nine Euros.

Figure 6: Distribution of final payoffs by types



Notes: Panel A shows the distribution and the mean final payoffs for self-regarding learners and panel B for other-regarding reciprocators. The lower payoffs of reciprocators demonstrate the additional costs for paying victimizations back by thefts.

In what follows, we estimate the explanatory power of the models for self-regarding behavior (section 4.3) and other-regarding behavior (section 4.4) and compare their fit with the data. We estimate the empirical fit by regression models of theft behavior. More specifically, equations from sections 4.3 and 4.4 are used as individual level predictors for theft. These equations return for each individual at each period the perfect self- and the perfect other-regarding strategy of how to respond to the specific numbers of prior victimizations or inspections with own theft behavior at the current period. We check the robustness of both model predictions by estimating all regressions separately for the short-term and the long-term learning models.

Table 7 shows the corresponding regression models with unstandardized coefficients (first line), standardized coefficients (second line) and t-values (third line). In the short-term learning models, predictors for theft behavior at period t are calculated from victimizations and inspections from period $t-1$. The long-term learning models use individually experienced victimizations and inspections from all prior periods to explain theft at period t. For short- and for long-term learning, four differently complex regression models are calculated. The first two models estimate the bivariate fit for other-regarding and self-regarding motives, the third model compares their relative explanatory power by controlling for each other and the forth model includes additional covariates. Since our data has a multi-level structure, where 50 theft decisions are clustered within each subject, random intercepts models are employed to adjust for clustering.

The variables are coded as follows. The variable „reciprocity strategy“ corresponds to the number of victimizations at the last period (short-term) or the average number of victimizations over all prior periods (long-term). The variable „selfish-learning“ corresponds to the number of prior inspections for the case of short-term learning. For the case of long-term learning, it reflects the optimal response to all previously experienced inspections; it is the minimum of zero if the expected inspection probability exceeds the threshold, where expected payoffs become negative and it is the maximum of ten if the expected inspection probability is below the threshold (see equation 7, 8 and 9 for computational details). „Reciprocity attitude" is the factor score including all nine items for negative reciprocity, weighted with their loadings from Table 6. „Reciprocity interaction" reflects the multiplicative interaction between „reciprocity strategy" and „reciprocity attitude". „Punishment severity" is a dummy variable for the punishment treatment, coded with zero for mild and one for severe punishment. „Detection rate" is the number of detected (and punished) thefts in the previous period (short-term) or the average over all prior periods (long-term).

Other-regarding reciprocity plays a major role in committing norm violations: there is a strong bivariate relationship between previously experienced victimizations and preceding thefts. This effect is robust over all controlled variables in the short-term models (M1-M4). It becomes weaker when all other explaining factors come into play, but remains significant. It also holds for the long-term models. It is highly significant in the bivariate (M5) and in the simple multivariate model (M7). The effect is still positive, but not anymore significant in the full long-term model (M8), mainly due to the additional interaction effect.

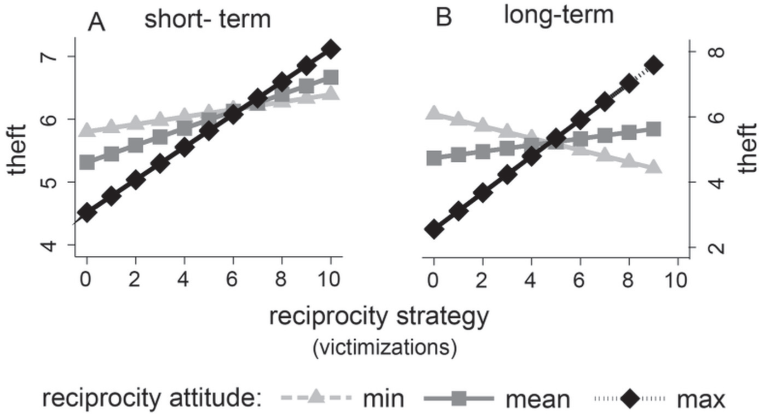
Self-regarding learning also has a positive effect on thefts. While it is insignificant in the bivariate short-term model (M2), it becomes significant in the multivariate model specifications (M3, M4). It is also significant in all long-term models (M6, M7, M8).[12] This means that the self-regarding motive to learn how to outplay the norm enforcer in order to commit as many norm violations as they pay off, is a second highly explanatory motive for norm violations. Thus, both are highly relevant mechanisms of norm violations; other-regarding reciprocity to pay back victimizations and self-regarding learning how to outplay enforcers to avoid detections.

We also included an interaction term between strategic and attitudinal reciprocity. This interaction is especially interesting for studying the underlying principles of how attitudes and strategies play together. The interaction effect has the same direction in the short- and the long-term models and is statistically significant in both model variants. We illustrate the interaction from the short- and the long-term models in Figure 7, facilitating the understanding of the interplay between negative reciprocity attitude, victimizations and thefts. Both panels show conditional effects plots based on model 4 in the short-term (Fig. 7A) and model 8 in the long-term version (Fig. 7B). The graphs plot a simple regression line for the following three values of the negative reciprocity index: the minimum (triangles), the mean (squares) and the maximum (diamonds). All other effects are kept fixed. If there was no interaction effect, the three lines would overlap. This is clearly not the case; there is an interaction effect between strategic reciprocity behavior, negative reciprocity attitude (questionnaire) and

12 Note that the additional significant positive effect of detected thefts may be misleading. Due to the general model structure of using random intercepts, this effect is overestimated. Detected thefts inherently combines the measurement of inspection and theft. Both need to be present in order for theft to be detected. Indirectly, a lag of the dependent variable theft is represented in the exogenous variable and therefore the uncorrelated error condition of the model is violated and its effects are consequently overestimated. Arellano and Bond (1991) developed a solution based on instrumental variables estimation for regressions including one or multiple lags of the dependent variable to avoid serial correlation of the error term. However, this approach does not allow the estimation of time invariant subject variables such as the reciprocity index. Since this index does carry a lot of weight in our model the decision was made in favor of the standard random intercepts model in order to keep the time invariant variable but with the restriction to overestimate the effect of detected theft and not to include a direct lag of theft. Instead of a direct lag of the dependent variable, detected thefts is being used as a compromise, with the disadvantage that it is likely to be overestimated. In the complex models with all lags included (right hand panels), the effect of detected thefts is much smaller. It is, however, probably still overestimated. It cannot be clearly said whether the direction of the effect of detected thefts in the previous round on thefts in the current round is positive or negative.

theft behavior. This is true for the short- and the long-term models. The effect for the long-term model is stronger, which can be seen by the wider spread of the three regression lines.

Figure 7: Conditional effects plot of the interaction between reciprocity strategy and reciprocity attitude on the number of committed thefts



Notes: Panel A displays regression effects of the short-term learning model (Table 7, model 4) for the minimum (triangle), mean (square) and maximum (diamond) values of the negative reciprocity attitude. Panel B displays respective regression effects of the long-term learning model (Table 7, model 8).

The interaction can be interpreted as follows. The stronger the negative reciprocity trait, the stronger are previously experienced victimizations reciprocated by own thefts. This means that target actors with a low negative reciprocity trait (light gray triangles) show little theft responses to suffered victimizations. In contrast, target actors with a strong negative reciprocity trait (black diamonds) show strong theft responses to suffered victimizations. The number of suffered victimizations has, therefore, different effects on people's own theft behaviors, depending on their reciprocity attitude. People with a strong reciprocity attitude, follow almost perfectly a *tit-for-tat* strategy and respond to a given number of victimizations with the same number of thefts. They reward few victimizations with little thefts and retribute many victimization with many thefts. In contrast, people with a low reciprocity attitude show about constant levels of own thefts, regardless of whether they were victimized few or many times.

7 Discussion

Reciprocity is an important mechanism for the evolution of cooperation norms. Yet, the current research on reciprocity has been limited to two kinds of reciprocity. The first line of research studies how positive reciprocity fosters cooperation norms. One example is that workers reciprocate high wages with high work effort. This „gift exchange" has been shown under controlled conditions in laboratory experiments (Fehr et al. 1993, 1998; Charness / Haruvy 2002) and in the field (Falk 2007). The fact that returns largely exceed competitive levels yields evidence for an other-regarding norm of positive reciprocity. The second line of research studies negative reciprocity inasmuch as uncooperative behavior is altruistically punished (Fehr / Gächter 2002; Gürerk et al. 2006). Here, group members are willing to punish free-riders even if they have to invest considerably punishment costs.

Table 7: Linear random intercepts models comparing the explanatory power of other- and self-regarding motives for theft behavior

	short-term learning				long-term learning			
	$theft_t$ (M1)	$theft_t$ (M2)	$theft_t$ (M3)	$theft_t$ (M4)	$theft_t$ (M5)	$theft_t$ (M6)	$theft_t$ (M7)	$theft_t$ (M8)
reciprocity strategy	0.481***		0.495***	0.135***	0.841***		0.313***	0.098
prior victimizations	0.259***		0.266***	0.073***	0.250***		0.093***	0.029
	(20.46)		(20.65)	(4.74)	(13.07)		(4.77)	(1.51)
selfish learning		0.018	–0.055**	–0.231***		0.254***	0.236***	0.054**
prior inspections		0.014	–0.042**	–0.178***		0.331***	0.307***	0.070**
		(0.97)	(–2.97)	(–10.10)		(25.53)	(21.74)	(3.04)
reciprocity attitude				–0.292*				–0.799**
factor scale				–0.076*				–0.207**
				(–2.19)				(–2.87)
reciprocity interaction				0.046*				0.168**
strategy × attitude				0.059*				0.189**
				(1.97)				(2.76)
punishment severity				–2.161***				–2.000***
mild vs. severe				–0.292***				–0.270***
				(–18.82)				(–12.06)
detection rate				0.266***				0.049*
prior inspected				0.153***				0.028*
& punished				(8.74)				(2.03)
intercept	2.379***	4.502***	2.487***	5.315***	0.815**	2.942***	1.690***	4.693***
	(14.20)	(32.83)	(14.78)	(27.10)	(2.59)	(21.91)	(5.64)	(12.38)
R^2	0.061	0.003	0.058	0.140	0.009	0.054	0.056	0.115
rho	0.125	0.107	0.117	0.042	0.120	0.110	0.110	0.086
$sigma_e$	3.357	3.489	3.353	3.209	3.417	3.266	3.272	3.240
$sigma_u$	1.268	1.206	1.220	0.672	1.262	1.148	1.149	0.994

Notes: First coefficient in each line denotes unstandardized effects, second standardized effects, third *t*-values (in parentheses). Multilevel structure with 5500 decisions at level one clustered in 110 subjects at level 2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Short term learning is implemented by one-lag and long-term by all-lag panel models.

Our contribution is novel in three ways: substantive, conceptual and methodological. First, we show the importance of a different kind of reciprocity, which has been paid little attention to: generalized negative reciprocity. Do people also reciprocate experienced damages and harms to uninvolved third parties whom they do not even know? We investigate generalized negative reciprocity in victims who return experienced thefts by stealing from third party actors who were not known to be the perpetrators. Our setup generalizes typical third party punishment experiments (Fehr / Fischbacher 2004; Henrich et al. 2006), because we show it for generalized negative reciprocity. Thus people even pay back to any others in contexts where norm violators are unknown.

The second novelty of our study is conceptual. We demonstrate the usefulness of inspection games for studying cooperation norms, which allows studying situations, where norm violators are unknown and have to be detected to be punished. The third novelty of our contribution is the presentation of a new measurement of strategic norm adherence and norm enforcement. Our design allows continuous choices and probability statement of violating a norm respectively performing control in frequentistic probability formats. This yields more fine-grained measures and higher construct validity of probability statements.

The results of our study can be summarized as follows. Our novel measurement of probabilistic choices in frequency formats proved to be useful. People utilize a large spectrum of the scale and graduate their level of norm violations and norm enforcement. While some play strategies at the extremes of either committing no or all possible thefts, a substantial fraction behaves in between. This is also true for inspection behavior, which scatters in between a laissez-faire and a big-brother control regime. This yields evidence for the usefulness of measuring probabilistic norm violations and inspection behaviors by frequency formats with more fine-grained scales.

Our substantive results show that both self-regarding and other-regarding motives play a role in understanding when norms are adhered to and when they are violated. This dichotomy of motives can be attributed to different actor types, who give a micro-explanation of the emergent, aggregated levels of norm adherence. On the one hand, there are self-regarding actors. These types are sensitive learners of the inspection rate and callibrate their thefts such that they yield positive expected payoffs. If inspected little, they commit many and if inspected much, they commit few thefts. On the other hand, there is a substantial fraction of other-regarding reciprocators. These reciprocators return experienced victimizations by stealing from other, unknown third parties. These reciprocators are more sensitive to victimizations from their fellows than to inspections by norm enforcers. This kind of reciprocity is other-regarding inasmuch as these types receive on average only one third of the earnings as self-regarding learners. This means that reciprocators pay back even under omnipresent control regimes and are willing to be detected and punished just to give back as many thefts as they were given.

We further substantiated the importance of generalized negative reciprocity by showing a strong interaction effect between reciprocity attitudes and behavioral reciprocity strategies on the number of committed thefts. The interaction effect shows how the approval of negative reciprocity moderates the strategic motive to respond to previously experienced victimizations by own thefts. More specifically, actors with strong approval of negative reciprocity of the kind that offenses should be retaliated by own offenses follow closely a tit-for-tat strategy: they steal almost exactly as much as they were victimized before. Actors with moderate approval of „tit-for-tat" show only moderate reciprocal response behavior: their own proclivity to steal increases only little if they experienced more prior victimizations. Finally, actors with little approval of „tit-for-tat" act almost completely independent from own victimization experiences: their theft behavior is unconditional on thefts from others. This interaction effect demonstrates the strong interplay between cost-free attitudes and costly strategies of reciprocity as mechanisms of norm adherence.

These results shed novel light on the dichotomy in sociology between self-regarding and other-regarding actor models for explaining social norms. These two opposed sociological schools of thought have long been deeply separated. The homo-sociologicus model conceptualizes social norms as a bridge between individual self- interests and functional prerequisites of society (Durkheim [1897]1979; Parsons 1937; Dahrendorf 2006). While this has been criticized as over-socialized conception of man (Wrong 1961), the rational-choice perspective has long been „under-socialized" by explaining the emergence of social norms only from one actor type, who is exclusively self-regarding. This literature studies conditions under which even self-regarding actors contribute to public goods and cooperation norms (Taylor 1976; Ullmann-Margalit 1977; Opp 1983; Coleman 1990; Voss 2001; Bicchieri 2006).

In the meanwhile, the boundaries between both schools fall slowly apart. Modern conceptions in behavioral game theory and analytical sociology allow for different actor types who either maximize self- or other-regarding motives (Camerer 2003; Fehr / Gintis 2007; Fischbacher / Gächter 2010; Winter et al. 2012). The assumption of heterogeneous populations in which both types coexist is more realistic and the emerging dynamics from interactions between both types is better able to explain when norms emerge and when they collapse. Our investigation contributes to this literature. We show that both types coexist: self- and other-regarding actors. Further, we show that the particular level of norm violations is an emergent property of the interaction between self- and other-regarding actors: one part of the population commits as many norm violations as it is individually payoff-maximizing for a given inspection rate and the other part pays back as many norm violations as they have received themselves.

Our investigation also contributes to the sociology of social norms and deviant behavior. There is recently a vivid discussion of the conditionality of normative behavior. A series of field experiments has shown that information of norm violations of others subsequently triggers more norm violations and eventually set off dynamics of normative decay and disorder. This „broken windows" dynamics has been tested in situations, where graffiti, litter, unreturned shopping carts, and illegal parking caused people to violate the same and even other norms (Keizer et al. 2008, 2013). Relatedly, it was shown that people also lie more if they observe others lying (Gino et al. 2009; Diekmann et al. 2011; Kroher / Wolbring 2013; Rauhut 2013).

One of the main problems in field studies on conditional normative behavior is to disentangle whether the „broken windows" effect is due to self- or other-regarding behavior. It could be self-regarding inasmuch as the observation of others' norm violations may make people conclude that the detection probability is low or that punishment is mild. Self-regarding learners would rationally update their subjective estimate of getting detected and commit subsequently more own norm violations, because violations pay more off for a lower detection probability. Alternatively, it could be other-regarding inasmuch as people condition their own norm violations directly on the level of norm violations of others irrespective of the detection probability. Our contribution has shown in a controlled laboratory context that both mechanisms play a role and that the population is fragmented into self- and other-regarding types. The interplay between both types is better able to explain the aggregate levels of conditional norm compliance than their separate analysis.

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Dr. Heiko Rauhut
Universität Zürich
Soziologisches Institut
Andreasstr. 15
8050 Zürich, Schweiz
heiko.rauhut@uzh.ch