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Games of corruption: How to suppress illegal logging

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HIGHLIGHTS

- We study an evolutionary game for the illegal logging and the corruption of rule enforcers.
- Harvesters cooperate (log legally) or defect; enforcers are honest or corrupt.
- The dynamics converge either to defecting harvesters or to cooperators.
- The education of enforcers is a potent means of curbing corruption.
- Information on corrupt enforcers enhances the likelihood of cooperative outcomes.

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ABSTRACT

Corruption is one of the most serious obstacles for ecosystem management and biodiversity conservation. In particular, more than half of the loss of forested area in many tropical countries is due to illegal logging, with corruption implicated in a lack of enforcement. Here we study an evolutionary game model to analyze the illegal harvesting of forest trees, coupled with the corruption of rule enforcers. We consider several types of harvesters, who may or may not be committed towards supporting an enforcer service, and who may cooperate (log legally) or defect (log illegally). We also consider two types of rule enforcers, honest and corrupt: while honest enforcers fulfill their function, corrupt enforcers accept bribes from defecting harvesters and refrain from fining them. We report three key findings. First, in the absence of strategy exploration, the harvester–enforcer dynamics are bistable: one continuum of equilibria consists of defecting harvesters and a low fraction of honest enforcers, while another consists of cooperating harvesters and a high fraction of honest enforcers. Both continua attract nearby strategy mixtures. Second, even a small rate of strategy exploration removes this bistability, rendering one of the outcomes globally stable. It is the relative rate of exploration among enforcers that then determines whether most harvesters cooperate or defect and most enforcers are honest or corrupt, respectively. This suggests that the education of enforcers, causing their more frequent trialing of honest conduct, can be a potent means of curbing corruption. Third, if information on corrupt enforcers is available, and players react opportunistically to it, the domain of attraction of cooperative outcomes widens considerably. We conclude by discussing policy implications of our results.

1. Introduction

Although the “tragedy of the commons” is ubiquitous (Hardin, 1968), field research on governing the commons, as well as laboratory experiments on public good games, show that, sometimes, cooperation can be maintained and the tragedy avoided (e.g., Ostrom, 1990; Henrich, 2006; Henrich et al., 2006; Rustagi et al., 2010). In particular, research by Ostrom and colleagues has shown that people are frequently able to discuss, establish, and enforce rules defining a system of punishment for rule breakers (Ostrom, 2000). In her view, institutions are tools for providing incentives to promote cooperation (Ostrom and Walker, 1997; Ostrom et al., 1994). Basic design principles of Ostrom (1990) for social settings that allow long-lasting resource use include the successful establishment of a monitoring and sanctioning system. Such systems provide examples of mechanisms that enforce cooperation by punishing defectors.

The general theory of sanctioning mechanisms has been studied extensively (e.g., Tyler and Degoey, 1995; Nakamaru and

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Iwasa, 2006; Rockenbach and Milinski, 2006; Dreber et al., 2008; Egas and Riedl, 2008; Sigmund, 2007; Casari and Luini, 2009; Nakamaru and Dieckmann, 2009; Kosfeld et al., 2009; Boyd et al., 2010; Baldassarri and Grossman, 2011; Chaudhuri, 2011; Iwasa and Lee, 2013; Shimao and Nakamaru, 2013). In some situations, individual players directly punish defectors (peer punishment; Fowler, 2005; Bochet et al., 2006; Cinyabuguma et al., 2006; Gürerk et al., 2006, 2008; Ertan et al., 2009). Alternatively, players may establish a costly police-like system for punishing defectors, which is specialized on spotting and fining defectors (pool punishment; Yamagishi, 1986; Van Vugt et al., 2009; Kamei et al., 2011; Sigmund et al., 2011; Andreoni and Gee, 2012; Traulsen et al., 2012). For such a system to function effectively, the hired rule enforcers (or inspectors, officers, janitors, sheriffs) have to work properly. In some situations, however, the rule enforcers can be corrupt, accepting bribes from defectors and then refrain from fining them.

Illegal logging is a typical example of how the tragedy of the commons may jeopardize a common good. Since each individual harvester can gain from logging more trees than other harvesters, preventing unsustainable overharvesting requires establishing standards for legal logging. And when the tasks of monitoring and sanctioning harvesters according to those standards are delegated to third parties, corruption may arise. Corruption is known to be positively correlated with illegal logging in many places around the world, including Indonesia, China, Southern Asia, and West and Central Africa (Seneca Creek Associates, 2004). For some countries, such as Cambodia, Indonesia, and Bolivia, indicative estimates of illegal logging even exceed 80% (Food and Agriculture Organization (FAO), 2005; European Forest Institute, 2005). Illegal logging occurs widely and persistently, at both state and community levels (Corbridge and Kumar, 2002; Véron et al., 2006; World Bank, 2006). A statistical analysis of forest management showed that efficient judicial systems deter rule breaking, increase the compliance of harvesting firms, and reduce corruption (Diarra and Marchand, 2011). At the theoretical end, Mishra (2006) discussed a game model in which a public official may siphon off public goods—an unlawful action that is supposed to be stopped by a politician, but may continue if the public official bribes the politician, as well as a major fraction of citizens. These studies underscore the general understanding that corruption tends to ruin joint efforts, leading to resource depletion and distorted distribution.

In this paper, we study conditions and mechanisms for curbing corruption, using very simplified models, rather than realistic models incorporating the many details that may affect corruption in particular situations. We deliberately focus on the simplest possible situations in order to identify the key elements for controlling the corruption of rule enforcers. We thus hope to derive general insights and conclusions that may be applicable to a broad range of other social dilemmas.

Specifically, we consider a situation in which a group of harvesters establish a rule to restrain logging. Hired enforcers monitor the harvesters who commit to the rule and fine defectors who harvest the common forest excessively. We assume that rule enforcers are paid by the harvesters, rather than being funded through an external source or organization: this corresponds to the 'grass roots' institutions studied by Ostrom (e.g., Ostrom and Walker, 1997; Ostrom, 2000). To investigate whether this rule enforcement system can emerge as a social institution in the modeled community, we use replicator dynamics describing social learning occurring through the imitation of successful role models (e.g., Sigmund, 2010). On this basis, we investigate conditions favoring cooperative harvesters and honest enforcers, respectively.

After establishing results for this simple model as a baseline, we extend our analyses in two directions. First, we study a series of models differing in exploration rates among strategies, and second, we investigate the effects arising from the availability of information on corrupt enforcers. The resulting dynamical systems show typical nonlinear behavior, such as a strong dependence on initial conditions, heteroclinic cycles, and stable long-term oscillations. Based on our findings, we conclude that the education of enforcers, as well as information on corrupt enforcers, have the potential to exert profound effects on levels of cooperation and corruption.

2. Model

2.1. Harvesters and enforcers, their strategies and payoffs

Harvesters may log legally and invest efforts into maintaining a forest in a healthy state, so it can sustainably provide ecosystem services benefiting all community members. Alternatively, harvesters may log illegally, harvesting trees in an unsustainable manner to enhance their own incomes. Individually, each harvester has an incentive to engage in the unsustainable harvesting of commonly owned forest trees. If all harvesters do so, however, the forest may eventually be lost, and every member of the community will suffer. This is a typical social dilemma known as the tragedy of the commons (Hardin, 1968). Maintaining the forest in a healthy state requires cooperation, while illegal logging corresponds to defection.

Faced with this social dilemma, harvesters may find it necessary to hire a "rule enforcer", who spots defecting harvesters and fines them. We model this situation in a minimalistic way by assuming that pairs of harvesters can commit to being monitored, and potentially punished, by an enforcer. Alternatively, harvesters might be tempted to bribe the enforcer, so as to enable them to cheat on their co-players with impunity. When a significant fraction of enforcers are corrupt, harvesters may benefit from refusing to commit to paying for an, then often useless, enforcer.

Considering two harvesters forming a pair, we set their baseline payoff to be the one achieved when both defect (illegal logging), and denote it by λ. If one harvester switches to cooperation (legal logging), we assume this improves both harvesters' payoffs by b, measuring the benefits accrued from cooperation, through the improved (i.e., less degraded) ecosystem service. The payoff for a harvester who defects against a cooperating harvester thus is $\lambda+b$. The cooperating player, in contrast, has to pay the cost of cooperation, causing a loss K, which measures the income reduction from restrained logging, and thus resulting in a payoff $\lambda+b-K$. We denote the net cost of cooperation by $c=K-b$, so the payoff of the cooperating harvester is $\lambda-c$. If both harvesters cooperate, each of them benefits from the double improvement of the ecosystem service, and thus obtains a payoff $\lambda+2b-K=\lambda+b-c$. Hence, a cooperator pays a cost c for providing a benefit b for the co-player. A defector, by contrast, refuses to pay this cost, but still receives this benefit, if the co-player cooperates. This payoff scheme is regularly adopted in theoretical studies of the evolution of cooperation: It has the structure of the donation game, which is a special case of the Prisoner's Dilemma game (Sigmund, 2010).

In addition to harvesters that may cooperate or defect and that may or may not be willing to commit to the enforcer service, we also consider conditional cooperators, who are willing to commit and cooperate if and only if their co-players are also willing to commit. Harvesters can only commit jointly; a single player cannot commit, just as a single party cannot sign a bilateral contract. There are thus five types of harvesters: conditional cooperators (at a fraction x_1 in the harvester population), committing cooperators (x_2), committing defectors (x_3), non-committing cooperators (x_4), and non-committing defectors (x_5), with $x_1+\cdots+x_5=1$.

Enforcers are of two types: honest and corrupt, at fractions y_1 and y_2, respectively, in the enforcer population, with $y_1+y_2=1$. Honest enforcers refuse to receive a bribe offered by a defecting harvester, while corrupt enforcers accept the bribe and refrain from fining the defector who bribed them.

To employ an enforcer, each harvester must pay a fee s for the enforcer's service. If one of the harvesters refuses paying this cost, no enforcer will be employed. We assume that the penalty A imposed on a defector is large enough to offset a defector's benefit b gained from a cooperator's contribution: $A>b$. We also assume that the cost s of hiring the enforcer service is smaller than the contribution cost c: $c>s$. In addition, we assume that the benefit b exceeds the sum of the contribution cost c and the commitment cost s, so that a conditional cooperator's payoff is positive: $b>c+s$. A defecting harvester provides a bribe B to a corrupt enforcer, instead of paying the penalty A. We assume that this bribe B is smaller than the contribution cost $c: c>B$. In summary, we assume $A>b>c>s\geq B$ and $b>c+s$.

In our model, we assume a community association exists that performs the punishment based on the report of the rule enforcer who is observing harvesters' behavior. The observation may be accompanied with two types of cost, the physical effort (time and resources) and the risk of retaliation by the defector, both of which are assumed to be negligible in the model. Enforcers make an effort to detect defection for either implementing their duty or taking bribe from defector. This cost is covered by fee s that guarantees positive net margin for enforcers. Additionally we assume that reporting a defector is costless for an enforcer. In certain situations, reporting defectors may incur a significant cost for enforcers, especially when defectors are not given the opportunity to approve a sanctioning beforehand, which may subsequently compel them to retaliate against those enforcers by whom they are subject to punishment. In the model studied here, the situation is quite different: harvesters are given the freedom to choose between using and not using the enforcement service, so enforcers are always consensually hired by two harvesters on the condition that they will detect defection. In such a case, we believe, the chance is small that defecting harvesters will retaliate against enforcers.

We assume no selection biases in how harvesters pair up and how a pair of harvesters chooses an enforcer. In both cases, individuals are chosen at random from the populations of harvesters and enforcers, respectively.

2.2. Social learning

The replicator dynamics for harvesters are given by

$$\frac{dx_i}{dt}=x_i\left(f_i(\mathbf{x},\mathbf{y})-\bar{f}\right) \tag{1a}$$

for $i=1,\ldots,5$, where $\bar{f}=\sum_{i=1}^{5}f_i(\mathbf{x},\mathbf{y})x_i$ is the mean payoff of harvesters. Here, $\mathbf{x}=(x_1,\ldots,x_5)^T$ and $\mathbf{y}=(y_1,y_2)^T$ are column vectors, where the superscript T indicates matrix transposition. The average payoff of harvester type i is given by

$$f_i(\mathbf{x},\mathbf{y})=y_1\sum_{j=1}^{5}\mathbf{H}_{\mathrm{h},ij}x_j+y_2\sum_{j=1}^{5}\mathbf{H}_{\mathrm{c},ij}x_j, \tag{1b}$$

for $i=1,\ldots,5$. The first term on the right-hand side of Eq. (1b) is the product of the probability y_1 that an enforcer recruited by a pair of harvesters is honest and the mean payoff accrued by harvester type i playing against all five harvester types j according to their proportion x_j in the harvester population. The payoff of harvester type i playing against harvester type j under the supervision of an honest enforcer is $\mathbf{H}_{\mathrm{h},ij}$; the matrix $\mathbf{H}_{\mathrm{h}}$ is given in Table 1a. Analogously, the second term on the right-hand side of Eq. (1b) is the corresponding expression when the recruited enforcer is corrupt, using the probability y_2 and the payoff matrix $\mathbf{H}_{\mathrm{c}}$ given in Table 1b. The multiplicative determination of payoffs in Eq. (1b) reflects the assumed random assortment among harvesters and enforcers.

In a similar manner, the replicator dynamics for enforcers are given by

$$\frac{dy_i}{dt}=y_i\left(g_i(\mathbf{x},\mathbf{y})-\bar{g}\right), \tag{2a}$$

for $i=1,2$, where $\bar{g}=\sum_{i=1}^{2}g_i(\mathbf{x},\mathbf{y})y_i$ is the mean payoff of enforcers. The average payoffs of honest and corrupt enforcers are given by

$$g_1(\mathbf{x},\mathbf{y})=\rho\mathbf{x}^{\mathrm{T}}\mathbf{E}_{\mathrm{h}}\mathbf{x}\ \text{ and }\ g_2(\mathbf{x},\mathbf{y})=\rho\mathbf{x}^{\mathrm{T}}\mathbf{E}_{\mathrm{c}}\mathbf{x}, \tag{2b}$$

respectively. The two payoff matrixes $\mathbf{E}_{\mathrm{h}}$ and $\mathbf{E}_{\mathrm{c}}$, for honest and corrupt enforcers, respectively, are given in Table 1c and d. The parameter $\rho\geq 0$ measures the relative speed of change by social learning, between the population of enforcers and the population of harvesters: if $\rho>1$, enforcers learn more quickly than harvesters. If ρ is zero, only the harvesters learn, whilst the fractions of honest and corrupt enforcers remain fixed.

2.3. Dominated strategies

From Table 1a and b, we can see that the payoffs of committing cooperators and non-committing cooperators are always less than those of conditional cooperators and non-committing defectors, respectively. This implies that, invariably, committing and non-committing cooperators will eventually disappear from the harvester population. Hence, we eliminate these two strategies from further analysis and focus on the following three types of harvesters: conditional cooperators, committing defectors, and non-committing defectors.

After committing and non-committing cooperators have disappeared from the population of harvesters, the only cooperative harvesters that remain are conditional cooperators: these cooperate only when their co-players are willing to hire an enforcer, which implies paying the associated cost. Thus, defecting harvesters have no chance of exploiting cooperating harvesters unless the former commit to hiring an enforcer. Under these circumstances, committing defectors may be superior to non-committing defectors.

3. Outcomes of social learning

Once committing and non-committing cooperators have disappeared from the harvester population, the fractions of the three remaining types of harvesters satisfy $x_1+x_3+x_5=1$. The state of the harvester population can thus be represented as a point within the triangle $\{(x_1,x_3,x_5)|x_1+x_3+x_5=1\}$. Similarly, the fractions of the two types of enforcers satisfy $y_1+y_2=1$. The state of the enforcer population can thus be represented as a point along the unit interval. Using the Cartesian product of these two sets, we can therefore represent the joint dynamics of harvesters and enforcers within a triangular prism, as illustrated in Fig. 1a.

3.1. Fixed enforcer fractions

We first consider the dynamics of the three harvester types when the fractions of the two enforcer types are fixed ($\rho=0$). For this case, we find

$$\frac{d}{dt}\frac{x_3}{x_1}>0\ \text{ if }\ y_1<\tilde{y}_1, \tag{3a}$$

Table 1
Payoffs when information on corrupt enforcers is not available.

	Conditional cooperator	Committing cooperator	Committing defector	Non-committing cooperator	Non-committing defector
(a) Payoffs for harvesters accompanied by an honest enforcer as a function of the pair of harvester strategies (matrix $\mathbf{H}_h$)					
Conditional cooperator	$b-c-s$	$b-c-s$	$-c-s$	b	0
Committing cooperator	$b-c-s$	$b-c-s$	$-c-s$	$b-c$	$-c$
Committing defector	$b-s-A$	$b-s-A$	$-s-A$	b	0
Non-committing cooperator	$-c$	$b-c$	$-c$	$b-c$	$-c$
Non-committing defector	0	b	0	b	0
(b) Payoffs for harvesters accompanied by a corrupt enforcer as a function of the pair of harvester strategies (matrix $\mathbf{H}_c$)					
Conditional cooperator	$b-c-s$	$b-c-s$	$-c-s$	b	0
Committing cooperator	$b-c-s$	$b-c-s$	$-c-s$	$b-c$	$-c$
Committing defector	$b-s-B$	$b-s-B$	$-s-B$	b	0
Non-committing cooperator	$-c$	$b-c$	$-c$	$b-c$	$-c$
Non-committing defector	0	b	0	b	0
(c) Payoffs for an honest enforcer as a function of the pair of harvester strategies (matrix $\mathbf{E}_h$)					
Conditional cooperator	$2s$	$2s$	$2s$	0	0
Committing cooperator	$2s$	$2s$	$2s$	0	0
Committing defector	$2s$	$2s$	$2s$	0	0
Non-committing cooperator	0	0	0	0	0
Non-committing defector	0	0	0	0	0
(d) Payoffs for a corrupt enforcer as a function of the pair of harvester strategies (matrix $\mathbf{E}_c$)					
Conditional cooperator	$2s$	$2s$	$2s+B$	0	0
Committing cooperator	$2s$	$2s$	$2s+B$	0	0
Committing defector	$2s+B$	$2s+B$	$2s+2B$	0	0
Non-committing cooperator	0	0	0	0	0
Non-committing defector	0	0	0	0	0

$$\frac{\mathrm{d}}{\mathrm{d}t}\frac{x_3}{x_1} < 0 \text{ if } y_1 > \tilde{y}_1, \tag{3b}$$

where $\tilde{y}_1 = (c-B)/(A-B)$ is the critical fraction of honest enforcers (Appendix A). Hence, we can distinguish between the following two cases:

- Case 1. For $y_1 < \tilde{y}_1$, Eq. (3a) indicates that the abundance of conditional cooperators monotonically decreases relative to that of committing defectors (Fig. 1b). Any trajectory starting within the triangle $\{(x_1, x_3, x_5) | x_1 + x_3 + x_5 = 1\}$ thus approaches the triangle's edge on which $x_1 = 0$. Along this edge, dynamics are given by $\mathrm{d}x_3/\mathrm{d}t = x_3^2(1-x_3)(-s-Ay_1-B_r y_2) < 0$, which shows that the non-committing defectors eventually take over the entire harvester population.
- Case 2. For $y_1 > \tilde{y}_1$, Eq. (3b) indicates that the abundance of conditional cooperators monotonically increases relative to that of committing defectors (Fig. 1c). Any trajectory starting within the triangle thus approaches the triangle's edge on which $x_3 = 0$. Along this edge, dynamics are given by $\mathrm{d}x_5/\mathrm{d}t = -(b-c-s)x_5(1-x_5)^2 < 0$, which shows that the conditional cooperators eventually take over the entire harvester population.

3.2. Dynamic enforcer fractions

Now we consider the case in which the dynamics of the enforcers occurs at a rate that is equivalent to that of the harvesters ($\rho = 1$). Fig. 1a shows trajectories of the resultant dynamics. Over time, the fraction of honest and corrupt enforcers changes according to the replicator dynamics

$$\frac{\mathrm{d}y_1}{\mathrm{d}t} = -2Bx_3(x_1+x_3)y_1(1-y_1). \tag{4}$$

As the payoff of corrupt enforcers always exceeds that of honest enforcers, the fraction of corrupt enforcers always increases over time, $\mathrm{d}y_1/\mathrm{d}t > 0$. Surprisingly, however, the corrupt enforcers do not take over the entire enforcer population, but instead end up reaching an intermediate value that depends on the initial condition.

For our further analysis, we consider the one-dimensional set $\{(\mathbf{x}, \mathbf{y}) | x_1 = 1, x_3 = x_5 = 0, \tilde{y}_1 < y_1 < 1\}$, which we call the "cooperative line segment of equilibria" (CLSE). On this line segment, the harvester and enforcer populations are stationary, so the CLSE describes a continuum of equilibria of the joint dynamics. Moreover, all harvesters are conditional cooperators. Analogously, we call the set $\{(\mathbf{x}, \mathbf{y}) | x_5 = 1, x_1 = x_3 = 0, 0 < y_1 < \tilde{y}_1\}$ the "defective line segment of equilibria" (DLSE). Along the DLSE, all harvesters are non-committing defectors. Both of these sets attract trajectories from the interior of the prism.

When the dynamics approach either the CLSE or the DLSE, the rate of change in y_1 slows down to zero, as shown by Eq. (4). Near the CLSE, y_1 changes even more slowly than the harvester composition, so trajectories converge to the CLSE orthogonally, as shown in Fig. 1d and derived in Appendix A. Hence, although y_1 always decreases over time, it converges to a positive level, instead of vanishing to zero. Other values of ρ lead to similar results.

3.3. Domains of attraction

To illustrate the domains of attraction associated with the two line segments of equilibria, we trace trajectories starting from 100 randomly chosen points in the interior of the prism. In this way, Fig. 1a shows how social learning in the harvester and enforcer populations leads to one of just two possible outcomes: starting from the 100 randomly distributed initial conditions, 72 trajectories (shown in green) converge to the CLSE, whereas the remaining 28 trajectories (shown in orange) converge to the DLSE. The joint social dynamics of the two populations thus lead to the coexistence either of conditionally cooperating harvesters with relatively honest enforcers, or of defecting harvesters with relatively corrupt enforcers.

Fig. 1e shows the fraction of trajectories leading to the CLSE as a function of the critical fraction $\tilde{y}_1$ of honest enforcers. The former fraction always monotonically decreases with $\tilde{y}_1$. When enforcers do not learn at all ($\rho = 0$), the fraction equals $1-\tilde{y}_1$, while when

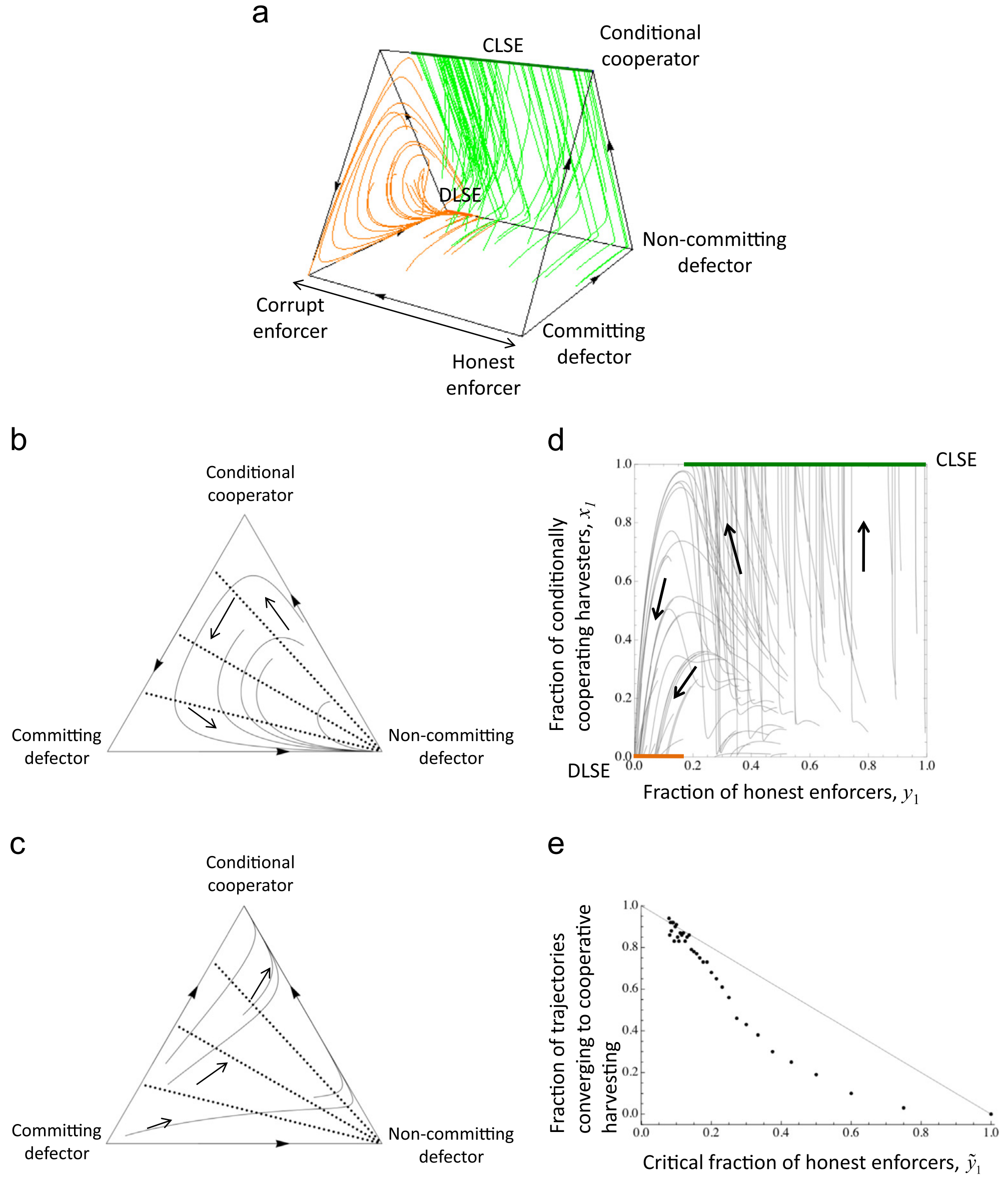


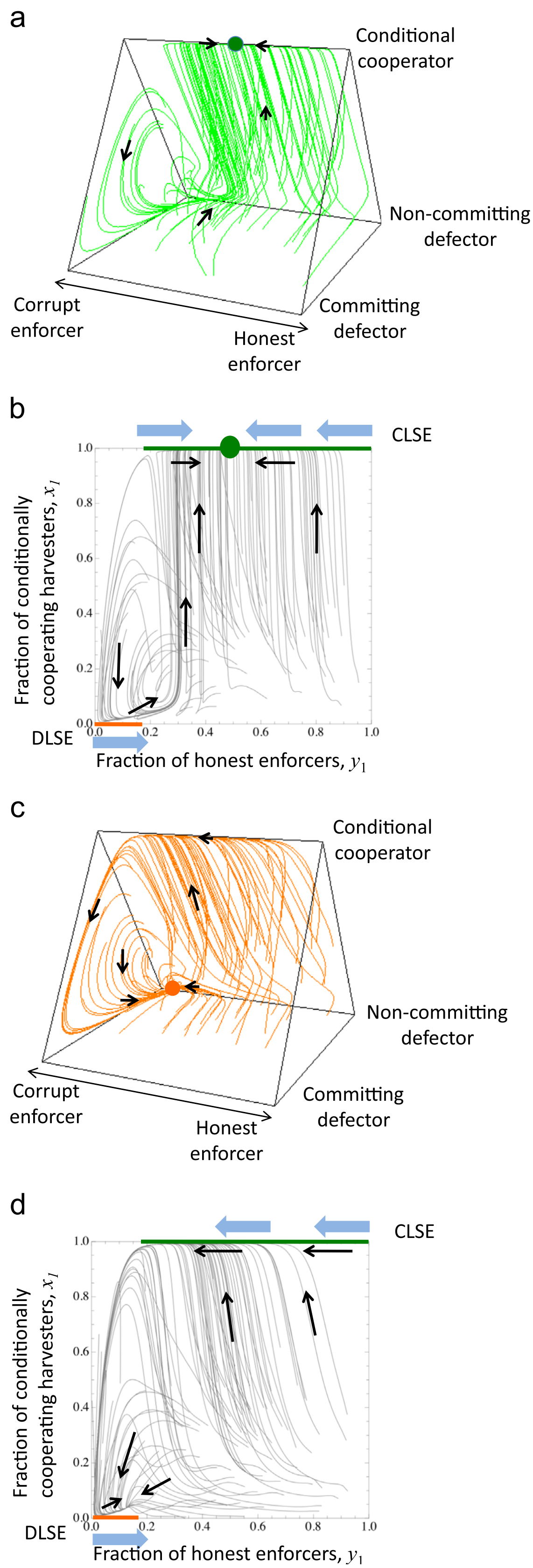
Fig. 1. Dynamics of harvester cooperation and enforcer corruption in the basic model. Harvesters can be of three types (conditional cooperators, committing defectors, and non-committing defectors, with fractions x_1, x_3, and x_5, respectively), while enforcers can be of two types (honest or corrupt, with fractions y_1, y_2, respectively). As $x_1+x_3+x_5=1$ and $y_1+y_2=1$, harvester fractions change within an equilateral triangle and enforcer fractions change within the unit interval, so their joint dynamics can be envisaged in the Cartesian product of those two sets, which is a prism. The corners of this prism, as well as its two edges with $x_1=1$ and $x_5=1$, consist of rest points of the harvester–enforcer replicator dynamics. (a) Social learning of harvesters and enforcers can lead to two distinct outcomes, as illustrated by the trajectories originating from 100 randomly chosen initial conditions: some trajectories (thin orange lines) end up with all harvesters being non-committing defectors and most enforcers being corrupt, while other trajectories (thin green lines) end up with all harvesters being conditional cooperators and many enforcers being honest. Thus, trajectories converge to either the defective line segment of equilibria (DLSE; thick orange line) or to the cooperative line segment of equilibria (CLSE; thick green line). (b) Dynamics of the three harvester types when all enforcers are corrupt ($y_1=0$; triangular prism face at the back of (a)). Dashed lines are contours of x_3/x_1. The boundary of the triangle consists of a heteroclinic cycle: conditional cooperators can be invaded by committing defectors, who can be invaded by non-committing defectors, who can be invaded by conditional cooperators. The interior of the triangle is filled with homoclinic orbits starting from and returning to the state of the harvester population comprising only non-committing defectors. Thus, arbitrarily small random shocks can lead to bursts of conditional cooperation, but these are short-lived; in the long run, non-committing defectors prevail. (c) Dynamics of the three harvester types when all enforcers are honest ($y_1=1$; triangular prism face at the front of (a)). Dashed lines again are contours of x_3/x_1. All trajectories converge to the equilibrium at which conditional cooperators prevail. (d) Projection of the trajectories in (a) onto the plane with $x_3=0$ (rectangular prism face at the back of (a)). In this projection, the fractions x_3 and x_5 are not distinguished; only their sum can be inferred as $1-x_1$. (e) Fraction of trajectories converging to cooperative harvesting as a function of the critical fraction of honest enforcers. Parameters: $b=1$, $c=0.5$, $A=2$, and $s=B=0.2$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

enforcers learn slowly ($\rho \approx 0$), the fraction remains close to $1-\tilde{y}_1$. When enforcers learn as quickly as harvesters ($\rho=1$), the fraction of trajectories converging to the CLSE is considerably smaller than $1-\tilde{y}_1$ (once $\tilde{y}_1$ exceeds about 0.2), because y_1 decreases with time, as shown by Eq. (4), so many trajectories can reach the DSLE. Independently of ρ, the considered fraction may become as low 0 ($\rho \gg 1$), but can never exceed $1-\tilde{y}_1$.

Remarkably, a fraction of honest enforcers can always persist, even though corrupt enforcers invariably obtain a higher payoff than honest enforcers in the interior of the prism. This is because the harvester dynamics always take trajectories to one of the prism edges where honest and corrupt enforcers are doing equally well. Along the CLSE, the residual fraction of honest enforcers is high enough to enable full cooperation among the harvesters.

4. Effects of strategy exploration

We now consider what happens when players have the possibility of randomly exploring alternative strategies, unaffected by how this affects their payoffs. Such exploration is thus qualitatively different from the social learning by imitating successful strategies, as described by the standard replicator dynamics in Eqs. (1a,b) and (2a,b). In models of population genetics, exploration occurs through random genetic mutations among a given set of alleles, whereas in models of social learning, such as in those considered here, exploration occurs when players try out alternative behaviors by randomly switching among a given set of strategies.



We assume that the exploration rate of the three harvester types is given by a small constant μ, and that harvesters switch with equal probability to one of the two other strategies. Thus, e.g., a conditional cooperator may change into a committing defector or into a non-committing defector, with both changes occurring at the rate $\mu/2$. We stress that this assumption of equal exploration rates among harvesters is not important, and does not affect the further analysis. By contrast, it will prove important to consider asymmetric exploration rates between the two enforcer types, which we denote by ν_i for $i=1,2$. To account for exploration, the replicator dynamics of harvesters, originally given by Eq. (1a), are now given by

$$\frac{dx_i}{dt} = x_i\left(f_i - \bar{f}\right) - \mu x_i + \frac{\mu}{2}(1-x_i), \tag{5a}$$

for $i=1,3,5$, where f_i is the payoff of harvester type i, given by Eq. (1b) with $x_2=x_4=0$. Likewise, the replicator dynamics of enforcers, originally given by Eq. (2a), are now given by

$$\frac{dy_1}{dt} = y_1(g_1-\bar{g}) - \nu_1 y_1 + \nu_2 y_2, \tag{5b}$$

$$\frac{dy_2}{dt} = y_2(g_2-\bar{g}) + \nu_1 y_1 - \nu_2 y_2, \tag{5c}$$

where g_i is the fitness of enforcer type i, given by Eq. (2b) with $x_2=x_4=0$.

4.1. Symmetric strategy exploration

We first consider the case of symmetric strategy exploration, $\mu=\nu_1=\nu_2$. Fig. 2a and b illustrate the resultant dynamics in the prism (Fig. 2a) and as a projection onto a vertical plane through the top prism edge (Fig. 2b). Crucially, the bistability disappears, giving way to global stability: starting from any initial condition, the dynamics converge to the same equilibrium.

Even trajectories starting from high frequencies of corruption converge to the unique equilibrium, at which almost all harvesters are conditional cooperators. This result may be understood by first considering harvester populations dominated either by conditional cooperators ($x_1=1,\ x_3=x_5=0$) or by non-committing defectors ($x_1=x_3=0,\ x_5=1$). The corresponding prism edges are line segments of equilibria, as honest and corrupt enforcers receive the same payoffs. The first terms on the right-hand sides of

Fig. 2. Effects of strategy exploration. (a) Trajectories of the harvester–enforcer dynamics for symmetric exploration, originating from 100 randomly chosen initial conditions. (b) Projection of the trajectories in (a) onto the face with $x_3=0$. Along the lines $x_1=1$ and $x_3=1$, which in the absence of strategy exploration contain line segments of equilibria of the harvester–enforcer dynamics, rare explorations between honest and corrupt enforcer strategies have a strong impact on the outcome. Note that trajectories starting with high frequencies of corruption also converge to the globally stable equilibrium, at which the harvester population is dominated by conditional cooperators. Many trajectories first pass through states with a high fraction of non-committing defectors, but due to the strategy exploration of enforcers, they eventually converge to a state of cooperative harvesting. (c) Trajectories of the harvester–enforcer dynamics for asymmetric exploration, originating from 100 randomly chosen initial conditions. (d) Projection of the trajectories in (c) onto the face with $x_3=0$. The fraction of honest enforcers at the exploration-induced equilibrium y_1^* lies below the critical fraction $\tilde{y}_1$ of honest enforcers, implying that most harvesters eventually become non-committing defectors and most enforcers eventually become corrupt. Parameters as in Fig. 1, except for $\mu=\nu_2=0.002$ and $\nu_1=0.002$ in (a) and (b) or $\nu_1=0.012$ in (c) and (d).

Eqs. (5b) and (5c) accordingly vanish, resulting in a stable equilibrium with a fraction $y_1^* = \nu_2/(\nu_1+\nu_2)$ of honest enforcers. Since this equilibrium is determined purely by strategy exploration, and not at all affected by social learning, we call it an "exploration-induced equilibrium". For the symmetric case shown in Fig. 2a and b, we naturally obtain $y_1^* = 0.5$. For $\mu > 0$, however, the harvester population cannot remain confined to the aforementioned edges with $x_1 = 1$ or $x_5 = 1$. Instead, rare strategy exploration in the harvester population will drive it slightly away from those edges. As a result, corrupt enforcers will receive a slightly higher payoff than honest enforcers, decreasing the equilibrium fraction of honest enforcers slightly below y_1^*. In accordance with this prediction, the numerically calculated equilibrium for the case shown in Fig. 2a and b (where $\mu = 0.002$) is located at $y_1 = 0.45$ (instead of at $y_1^* = 0.5$).

When harvesters are confronted with a high frequency of corruption, their social learning first leads to a high fraction of non-committing defectors, after which strategy exploration by enforcers enables an escape to the globally stable equilibrium featuring a very large fraction of conditionally cooperating harvesters. The subtlety of this finding lies in the fact that it is only after social learning has made non-committing defectors dominant that very small exploration rates suffice to overcome, for $y_1 > y_1^*$, the drive towards increased corruption.

4.2. Asymmetric strategy exploration

In general, if the exploration-induced equilibrium y_1^* exceeds the corruption threshold $\tilde{y}_1$, the dynamics will converge to an equilibrium close to the CLSE, characterized by a dominance of conditional cooperators.

In contrast, if the exploration-induced equilibrium is smaller than the corruption threshold, the dynamics will converge to an equilibrium close to the DLSE, characterized by the dominance of non-committing defectors. An example is shown in Fig. 2c and d, for asymmetric exploration rates in the harvester population, $\nu_1 = 6\nu_2$. The exploration-induced equilibrium is then located at $y_1^* = 1/7 \approx 0.14$, i.e., outside the CLSE. In Fig. 2c and d, the globally stable equilibrium is located at $y_1 = 0.13$ (as expected, this is slightly below the exploration-induced equilibrium) and $(x_1, x_3, x_5) = (0.06, 0.08, 0.86)$ (as expected, the harvester population is dominated by non-committing defectors).

Small exploration rates among the three harvester types do not alter outcomes. In contrast, as we have seen, the exploration rates between the two enforcer types have a profound effect on outcomes, even if they are very small. It is the ratio of the two enforcer exploration rates that determines whether the harvester–enforcer system ends up with cooperation (Fig. 2a and b) or defection (Fig. 2c and d). The higher the enforcers' tendency to switch from corrupt to honest, the likelier is a cooperative outcome. This effect can be achieved by means not mechanistically described by our model: important options for achieving such an effect would be education of the enforcers, appeals to the long-term interests of enforcers, or incentives provided to enforcers by a higher authority.

Since the payoff of corrupt enforcers is never smaller than that of honest enforcers, it is tempting to think that corrupt enforcers will always dominate, and that a small exploration rate cannot have much effect on the outcomes. However, through social learning among the harvesters, harvesters paying bribes disappear quickly, so the harvester population becomes dominated either by conditional cooperators (who do not pay bribes) or by non-committing defectors (who do not commit to the service of an enforcer). Under these circumstances, the payoff difference between the two enforcer types vanishes. Hence, even if the exploration rates of enforcers are very low, they can be decisive for the outcome.

5. Effects of information on corrupt enforcers

In the basic model, once dynamics converge to the DLSE, the harvester–enforcer system is trapped. A possible mechanism to escape this situation is the sharing of information concerning the honesty of enforcers, which we thus examine next.

When the enforcer's type is known, opportunistic versions of conditional cooperators and committing defectors will act in different ways. Specifically, if the enforcer is known to be corrupt, an opportunistic conditional cooperator will choose defection and refuse the enforcer's service, while if the enforcer is honest, an opportunistic committing defector will refuse the enforcer's service. Hence opportunistic conditional cooperators behave like non-committing defectors if the enforcer is known to be corrupt, while opportunistic committing defectors behave like non-committing defectors if the enforcer is known to be honest.

We assume that honest enforcers are always known to be honest to all harvesters, whereas corrupt enforcers are identified as being corrupt with probability $p \le 1$. This assumption is based on the understanding that harvesters might hesitate more to share negative information about an enforcer's corruption than positive information about an enforcer's honesty. Such a difference could ultimately be caused by differential personal risks resulting from sharing positive or negative information. An alternative mechanism is that harvesters might assume an enforcer to be honest until proved otherwise. We assume that information on corrupt enforcers is obtained by harvesters independently, and without extra cost.

We thus have to consider three possible constellations in games between two committing harvesters and a corrupt enforcer: the enforcer is evaluated as honest by both harvesters with probability $(1-p)^2$, evaluated as honest by one harvester but as corrupt by the other with probability $2p(1-p)$, and evaluated as corrupt by both harvesters with probability p^2.

If all enforcers are honest, only pairs of opportunistic conditional cooperators use the enforcer service, because all opportunistic committing defectors will not dare to commit. If all enforcers are corrupt, opportunistic conditional cooperators mistakenly assume that an enforcer is honest with probability $(1-p)$, while opportunistic committing defectors recognize the enforcer as being corrupt with probability p. In this way, we obtain the payoffs for the harvesters shown in Table 2a. (The dynamics resulting among the three harvester types when all enforcers are either honest or corrupt are discussed in Appendix B and shown in Fig. 4.)

The payoffs for the enforcers depend on the fraction of committing players. Honest enforcers are paid $2s$ by pairs of opportunistic conditional cooperators, while corrupt enforcers benefit from various combinations of committing harvesters. In this way, we obtain the payoffs for the enforcers shown in Table 2b (for the derivation, see Appendix C).

Fig. 3a illustrates the resultant dynamics in the prism. On the edge along which opportunistic conditional cooperators dominate $(x_1 = 1)$, honest enforcers receive a higher payoff than corrupt enforcers, because $g_1 - g_2 = 2s\left(1-(1-p)^2\right) > 0$. On this edge, therefore, the fraction of honest enforcers increases towards $y_1 = 1$. In contrast, on the edge along which opportunistic committing defectors dominate $(x_3 = 1)$, honest enforcers receive a smaller payoff than corrupt enforcers, because $g_1 - g_2 = -2sp^2(s+B) < 0$. On this edge, therefore, the fraction of corrupt enforcers increase towards $y_2 = 1$.

By comparing Fig. 3a with Fig. 1a, we thus see that information on corrupt enforcers favors the evolution of cooperation. Again starting from 100 randomly chosen initial conditions, 95 trajectories end up with cooperative harvesting, compared with 72 trajectories when there is no such information. This quantitative comparison obviously depends on the parameters, but the general trend is robust: more information makes cooperation more likely.

Table 2
Payoffs when information on corrupt enforcers is available.

	Opportunistic conditional cooperator	Opportunistic committing defector	Non-committing defector
(a) Payoffs for harvesters			
Opportunistic conditional cooperator	$\left(y_1+y_2(1-p)^2\right)(b-c-s)$	$(1-p)py_2(-c-s)$	0
Opportunistic committing defector	$p(1-p)y_2(b-s-B)$	$p^2y_2(-s-B)$	0
Non-committing defector	0	0	0
(b) Payoffs for enforcers			
Honest enforcer	$2sx_1^2$		
Corrupt enforcer	$2s[(1-p)x_1+px_3]^2+2B[(1-p)x_1+px_3]px_3$		

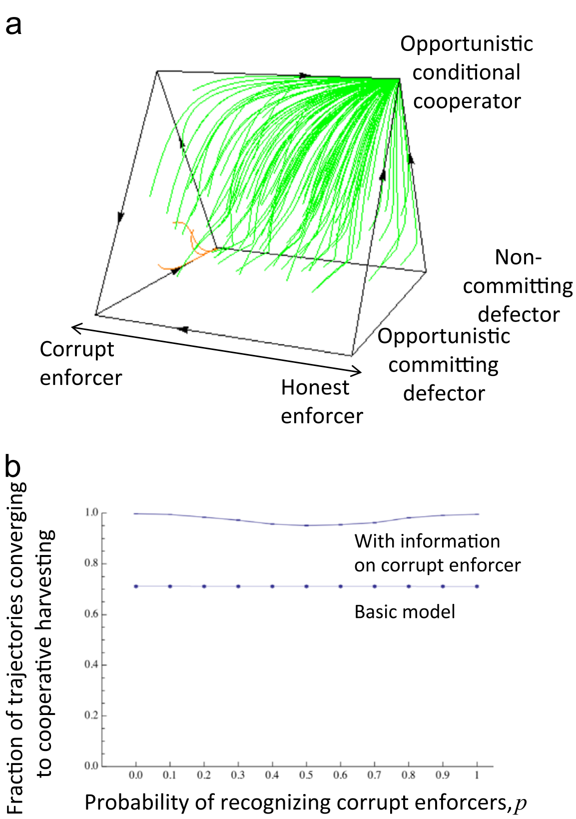


Fig. 3. Effects of information on corrupt enforcers. (a) Trajectories of the harvester–enforcer dynamics originating from 100 randomly chosen initial conditions. Most trajectories converge to opportunistic conditionally cooperative harvesters and honest enforcers, while some trajectories converge to non-committing defecting harvesters and corrupt enforcers. (b) Fraction of trajectories converging to cooperative harvesting as a function of the probability p of recognizing corrupt enforcers. For all values of p, many more trajectories end up with cooperative harvesting than in the basic model without information on corrupt enforcers. Parameters as in Fig. 1, except for $p=0.34$ in (a).

Fig. 3b illustrates the fraction of trajectories that end up with cooperative harvesting as a function of the probability p of recognizing corrupt enforcers. For all values of p, information on corrupt enforcers greatly increases the fraction of cooperative outcomes, almost to its maximal level. The figure also shows that small and large probabilities p favor maximally cooperative harvesting, while intermediate probabilities work slightly less well (this is because, for intermediate p, the harm $-p(1-p)y_2(c+s)$ done by opportunistic committing defectors to opportunistic conditional cooperators, as shown in Table 2a, is not negligible, resulting in a reduced level of cooperation). We emphasize that a vanishing value of p is not equivalent to the basic model without information on corrupt enforcers, as even for $p=0$ honest enforcers remain known with certainty in the extended model.

6. Discussion

In this paper, we have analyzed evolutionary game dynamics describing the interplay of harvesters tempted by illegal logging and enforcers tempted by corruption. Through mutual agreement, a pair of harvesters may hire an enforcer to check whether each of them is logging legally. This is a minimalistic form of a social contract. An honest enforcer promotes cooperation by penalizing defecting harvesters. Under the oversight of an honest enforcer, harvesters can either cooperate and pay the cost of legal logging, or defect and pay the penalty imposed by the enforcer. When the enforcer is corrupt, harvesters have an additional option: they can defect and pay a bribe to the enforcer in order to avoid having to pay a fine.

Analyzing the replicator dynamics of this harvester–enforcer game, we can draw the following conclusions. First, the dynamics resulting from social learning (by imitating players receiving higher payoffs) is often bistable (Fig. 1a and d), featuring two line segments of equilibria. As one outcome, the harvester–enforcer dynamics may converge to a defective line segment of equilibria (DLSE). At each point of the DLSE, all harvesters defect and pay bribes to the enforcers, most of whom are corrupt. Harvesters, in such a situation, will stop to hire an enforcer, and the forest's ecosystem services may soon be lost through unrestrained illegal logging. Bistability implies that there is also another outcome, which arises when the harvester–enforcer dynamics converge to a cooperative line segment of equilibria (CLSE). At each point of the CLSE, all harvesters are cooperative, and many enforcers are honest. Although some enforcers are corrupt even along the CLSE, there are sufficiently many honest enforcers to prevent the spread of illegal logging.

Second, a fraction of enforcers always remain honest in spite of the fact that the payoff for corrupt enforcers is invariably higher than that for honest enforcers if all harvester types are present. This counterintuitive result arises because the payoff difference caused by bribery disappears when all harvesters are cooperative and do not pay bribes, or when all harvesters are defective and do not commit to the enforcer service. The fraction of honest enforcers thus remaining may suffice to foster perfect cooperation among the harvesters.

Third, a small rate of strategy exploration can drastically change the harvester–enforcer dynamics. Both the bistability of the dynamics and the line segments of equilibria disappear. Depending on asymmetries in the exploration rates of enforcers, the dynamics converge either to a globally stable cooperative equilibrium (Fig. 2a and b) or to a globally stable defective equilibrium (Fig. 2c and d). When corruption is rife, social learning among harvesters leaves enforcers mostly deprived of fees and bribes, and it is in such near-neutral situations that said asymmetries can unfold their unexpectedly consequential impact.

Fourth, information about the honesty of enforcers has a large impact on whether or not cooperative harvesting can be sustained.

If such information is available, the harvester–enforcer dynamics converge to a regime of cooperative harvesting for a much broader range of initial conditions (Fig. 3).

The harvester–enforcer game studied here is an example of the evolution of cooperation by punishment, which has been a prominent research focus of evolutionary game theory, especially throughout the last decade (e.g., Sigmund et al., 2001; Gardner and West, 2004; Brandt et al., 2006; Nakamaru and Iwasa, 2006; Hauert et al., 2007; Sigmund et al., 2010). Most studies explore situations in which players can inflict punishment on each other. Such so-called 'peer punishment' can be effective under certain conditions (Fehr and Gächter, 2000). However, it can easily be subverted by asocial punishment, not directed against the defectors, but rather against the cooperators (Fehr and Rockenbach, 2003; Denant-Boemont et al., 2007; Herrmann et al., 2008; Nikiforakis, 2008; Nikiforakis and Engelmann, 2011). While the self-justice involved in peer punishment may be important for the ancestral establishment of cooperation, it is not normally used in developed societies to promote cooperation (Guala, 2012). In such societies, the act of punishment is often delegated to an institution, such as a janitor, a sheriff, or a police force (e.g., Yamagishi, 1986; Ostrom, 2005). This implies a kind of social contract: players abstain from self-justice and instead commit to an authority. To secure the investments required for establishing and maintaining such an authority, players may voluntarily pool their resources (resulting in so-called 'pool punishment'; e.g., Sigmund et al., 2010), or the sanctioning institution may levy an inescapable tax from all players (resulting in so-called 'institutional punishment'; e.g., Sasaki et al., 2012). Theoretical models and lab experiments show that, whereas institutionalized forms of sanctioning are generally less efficient than self-justice, they tend to be more stable (Kamei et al., 2011; Markussen et al., 2011; Puttermann et al., 2011; Sigmund et al., 2011; Traulsen et al., 2012). The voluntary commitment of harvesters to an enforcer service we have considered here is a minimalistic form of a sanctioning institution organized according to the principles of pool punishment.

Just as self-justice is threatened by the escalation of conflicts between players, so institutionalized sanctioning is threatened by corruption. If punishment is not directed consistently and exclusively against defectors, it subverts cooperation. Corruption is a pervasive feature of many societies, and can be seen as one of the major obstacles to cooperation. To the best of our knowledge, this is the first study in terms of evolutionary game theory that addresses the threat of corruption both among the users and the providers of sanctions. It is clear that we have studied here merely a first simple model. In extensions of this work, it will be desirable to remove some of its most obvious limitations. In particular, it will be interesting to consider finite populations (the replicator equations used here describe the limiting case of infinitely large populations), larger teams of harvesters (the harvester pairs examined here are the smallest social unit in which cooperation can conceivably be established and enforced), and the effect of spatial distribution and localized interaction (the well-mixed populations studied here are a worst-case scenario, as they enable defectors to suffer less from their deeds). As another extension, and a promising way of promoting the honesty of enforcers, we would like to incorporate a tax to be paid to the enforcers in proportion to the payoffs received by the harvesters, an idea inspired by Yamagishi (1986).

Our study suggests several policy-related implications for the management of forest ecosystems. The first stems from the inherent bistability of the harvester–enforcer dynamics. While many initial conditions of the harvester–enforcer dynamics will smoothly lead to the dominance of cooperative harvesters, others lead to the dominance of defectors. This means that, once defectors prevail, it will usually be very difficult to change this situation, unless a strong effort is made. This may be one of the reasons why illegal logging is prevalent in some countries, but not in others. People living in a highly cooperative society tend to find it difficult to imagine the situation in a country where defection and corruption are very prevalent, and vice versa. This is because the described bistability fundamentally affects both economic

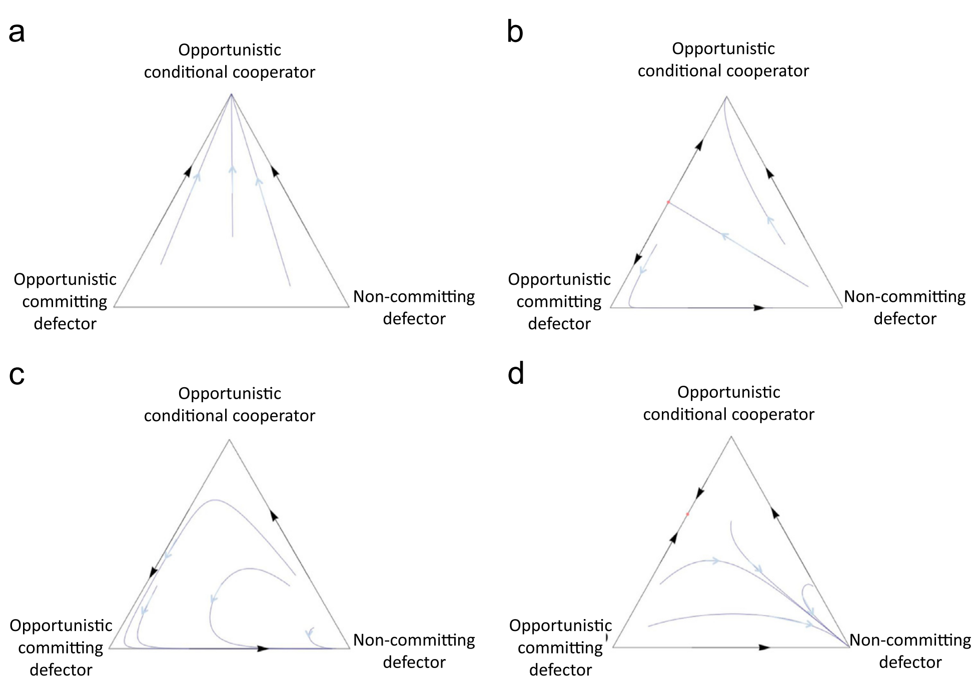


Fig. 4. (To be located in Appendix B). Effects on harvester dynamics of information on corrupt enforcers. (a) Trajectories of the harvester dynamics when all enforcers are honest. Regardless of the probability p of recognizing corrupt enforcers, and for any initial condition, opportunistic conditional cooperators prevail. (b) Trajectories when all enforcers are corrupt and p is small ($p = 0.2$). The triangle is divided into two sectors, implying bistability. For initial conditions in the upper sector, conditional cooperators prevail. Initial conditions in the lower sector converge to a heteroclinic cycle, along which defectors prevail. The size of the upper sector decreases as p increases. (c) Trajectories when all enforcers are corrupt and p is intermediate ($p = 0.34$). The triangle edges form a heteroclinic cycle, along which defectors prevail. (d) Trajectories when all enforcers are corrupt and p is large ($p = 0.8$). The triangle is divided into two sectors, implying bistability. For initial conditions in the lower sector, non-committing defectors prevail. Initial conditions in the upper sector converge to a heteroclinic cycle, along which defectors prevail. The size of the upper sector decreases as p increases.

payoffs and social expectations about the rule adherence of other players. To promote a better understanding of why investing into the establishment of cooperative harvesting regimes will ultimately be worthwhile, we need to strengthen activities fostering insights into successes achieved, and ‘best practices’ adopted, by different communities and countries.

Second, the education of enforcers is likely to have a strong effect on the likelihood that cooperative harvesting can get established. Since it is the harvesters who potentially engage in illegal logging, cutting an excess of trees, it is tempting to focus attention on their behavior. According to our analysis, however, investing into changing the conduct of enforcers could be far more important and effective. This conclusion has a mathematical basis: in our model, social learning among harvesters causes enforcers to be mostly deprived of fees and bribes, equalizing the economic incentives for honest and corrupt enforcers and thus preparing the ground for even a weak predilection by enforcers to switch from corrupt to honest behavior, rather than vice versa, to be very effective in determining the final outcome. Such a predilection can be fostered by education, incentives, or other externally imposed factors. Even a small bias among enforcers to choose honesty over corruption will thus have a profound influence. Thus, it might indeed be cost-efficient to focus educational efforts and incentives provided by governments on the enforcers.

Third, the availability of information on the honesty and reliability of each enforcer has a huge impact, greatly enhancing the likelihood of cooperative harvesting. Interestingly, this conclusion holds even if the chance of identifying a corrupt enforcer is less than perfect. This suggests that any measures governments could take to make the sharing of information about corrupt enforcers anonymous, risk-free, and widely accessible would make an important contribution to promoting cooperative harvesting.

We close by emphasizing the importance of further studies on corruption. Corruption is one of the most serious scourges in economic development and ecosystem management, possibly even more devastating than ignorance. The model studied here may be too simple to be immediately applicable to particular cases, but it captures essential aspects of the perennial problems associated with corruption. We hope that this study will stimulate future theoretical work on the mechanisms underlying the spread and curbing of corruption.

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Appendix A. Analysis of the basic model

Here we consider the dynamics of social learning among the three non-dominated harvester strategies when the fractions of enforcer types are fixed.

The payoffs of the three non-dominated harvester strategies – conditional cooperators, committing defectors, and non-committing defectors – (Table 1a and b) are, respectively,

$$f_1=(b-c-s)x_1+(-c-s)x_3,$$
$$f_3=(b-s-Ay_1-B_ry_2)x_1+(-s-Ay_1-By_2)x_3,$$
$$f_5=0. \quad \text{(A.1)}$$

By setting $\alpha=b-c-s$, $\beta=-c-s$, $\gamma=b-s-Ay_1-By_2$, and $\delta=-s-Ay_1-By_2$, we obtain $f_1=\alpha x_1+\beta x_3$, and $f_3=\gamma x_1+\delta x_3$. The mean fitness is $\bar{f}=f_1x_1+f_3x_3$, since $f_5=0$.

A.1. Global dynamics of harvesters for fixed enforcer fractions

We consider the dynamics of the two fractions x_1 and x_3, noting that $x_5=1-x_1-x_3$,

$$\frac{dx_1}{dt}=x_1\left(f_1-\bar{f}\right)=x_1\left(f_1(1-x_1)-f_3x_3\right), \quad \text{(A.2a)}$$

$$\frac{dx_3}{dt}=x_3\left(f_3-\bar{f}\right)=x_3\left(-f_1x_1+f_3(1-x_3)\right). \quad \text{(A.2b)}$$

From this, we obtain the dynamics of the ratio x_3/x_1 as

$$\frac{d}{dt}\frac{x_3}{x_1}=x_3\left(1+\frac{x_3}{x_1}\right)(c-Ay_1-By_2),$$

which implies that

If $c>Ay_1+By_2$, the ratio x_3/x_1 increases over time, whereas (A.3a)

If $c<Ay_1+By_2$, the ratio x_3/x_1 decreases over time. (A.3b)

We denote by $\tilde{y}_1=(c-B)/(A-B)$ the critical fraction of honest enforcers. If $y_1<\tilde{y}_1$, the ratio x_3/x_1 increases over time and diverges to infinity, implying that all trajectories starting from the inside of the triangle $\{(x_1,x_3,x_5)|x_1+x_3+x_5=1\}$ approach the line $x_1=0$. In contrast, if $y_1>\tilde{y}_1$, the ratio x_3/x_1 decreases over time and converges to zero, implying that all trajectories starting from the inside of the triangle approach the line $x_3=0$.

Note that the argument above holds for all points within the triangle, so the dynamics of the ratio x_3/x_1 provides information on the global dynamics among all three harvester strategies.

A.2. Dynamics of harvesters along edges for fixed enforcer fractions

Next, we examine the dynamics along the three edges of the triangle, where one of the three non-dominated harvester strategies is absent.

(1) On the line $(x_1=0,\ x_5=1-x_3)$, we have the following dynamics for x_3,

$$\frac{dx_3}{dt}=(-s-Ay_1-By_2)x_3{}^2(1-x_3)<0. \quad \text{(A.4a)}$$

Hence an orbit leads from $(x_1,\ x_3,\ x_5)=(0,\ 1,\ 0)$ to $(0,\ 0,\ 1)$.

(2) On the line $(x_3=0,\ x_1=1-x_5)$, we have the following dynamics for x_5,

$$\frac{dx_5}{dt}=-(b-c-s)x_5(1-x_5)^2<0. \quad \text{(A.4b)}$$

Hence an orbit leads from $(x_1,\ x_3,\ x_5)=(0,\ 0,\ 1)$ to $(1,\ 0,\ 0)$. Combining Eqs. (A.3a) and (A.3b) with Eqs. (A.4a) and (A.4b), we obtain the conclusion described in the main text: if $y_1>\tilde{y}_1$, all trajectories within the triangle converge to $(1,\ 0,\ 0)$, whilst if $y_1<\tilde{y}_1$, all trajectories converge to $(0,\ 0,1)$.

(3) On the line ($x_5=0,\ x_3=1-x_1$), we have the following dynamics for x_1,

$$\frac{dx_1}{dt}=x_1(1-x_1)((\beta-\delta)+(\alpha-\gamma-\beta+\delta)x_1)$$
$$=x_1(1-x_1)(-c+Ay_1+By_2). \tag{A.4c}$$

This expression is positive for $y_1>\tilde{y}_1$ and negative for $y_1<\tilde{y}_1$. Hence, an orbit leads from (0, 1, 0) to (1, 0, 0) for $y_1>\tilde{y}_1$, and in the opposite direction for $y_1<\tilde{y}_1$.

A.3 Dynamics of harvesters around vertices for fixed enforcer fractions

We now examine the dynamics around the three vertices of the triangle, where one of the three non-dominated harvester strategies is much more common than the other two.

(1) First, we analyze the dynamics in the vicinity of the vertex ($x_1=1,\ x_3=x_5=0$) by considering the two directions in which this vertex can be left, by increasing x_3 or by increasing x_5. The former happens when the following rate is positive,

$$\frac{dx_3}{dt}=x_3\left(f_3-\bar{f}\right)$$
$$=x_3(-x_1(\alpha x_1+\beta x_3)+(1-x_3)(\gamma x_1+\delta x_3))$$
$$=x_3((\gamma-\alpha)+\text{h.o.t.})$$
$$=x_3((c-Ay_1-By_2)+\text{h.o.t.}), \tag{A.5a}$$

where the abbreviation "h.o.t." stands for higher-order terms in x_3. Near the considered vertex, this rate is positive for $c>Ay_1+By_2$, and negative for $c<Ay_1+By_2$. In a similar manner, we examine

$$\frac{dx_5}{dt}=x_5\left(f_5-\bar{f}\right)$$
$$=x_5(-\alpha+\text{h.o.t.})$$
$$=x_5(-(b-c-s)+\text{h.o.t.}), \tag{A.5b}$$

where the abbreviation "h.o.t." stands for higher-order terms in x_5. This rate is always negative near the considered vertex.
Hence, the vertex ($x_1=1,\ x_3=x_5=0$) is a stable node if $y_2<(A-c)/(A-B)$, and a saddle (and thus unstable) if $y_2>(A-c)/(A-B)$. When the vertex is unstable, it is the fraction x_3 of committing defectors that increases upon departure from the vertex.

(2) Next, we analyze the dynamics in the vicinity of the vertex ($x_3=1,\ x_1=x_5=0$) by examining

$$\frac{dx_1}{dt}=x_1\left(f_1-\bar{f}\right)$$
$$=x_1((\beta-\delta)+\text{h.o.t.})$$
$$=x_1((-c+Ay_1+By_2)+\text{h.o.t.}). \tag{A.6a}$$

Near the considered vertex, this rate is negative when $c>Ay_1+By_2$, and positive when $c<Ay_1+By_2$. In a similar manner, we examine

$$\frac{dx_5}{dt}=x_5\left(f_5-\bar{f}\right)$$
$$=x_5(-\delta+\text{h.o.t.})$$
$$=x_5(s+Ay_1+By_2+\text{h.o.t.}), \tag{A.6b}$$

which is always positive near the considered vertex.
Hence, the vertex ($x_3=1,\ x_1=x_5=0$) is always unstable. It is an unstable node if $y_2<(A-c)/(A-B)$, and a saddle if $y_2>(A-c)/(A-B)$.

(3) Finally, we analyze the dynamics in the vicinity of the vertex ($x_5=1,\ x_1=x_3=0$), which can be inferred from the global dynamics investigated above: for $y_1<\tilde{y}_1$, the ratio x_3/x_1 increases over time. From this, we can conclude that all trajectories starting from the triangle's interior first approach to the edge $x_1=0$ and then converge to the considered vertex (Fig. 1b). Yet, this vertex itself is unstable, because x_1 grows along the edge $x_3=0$. In contrast, for $y_1>\tilde{y}_1$, the ratio x_3/x_1 decreases over time, so the fraction x_1 of conditional cooperators increases along all trajectories starting from the triangle's interior (Fig. 1c).

A.4 Summary of the dynamics of harvesters for fixed enforcer fractions

Throughout the analyses in Sections A.1–A.3 above, the deduced switches of stability all occur at the same critical fraction of honest enforcers, $\tilde{y}_1=(c-B)/(A-B)$. In summary, we can therefore distinguish between the following two fundamental cases:

- Case 1. When $y_1<\tilde{y}_1$, the vertex $(x_1,\ x_3,\ x_5)=(1,\ 0,\ 0)$ is a saddle that is unstable in the direction of increasing x_3, the vertex $(x_1,\ x_3,\ x_5)=(0,\ 1,\ 0)$ is a saddle that is unstable in the direction of increasing x_5, and the vertex $(x_1,\ x_3,\ x_5)=(0,\ 0,\ 1)$ is a higher-order equilibrium that attracts almost all trajectories in its vicinity, although it is unstable in the direction of increasing x_1. For this case, trajectories within the triangle are topologically equivalent to those shown in Fig. 1b for $y_1=0$.
- Case 2. When $y_1>\tilde{y}_1$, the vertex $(x_1,\ x_3,\ x_5)=(1,\ 0,\ 0)$ is a stable node, the vertex $(x_1,\ x_3,\ x_5)=(0,\ 1,\ 0)$ is an unstable node, and the vertex $(x_1,\ x_3,\ x_5)=(0,\ 0,\ 1)$ is a higher-order equilibrium that repels almost all trajectories in its vicinity toward the direction of increasing x_1, although it is stable in the direction of decreasing x_3. For this case, trajectories within the triangle are topologically equivalent to those shown in Fig. 1c for $y_1=1$.

A.5 Joint dynamics of harvesters and enforcers

Now we consider the dynamics of y_1 and $y_2=1-y_1$,

$$\frac{dy_1}{dt}=y_1(1-y_1)(g_1-g_2)=y_1(1-y_1)(-1)2Bx_3(x_1+x_3). \tag{A.7}$$

We refer to the set of equilibria $\{(\mathbf{x},\mathbf{y})|x_1=1,x_3=x_5=0,\ \tilde{y}_1<y_1<1\}$ as the "cooperative line segment of equilibria" (CLSE), while we refer to the set of equilibria $\{(\mathbf{x},\mathbf{y})|x_5=1,x_1=x_3=0,\ 0<y_1<\tilde{y}_1\}$ as the "defective line segment of equilibria" (DLSE). On both line segments, the three non-dominated harvester strategies are stationary, and also the fraction of honest enforcers remains constant, Eq. (A.7).

Near the CLSE, x_3 decreases first and then x_5 decreases exponentially, as predicted by Eq. (A.5a,b). The change in y_1 is thus very slow, and becomes negligible during the final approach toward the CLSE. Hence, trajectories converge to any point along the CLSE from a direction that is vertical to the CLSE.

Near the DLSE, x_1 decreases first and then x_3 decreases very slowly, as a hyperbolic (algebraic) function of time, $dx_3/dt=(-s-Ay_1-By_2)x_3^2(1-x_3)<0$. During this approach to the DLSE, y_1 decreases according to $dy_1/dt=y_1(1-y_1)(-1)2Bx_3^2<0$. Comparing these two rates of convergence, we obtain the limiting slope of the trajectories as

$$\frac{dx_3}{dy_1}=\frac{dx_3/dt}{dy_1/dt}=\frac{(-s-Ay_1-By_2)x_3^2(1-x_3)}{y_1(1-y_1)(-1)2Bx_3^2}=\frac{s+Ay_1+By_2}{2By_1(1-y_1)}(1-x_3)>0, \tag{A.8}$$

which implies that any point on the DLSE has trajectories that converge to that point as x_3 converges to zero, and that these trajectories have a positive slope given by Eq. (A.8). Note that this slope does not appear in Fig. 1d, as the vertical axis there is x_1, and all trajectories converging to a point along the DLSE have a slope of zero, because x_1 vanishes first.

Appendix B. Effects of information on corrupt enforcers

When information is available on corrupt enforcers, the payoffs of the three non-dominated harvester strategies – conditional cooperators, committing defectors, and non-committing defectors – (Table 2a) are, respectively,

$$f_1=\left(y_1+y_2(1-p)^2\right)(b-c-s)x_1+p(1-p)y_2(-c-s)x_3,$$
$$f_3=p(1-p)y_2(b-s-B)x_1+p^2y_2(-s-B)x_3,$$
$$f_5=0. \tag{B.1}$$

When all enforcers are honest ($y_1=1$ and $y_2=0$), $\mathrm{d}(x_3/x_1)/\mathrm{d}t=(x_3/x_1)(f_3-f_1)$ yields

$$\mathrm{d}\frac{(x_3/x_1)}{\mathrm{d}t}=\left(\frac{x_3}{x_1}\right)(-1)(b-c-s)x_1<0, \tag{B.2}$$

so all trajectories within the triangle $\{(x_1,x_3,x_5)|x_1+x_3+x_5=1\}$ eventually converge to $x_1=1$ (Fig. 4a).

Similarly, when all enforcers are corrupt ($y_1=0$ and $y_2=1$), Eqs. (B.1) yield,

$$\mathrm{d}\frac{(x_3/x_1)}{\mathrm{d}t}=\left(\frac{x_3}{x_1}\right)(f_3-f_1)=x_3\left[Q+R\left(\frac{x_3}{x_1}\right)\right], \tag{B.3}$$

with $Q=[p(b-s-B)-(1-p)(b-c-s)](1-p)$ and $R=[p(-s-B_r)-(1-p)(-c-s)]p$. Using the abbreviation $\alpha=-Q/R$, we thus obtain the following classification:

- Case 1. If p is small, $Q<0$ and $R>0$ hold. From Eq. (B.3), we can then conclude that $\mathrm{d}(x_3/x_1)/\mathrm{d}t>0$ for $0<x_3/x_1<\alpha$, and $\mathrm{d}(x_3/x_1)/\mathrm{d}t>0$ for $x_3/x_1>\alpha$. Fig. 4b illustrates this for $p=0.2$.
- Case 2. If p is intermediate, $Q>0$ and $R>0$ hold. From Eq. (B.3), we can then conclude that $\mathrm{d}(x_3/x_1)/\mathrm{d}t>0$ for all $x_3/x_1>0$. Fig. 4c illustrates this for $p=0.34$.
- Case 3. If p is large, $Q>0$ and $R<0$ hold. From Eq. (B.3), we can then conclude that $\mathrm{d}(x_3/x_1)/\mathrm{d}t>0$ for $0<x_3/x_1<\alpha$, and $\mathrm{d}(x_3/x_1)/\mathrm{d}t>0$ for $x_3/x_1>\alpha$. Fig. 4d illustrates this for $p=0.8$.

The transition between Case 1 and Case 2 occurs for $Q=0$, which implies the threshold $p=(b-c-s)/(2b-2s-c-B)$. The transition between Case 2 and Case 3 occurs for $R=0$, which implies the threshold $p=(c+s)/(2s+c+B)$.

Appendix C. Payoffs for enforcers when information on corrupt enforcers is available

To determine the payoff for corrupt enforcers when information on corrupt enforcers is available, we have to examine how pairs of the three non-dominated harvester strategies act when they consider their enforcer as being corrupt (which happens with probability p) or honest (which happens with probability $1-p$). Considering three harvester strategies and two enforcer assessments yields six combinations. For example, opportunistic conditional cooperators regarding the enforcer as being honest occur with probability $(1-p)x_1$, while opportunistic committing defectors regarding the enforcer as being corrupt occur with probability px_3.

Since the two harvesters in a pair are each sampled randomly from these six combinations, we have to consider $6\times6=36$ combinations for the pair. We thus obtain the following expected payoff for a corrupt enforcer,

$$g_2=[(1-p)x_1]^2 2s+2(1-p)x_1px_3(2s+B)+[px_3]^2(2s+2B). \tag{C.1a}$$

The first term is the contribution when both harvesters are opportunistic conditional cooperators regarding the enforcer as being honest, in which case the payoff for the enforcer is $2s$. The second term is the contribution when one harvester is an opportunistic conditional cooperator regarding the enforcer as being honest and the other is an opportunistic committing defector regarding the enforcer as being corrupt, in which case the payoff for the enforcer is $2s+B$. The third term is the contribution when both harvesters are opportunistic committing defectors regarding the enforcer as being corrupt, in which case the payoff for the enforcer is $2s+2B$. For all other combinations, the enforcer receives no payoff, because at least one of the two harvesters is not willing to hire an enforcer. The payoff expression above can be rewritten as

$$g_2=2s[(1-p)x_1+px_3]^2+2B[(1-p)x_1+px_3]px_3, \tag{C.1b}$$

which is shown in Table 2b.

Analogously, we obtain the expected payoff for an honest enforcer. In this case, the enforcer is known to be honest to both harvesters forming a pair, so we have to consider only $3\times3=9$ combinations for the pair. From these pairs, the enforcer accepts no bribes and collects the fee $2s$ only when both harvesters are opportunistic conditional cooperators. This yields

$$g_1=2sx_1^2, \tag{C.2}$$

which is also shown in Table 2b.

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