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Discussion Paper

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Learning to cooperate in the shadow of the law*

Roberto Galbiati† Emeric Henry‡ Nicolas Jacquemet§

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Abstract

How does the exposure to enforcement in the past affect current cooperation? While a recent literature highlights the role played by enforcement in shaping social norms, we study the effect of enforcement on the ability to learn about the cooperativeness of other members of the group. Using a lab experiment with independent interactions and random rematching, we observe that, in early interactions, having faced an environment with fines in the past decreases current cooperation. This finding can be explained by the interaction of fines and learning: when incentivized by fines, cooperation becomes less informative about intrinsic cooperative values in the group. We show that participants in the experiment behave in accordance with a learning model, and in particular react differently to actions of past partners whether they were played in an environment with coercive enforcement or not. These results highlight a new channel through which enforcement affects the dynamics of cooperation: the ability to learn about prevalent norms interact with enforcement and affects future cooperation.

JEL Classification: C91, C73, D02, K49, P16, Z1.

Keywords: Enforcement, social values, cooperation, learning, spillovers, repeated games, experiments.

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†CNRS-Sciences Po and CEPR. Department of Economics, 28 rue des Saints-Pères 75007 Paris, France. roberto.galbiati@sciencepo.fr

‡Sciences Po and CEPR. Department of Economics, 28 rue des Saints-Pères 75007 Paris, France. emeric.henry@sciencepo.fr

§Paris School of Economics and University Paris 1 Panthéon-Sorbonne. Centre d'Economie de la Sorbonne, 106 Bd de l'hopital, 75013 Paris, France. nicolas.jacquemet@univ-paris1.fr

1 Introduction

Why does the level of cooperation vary across societies and organizations? A natural answer is that rules, and the strength of their enforcement, might differ. One expects high levels of cooperation where formal enforcement punishes defectors, for instance by the means of high fines. When strong formal enforcement is absent, cooperation can be sustained if cooperative values are prevalent enough in the group. For this second driver of cooperation, learning about the cooperativeness of the group becomes essential. In this paper we study the interaction between these two drivers of cooperation. We explore a simple intuition: formal enforcement does not only affect the individual decisions to cooperate, it also impacts on the capacity to learn about the group's cooperativeness. In contexts with high fines for those who do not cooperate, it is difficult to tell apart people who do so because of the threat of fines from those who are intrinsically cooperative types. Our study thus sheds light on the effect of enforcement on the dynamics of cooperation by unveiling how the shadow of enforcement affects learning and hence future cooperation.

We rely on the combination of theory and empirics, using a lab experiment where participants play a series of indefinitely repeated prisoner' dilemma. At the beginning of each game, it is randomly determined whether a formal enforcement in the form of a fine will be imposed in all rounds of the game when a participant chooses to deviate rather than cooperate.[1] At the end of the game, each participant is re-matched with a new one and it is randomly determined whether the new game is played with fines. The design ensures that each participant *(i)* has a different history of exposure to fines and of past behavior of partners, and that this history both *(ii)* does not depend on self-selection into particular environments, and *(iii)* is independent from the current environment faced by each individual. Each experimental subject thus faces a different history of past cooperation observed in different enforcement environments.

Our first main result shows that, in early games, past enforcement negatively affects current cooperation. We argue that the interaction between cooperation-enforcing institutions and learning can potentially explain such a pattern. Consider the case where the population is fairly non cooperative (i.e., less cooperative than expected). In this case, experiencing a fine can speed up learning the bad news, since observing deviation in an environment with fines is a strong indicator that the partner is non-cooperative. Conversely, learning will be slow within a cooperative group in an environment with fines. In such a context it will not be possible to learn whether cooperation is driven by fines or by partners' willingness to cooperate. This interaction between fines and learning is the key driving force of our model, whose findings are confirmed in the data.

The finding that enforcement in the past decreases current cooperation in early games contrasts with what would be expected based on the literature documenting the behavioral spillovers of

[1] In our setting when fines are present they are exogenously enforced. In this sense our setting differs from other studies like Acemoglu and Jackson (2017) or Zasu (2007) studying complementarities in the enforcement of cooperation between laws and social norms.

enforcement institutions—i.e., the fact that enforcement institutions faced either in the past (e.g., Peysakhovich and Rand, 2016; Duffy and Fehr, 2018; Galizzi and Whitmarsh, 2019, for a survey) or in other games (Engl, Riedl, and Weber, 2021), affect the current willingness to cooperate through behavioral channels.[2] Galbiati, Henry, and Jacquemet (2018) show that enforcement institutions foster future cooperation through indirect spillovers—fines increase the likelihood that the current partner cooperates, which in turn induces more cooperation in the future through indirect reciprocity (Nowak and Roch, 2007).[3] This previous study uses the same experiment as in the current paper, but focuses only on games occurring late in the experiment under the assumption that learning has converged. In this paper, we focus on the interaction between fines and rational learning. In early games, there is uncertainty about intrinsic values in the group (i.e. about whether the average partner is of a cooperative or a non-cooperative type). In such circumstances, our theoretical model shows that partners' behavior in previous games brings information about how cooperative the group is and thus affects current behavior. From an empirical point of view, observing learning becomes challenging due to the simultaneous effect of behavioral spillovers. We propose two identification strategies to identify learning separately from spillovers.

The main identification strategy exploits the idea that behavioral spillovers do not last (as shown in Galbiati, Henry, and Jacquemet, 2018) while learning is cumulative: whether cooperation was observed one or two periods ago does not matter for learning, as the information it delivers remains the same, but will matter for spillovers if they decay over time. Thanks to the assumption that spillovers are short-lived, we can disentangle the two by regressing current cooperation levels on variables that are history dependent (spillovers) and history independent (learning). Our results show that replacing in the history one signal of deviation without fine by a signal of cooperation without fine, increases current cooperation by 10%; while replacing it by a signal of cooperation with fine increases current cooperation only by 5%. This is coherent with rational learning dynamics.

As a robustness check, we also provide a structural analysis (provided in the Appendix, Section B) which identifies learning in early games conditional on behavioral spillover parameters, under the assumption that learning has converged in late games. We first generalize our theoretical model to the case in which individual values evolve over time as a result of past experience. This extended model allows us to express the probability of cooperation as a function of both learning and spillover parameters that we can estimate with our experimental data. The results confirm that lab participants behave in accordance with the learning dynamics described by the model: cooperation by the partner in the previous game, if it was played with a fine, has a smaller

[2]Another strand of recent literature highlights the existence of possible unexpected effects of naive policy interventions in the presence of social norms by focusing on how the incentives introduced by policies interact with the endogenous emergence of these norms (see for instance Dutta, Levine, and Modica, 2021).

[3]This paper relies on the same data as Galbiati, Henry, and Jacquemet (2018), who focus on games occurring late in the experiment, when learning about norms prevalent in the group has converged. Herein, we rather analyze the entire dataset, including early games.

positive effect than if this cooperation took place in a game without fines. This learning effect may imply that current fines negatively affect future cooperation. If the group is non cooperative, fines may speed up learning, since more individuals will be observed deviating in a coercive environment.

By documenting the dynamic interaction between enforcement and learning about group values, our study provides several contributions to the existing literature.[4] Acemoglu and Jackson (2015), study how norms of cooperation can emerge in an environment where current generations learn from observed cooperation in past generations. They do not consider, however, the effect of institutional variations in the past and their interactions with learning. A recent literature shows that formal rules (Sliwka, 2007; van der Weele, 2009; Deffains and Fluet, 2020) or principals' interventions (Friebel and Schnedler, 2011; Galbiati, Schlag, and Van Der Weele, 2013) can convey information on their own about either the distribution of preferences or values in a group, or the type of the principal (Falk and Kosfeld, 2006; Bowles, 2008), thus leading to ambiguous contemporaneous effects of sanctions. The main focus of our study is rather on the information delivered by agents actions' depending on the enforcing institutions, as in Benabou and Tirole (2011). In their setup, individuals care about their social-image, which is based on inferences made by other group members about their types. Institutions shape equilibrium behaviors and thus the inference induced by different actions. In our study, we rather focus on the informativeness of actions about cooperative types under different enforcement environments. We show that differential learning due to enforcement institutions lead to countervailing spillover effects on future cooperation as long as learning is in progress: strong enforcement weakens the signal of cooperativeness sent by cooperative types, and slows down future cooperation.

Our results are also informative on the impact of enforcement on learning, and could thus be very relevant for the performance of young organizations where members have not yet learned about the cooperativeness of the others. Last, we contribute to the experimental literature on repeated games. Our results show how learning generates interdependence across games even when subjects are randomly re-matched. This suggests that independence across games is not granted even in settings with random matching and incentive compatible choices within each game. This point is coherent with previous findings showing that learning about the properties of the group matters for subjects' choices (Dal Bó and Fréchette, 2011)[5] and with the theoretical results of Azrieli, Chambers, and Healy (2018), showing how uncertainty about the population can generate failure of incentive compatibility of the random incentive system.

[4]In a related work, Dal Bó and Dal Bó (2014) show that explicit information about moral values affect cooperation in a standard voluntary contribution game. In their setting however the information is provided by the experimenter and does not allow for dynamic learning about the distribution of prevalent types in the lab.

[5]More precisely Dal Bó and Fréchette (2011) document that the behavior of the partner in the previous match affects the subjects' behavior.

Table 1: Stage-game payoff matrices

	C	D
C	40 ; 40	12 ; 60
D	60 ; 12	35 ; 35

(a) Baseline game

	C	D
C	40 ; 40	12 ; 60-F
D	60-F ; 12	35-F ; 35-F

(b) With fine

2 Descriptive experimental evidence

2.1 Experimental design

The design of the baseline experiment closely follows the experimental literature on infinitely repeated games and in particular Dal Bó and Fréchette (2011). Subjects in the experiment play infinitely repeated games implemented through a random continuation rule. At the end of each round, the computer randomly determines whether or not another round is to be played in the current repeated game ("match"). This probability of continuation is fixed at $\delta = 0.75$ and is independent of any choices players make during the match. Participants therefore play a series of matches of random length, with expected length of 4 rounds. At the end of each match, players are randomly and anonymously reassigned to a new partner to play the next match. This corresponds to a quasi-stranger design since there is a non zero probability of being matched more than once with the same partner during the experiment. The experiment terminates once the match being played at the 15th minute ends.

The stage-game in all interactions is a prisoner's dilemma. Enforcing institutions are randomly assigned: at the beginning of each match, the computer randomly determines whether the match is played with a fine imposed in case of defection (payoffs in Table 1b) or without (Table 1a); the two events occur with equal probability. The result from this draw applies to both players of the current match, and to all its rounds. The fine when imposed is set at $F = 10$ so that the resulting stage-game payoff matrix is isomorphic to Dal Bó and Fréchette (2011) $\{\delta = 3/4; R = 40\}$ treatment, in which cooperation is a sub-game perfect and risk dominant action. When matched with a new partner, subjects are not provided with any information about the partner's history. Players however receive full feedback at the end of each round about the actions taken within the current match.[6]

2.2 Experimental data

Our data come from three sessions of the experiment conducted at Ecole Polytechnique experimental laboratory. The 46 participants are both students (85% of the experiment pool) and employees of the university (15%). Individual earnings are computed as the sum of all tokens

[6]See Appendix A for a detailed description of the experimental procedures.

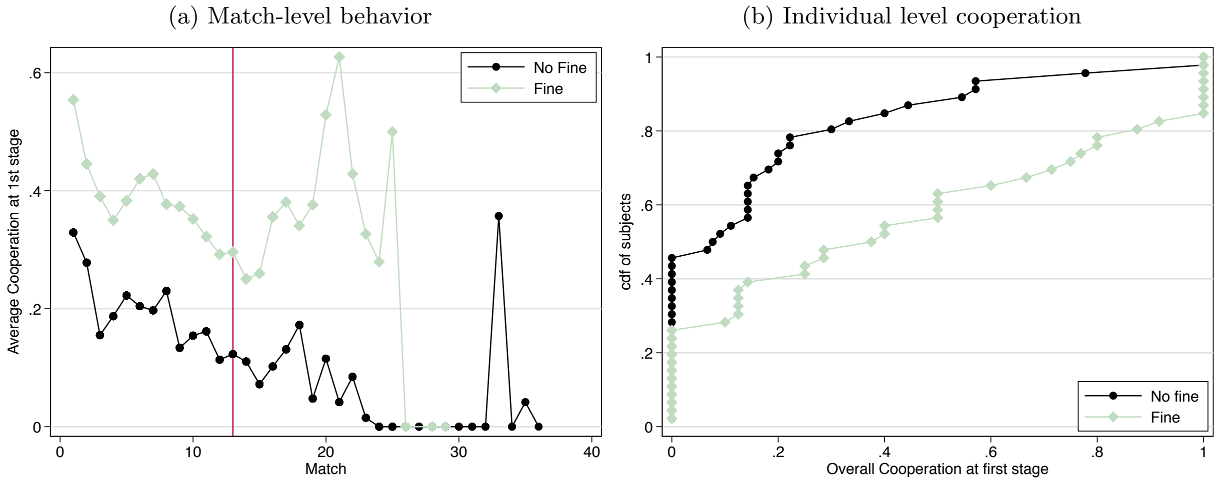
earned during the experiment, with an exchange rate equal to 100 tokens for 1 Euro. At the end of the experiment, participants are asked to answer a socio-demographic questionnaire about their gender, age, level of education, labor market status (student/worker/unemployed) as well as the Dohmen, Falk, Huffman, Sunde, Schupp, and Wagner (2011) self-reported measure of risk-aversion. Participants earned on average 12.1 Euros from an average of 20 matches, each featuring 3.8 rounds. This data delivers 934 game observations, 48% of which are played with no fine.

All our analysis in this paper will be based on the action chosen in the first round of each match. While this first round decision captures the effect of past history of play on individual behavior, the decisions made within the course of a match are a mix of this component and of the strategic interaction with the current partner, and would thus be noisy measures of learning. To render this restriction meaningful, and also to be consistent with the model we introduce in Section 3, we thus restrict the sample to player-game observations for which the first round decision summarizes the future history (Section C in the Appendix provides a replication of our statistical analysis on the full sample). As shown in the Appendix, Section A, if subjects choose among the following repeated-game strategies, Always Defect (AD), Tit-For-tat (TFT) or Grim Trigger (GT), the first round decision is a sufficient statistic for the future sequence of play. While AD dictates defection at the first round, TFT and GT induce cooperation at the first round and are both observationally equivalent if the partner chooses within the set restricted to these three strategies and give rise to the same expected payoff. The resulting working sample is made of 785 games among which 50.3% are played with a fine. Our outcome variable of interest is the first round decision made by each player in each of these matches. Importantly, all lagged variables are computed according to actual past experience: one's own cooperation at previous match, partner's decision and whether the previous match was played with a fine are all defined according to the match played just before the current one, whether or not this previous match belongs to the working sample.

2.3 Learning to Cooperate: Descriptive Evidence

Figure 1 provides an overview of the cooperation rate observed in each of the two institutional environments. The overall average cooperation rate is 32%, with a strong gap depending on whether a fine enforces cooperation: the average cooperation rate jumps from 19% in the baseline, to 46% with a fine. This is clear evidence of a strong disciplining effect of current enforcement. Figure 1a documents the time trend of cooperation over matches. The vertical line identifies the point in time beyond which we no longer observe a balanced panel—the number of matches played within the duration of the experiment is individual specific, since it depends on game lengths. Time trends beyond this point are to a large extent driven by the size of the sample. Focusing on the balanced panel, our experiment replicates in both environments the standard decrease in cooperation rates: from 15% at the initial match in the baseline, 69% with a fine, to 11% and 41% at the 13th game. The time trends are parallel between the two conditions. Note that since

Figure 1: The disciplining effect of current enforcement



Note. Cooperation observed at first round of each match in the working sample as a function of the current fine. *Left-hand side*: evolution of the average rate of cooperation among players over the number of matches played. The vertical line identifies the point in time beyond which we no longer observe a balanced panel. *Right-hand side*: cumulative distribution of individual cooperation rate at first round of all matches played respectively with and without a fine.

the history of past enforcement is both individual specific and random, it is statistically the same for the two curves for any match number.

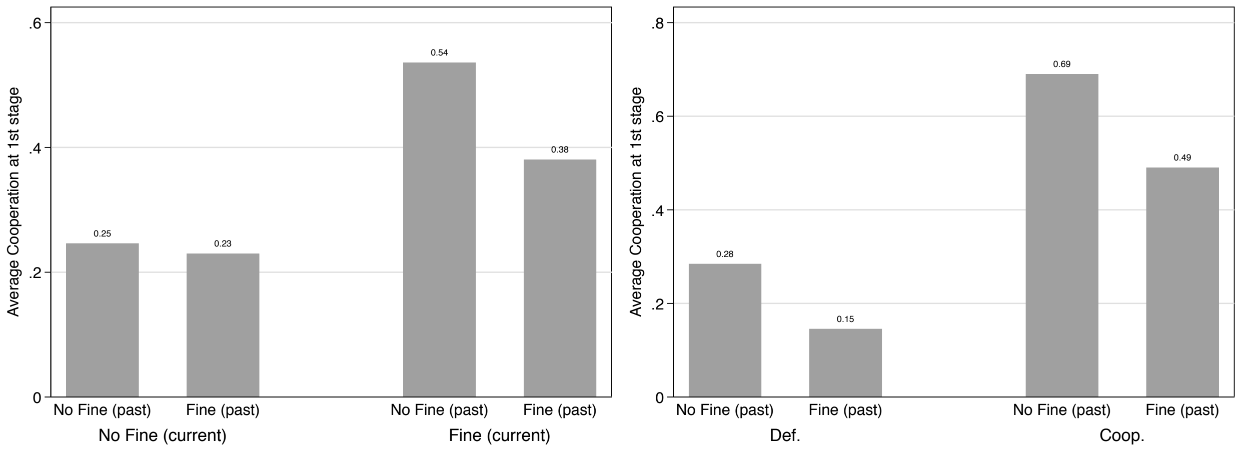
Figure 1b reorganizes the same data but at the individual level, and displays the cumulative distribution of cooperation in a given environment. We observe variations in both the intensive and the extensive margin of cooperation in the adjustment to the fine—resulting in first order stochastic dominance of the distribution of cooperation with no fine. First, regarding the extensive margin, we observe a switch in the mass probability of subjects who always choose the same first round response: 45% never cooperate with a fine, while only 26% do so with a fine, and the share of subjects who always cooperate raises from 4% to 17% when a fine is implemented. More than half the difference in mass at 0 thus moves to 1. Turning to the intensive margin, the distribution of cooperative decisions with no fine is more concentrated towards the left: 70% of individuals who switch between cooperation and defection cooperate less than 30% of the time with no fine, while it is the case of only 40% of individuals who switch from one match to the other in the fine environment.

We now turn to the main focus of the paper. To present the evidence graphically, we restrict to early games where the uncertainty about group cooperativeness is large.[7] Figure 2a documents the surprising effect of fines experienced in previous matches on current cooperation. Comparing

[7]We distinguish early and late games by splitting the matches in three groups, in such a way that one third of the observed decisions are classified as "early", and one third as "late". Observed matches are accordingly defined as "early" up to the 7^{th}, as late after the 13^{th}, in line with the definitions used in the Appendix, Section B. Note that the matches we exclude from the working sample all appear in late games. As a result, Figure 2a is not affected by the choice of the working sample.

Figure 2: Observed dynamics of cooperation in early games

(a) The effect of past enforcement (b) The effect of the history of play



Note. Cooperation at first stage in the working sample in early games (see footnote 7) according to individual history. In each figure, the data is split according to whether the previous match was played with No fine ("*No fine (past)*") or with a fine ("*Fine (past)*"). *Left-hand side*: each subpanel refers to current enforcement; *Right-hand side* each sub-panel refers to the partner's decision experienced at previous match.

the two left-hand side bars to the right-hand side ones unambiguously demonstrates that current enforcement has a strong disciplining effect. For instance, restricting to matches where no fine was experienced in the past, the average rate of cooperation increases from 0.25 to 0.54 in environments with enforcement (bars 1 and 3). On the contrary, enforcement in the past induces a fall in current cooperation. For instance, comparing the two bars on the right hand side, corresponding to matches where a fine is currently in place, having played the previous match with fines decreases cooperation from an average of 0.54 to 0.38 (bars 3 and 4). Such an effect of past enforcement is puzzling, since one would expect that past fines are either neutral or exert a positive effect on current cooperation through behavioral channels (e.g., Peysakhovich and Rand, 2016).

The interaction between cooperation-enforcing institutions and learning can potentially explain such a pattern. Consider the case where the news are bad (i.e., the population is less cooperative than expected; as seems to be the case according to the evolution of cooperation over time shown in Figure 1). In this case, experiencing a fine can speed up learning the bad news, since observing deviation in an environment with fines is a strong indicator that the partner is non-cooperative. This interaction between enforcement and learning is presented in Figure 2b, which reports the level of cooperation depending on whether cooperation (right panel) or a deviation (left panel) has been observed in the previous match in an environment with or without a fine. Comparing the two left hand side bars to the right hand side ones shows that cooperation by the partner in the previous match increases cooperation in the current match, consistent with the idea that experimental subjects learn about the willingness to cooperate of their partners. However this learning is clearly affected by the institutional environment. When the action (cooperation or deviation) was taken in an environment without fines, it leads to higher levels of current cooperation. For instance, comparing the two bars on the right hand side, corresponding to matches where the partner cooperated in the previous match, if that cooperation was observed in an environment with no enforcement, the average level of cooperation is 0.69 while it falls to 0.49 if the previous match was played with fines (bars 3 and 4).

Changes in cooperation according to the history of institutional exposure however combine the effect of learning as well as the direct effect of past enforcement on cooperation behavior. To clarify the link between learning and enforcement institutions, we now turn to a theoretical model that formalizes the interaction between the institutional environment and learning about group cooperativeness.

3 A theoretical model of cooperation dynamics

In each match (we use index t for the match number), the players simultaneously choose between actions C and D to maximize their payoff in the current match. At the end of the match, players observe the partner's decision. In the case where a match is a repeated prisoner's dilemma, as is the case in the experiment, this requires the first period action in a match to fully summarize strategies. To ease exposition, we denote i the player under consideration and j_t the partner of i in match t. Whether player ℓ experience a fine in match t is tracked by the variable $F_{\ell,t} \in \{0, 1\}$ and the action of player ℓ in match t is denoted $a_{\ell,t} \in \{C, D\}$.

The payoff of player i from playing $a_{it} \in \{C, D\}$ in match t is denoted U_{it}^a and is given by:[8]

$$\begin{cases} U_{it}^C(F_{it}, p_{it}) &= V_{it}^C(F_{it}, p_{it}) \ + \beta_i \ , \\ U_{it}^D(F_{it}, p_{it}) &= V_{it}^D(F_{it}, p_{it}) \ , \end{cases}$$

where $V_{it}^a(F_{it}, p_{it})$ is the material payoff player i expects from choosing action a in match t. This expected payoff depends in particular on the beliefs player i holds on the probability that the partner j_t cooperates, p_{it}, and on whether the current match is played with a fine, F_{it}. Note that p_{it} is in fact a function of F_{it}, since the presence of a fine affects the probability that the partner cooperates.[9]

The parameter β_i measures player i's intrinsic values, i.e. the individual propensity to cooperate.[10] We suppose there is uncertainty on the set of group's values, i.e. the set of individual values β_i. We consider two possible states of the world. With probability q_0 the state is high and β_i is drawn from the normal distribution $\Phi(\mu_H, \sigma^2)$, while with probability $1 - q_0$, β_i is drawn from $\Phi(\mu_L, \sigma^2)$, with $\mu_L < \mu_H$. The value attached to cooperation by society is higher in the high state.

[8]This is a specific functional form of the more general function in, e.g., Kartal and Müller (2018).

[9]We drop this dependency of p_{it} on F_{it} in the notation.

[10]In the generalized model presented in the Appendix, Section B.1, we introduce spillovers by assuming that the values β_{it} depend on t and in particular can be affected by past experiences.

3.1 Benchmark model

First consider a benchmark model with no uncertainty on values ($q = 1$). We now use the specific payoffs corresponding to the prisoner's dilemma in order to explicitly describe the impact of fines on payoffs. Denote $\pi_{a_{it},a_{jt}}$ the monetary payoff of i in a match where a_{it} is played against a_{jt}. Individual i, with beliefs p_{it} that her partner will cooperate, chooses action C if and only if the following condition is satisfied:[11]

$$\begin{aligned} p_{it}\frac{1}{1-\delta}\pi_{C,C} \quad &+ \quad (1-p_{it})\left[\pi_{C,D} + \left(\pi_{D,D} - F \times \mathbb{1}_{\{F_{it}=1\}}\right)\frac{\delta}{1-\delta}\right] \quad + \quad \beta_i \\ &\geq \quad p_{it}\left[\left(\pi_{D,C} - F \times \mathbb{1}_{\{F_{it}=1\}}\right) + \left(\pi_{D,D} - F \times \mathbb{1}_{\{F_{it}=1\}}\right)\frac{\delta}{1-\delta}\right] \\ &+ \quad (1-p_{it})\frac{1}{1-\delta}\left(\pi_{D,D} - F \times \mathbb{1}_{\{F_{it}=1\}}\right). \end{aligned}$$

This condition can be re-expressed as

$$\beta_i \quad \geq \quad \beta^*(F_{it}) \equiv \Pi_1 - F \times \mathbb{1}_{\{F_{it}=1\}} \; + \; p_{it} \left[\Pi_2 \; - \; \frac{\delta}{1-\delta}\left(F \times \mathbb{1}_{\{F_{it}=1\}} + \Pi_3\right)\right] , \tag{1}$$

with the parameters defined as $\Pi_1 \equiv \pi_{D,D} - \pi_{C,D} > 0$, $\Pi_2 \equiv (\pi_{D,C} - \pi_{D,D}) - (\pi_{C,C} - \pi_{C,D})$ and $\Pi_3 \equiv \pi_{C,C} - \pi_{D,D} > 0$.[12]

Condition (1) implies that the decision to cooperate follows a cutoff rule, such that an individual i cooperates if and only if she attaches a sufficiently strong value to cooperation $\beta_i \geq \beta^*(F_{it})$, where the cutoff β^* depends on whether the current match is played with a fine. Since there is no uncertainty, and thus no learning, all players share the same belief over the probability that the partner cooperates, given by $p_{it}(F_{it}) = P[\beta_j \geq \beta^*(F_{it})] = 1 - \Phi_H[\beta^*(F_{it})]$. The cutoff value $\beta^*(F_{it})$ is thus defined by the indifference condition:

$$\beta^*(F_{it}) \; = \; \Pi_1 - F \times \mathbb{1}_{\{F_{it}=1\}} \; + \; [1 - \Phi_H[\beta^*(F_{it})]] \left[\Pi_2 \; - \; \frac{\delta}{1-\delta}\left(F \times \mathbb{1}_{\{F_{it}=1\}} + \Pi_3\right)\right] . \tag{2}$$

We show in Proposition 1 below that there always exists at least one equilibrium, and this equilibrium is of the cutoff form. There could exist multiple equilibria, but all stable equilibria share the intuitive property that individuals are more likely to cooperate in an environment with fines.

Proposition 1 *In an environment with no uncertainty on values ($q = 1$), there exists at least one equilibrium. Furthermore all equilibria are of the cutoff form, i.e. individuals cooperate if and only if $\beta_i \geq \beta^*(F_{it})$ and, in all stable equilibria, β^* decreases with F and with μ_H.*

[11] We explicitly use the fact that players are restricted to choosing between Grim Trigger, Tit For Tat and Always Defect.

[12] In the case of the experiment, $\Pi_1 = 23$, $\Pi_2 = -3$ and $\Pi_3 = 5$.

Proof. See Appendix, Section E. ■

The benefit of cooperation is increasing in the probability that the partner cooperates. There exist equilibria where cooperation is prevalent, which indeed makes cooperation individually attractive. On the contrary there are equilibria with low levels of cooperation which makes cooperation unattractive. These equilibria can be thought of as different norms of cooperativeness in the group, driven by complementarities in cooperation.

3.2 Learning in the shadow of the law

We now consider the more general formulation with uncertainty about the group's values. We denote q_{it} the belief held by player i at match t that the state is H. All group members initially share the same beliefs $q_{i0} = q_0$. They gradually learn about the group's values when observing the decisions of partners in previous matches and we show how fines impact learning.

First consider the initial match, $t = 1$. All members of the group share the same belief q_0 that the state is H. The equilibrium is defined by a single cutoff value $\beta^*(F_{it})$ as in the benchmark model,

$$\beta^*(F_{i1}) \quad = \quad \Pi_1 - F \times \mathbb{1}_{\{F_{i1}=1\}} \; + \; p_1^*(F_{i1}) \left[\Pi_2 \; - \; \frac{\delta}{1-\delta} \left(F \times \mathbb{1}_{\{F_{i1}=1\}} + \Pi_3 \right) \right] \; .$$

The only difference with the benchmark model is that the probability that the partner cooperates takes into account the uncertainty about the group's values:

$$p_1^*(F_{i1}) \; = \; q_0 \; \left[1 - \Phi_H \left[\beta^*(F_{i1})\right]\right] \; + \; (1 - q_0) \; \left[1 - \Phi_L \left[\beta^*(F_{i1})\right]\right] \; .$$

We now consider how beliefs about the state of the world are updated following the initial match. The updating following this initial match provides all the intuitions for the more general updating process. The update depends on the action of the partner and whether the match was played with or without a fine. The general notation we use is $q_{it}(F_{it-1}, a_{j_{t-1}}, q_{it-1})$. For the update following the first match, we can drop the dependence on q_{it-1}, since all individuals initially share the same belief.

Clearly, the belief that the state is H decreases if the partner chose D, while it increases if the choice was C. The update however depends as well on whether the previous match was played with a fine or not. If the partner cooperated in presence of a fine, it is a less convincing signal that society is cooperative than if he cooperated in the absence of the fine—$q_{i2}(0, C) > q_{i2}(1, C)$. Similarly, deviation in the presence of a fine decreases particularly strongly the belief that the state is high—$q_{i2}(1, D) < q_{i2}(0, D)$. This is summarized in the following Lemma:[13]

[13]Stability guarantees that when the current match is played with a fine, the probability of cooperation increases.

Lemma 1 *In any stable equilibrium, beliefs following the first period actions are updated in the following way:*

$$q_{i2}(0, C) > q_{i2}(1, C) > q_0 \ ,$$
$$q_{i2}(1, D) < q_{i2}(0, D) < q_0 \ .$$

Proof. See Appendix, Section E. ■

We show in Proposition 2 that this updating property is true in general for later matches. The beliefs on how likely it is that the partner cooperates in match t, $p_t^*(F_{it}, q_{it})$, depends both on player i's history, but also on the beliefs about the partner's history. For instance if the partner faced a lot of cooperation in previous games, she becomes more likely to cooperate. The general problem requires to keep track of the higher order beliefs. However if a stationary equilibrium exists, with the property that $\beta^*(0, q) > \beta^*(1, q)$ for all beliefs q, then the updating property of Lemma 1 is preserved. Furthermore, in the Appendix, Section E, we show existence of such a stationary equilibrium, under a natural restriction on higher order beliefs, i.e. if we assume that a player who had belief q_{it} in match t believes that players in the preceding match had the same beliefs $q_{j',t-1} = q_{it}$.

Proposition 2 ***(Learning)*** *In an environment with spillovers and learning, if an equilibrium exists, all equilibria are of the cutoff form, i.e. individuals cooperate if and only if $\beta_i \geq \beta^*(F_{it}, q_{it})$. Furthermore, if in equilibrium $\beta^*(0, q) > \beta^*(1, q)$ for all beliefs q, then the beliefs are updated in the following way following the history in the previous interaction:*

$$q_{it}(0, C, q_{it-1}) > q_{it}(1, C, q_{it-1}) > q_{it-1},$$
$$q_{it}(1, D, q_{it-1}) < q_{it}(0, D, q_{it-1}) < q_{it-1}.$$

Proof. The Appendix, Section E, proves the result in the more general case with spillovers. ■

Lemma 1 and Proposition 2 show how enforcing institutions affect learning. These results imply that having fines in the previous match can potentially decrease average cooperation in the current match. If the state is low, a fine can accelerate learning if, on average, sufficiently many people deviate in the presence of a fine. This in turn decreases cooperation in the current match.

4 Results

We now study empirically the interaction between enforcement and learning highlighted in the model. The descriptive evidence provided in Figure 2b (Section 2.3), suggests that the pattern of cooperation observed in the current match is consistent with the ranking of posterior beliefs predicted in Lemma 1 and Proposition 2, $q_{it}(0,C) > q_{it}(1,C) > q_{it}(0,D) > q_{it}(1,D)$.[14]

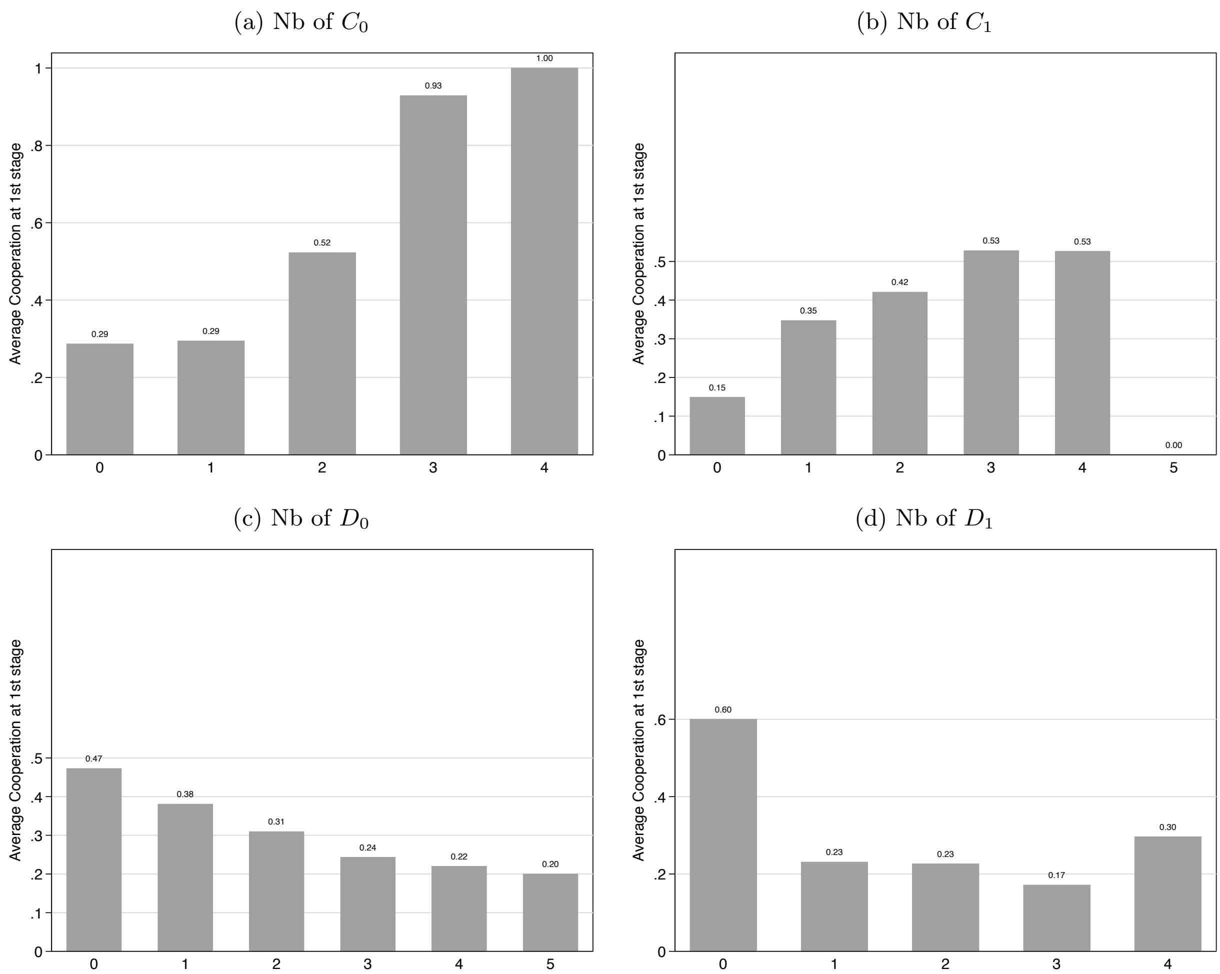
The identification of learning effects is however complicated by the fact that both enforcing institutions and cooperation by the partner in previous matches can also create spillovers on current cooperation. Two types of such spillovers of past enforcing institutions can be at stake: direct spillovers, where the fine experienced in the immediate past directly affects preferences and increases current cooperation, and indirect spillovers, where fines in the past increase cooperation of the previous partner, which in turn increases current cooperation. If such spillovers exist, they both interfere with the identification of learning effects. On the one hand, cooperation by the previous partner affects current cooperation both because it provides information on the cooperativeness of the group, but also because of indirect spillovers. On the other hand, a fine in the previous period similarly impacts learning as explained in the model, but also gives rise to direct spillovers. Galbiati, Henry, and Jacquemet (2018) show that these spillovers are short-living: cooperation by the partner two matches ago has a much weaker effect on current cooperation than cooperation by the partner in the previous match.

We use these findings to identify separately learning from spillovers. To illustrate the idea, compare two situations, with identical institutional histories: the first where the partner in the previous match cooperated while the one two matches ago did not and the second, with the opposite behavior, the partner in the previous match deviated and the one two matches ago did not. From the point of view of learning, both situations are equivalent since the information obtained is identical: one of the two previous partners did cooperate. However, in terms of spillovers, the first situation should lead to higher levels of current cooperation: if spillovers decay over time, facing cooperation two periods ago has a smaller spillover effect than cooperation one period ago.

We exploit this idea in Figure 3, where we examine the effect of the history, in terms of fines and behavior of the partner, in the five previous matches independently of the order in which this history occurred. Figure 3a for instance displays how average cooperation is affected by the number of matches without fines where the partner cooperated (an outcome we denote C_0). An increase in the number of C_0 has a very strong effect on current cooperation, with an average rate of cooperation of 0.29 when it never occurred in the 5 previous matches to full cooperation when it occurred 4 times. Another striking feature visible in Figure 3, is that the rate of increase in cooperation is much faster as a function of the number of C_0 than as a function of the number of C_1 (cooperation of the partner in an environment with fines). As visible in Figure 3b, the average rate of cooperation increases from 0.15 when C_1 never occurred in the 5 previous matches to 0.53 when it occurred 4 times. This reflects the idea, highlighted in the model, that cooperation in the absence of fine is a much stronger signal on underlying values than cooperation in the presence of fines. The behavior for D_0 and D_1 is similar. The rate of cooperation tends to decrease more sharply with the number of D_1 than with the number of D_0, even though the pattern is less

[14] $q_{it}(0,C)$ corresponds to the third bar in Figure 2b, $q_{it}(0,C)$ to the fourth, $q_{it}(0,D)$ to the first and $q_{it}(1,D)$ to the second.

Figure 3: Current cooperation as a function of history in the previous 5 games



Note. Each panel reports the average level of cooperation in t as a function of the number of decisions $a_{j,t-s}, s = 1, ..., 5$ in the current history. The abscissa is $\sum_{s=1}^{5} C^0_{t-s}$ in panel 3a, $\sum_{s=1}^{5} C^1_{t-s}$ in panel 3b, $\sum_{s=1}^{5} D^0_{t-s}$ in panel 3c and $\sum_{s=1}^{5} D^1_{t-s}$ in panel 3d. For both C_0 and D_1, observed histories only range from 0 to 4. For D_1, the observed level of cooperation when 5 of them belong to history is 0%.

striking than in the case of cooperation.

We confirm these graphical results in Table 2 where we estimate a Probit model on $C_{it} = \mathbb{1}_{\{a_{it}=C\}} \in \{0, 1\}$, the observed decision to cooperate of participant i in the first round of match t in the experiment. In all columns we control for current enforcement. Current fines have a very strong disciplining effect on current cooperation, increasing the probability of cooperation by more than 30%. In column (1), we do not account for spillovers and examine the effect of the history in the five previous matches.[15] The ranking of the effect is perfectly coherent with the results of

[15]The specification of the empirical model is the same as the one used in the Appendix, Section B. All results are robust to alternative definitions of the number of previous matches included in the past history. The results are

Table 2: Statistical evidence on the interaction between enforcement and learning

	(1)		(2)		(3)	
	Coef.	Marg. eff.	Coef.	Marg. eff.	Coef.	Marg. eff.
Constant	0.040		0.147		0.179	
	(0.274)		(0.306)		(0.152)	
$\mathbb{1}_{\{F_t=1\}}$	1.356***	0.305***	1.361***	0.303***	1.355***	0.302***
	(0.270)	(0.052)	(0.271)	(0.051)	(0.268)	(0.047)
$\overline{C}_0 = \sum_{s=1}^{5} C^0_{t-s}$	0.410***	0.092***	0.406***	0.091***	0.433***	0.097***
	(0.061)	(0.013)	(0.056)	(0.011)	(0.083)	(0.017)
$\overline{C}_1 = \sum_{s=1}^{5} C^1_{t-s}$	0.210***	0.047***	0.164***	0.037***	0.167*	0.037*
	(0.016)	(0.006)	(0.009)	(0.003)	(0.092)	(0.020)
$\overline{D}_1 = \sum_{s=1}^{5} D^1_{t-s}$	-0.123***	-0.028***	-0.180***	-0.040***	-0.195***	-0.043***
	(0.046)	(0.008)	(0.038)	(0.006)	(0.063)	(0.014)
$\mathbb{1}_{\{F_{t-1}=1\}}$			0.230***	0.051***	0.199	0.044
			(0.070)	(0.019)	(0.275)	(0.061)
$\mathbb{1}_{\{a_{jt-1}=C\}}$			-0.019	-0.004	0.073	0.016
			(0.037)	(0.008)	(0.111)	(0.025)
$a_{jt} = C$ in a row					-0.059	-0.013*
					(0.037)	(0.008)
F_{it} in a row					0.020	0.004
					(0.152)	(0.034)
N	599	—	599	—	599	—
σ_u	1.196	—	1.201	—	1.208	—
ρ	0.588	—	0.591	—	0.593	—
LL	-220.466	—	-219.610	—	-219.454	—

Note. Probit models with individual random effects on the decision to cooperate at first stage estimated on the working sample. Standard errors (in parenthesis) are clustered at the session level. All specifications include control variables for gender, age, whether participant is a student, whether a fine applies to the first match, the decision to cooperate at first match, the length of the previous game and match number. Marginal effects are computed at sample mean, assuming random effects are 0. *Significance levels*: *10%, **5%, ***1%.

Proposition 2: the signal C_0 (variable $\overline{C}_0$ in the table) has a positive significant effect compared to D_0 (the reference) and the effect is larger than C_1 (variable $\overline{C}_1$). Similarly, D_1 (variable $\overline{D}_1$) decreases cooperation relative to D_0. In terms of magnitudes, replacing in the history one signal D_0 by a signal C_0 increases the probability of cooperation by 10% while replacing it by a signal C_1 only increases the probability of cooperation by 5%. Replacing in the history one signal D_0 by a signal D_1 decreases the probability of cooperation by 3%.

In columns (2) to (3) we control for potential spillovers. In column (2), we introduce short-living spillovers by controlling for whether the previous match was played with a fine and whether

available from the authors upon request.. The Appendix, Section D, provides the results from a robustness exercise with bootstrapped standard errors.

the partner cooperated in the previous match. As explained previously, identification here relies on the assumption that spillovers are short lived, whereas learning is cumulative. Controlling for spillovers does not change the ordering of histories and only marginally affects magnitudes. Finally, in column (3), we relax the identifying assumption and allow spillovers to be longer lasting. We add a control for the number of matches in a row where partners cooperated, as well as the number of fines in a row in all previous matches. Identification here relies on the assumption that learning does not depend on the order in which signals were received, while it affects the strength of the effect of spillovers. None of these controls impact the results on learning, which still strongly affects how current cooperation react to past enforcement and behavior.

We provide an alternative identification strategy in the Appendix, Section B, where we model explicitly the interaction between learning and spillovers. To that end, we extend the model in Section 3 to the assumption that the taste for cooperation, β_i, is directly affected by the history of partner's behavior and institutional settings. Proposition D shows that updated beliefs obeys the same ranking as in Proposition 2. This model explicitly shows that the learning and spillovers parameters cannot be separately identified when both affect cooperation. The empirical analysis provided in Section B.1.2 relies on the assumption that learning has converged in games occurring late in the experiment to achieve separate identification of both kinds of parameters. We test the predictions of the model and confirm in Table C the ranking predicted in Proposition D.

5 Conclusion

This paper studies cooperative behavior in a setting in which individuals interact without knowing each others' propensity to cooperate. In these situations, exogenous enforcement of cooperation may affect individuals' capacity to make inferences about the prevalent types in the society and, as a consequence, their propensity to cooperate.

We analyze this setting through the lens of a theoretical model tailored to interpret the results from an experiment where individuals play a series of infinitely repeated games with random re-matching. We rely on two different identification strategies to disentangle institution-specific learning from the effect of past enforcement on one's own willingness to cooperate (i.e., behavioral spillovers). The first relies on the fact that institution-specific learning, in contrast with spillovers, does not depend on the order in which a given history of cooperation occurred. The second, presented in the Appendix, relies on the structure of the model and the (untestable) assumption that learning has converged in games occurring late in the experiment. The results provide strong support for the main behavioral insights of the model. The presence or absence of cooperation enforcing institutions affects the dynamics of learning about others' likely behavior: cooperation from partners faced in the past fosters cooperation today (with different partners) differently according to the institutional environment of past interactions. Past cooperation is more informative about other's likely behavior when it is observed under weak institutional enforcement of cooperation. Similarly, defection is more detrimental to cooperation when it was observed in an environment with strong enforcement.

Our findings also suggest that identifying spillovers, the focus of a large recent literature (see Galizzi and Whitmarsh, 2019, for a survey), can be challenging when the group members are also learning about prevalent values. In particular, this might lead to an underestimation of the size of spillovers in the case where the group has a low level of cooperation, since having fines might speed up learning and thus initially have a negative effect on cooperation.

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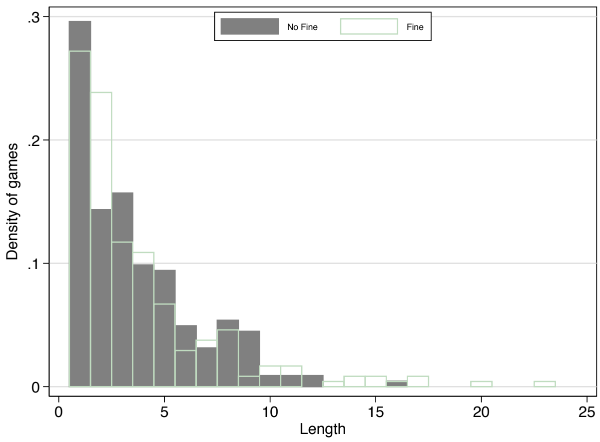
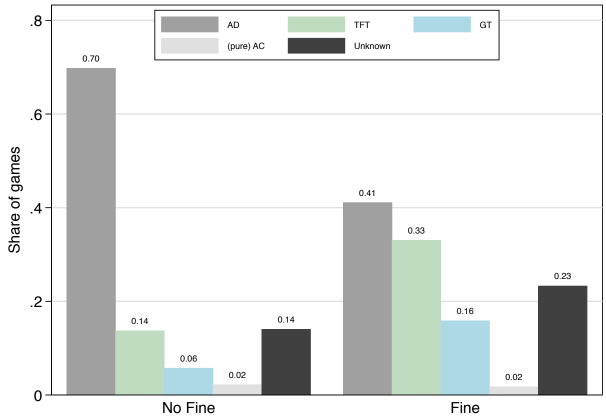
Figure D: Sample characteristics: distribution of game lengths and repeated-game strategies

(a) Distribution of game lengths



(b) Individual strategies



Note. *Left-hand side*: empirical distribution of game lengths in the experiment, split according to the draw of the fine. *Right-hand side*: distribution of repeated-games strategies observed in the experiment. One-round matches are excluded. AD: Always Defect; AC: Always Cooperate; TFT: Tit-For-Tat; GT: Grimm Trigger.

Appendix

A Data description

Our data delivers 934 game observations, 48% of which are played with no fine. Figure Da displays the empirical distribution of game lengths in the sample split according to the draw of a fine. With the exception of two-rounds matches, the distributions are very similar between the two environments. This difference in the share of two-rounds matches mainly induces a slightly higher share of matches longer than 10 rounds played with a fine. In both environments, one third of the matches we observe lasts one round, and one half of the repeated matches last between 2 and 5 rounds. A very small fraction of matches (less than 5% with a fine, less than 2% with no fine) feature lengths of 10 rounds or more.

As explained in the text, Section 2.2, for matches that last more than one round (2/3 of the sample), we thus reduce the observed outcomes to the first round decision in each match, consistently with the theory. The first round decision is a sufficient statistic for the future sequence of play if subjects choose among the following repeated-game strategies: Always Defect (AD), Tit-For-tat (TFT) or Grim Trigger (GT). While AD dictates defection at the first round, both TFT and GT induce cooperation and are observationally equivalent if the partner chooses within the set restricted to these three strategies and give rise to the same expected payoff. Figure Db displays the distribution of strategies we observe in the experiment (excluding games that last one round only). Decisions are classified in each repeated game and for each player based on the observed sequence of play. For instance, a player who starts with C and switches forever to D when the partner starts playing D will be classified as playing GT. In many instances, TFT and GT cannot be distinguished (so that the classes displayed in Figure Db overlap): it happens for instance for subjects who always cooperate against a partner who does the same (in which case, TFT and GT also include Always Cooperate, AC), or if defection is played forever by both players once it occurs. Last, the Figure also reports the share of Always Cooperate that can be distinguished from other match strategies—when AC is played against partners who do defect at least once.

All sequences of decisions that do not fall in any of these strategies cannot be classified—this accounts for 14% of the games played without a fine, and 24% of those played with fine. The three strategies on which we focus are thus enough to summarize a vast majority of match decisions: AD accounts for 70% of the repeated-game observations with no fine, and 41% with a fine, while TFT and GT account for 14% and 34% of them.

B Alternative identification strategy

The empirical evidence presented in the paper relies on the insights from the model to provide a reduced-form statistical analysis of the interaction between learning and enforcement institutions. As a complement to this evidence, this section provides a structural analysis which takes into account both learning and behavioral spillovers. To that end, we first generalize the model presented in Section 3.2 to the case in which individual values evolve over time as a result of past experience. We then estimate the parameters of the model. This provides an alternative strategy to separately estimate learning and spillovers.

B.1 The dynamics of learning with behavioral spillovers

Consistent with Galbiati, Henry, and Jacquemet (2018), we allow both for past fines and past behaviors of the partners to affect values:

$$\beta_{it} \;=\; \beta_i \;+\; \phi_F \; \mathbb{1}_{\{F_{it-1}=1\}} \;+\; \phi_C \; \mathbb{1}_{\{a_{j_{t-1},t-1}=C\}} \;. \tag{3}$$

According to this simple specification, personal values evolve through two channels. First, direct spillovers increase the value attached to cooperation in the current match if the previous one was played with a fine, as measured by parameter ϕ_F. Second, indirect spillovers, measured by ϕ_C, increase the value attached to cooperation if in the previous match the partner cooperated.[16]

B.1.1 Introducing behavioral spillovers in the benchmark

We start by introducing spillovers in the benchmark model. Under the assumption that values follow the process in (3) and $\phi_F > 0, \phi_C > 0$, the indifference condition (1) remains unchanged,[17] but now β_{it} is no longer constant and equal to β_i since past shocks affect values. In this context, individual i cooperates at

[16]The model can easily be extended to allow for longer histories to impact values. For instance, the effect on past institutions on values could be extended to:

$$\beta_{it} \;=\; \beta_i \;+\; \sum_{\tau=1}^{T} \phi_{F\tau} \; \mathbb{1}_{\{F_{it-\tau}=1\}} \;+\; \sum_{j=1}^{T} \phi_{C\tau} \; \mathbb{1}_{\{a_{j_{t-\tau},t-\tau}=C\}},$$

with $\phi_{F\tau}$ and $\phi_{C\tau}$ increase in τ, in other words the more recent history having more impact. This could be introduced at the cost of added complexity.

[17]As stated above, we work under the assumption that players are myopic and choose between C and D to maximize their payoff in the current match. Without this assumption, when spillover are introduced, a player would need to take into account that her current action would influence her partner's future actions and thus influence the partner's future partners. An alternative would be to assume that players are negligible enough so that current actions cannot influence future beliefs.

t if and only if:

$$\beta_{it} \quad \geq \quad \Pi_1 - F \times \mathbb{1}_{\{F_{it}=1\}} \; + \; p_{it}\Pi_2 \; - \; \frac{\delta}{1-\delta} p_{it} \left(F \times \mathbb{1}_{\{F_{it}=1\}} + \Pi_3 \right) \; .$$

The cutoff value is defined in the same way as before:

$$\beta_t^*(F_{it}) \quad = \quad \Pi_1 - F \times \mathbb{1}_{\{F_{it}=1\}} \; + \; p_t^*(F_{it}) \left[\Pi_2 \; - \; \frac{\delta}{1-\delta} \left(F \times \mathbb{1}_{\{F_{it}=1\}} + \Pi_3 \right) \right] \; . \tag{4}$$

The main difference with the benchmark model is in the value of $p_t^*(F_{it})$. There is now a linkage between the values of the cutoffs at match t, β_t^*, and the values of the cutoffs $\beta_{t'}^*$ in all the preceding matches $t' < t$ through $p_t^*(F_{it})$. Indeed, when an individual evaluates the probability that her current partner in t, player j_t, will cooperate, she needs to determine how likely it is that she received a direct and/or an indirect spillover from the previous period. The probability of having a direct spillover is given by $P[F_{jt-1} = 1] = 1/2$ and is independent of any equilibrium decision. By contrast, the probability of having an indirect spillover is linked to whether the partner of j_t in her previous match cooperated or not. This probability in turn depends on the cutoffs in $t-1$, β_{t-1}^*, which also depends on whether that individual himself received indirect spillovers, i.e on the cutoff in $t-2$. Overall, these cutoffs in t depend on the entire sequence of cutoffs.

In the remaining, we focus on stationary equilibria, such that β^* is independent of t. We show in Proposition C that such equilibria do exist.

Proposition C ***(Spillovers)*** *In an environment with spillovers ($\phi_F > 0$ and $\phi_C > 0$) and no uncertainty on values, there exists a stationary equilibrium. Furthermore all equilibria are of the cutoff form, i.e individuals cooperate if and only if $\beta_{it} \geq \beta^*(F_{it})$.*

Proof. See Section E. ■

Proposition C proves the existence of an equilibrium and presents the shape of the cutoffs. The Proposition also allows to express the probability that a random individual cooperates as:

$$1 - \Phi_H \left[\Lambda_1 - \phi_F \; \mathbb{1}_{\{F_{it-1}=1\}} \; - \; \phi_C \; \mathbb{1}_{\{a_{j_{t-1},t-1}=C\}} \; - \Lambda_2 \mathbb{1}_{\{F_{it}=1\}} \right] \; , \tag{5}$$

where:

$$\begin{aligned}
\Lambda_1 \quad &\equiv \quad \beta^*(0) \; = \; \Pi_1 \; + \; p^*(0) \left[\Pi_2 \; - \; \frac{\delta}{1-\delta} \Pi_3 \right] \; , \\
\Lambda_2 \quad &\equiv \quad \beta^*(1) - \beta^*(0) \; = \; F \; + \; [p^*(0) - p^*(1)] \left[\Pi_2 \; - \; \frac{\delta}{1-\delta} \Pi_3 \right] + \frac{\delta}{1-\delta} p^*(1) F \; .
\end{aligned}$$

B.1.2 The dynamics of cooperation with learning and spillovers

We now solve the full model with uncertainty about the group's values and with spillovers. As in the main text, we denote q_{it} the belief held by player i at match t that the state is H.

In this expanded model, the beliefs on how likely it is that the partner cooperates in match t, $p_t^*(F_{it}, q_{it})$, depends on the probability that the partner experienced spillovers. In addition, the probability that the partner j had an indirect spillover itself depends on whether his own partner k in the previous match did cooperate, and thus depends on the beliefs q_{kt-1} of that partner in the previous match. The general problem requires to keep track of the higher order beliefs. The proof of the following Proposition shows the existence of such a stationary equilibrium, under a natural restriction on higher order beliefs, i.e if we assume that a player who had belief q_{it} in match t believes that players in the preceding match had the same beliefs $q_{j',t-1} = q_{it}$.

Proposition D *In an environment with spillovers and learning, if an equilibrium exists, all equilibria are of the cutoff form, i.e individuals cooperate if and only if* $\beta_i \geq \beta^*(F_{it}, q_{it})$. *Furthermore, if in equilibrium* $\beta^*(0,q) > \beta^*(1,q)$ *for all beliefs* q, *then the beliefs are updated in the following way given the history in the previous interaction:*

$$q_{it}(0, C, q_{it-1}) > q_{it}(1, C, q_{it-1}) > q_{it-1} \ ,$$
$$q_{it}(1, D, q_{it-1}) < q_{it}(0, D, q_{it-1}) < q_{it-1} \ .$$

Proof. See Section E. ■

Proposition D derives a general property of equilibria. The Proposition also allows to express the probability of cooperation for given belief q_{it-1} as:

$$1 - \Phi_H \Big[\Lambda_3 - \phi_F \ \mathbb{1}_{\{F_{it-1}=1\}} \ - \ \phi_C \ \mathbb{1}_{\{a_{j_{t-1},t-1}=C\}} \ - \Lambda_4 \mathbb{1}_{\{F_{it}=1\}} - \sum_{j,k \in \{0,1\}, l \in \{C,D\}} \Lambda^j_{k,l} \ \mathbb{1}_{\{F_{it}=j, F_{it-1}=k, a_{j_{t-1},t-1}=l\}} \Big] \ . \tag{6}$$

where:

$$\Lambda_3 \ \equiv \ \Pi_1 \ + \ p^*(0,0,D,q) \left[\Pi_2 \ - \ \frac{\delta}{1-\delta} \Pi_3 \right] \ ,$$
$$\Lambda_4 \ \equiv \ F \ - \ [p^*(1,0,D,q) - p^*(0,0,D,q)] \left[\Pi_2 \ - \ \frac{\delta}{1-\delta} \Pi_3 \right] + \frac{\delta}{1-\delta} p^*(1,0,D,q) F > 0 \ ,$$
$$\Lambda^0_{k,l} \ \equiv \ [p^*(0,k,l,q) - p^*(0,0,D,q)] \left[\Pi_2 \ - \ \frac{\delta}{1-\delta} \Pi_3 \right] \ ,$$
$$\Lambda^1_{k,l} \ \equiv \ -[p^*(0,k,l,q) - p^*(0,0,D,q)] \left[\Pi_2 \ - \ \frac{\delta}{1-\delta} (F + \Pi_3) \right] \ .$$

Note that the parameters Λ_3, Λ_4 and $\Lambda^j_{k,l}$ in equation (6) depend on q_{it-1}. Compared to the case without learning, there are 6 additional parameters, reflecting the updating of beliefs. According to the result in Proposition D, these parameters, both in the case where the current match is played with a fine and when it is not, are such that:

$$\Lambda^1_{0,C} > \Lambda^1_{1,C} > 0 > \Lambda^1_{1,D} \ ,$$
$$\Lambda^0_{0,C} > \Lambda^0_{1,C} > 0 > \Lambda^0_{1,D} \ . \tag{7}$$

Overall, having fines in the previous match can potentially decrease average cooperation in the current match. There are two countervailing effects. On the one hand, a fine in the previous match increases the direct and indirect spillovers and thus increases cooperation. On the other hand, if the state is low, a fine can accelerate learning if, on average, sufficiently many people deviate in the presence of a fine. This then decreases cooperation in the current match.

B.1.3 Statistical implementation of the model

The main behavioral insights from the model are summarized by equation (6), which involves both learning and spillover parameters. As the equation clearly shows, exogenous variations in legal enforcement are not enough to achieve separate identification of learning and spillover parameters—an exogenous change in any of the enforcement variables, or past behavior of the partner, involves both learning and a change in the values β_{it}. In the main text, identification relies on the assumption that spillovers are short-living in the sense that their effect on behavior is smaller the earlier they happen in one's own history—while learning should not depend on the order in which a given sequence of actions happens. In this section, we report the results from an alternative identification strategy that relies on the assumption that learning has converged once a large enough number of matches has been played. Under this assumption, in late games, behavior is described by equation (5), which involves only spillover parameters. Exogenous variations in enforcement thus provide identification of spillover parameters in late games, which in turn allows to identify learning parameters in early ones.

To that end, as explained in the text, we split the matches in three groups, in such a way that one third of the observed decisions are classified as "early", and one third as "late". We use matches, rather than periods, as a measure of time since we focus on games for which the first stage decision summarizes all future actions within the current repeated game—hence ruling out learning within a match. Observed matches are accordingly defined as "early" up to the 7$^{\text{th}}$, as late after the 13$^{\text{th}}$—we disregard data coming from intermediary stages.[18] Denote $\mathbb{1}_{\{\text{Early}\}}$ the dummy variable equal to 1 in early games and to 0 in late games. Under the identifying assumption that learning has converged in late games, the model predicts that behavior in the experiment is described by:

$$P(C_{it}=1) = 1 - \Phi_H \Big[\Lambda_1 + (\Lambda_3 - \Lambda_1)\ \mathbb{1}_{\{\text{Early}\}} - \phi_F\ \mathbb{1}_{\{F_{it-1}=1\}}\ -\ \phi_C\ \mathbb{1}_{\{a_{j_{t-1},t-1}=C\}}\ - \Lambda_2 \mathbb{1}_{\{F_{it}=1\}}$$
$$- (\Lambda_4 - \Lambda_2)\ \mathbb{1}_{\{F_{it}=1\}} \times \mathbb{1}_{\{\text{Early}\}} - \sum_{j,k\in\{0,1\},l\in\{C,D\}} \Lambda^j_{k,l}\ \mathbb{1}_{\{F_{it}=j,F_{it-1}=k,a_{j_{t-1},t-1}=l\}} \times \mathbb{1}_{\{\text{Early}\}} \Big]$$

which is the structural form of a Probit model on the individual decision to cooperate. This probability results from equilibria of the cutoff form involving the primitives of the model. Denoting ε_{it} observation specific unobserved heterogeneity, $\boldsymbol{\theta}$ the vector of unknown parameters embedded in the above equation, $\boldsymbol{x}_{it}$ the associated set of observable describing participant i experience up to t and C^*_{it} the latent function generating player i willingness to cooperate at match t, observed decisions inform about the model parameters according to:

$$C_{it} = \mathbb{1}[C^*_{it} = \boldsymbol{x}_{it}\boldsymbol{\theta} + \varepsilon_{it} > 0]$$

The structural parameters govern the latent equation of the model. Our empirical test of the model is thus based on estimated coefficients, $\boldsymbol{\theta} = \frac{\partial C^*}{\partial \boldsymbol{x}_{it}}$, rather than marginal effects, $\frac{\partial C}{\partial \boldsymbol{x}_{it}} = \boldsymbol{\theta}\frac{\partial\Phi(\boldsymbol{x}_{it}\boldsymbol{\theta})}{\partial \boldsymbol{x}_{it}}$.

In the set of covariates, both current ($\mathbb{1}_{\{F_{it}=1\}}$) and past enforcement ($\mathbb{1}_{\{F_{it-1}=1\}}$) are exogenous by design. The partner's past decision to cooperate, C_{jt-1}, is exogenous to C_{it} as long as player i and j have

[18] All results are robust to alternative definitions of these thresholds. The results are available from authors upon request.

no other player in common in their history. Moreover, due to the rematching of players from one match to the other, between subjects correlation might arise if player j met another player with whom i has already played once. We address these concerns in three ways. We include the decision to cooperate at the first stage of the first match in the set of control variables, as a measure of individual unobserved *ex ante* willingness to cooperate. To further account for the correlation structure in the error of the model, we specify a panel data model with random effects at the individual level, control for the effect of time thanks to the inclusion of the match number, and cluster the errors at the session level to account in a flexible way for within sessions correlation.

Table C reports the estimation results from several specifications, in which each piece of the model is introduced sequentially. The parameters of interest are the learning parameters $\Lambda_{k,l}, k \in \{0,1\}, l \in \{C,D\}$.[19] Columns (1) and (2) focus on the effect of past and current enforcement. While we do not find any significant change due to moving from early to late games *per se* (the Early variable is not significant), the effect of current enforcement on the current willingness to cooperate is much weaker in early games. This is consistent with participants becoming less confident that the group is cooperative, thus less likely to cooperate, as time passes—i.e., prior belief over-estimate the average cooperativeness of the group. The disciplining effect of current fines is thus stronger in late games.

Column (3) introduces learning parameters. As stressed above, the learning parameters play a role before beliefs have converged. They are thus estimated in interaction with the Early dummy variable. Once learning is taken into account, enforcement spillovers turn-out significant. More importantly, the model predicts that learning is stronger when observed decisions are more informative about societal values, which in turn depends on the enforcement regime under which behavior has been observed—i.e., cooperation (defection) is more informative under weak (strong) enforcement. This results in a clear ranking between learning parameters—see equation (7). We use defection under weak enforcement as a reference for the estimated learning parameters. The results show that cooperation under weak enforcement (Early $\times$ C_0) leads to the strongest increase in the current willingness to cooperate. Observing this same decision but under strong enforcement institutions rather than weak ones (Early $\times$ C_1) has almost the same impact as observing defection under strong institutions (the reference): in both cases, behavior is aligned with the incentives implemented by the rules and barely provides any additional insights about the distribution of values in the group. Last, defection under strong institutions (Early $\times$ D_0) is informative about a low willingness to cooperate in the group, and results in a strongly significant drop in current cooperation.

Column (4) adds indirect spillovers, induced by the cooperation of the partner in the previous game. The identification of learning parameters in this specification is quite demanding since both past enforcement and past cooperation are included as dummy variables in this specification. We nevertheless observe a statistically significant effect of learning in early games, with the expected ordering according to how informative the signal is, with the exception of C_1—i.e., when cooperation has been observed under fines. Finally, column (5) provides a robustness check for the reliability of the assumption that learning has converged in late games. To that end, we further add the interaction between observed behavior from partner in the previous game and the enforcement regime. Once learning has converged, past behavior is assumed to affect the current willingness to cooperate through indirect spillovers only. Absent learning, this effect should not interact with the enforcement rule that elicited this behavior. As expected, this interaction term is not significant: in late games, it is cooperation per se, rather than the enforcement regime giving

[19] Note that we do not separately estimate these parameters according to the current enforcement environment, but rather estimate weighted averages $\Lambda_{k,l} = \mathbb{1}_{\{F_{it}=0\}}\Lambda^0_{k,l} + \mathbb{1}_{\{F_{it}=1\}}\Lambda^1_{k,l}$.

Table C: Learning and spillovers arising from past enforcement

Variable	*Model parameter*	(1)	(2)	(3)	(4)	(5)
Constant	$(-\Lambda_1)$	-1.986***	-2.020***	-2.290***	-2.302***	-2.291***
		(0.392)	(0.362)	(0.298)	(0.317)	(0.220)
$\mathbb{1}_{\{F_{it}\}}$	(Λ_2)	1.448***	1.454***	1.480***	1.473***	1.472***
		(0.164)	(0.149)	(0.150)	(0.142)	(0.137)
Early	$(-\Lambda_3 + \Lambda_1)$	0.285	0.292	0.348	0.460	0.453
		(0.411)	(0.415)	(0.440)	(0.383)	(0.377)
Early $\times \mathbb{1}_{\{F_{it}\}}$	$(\Lambda_4 - \Lambda_2)$	-0.698***	-0.698***	-0.646**	-0.644**	-0.643**
		(0.243)	(0.245)	(0.258)	(0.261)	(0.271)
$\mathbb{1}_{\{F_{it-1}\}}$	(ϕ_F)		0.049	0.306**	0.094	0.085
			(0.120)	(0.140)	(0.193)	(0.306)
$\mathbb{1}_{\{a_{jt-1}=C\}}$	(ϕ_C)				0.693***	0.674***
					(0.169)	(0.121)
Early $\times C_0$	$(\Lambda_{0,C})$			1.066***	0.430	0.448*
				(0.186)	(0.363)	(0.246)
Early $\times C_1$	$(\Lambda_{1,C})$			0.233	-0.228**	-0.230**
				(0.168)	(0.096)	(0.094)
Early $\times D_1$	$(\Lambda_{1,D})$			-0.876**	-0.631*	-0.621*
				(0.423)	(0.329)	(0.334)
C_1						0.029
						(0.380)
N		553	553	553	553	553
σ_u		1.063	1.064	1.063	1.060	1.060
ρ		0.531	0.531	0.530	0.529	0.529
LL		-234.677	-234.624	-224.416	-220.033	-220.031

Note. Probit models with individual random effects on the decision to cooperate at first stage estimated on the working sample restricted to early (before the 7$^{\text{th}}$) and late (beyond the 13$^{\text{th}}$) games. Standard errors (in parenthesis) are clustered at the session level. All specifications include control variables for gender, age, whether participant is a student, whether a fine applies to the first match, the decision to cooperate at first match, the length of the previous game and match number. *Significance levels*: *10%, **5%, ***1%.

rise to this decision, that matters for current cooperation.

C Replication of the statistical analysis on the full sample

In this section, we replicate the results on the full sample of observations: instead of restricting the analysis to the working sample made of decisions consistent with the subset of repeated-game strategies described in Section 2.2, we include all available observations. As already mentioned in the text, the matches we exclude from the working sample all appear in late games so that Figure 2a is not affected by the choice of the working sample. Figure E below replicates Figure 3 in the paper; and Table D replicates Table 2. In both instances, the data is more noisy but the qualitative conclusions all remain the same.

Figure E: Current cooperation as a function of history in the previous 5 games, computed on the full sample

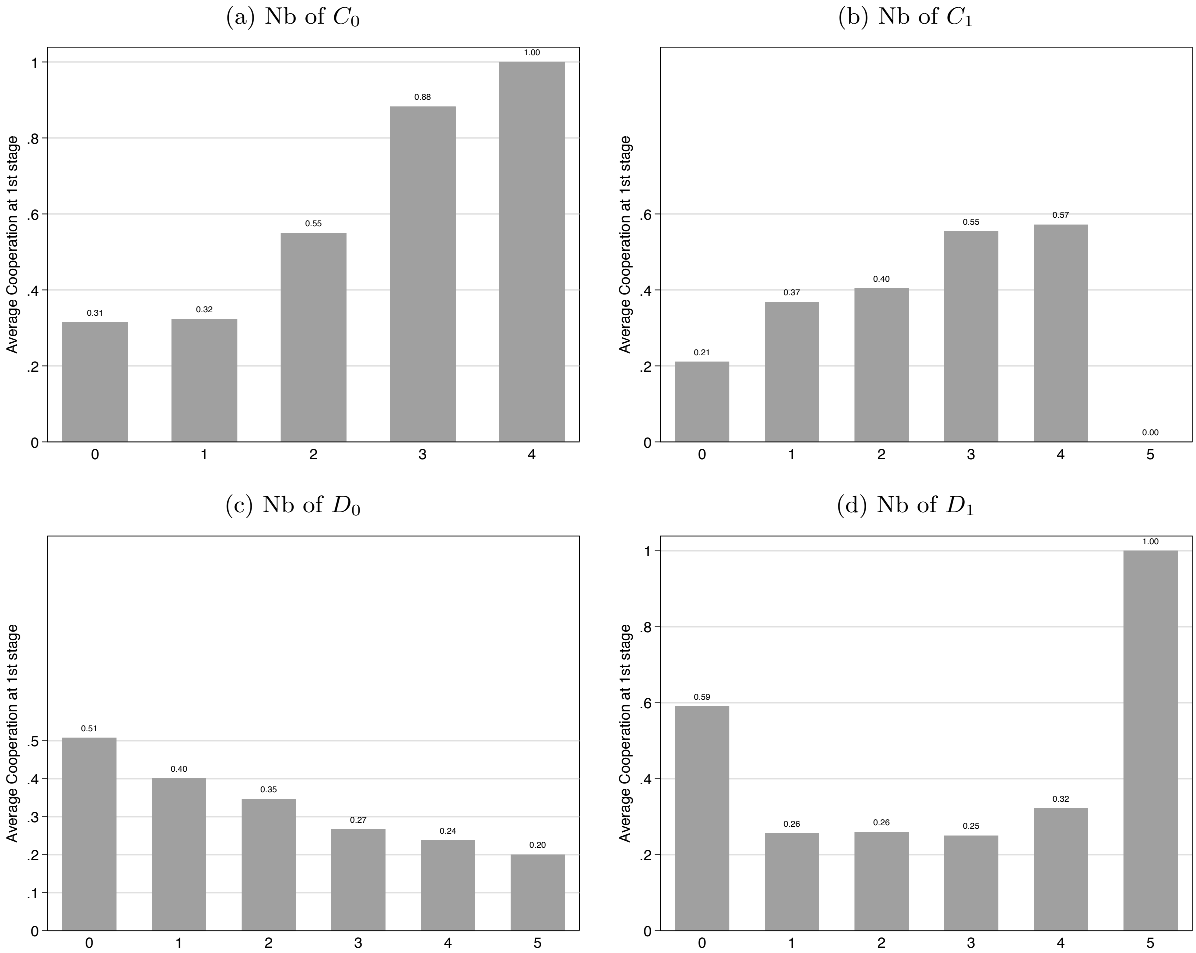


Table D: Replication of Table 2 on the full sample

	(1) Enforcement	(2) Spillovers	(3)	(4)	(5)	(6) est6
Constant	-0.029		0.037		0.126	
	(0.736)		(0.733)		(0.847)	
$\mathbb{1}_{\{F_t=1\}}$	1.172***	0.310***	1.168***	0.307***	1.165***	0.306***
	(0.279)	(0.034)	(0.278)	(0.034)	(0.265)	(0.031)
$\overline{C}_0 = \sum_{s=1}^{5} C_{t-s}^0$	0.347**	0.092***	0.321**	0.084**	0.361*	0.095**
	(0.142)	(0.032)	(0.149)	(0.034)	(0.185)	(0.040)
$\overline{C}_1 = \sum_{s=1}^{5} C_{t-s}^1$	0.196**	0.052**	0.122	0.032	0.101	0.027
	(0.090)	(0.022)	(0.086)	(0.022)	(0.148)	(0.037)
$\overline{D}_1 = \sum_{s=1}^{5} D_{t-s}^1$	-0.049	-0.013*	-0.090*	-0.024**	-0.133**	-0.035**
	(0.036)	(0.008)	(0.052)	(0.011)	(0.060)	(0.015)
$\mathbb{1}_{\{F_{t-1}=1\}}$			0.195**	0.051***	0.089	0.023
			(0.083)	(0.017)	(0.232)	(0.059)
$\mathbb{1}_{\{a_{jt-1}=C\}}$			0.146**	0.039*	0.258*	0.068**
			(0.074)	(0.022)	(0.137)	(0.031)
$a_{jt} = C$ in a row					-0.079	-0.021
					(0.081)	(0.019)
F_{it} in a row					0.071	0.019
					(0.109)	(0.030)
N	694	–	694	—	694	—
σ_u	1.099	—	1.100	—	1.113	—
ρ	0.547	—	0.547	—	0.553	—
LL	-300.754	—	-298.972	—	-298.235	—

Note. Marginal effects are computed at sample mean, assuming random effects are 0. *Significance levels*: *10%, **5%, ***1%.

D Replication of the main results with bootstrapped standard errors

As explained in the main text, the statistical analysis presented in Table 2 clusters the standard errors at the session level, so as to take into account in a flexible way the possible correlations between subjects due to random rematching of subjects within pairs. While this approach is conservative (since it does not impose any structure on the correlation between subjects over time), the number of clusters is small and there is a risk of small sample downward bias in the estimated standard errors. Table E provides the results from a robustness exercise replicating Table 2 in the text with bootstrapped standard error based a delete-one jackknife procedure (see Bell and McCaffrey, 2002; Cameron, Gelbach, and Miller, 2008).

Table E: Replication of Table 2 using bootstrapped errors

	(1) Enforcement	(2) Spillovers	(3)	(4)	(5)	(6) est6
main						
Constant	0.040		0.147		0.179	
	(0.167)		(0.217)		(0.258)	
$\mathbb{1}_{\{F_t=1\}}$	1.356**	0.305**	1.361**	0.303**	1.355**	0.302**
	(0.281)	(0.056)	(0.280)	(0.055)	(0.285)	(0.052)
$\overline{C}_0 = \sum_{s=1}^{5} C^0_{t-s}$	0.410**	0.092**	0.406**	0.091**	0.433**	0.097**
	(0.078)	(0.015)	(0.074)	(0.014)	(0.095)	(0.018)
$\overline{C}_1 = \sum_{s=1}^{5} C^1_{t-s}$	0.210***	0.047**	0.164***	0.037***	0.167	0.037
	(0.018)	(0.007)	(0.006)	(0.003)	(0.111)	(0.024)
$\overline{D}_0 = \sum_{s=1}^{5} D^1_{t-s}$	-0.123	-0.028*	-0.180**	-0.040**	-0.195	-0.043
	(0.048)	(0.009)	(0.041)	(0.007)	(0.073)	(0.016)
$\mathbb{1}_{\{F_{t-1}=1\}}$			0.230*	0.051*	0.199	0.044
			(0.060)	(0.017)	(0.323)	(0.072)
$\mathbb{1}_{\{a_{jt-1}=C\}}$			-0.019	-0.004	0.073	0.016
			(0.041)	(0.009)	(0.140)	(0.031)
$a_{jt} = C$ in a row					-0.059	-0.013
					(0.053)	(0.011)
F_{it} in a row					0.020	0.004
					(0.182)	(0.041)
N	599	599	599	599	599	599
σ_u	1.196	1.196	1.201	1.201	1.208	1.208
ρ	0.588	0.588	0.591	0.591	0.593	0.593
LL	-220.466	-220.466	-219.610	-219.610	-219.454	-219.454

Note. Marginal effects are computed at sample mean, assuming random effects are 0. *Significance levels*: *10%, **5%, ***1%.

E Proofs

Proof of Proposition 1

As derived in the main text, if an equilibrium exists, it is necessarily such that players use cutoff strategies. Reexpressing characteristic equation (2), we can show that the cutoffs are determined by the equation $g(\beta^*[F_{it}]) = 0$, where g is given by

$$g(x) = -x \; + \; \Pi_1 - F \; \mathbb{1}_{\{F_{it}=1\}} \; + \; (1 - \Phi_H(x)) \left[\Pi_2 \; - \; \frac{\delta}{1-\delta} \left(F \; \mathbb{1}_{\{F_{it}=1\}} + \Pi_3 \right) \right].$$

The function g has the following properties: $g(x) > 0$ when x converges to $-\infty$ and $g(x) < 0$ when x converges to $+\infty$. Thus, since g is continuous, there is at least one solution to the equation $g(\beta^*[F_{it})] = 0$. At least one equilibrium exists.

If g is non monotonic, there could exist multiple equilibria. However, in all stable equilibria, β^* is such that g is decreasing at β^*, i.e.

$$- 1 - \phi_H\left[\beta^*\right] \left[\Pi_2 \; - \; \frac{\delta}{1-\delta} \left(F \; \mathbb{1}_{\{F_{it}=1\}} + \Pi_3\right)\right] < 0 \; . \tag{8}$$

Using the implicit theorem we have:

$$\frac{\partial \beta^*}{\partial F} = - \frac{\partial g}{\partial F} \Big/ \frac{\partial g}{\partial \beta^*} = - \frac{-1 - \left(1 - \Phi_H\left[\beta^*\right]\right) \frac{\delta}{1-\delta}}{-1 - \phi_H\left[\beta^*\right] \left[\Pi_2 \; - \; \frac{\delta}{1-\delta} \left(F \; \mathbb{1}_{\{F_{it}=1\}} + \Pi_3\right)\right]} \; ,$$

where ϕ_H is the density corresponding to distribution Φ_H. For stable equilibria, the denominator is negative as shown in (8), so that overall

$$\frac{\partial \beta^*}{\partial F} < 0 \; .$$

Similarly,

$$\frac{\partial \beta^*}{\partial \mu_H} \quad = \quad - \frac{- \frac{\partial \Phi_H[\beta^*]}{\partial \mu_H} \left[\Gamma_2 \; - \; \frac{\delta}{1-\delta} \left(F \; \mathbb{1}_{\{F_{it}=1\}} + \Pi_3\right)\right]}{-1 - \phi_H\left[\beta^*\right] \left[\Pi_2 \; - \; \frac{\delta}{1-\delta} \left(F \; \mathbb{1}_{\{F_{it}=1\}} + \Pi_3\right)\right]} \; .$$

Again, in stable equilibria the denominator is negative by (8). Furthermore we have $\frac{\partial \Phi_H[\beta^*]}{\partial \mu_H} < 0$ since an increase in the mean of the normal distribution decreases $\Phi_H\left[x\right]$ for any x. Overall we get

$$\frac{\partial \beta^*}{\partial \mu_H} < 0 \; .$$

Proof of Lemma 1

We first show the result: $q_{i2}(1, D) < q_{i2}(0, D) < q_0$. According to Baye's rule, the belief that the state is H following a deviation by the partner in the first match (which has been played with a fine) is:

$$\begin{aligned} q_{i2}(1, D) \quad &= \quad \frac{q_0 \; P[D|F_{i1} = 1, s = H]}{q_0 \; P[D|F_{i1} = 1, s = H] + (1 - q_0) \; P[D|F_{i1} = 1, s = L]} \\ &= \quad \frac{q_0 \; \Phi_H\left[\beta^*(1)\right]}{q_0 \; \Phi_H\left[\beta^*(1)\right] + (1 - q_0) \; \Phi_L\left[\beta^*(1)\right]} \\ &= \quad \frac{1}{1 + \frac{1-q_0}{q_0} \; \frac{\Phi_L[\beta^*(1)]}{\Phi_H[\beta^*(1)]}} \; . \end{aligned} \tag{9}$$

Furthermore, since $\Phi_L\left[\beta^*(1)\right] > \Phi_L\left[\beta^*(1)\right]$, we have $q_{i2}(1, D) > q_0$. Similarly we have:

$$q_{i2}(0, D) \quad = \quad \frac{1}{1 + \frac{1-q_0}{q_0} \; \frac{\Phi_L[\beta^*(0)]}{\Phi_H[\beta^*(0)]}} \; > q_0 \; . \tag{10}$$

Thus,

$$q_{i2}(1, D) < q_{i2}(0, D) \Leftrightarrow \frac{\Phi_L\left[\beta^*(0)\right]}{\Phi_H\left[\beta^*(0)\right]} < \frac{\Phi_L\left[\beta^*(1)\right]}{\Phi_H\left[\beta^*(1)\right]} \; .$$

Using the fact that $\frac{\Phi_L[x]}{\Phi_H[x]}$ is decreasing in x as shown in Property 1 below, and the fact that in stable equilibria, we have $\beta^*(1) \leq \beta^*(0)$, as shown in Proposition 1, implies directly that $q_{i2}(1, D) < q_{i2}(0, D)$. The proof that $q_{i2}(0, C) > q_{i2}(1, C) > q_0$ follows similar lines.

Property 1 $\frac{\Phi_H[x]}{\Phi_L[x]}$ *is increasing in* x.

Proof. Denote ϕ_H (resp. ϕ_L) the density of Φ_H (resp. Φ_L). Given that ϕ_H (resp. ϕ_L) is the density of a normal distribution with standard deviation σ and mean μ_H (resp. μ_L), it is the case that:

$$\begin{aligned}\frac{\phi_H[x]}{\phi_L[x]} &= \frac{\frac{1}{\sigma\sqrt{2\pi}}e^{-(x-\mu_H)^2/\sigma^2}}{\frac{1}{\sigma\sqrt{2\pi}}e^{-(x-\mu_L)^2/\sigma^2}} \\ &= e^{-(x-\mu_H)^2/\sigma^2+(x-\mu_L)^2/\sigma^2} \\ &= e^{\frac{1}{\sigma^2}(\mu_H-\mu_L)(2x-\mu_L-\mu_H)} .\end{aligned}$$

Thus $\frac{\phi_H}{\phi_L}$ is increasing in x. In particular for $y < x$, we have: $\phi_H[y]\phi_L[x] < \phi_L[y]\phi_H[x]$. By definition, $\Phi_s(x) = \int_{-\infty}^{x}\phi_s(y)dy$. Integrating with respect to y between $-\infty$ and x thus yields:

$$\Phi_H[x]\phi_L[x] < \Phi_L[x]\phi_H[x] \ . \tag{11}$$

Consider now the function $\frac{\Phi_H}{\Phi_L}$. The derivative of this function is given by $\frac{\phi_H\Phi_L-\phi_L\Phi_H}{\Phi_L^2}$, which is positive by equation (11). This establishes Property 1 that $\frac{\Phi_H[x]}{\Phi_L[x]}$ is increasing in x. ■

Proof of Proposition D (that generalizes Proposition 2)

In the first part of the proof we assume a stationary equilibrium exists and is such that the equilibrium cutoffs are always higher without a fine in the current match $\beta^*(0, q) > \beta^*(1, q)$ for any given belief q. We then derive the property on updating of beliefs. In the second part of the proof we show existence under a natural restriction on beliefs.

Part 1: We first derive the properties on updating. We have

$$q_{it}(F_{it-1}, a_{j_{t-1},t-1}, q_{it-1}) = \frac{q_{it-1}P[a_{j_{t-1},t-1}|F_{it-1}, s = H]}{q_{it-1}P[a_{j_{t-1},t-1}|F_{it-1}, s = H] + (1 - q_{it-1})P[a_{j_{t-1},t-1}|F_{it-1}, s = L]} \ . \tag{12}$$

We can express the probability that the partner j_{t-1} in match $t-1$ cooperated, by considering all the possible environments this individual might have faced in the past, in particular what his partner in match $t-2$, individual k_{t-1} chose:

$$\begin{aligned}P[a_{j_{t-1},t-1} = D \quad | \quad & F_{it-1}, s = H] = \\ & \sum_{F_{j_{t-1},t-2}, a_{k_{t-1},t-2}, q_{j_{t-1},t-1}} \Phi_H\left[\beta^*(1, q_{j_{t-1},t-1}) - \phi_F \ \mathbb{1}_{\{F_{j_{t-1},t-2}=1\}} \ - \ \phi_C \ \mathbb{1}_{\{a_{k_{t-1},t-2}=C\}}\right] \\ & \times P[F_{j_{t-1},t-2}, a_{k_{t-1},t-2}, q_{j_{t-1},t-1}].\end{aligned}$$

Denote

$$\gamma^*\left(F_{j_{t-1},t-2}, a_{k_{t-1},t-2}, q_{j_{t-1},t-1}\right) = \beta^*(1, q_{j_{t-1},t-1}) - \phi_F\ \mathbb{1}_{\{F_{j_{t-1},t-2}=1\}}\ -\ \phi_C\ \mathbb{1}_{\{a_{k_{t-1},t-2}=C\}}.$$

and

$$R(x) \equiv \frac{\sum_{F_{j_{t-1},t-2}, a_{k_{t-1},t-2}, q_{j_{t-1},t-1}} \Phi_H\left[\gamma^*\left(x, a_{k_{t-1},t-2}, q_{j_{t-1},t-1}\right)\right] P[F_{j_{t-1},t-2}, a_{k_{t-1},t-2}, q_{j_{t-1},t-1}]}{\sum_{F_{j_{t-1},t-2}, a_{k_{t-1},t-2}, q_{j_{t-1},t-1}} \Phi_L\left[\gamma^*\left(x, a_{k_{t-1},t-2}, q_{j_{t-1},t-1}\right)\right] P[F_{j_{t-1},t-2}, a_{k_{t-1},t-2}, q_{j_{t-1},t-1}]}\ .$$

Using expression (12), we have:

$$q_{it}(1, D, q_{it-1}) < q_{it}(0, D, q_{it-1}) \Leftrightarrow R(1) \geq R(0)\ .$$

We then use all possible values of the vector $(F_{j_{t-1},t-2}, a_{k_{t-1},t-2}, q_{j_{t-1},t-1})$ in turn. Take such a value v for this vector and denote

$$a \equiv \sum_{(F_{j_{t-1},t-2}, a_{k_{t-1},t-2}, q_{j_{t-1},t-1}) \neq v} \Phi_H\left[\gamma^*\left(x, a_{k_{t-1},t-2}, q_{j_{t-1},t-1}\right)\right] P[F_{j_{t-1},t-2}, a_{k_{t-1},t-2}, q_{j_{t-1},t-1}]\ ,$$
$$b \equiv \sum_{(F_{j_{t-1},t-2}, a_{k_{t-1},t-2}, q_{j_{t-1},t-1}) \neq v} \Phi_L\left[\gamma^*\left(x, a_{k_{t-1},t-2}, q_{j_{t-1},t-1}\right)\right] P[F_{j_{t-1},t-2}, a_{k_{t-1},t-2}, q_{j_{t-1},t-1}]\ .$$

We clearly have $a < b$. Furthermore, we can write

$$R(x) \equiv \frac{a + \Phi_H\left[\gamma^*\left(v\right)\right] P[v]}{b + \Phi_L\left[\gamma^*\left(v\right)\right] P[v]}$$

We have $\beta^*(0, q) > \beta^*(1, q)$ imply that $\gamma^*\left(0, a_{k't-2}, q_{j't-1}\right) > \gamma^*\left(1, a_{k't-2}, q_{j't-1}\right)$. Thus using Property 2 below, it implies that $R(1) \geq R(0)$ and thus $q_{it}(1, D, q_{it-1}) < q_{it}(0, D, q_{it-1})$.

Property 2 $\frac{a+p\Phi_H[x]}{b+p\Phi_L[x]}$ *where* $b > a$ *is increasing in* x.

Proof. The derivative of the ratio is given by

$$\frac{\phi_H\left(b + p\Phi_L\right) - \phi_L\left(a + p\Phi_H\right)}{\left(b + p\Phi_L\right)^2} \tag{13}$$

We showed in the proof of Property 1 that: $\phi_H\Phi_L - \phi_L\Phi_H > 0$. Furthermore, we also showed that $\frac{\phi_H}{\phi_L}$ is increasing and since $a < b$ this implies: $\phi_H b - \phi_L a > 0$. Combining these two results in condition (13) establishes Property 2. ■

Part 2: We show that an equilibrium exists if we assume that a player who has belief q_{it} in match t believes that other players in match t and $t-1$ shared the same belief $q_{j_t,t} = q_{k_t,t} = q_{it}$.

If a stationary equilibrium exists, it is necessarily such that players use cutoff strategies where the cutoff is defined by:

$$\beta_t^*(F_{it}, q_{it}) \quad = \quad \Pi_1 - F\ \mathbb{1}_{\{F_{it}=1\}}\ +\ p_t^*(F_{it}, q_{it})\left[\Pi_2\ -\ \frac{\delta}{1-\delta}\left(F\ \mathbb{1}_{\{F_{it}=1\}} + \Pi_3\right)\right]$$

We have:

$$
\begin{aligned}
p_t^*(F_{it}, q_{it}) &= P[a_{j_t,t} = C | F_{it}, q_{it}] \\
&= q_{it} \sum_{(F_{j_t,t-1}, a_{k_t,t-1}, q_{j_t,t-1})} \left[1 - \Phi_H \left[\beta^*(F_{j_t,t}, q_{j_t,t-1}) - \phi_F \ \mathbb{1}_{\{F_{j_t,t-1}=1\}} \ - \ \phi_C \ \mathbb{1}_{\{a_{k_t,t-1}=C\}}\right]\right] \\
&\quad \times P[F_{j_t,t-1}, a_{k_t t-1}, q_{j_t,t-1} | s = H] \\
&+ (1 - q_{it}) \sum_{(F_{j_t,t-1}, a_{k_t,t-1}, q_{j_t,t-1})} \left[1 - \Phi_L \left[\beta^*(F_{j_t,t}, q_{j_t,t-1}) - \phi_F \ \mathbb{1}_{\{F_{j_t,t-1}=1\}} \ - \ \phi_C \ \mathbb{1}_{\{a_{k_t,t-1}=C\}}\right]\right] \\
&\quad \times P[F_{j_t,t-1}, a_{k_t t-1}, q_{j_t,t-1} | s = L]
\end{aligned}
$$

Furthermore, we have

$$
\begin{aligned}
P[F_{j_t,t-1}, a_{k_t,t-1}, q_{j_t,t-1} | s = H] &= P[F_{j_t,t-1}] \ P[a_{k_t,t-1} | F_{j_t,t-1}, s = H] \ f_t(q_{j_t,t-1} | s = H) \\
&= \frac{1}{2} \ P[a_{k_t,t-1} | F_{j_t,t-1}, s = H] \ f_t(q_{j_t,t-1} | s = H)
\end{aligned}
$$

we assumed that a player who had belief q_{it-1} in match $t-1$ believes that all other players in that match share the same belief q_{it-1}. Under this restriction, we have $f_t(q_{j't-1} | s = .) = \mathbb{1}_{(q_{j't-1} = q_{it-1})}$

$$
P[1, D, q | s = H] = \frac{1}{2} \ p_t^*(1, q)
$$

We get a similar expression as in the proof of Proposition 2:

$$
\begin{aligned}
p^*(F_{it}, q_{it}) &= [1 - \Phi_H [\beta^*(F_{it}, q_{it}) - \phi_F - \phi_C]] \frac{1}{2} p^*(1, q_{it}) + [1 - \Phi_H [\beta^*(F_{it}, q_{it}) - \phi_F]] \frac{1}{2} [1 - p^*(1, q_{it})] \\
&+ [1 - \Phi_H [\beta^*(F_{it}, q_{it}) - \phi_C]] \frac{1}{2} p^*(0, q_{it}) + [1 - \Phi_H [\beta^*(F_{it}, q_{it})]] \frac{1}{2} [1 - p^*(0, q_{it})] \ . \qquad (14)
\end{aligned}
$$

This implies that for each belief q, there is a system of equation equivalent to system A in the proof if Proposition 2. We thus have a solution of this system for each value q.