Maximal Fines and Corruption: An Experimental Study on Illegal Waste Disposal

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Abstract

Corruption is known to be one of the real life situations which may jeopardize the effectiveness of fines in deterring crime. We present a model of 'crime with corruption' by which both the dilution of crime deterrence due to corruption, as well as the possibility of crime encouraging fines are formally highlighted. More importantly, by running an experiment on a subject pool of students for the case of illegal waste disposal, we provide experimental evidence on the validity of our theoretical predictions. We find that increasing fine rate may become crime encouraging or at least ineffective, beyond a context-specific fine threshold. In a policy perspective, we suggest that the optimal design of a crime-deterring sanctioning system must simultaneously account for both corruption practices and anti-corruption policies.

Keywords: *corruption, crime*, *fine, waste*

JEL codes: H10, C91, K14, K42, Q50

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1 Introduction

Provided that criminals are rational expected utility maximizers (Becker 1968), the optimality of the maximal fine is usually evoked to point out that crime deterrence can be always strengthened by increasing the fine, and that there exists a fine rate that is high enough (i.e. maximal) to fully eradicate crime. In this vein, many empirical studies suggest that crime rates are in fact decreasing in fines and in the probability of apprehension (e.g. DeAngelo and Hansen 2014; Hansen 2015; Haselhuhn et al. 2012; Levitt 1998).[3]

Nevertheless, several theoretical contributions have challenged the optimality of the maximal fine by bringing back attention to situations that may jeopardize the effectiveness of fines, and punishments in general (Bebchuk and Kaplow 1992; Kaplow 1990; Polinsky and Shavell 1979, 1991, 1992; Stigler 1970). Corruption of public officials (the enforcers) in reporting detected crimes is known to be one of these situations since, in the presence of corruption, fines may be less effective in terms of crime deterrence (Becker and Stigler 1974) or, even, crime encouraging when excessively high (Bowles and Garoupa 1997, Chang et al. 2000, Kugler et al. 2005). This may happen to be the case since excessive fines may be used for financing bribes to be paid to public officials in exchange for under-reporting or non-reporting detected crimes.[4]

In this paper, we provide experimental evidence on the impact of corruption – intended as 'corruption with theft' of public officials (Schleifer and Vishny 1993) – on both (i) the dilution of crime deterrence induced by the fine, and (ii) the possibility of ineffective or even crime-encouraging fine rates. With this

[3] See Chalfin and McCrary (2017) and Feess et at. (2018) for a recent review of the literature.

[4] As observed in Becker and Stigler (1974, p.2), "if a person violates a law carrying a punishment equivalent to a fine of $10,000 he would be willing to spend up to $10,000 to avoid apprehension and conviction. He could, for example, bribe, intimidate, harass or cultivate the police to avoid apprehension, and prosecutors or judges to avoid conviction if apprehended."

purpose in mind, we run an experiment with a criminal exerting an effort for illegal waste disposal in the presence of a public official who may detect this crime and under-report it in exchange for a bribe. We also present a very basic model by which, in the presence of corruption, the theoretical (expected) impact of fines in terms of both dilution of crime deterrence and crime encouragement is identified on *a priori* grounds.

In the existing literature, two major contributions have investigated the possibility of a crime-encouraging fine in the presence of corruption. Following the seminal paper by Becker and Stigler (1974), Bowles and Garoupa (1997) investigate the impact of bribery on deterrence by focusing on the optimal allocation of resources when an authority is expected to prevent both crimes and public officials' corruption. In their model, any increase in the fine imposed to the criminal induces two oppositely signed effects: a direct effect, which is the standard increase in deterrence due to a higher fine if the criminal is caught; an indirect effect, which is instead reducing deterrence, in that an increase in the fine makes corruption more profitable for the public official and, in turn, reduces the minimum benefit required for criminal action to be profitable. In this framework, they prove that, if one allows for a third actor, e.g. the policy department, bearing a social cost of corruption, then the indirect effect of the fine may become dominating so as to observe a greater supply of crime when the fine is increased.[5]

Kugler et al. (2005) investigate an oligopoly model in which differentiated criminal organizations globally compete *à la* Cournot on criminal activities and engage in local corruption of enforcers (judges) to avoid punishment. They show that increasing detection probabilities and fines can generate higher crime rates in some cases. This may happen since criminal organizations hire criminals in the presence

[5] Chang et al. (2000) obtain similar results by introducing social stigma costs for caught corrupt officers. They show that, when corruption is widespread, social norms cannot generate a sufficient sanction to deter corrupt officers, and raising fines can in fact result in more crime.

of a reservation wage which is decreasing in corruption due to a lower risk premium; hence, when corruption becomes higher, the wage premium decreases and criminal activity becomes more profitable.

In this paper, we propose a simple model by which, in the spirit of Bowles and Garoupa (1997) and Kugler et al. (2005), the optimality of the maximal fine is shown to fail due to the possibility of corruption of the public official. This result is obtained by considering a sequential setting in which, at the first stage, the criminal chooses the optimal effort to be exerted in the illegal activity, given the optimal corruption decision of the public official occurring at the second stage (backward induction). We show that, within our sequential setting, a non-maximal fine may be optimal provided that a quadratic cost function is assumed for both, the disutility of effort exerted in the illegal activity by the criminal and the concealment or psychological cost of the public official. In this sense, a U-shape may characterize the optimal effort in crime at different fine rates, with a context-specific optimal fine – that is minimizing crime – which is simultaneously affected by both anti-crime and anti-corruption parameters.

Our theoretical framework shares with Bowles and Garoupa (1997) the application of Becker setting to the criminal and the public official. However, we adopt a sequential setting to model the optimal decisions of both the criminal and the public official, whereas Bowles and Garoupa (1997) derive the supply of crime from the optimal bribe obtained as a Nash bargaining between criminals and public officials. Most importantly, in our model, the direct effect of the fine on deterrence is not necessarily overwhelming, and the maximal fine hypothesis is shown to be violated independently from the presence of a social cost of corruption. In a similar way to Kugler et al. (2005), we find that corruption can both dilute crime deterrence of fines and, under some circumstances, make an increase in the fine even crime-encouraging. However, our result is not restricted to the case of oligopolistic competition among criminal organizations, so that it applies to criminal activities in general.

The setting of the theoretical model is replicated in our experiment with a subject pool composed by 158 students, recruited on the social web page of the largest Italian network of Italian students of economics.

All subjects are asked to complete a questionnaire, in which they are assigned the role of private citizen (entrepreneur), while the other roles, respectively the public official and a third actor detecting corruption (e.g. Internal Division), are played by the nature. Subjects are asked to fill two different versions of the questionnaire, that is, with and without the possibility of corruption; to avoid potential ordering effects, the experiment has been replicated by inverting the order of the two questionnaires.

The results of the experiment confirm that corruption is generally diluting crime deterrence of fines and that fines, which are initially observed to be crime-deterring, may become no longer crime-deterring, or even crime-encouraging, beyond a context-specific threshold, that is the optimal fine. More specifically, a strictly decreasing pattern for crime is observed for 58% of the subject pool, whereas the fine is found to become ineffective, or even crime-encouraging, for 28% of the subjects (with the rest of the pool not significantly affected by the fine).

Our contribution is twofold. On the one hand, we prove by experimental evidence that – as predicted by the theoretical model – the possibility of corruption significantly jeopardizes crime deterrence of the fine. We also find that, in the presence of corruption, fines may become ineffective or, even, crime-encouraging beyond a context-specific threshold influenced by both anti-crime and anti-corruption policies. From a policy perspective, both contributions highlight the key role of the optimal balance between anti-crime and anticorruption policies for improving the effectiveness of fines so as to minimize effort in crime.

2 The model

Consider two risk-neutral agents, a criminal exerting a finite effort in crime, $x \in \Re_0^+$, at time 1 (e.g. illegal waste disposal), and a public official (enforcer) who may detect and prevent crime with probability p at time 2.[6] The marginal productivity of criminal effort is $b > 0$, so that the overall return from crime – if not detected – is bx. A penalty rate $f > 0$ (hereafter fine) applies to overall returns if the crime is detected and reported; the total amount of the fine due by the criminal is proportional to the money value of the offense, i.e. fbx.[7]

At time 2, corruption may occur. Provided that crime has been detected and prevented (incapacitation[8]), the public official may be willing to under-report a share $\rho \in (0,1)$ of the crime in exchange for a bribe – to be paid by the criminal – assumed as half of the amount of the unpaid fine, i.e. $(1/2)\rho fbx$.[9] We also assume that the corruption effort exerted by the public official (ρ) generates a quadratic disutility or corruption cost, $(1/2)c_\rho \rho^2$ with $c_\rho > 0$, which may be intended as concealment or psychological cost (e.g., Rose-Ackerman 1975, Schleifer and Vishny 1993).

Corruption of the public official may be detected by a third actor (i.e. an Internal Affairs Division or Police Department, or Tax Agency), with probability $\hat{p}$. If corruption is not detected, then the criminal pays a (discounted) fine equal to $(1-\rho)fbx$ and a bribe, $(1/2)\rho fbx$, which is pocketed by the public official. Instead, provided that both the fine (i.e. $(1-\rho)fbx$) and the bribe (i.e. $(1/2)\rho fbx$) have been paid, if the public official is caught, then the criminal is also required to pay back the unpaid fine,

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[6] The prevention of the crime in case of detection, with loss of the overall return from crime, is very common for some crimes, especially for environmental offences. Remarkably, the main result of our model holds independently from crime prevention with detection.

[7] In line with the existing literature (Becker and Stigler 1974), the fine, f, may be intended as a monetization of any kind of punishment cost for crime (e.g. incarceration, social stigma).

[8] On the relevance of the distinction between deterrence and incapacitation, see Chalfin and McCrary (2017).

[9] Provided that the identification of the optimal sharing rule goes beyond the objectives of this research, note that a fifty-fifty sharing rule is the most obvious outcome of Nash bargaining (Mookherjee and Png 1995). In addition, the main result of the model (i.e. Proposition 2.1) can be generalized for any exogenous value of the sharing rule.

$(1/2)\rho f b x$, with an overall negative payoff equal to fbx.[10] As for the public official, the bribe is confiscated and a proportional sanction, ρS, is imposed. Notably, the sanction – intended as a pecuniary penalty, or wage loss, or any other possible monetization of the sanctioning procedure – is equal to S in the case of full under-reporting ($\rho = 1$), but proportionally increasing in the share of under-reporting when the illegal activity is partially reported ($\rho < 1$). This allows to simplify the analytics of the model while preserving the standard results of rational expected utility maximizers.

Let $\widehat{EU}$ be the public official's expected utility. The optimal share of under-reporting chosen at time 2 is

$$\rho^* = arg\max_{\rho} \ \widehat{EU}(\rho) = \hat{p}(-\rho S - \tfrac{1}{2} c_\rho \rho^2) + (1 - \hat{p})(\tfrac{1}{2} \rho f b x - \tfrac{1}{2} c_\rho \rho^2) \tag{1}$$

implying

$$\rho^*(x) = \frac{(1-\hat{p}) f b x - 2\hat{p}S}{2c_\rho} \tag{2}$$

Under-reporting occurs if, at the margin, the expected bribe is greater than the expected sanction for the public official; as one would expect, corruption is decreasing with respect to the corruption cost c_ρ. Remarkably,

$$\rho^*(x) = \begin{cases} 0 \Leftrightarrow bx \leq \frac{\hat{p}}{1-\hat{p}} \frac{2S}{f} \\ 1 \Leftrightarrow bx \geq \frac{2c_\rho + 2\hat{p}S}{(1-\hat{p})f} \end{cases} \tag{3}$$

which clearly highlights that (i) for corruption to be profitable for the public official, the overall return from crime must be sufficiently high, something often involving criminal organizations (Kugler *et al.* 2005), and (ii) if returns from crime are too high compared to corruption costs and expected sanction, then corruption becomes systemic or endemic for that crime (Khan 2008).

[10] To keep the model as simple as possible, we disregard the possibility for the criminal to be charged with an additional fine for being party to public official corruption (e.g. Mookherjee and Png 1995).

Most importantly, from eq. (3) it is evident itself that, for corruption to occur, the fine f must be sufficiently high since it increases the bribe payment for the public official. Basically, the fine is directly deterring crime but indirectly diluting crime deterrence by feeding corruption.

Given the optimal share of under-reporting the public official will opt for (time 2), at time 1 the criminal chooses effort to be exerted in the illegal activity by maximizing his or her expected utility $EU(x)$. Three possible states of the world are possible: (i) both the criminal and the public official are caught with probability $p\hat{p}$; (ii) with probability $p(1-\hat{p})$, the criminal is caught, not the public official, so that the share $\rho^*(x)$ of returns from crime are not reported; (iii) the illegal activity is not detected by the public official with probability $(1-p)$.

Let $EU(x)$ be the criminal's expected utility. Given a quadratic disutility cost from effort in crime, $\frac{1}{2}c_c x^2$ with $c_c > 0$, the criminal chooses the level of effort to be exerted in the illegal activity, x^*, as follows:

$$x^* = \underset{x}{argmax} \quad EU(x) = p\hat{p}[-fbx - \frac{1}{2}c_c x^2] +$$

$$+p(1-\hat{p})\left[-(1-\rho^*(x))fbx - \tfrac{1}{2}\rho^*(x)fbx - \tfrac{1}{2}c_c x^2\right] + (1-p)(bx - \tfrac{1}{2}c_c x^2) \qquad (4)$$

It is worth highlighting that the existence of corruption practices does not only enforce the effort in crime but it may even make profitable criminal activities when these would not be profitable otherwise. Indeed, by re-arranging criminal's expected utility one obtains

$$EU(x) = bx[1-p(1+f)] - \tfrac{1}{2}c_c x^2 + \tfrac{1}{2}(1-\hat{p})pfbx\rho^*(x) \qquad (5)$$

where the last term on the right-hand side, i.e. the corruption term, cannot be negative by construction, implying that the criminal is always willing to accept corruption in our model.[11]

[11] Even if plausible, this result may be easily avoided by considering assumptions like, outrage costs, bribe waste in case of corruption detection, etc. All of these assumptions would not jeopardize the main contribution of this paper, so we opted for simplifying the notations.

Not surprisingly, if $\hat{p} = 1$ and/or S large enough so as to obtain $\rho^* = 0$ (see eq. 2), the corruption term in eq. (5) disappears and the model goes back to the standard Becker set up, where the maximal fine hypothesis is verified for crime; in the latter case, there must be $f \geq \bar{f}$ such that $x^* = 0$.[12] As far as we are supposed to investigate the effect of corruption on the identification of the optimal fine, in what follows we assume that corruption is profitable for the public official (i.e. $\rho^*(x) > 0$), which implies $\hat{p} < 1$ and $S < \frac{1}{2}\left(\frac{1-\hat{p}}{\hat{p}}\right) fbx$.

From the maximization program in eq. (4), we obtain the following First-Order Condition:

$$FOC(x): b[1 - p(1 + f)] - c_c x + \frac{1}{2}(1 - \hat{p})pfb\rho^*(x) + \frac{1}{2}(1 - \hat{p})pfbx\frac{\partial\rho^*(x)}{\partial x} = 0 \qquad (6)$$

It is worth observing that corruption is responsible for the two last terms in eq. (6). On the one hand, an increase in criminal effort enhances the expected savings the criminal can obtain by paying the bribe in place of a full payment of the fine. The last term, on the other hand, captures the marginal impact of the size of criminal effort on the profitability of under-reporting for the public official. Most importantly, while both terms disappear when corruption is not profitable at all (i.e. $\rho^*(x) = 0$), the last term only disappears when the profitability becomes systemic (i.e. $\rho^*(x) = 1$).

From eq. (6), the optimal effort in crime is:

$$x^* = \frac{2bc_\rho[1-p(1+f)] - bfpS(1-\hat{p})\hat{p}}{2c_c c_\rho - b^2 f^2 (1-\hat{p})^2 p} \qquad (7)$$

with $[2c_c c_\rho - b^2 f^2 (1 - \hat{p})^2 p] > 0$ in (4) for x_i^* to be a finite maximum (Second-Order Condition).[13]

[12] As far as the benefit from crime cannot be lower than its cost, a *necessary condition* for crime to be profitable is $2b > c_c x$.

[13] If SOC does not hold, then $EU(x)$ is a parabola with a vertex corresponding to a minimum, so that $x^* = x: \rho^*(x) = 1$. On the contrary, if SOC holds then $EU(x)$ is a parabola with a vertex corresponding to a maximum, which can be either positive or negative depending on the sign of the numerator in (7).

Intuitively, the criminal is engaged in a positive effort, i.e. $x^* > 0$, whenever the marginal return from crime – at the net value of the cost of criminal effort – is greater than the marginal increase in the expected fine to be paid at the net value of corruption "discounts".

Optimal effort in crime, x^*, is decreasing with respect to anti-corruption policies applied to the public official, i.e. $(\hat{p}, s)$, as well as with respect to the probability of crime detection, p. As one may expect, x^* is increasing with the marginal benefit from criminal activity, b.[14] Most importantly, as formalized in the following Proposition, effort in crime may not be strictly decreasing with the fine f.

Proposition: *If (i) there exists a finite and positive optimal effort in crime and (ii) corruption is profitable for both the criminal and the public official, then there exists a set of parameters,* $(c_c, c_\rho, b, p, \hat{p}, S)$*, such that effort in crime,* x^**, is U-shaped with respect to the fine* f*.*

Proof. (see appendix A.2)

The Proposition proves that, while crime may still be found strictly decreasing with the size of the fine, this is not necessarily the case, in that there exists a set of parameters such that effort in crime is first decreasing and then increasing in the fine for any fine rate above a threshold level, f^* (see appendix A.2).

[14] Consider $FOC(x)$ in eq. (6). It is easy to verify that $\left(\frac{\partial FOC(x)}{\partial \hat{p}}, \frac{\partial FOC(x)}{\partial s}\right) < 0$. To prove that $\frac{\partial FOC(x)}{\partial b} > 0$, obtain $b(1 - pf)$ from $FOC(x)$, then replace it in $b\frac{\partial FOC(x)}{\partial b}$. To prove $\frac{\partial FOC(x)}{\partial p} < 0$, consider $p\frac{\partial FOC(x)}{\partial p}$ and replace $\frac{1}{2}(1-\hat{p})pfb\rho^*(x) + \frac{1}{2}(1-\hat{p})pfbx\frac{\partial \rho^*(x)}{\partial x} = -b[1 - p(1+f)] + c_c x$ from eq. (6), so as to obtain $p\frac{\partial FOC(x)}{\partial p} = -b + c_c x$. The latter must be negative at the optimum since, in case of no deterrence at all (i.e. $p = 0$), $x^*|_{p=0} \geq x^*$, which implies $FOC\left(x^*|_{p=0}\right) = b - c_c x^* \geq 0$ by continuity.

Intuitively, in the presence of corruption, an increase in the fine, f, induces two oppositely signed effects for the criminal. On the one hand, a higher fine causes a negative direct effect for the criminal, due to the increase of the expected overall expenditure from policing – fine and bribe as a whole – which is captured by the first and the third factor in eq. (6); recall that, by construction, the bribe allows the criminal to obtain expenditure "discounts" if caught, not gains, implying that a marginal increase in the fine – when considering the direct effect only – must reduce the optimal effort in crime, x^*. On the other hand, a higher fine makes corruption more profitable for the public official – the last factor in eq. (6) – who is optimally expected to increase under-reporting. Hence, while the dilution of crime deterrence of fines is generally originating from the presence of corruption, the possibility of a crime encouraging fine is uniquely motivated by the impact of the fine on the incentives for corruption of the public official. In this vein, a U-shape is never expected to be observed when corruption is systemic (i.e. $\rho^*(x) = 1$), since a greater fine cannot further increase the incentive for corruption of the public official.

3 Experimental evidence

3.1 The experimental design

We designed an individual decision-making experiment, conducted online through the Microsoft Forms platform. The subject pool was composed of 158 students, recruited on the social web page of the largest Italian network of economics students in Italy.[15] The proposed framework is the following, in which we assume three subjects:

(i) a Private Citizen, PC (e.g. an entrepreneur), who has the opportunity to dispose of waste illegally. This illegal activity requires an effort "x" that, at the optimal level, depends on the

[15] The network is called "Economia del Suicidio", and it counts over 170.000 Italian economics students on social networks.

operative cost to dump waste illegally and it is an opportunity cost associated to the illegal disposal of waste;

(ii) the Public Official, PO, is a special pollution enforcement unit that inspects business waste management operations;

(iii) the Internal Affairs Division, IAD, investigates the PO's misconduct.

All subjects were asked to complete a questionnaire, in which they were assigned the role of Private Citizen (PC), while the other roles were played by the nature. We informed the participants that, at the end of the experiment, one of them would have been randomly selected, and he or she would have gotten the monetary payoff correspondent to a randomly selected scenario that he or she played (with the exchange rate 100ECU=1€, where ECU stands for experimental currency units).[16]

Each subject playing the role of a Private Citizen faced the hypothetical opportunity to dispose up to 100 tons of waste illegally ($x_i = 0; 25; 50; 75; 100$), knowing that the marginal benefit for each unit of illegal waste is equal to 200ECU, and that the fixed cost for the illegal disposal of the first 50 tons ($x_i \leq 50\ tons$) is equal to 800ECU, while it rises to 7500ECU if $x_i > 50$ tons.

The participants knew that the market was composed of 10 PC and 1 PO, and that the latter was supposed to randomly control and sanction 1 out of 10 ($p = 10\%$) Private Citizens, in case of illegal disposal of

[16] The survey has been published on the 1st of June 2022, and it remained available until the 2nd of June 2022. The average time to complete the survey has been about 12.36 minutes. The randomly extracted participant received a payoff of 42€ (4200 ECUs) with a time to complete the questionnaire of about 9 minutes. This implies a gross hourly wage of 280€/h, which represents a relatively high stake. According to Anderson et al. (2022), paying high stakes to just some subjects rather than paying all of them lower stakes may elicit risk preferences that more closely approximate the ideal condition of paying all subjects high stakes than paying all subjects lower stakes. This evidence motivated us to apply a probabilistic high stake payment design.

waste, with a fine equal to $F = f * 200ECU * x_i$. We proposed four fine rates ($f = 0.1;\ 2;\ 4;\ 6$). Once provided all this information, we let participants make four decisions about the level of illegal waste, in each of the following two treatments (T1, T2).

Treatment 1: No corruption (T1)

In this treatment, subjects knew that PO would have randomly controlled 10% of the market sanctioning on the entire amount of illegal disposal detected, without any possibility of corruption. Then, we asked subjects to choose how much to dispose illegally (x^*), according to each level of the fine (f). The first set of four decisions was displayed in the following way:

"Indicate (with a number from 0 to 100) how many tons (x) you dispose of illegally when the fine (f) is fixed at:

	0	25	50	75	100
(f) = 0.1	○	○	○	○	○
(f) = 2	○	○	○	○	○
(f) = 4	○	○	○	○	○
(f) = 6	○	○	○	○	○

According to the theoretical framework, we expect that an increase in deterrence factors (i.e., an increase in the fine) would monotonically reduce the level of illegal waste, that is: $dx^*(.)/df < 0$; this is a standard result provided that individuals behave, at least, as rational expected utility maximizers. Once chosen the level of illegal waste for the respective level of fine, $x^*(f)$, each participant passed to the next treatment.

Treatment 2: Possibility of corruption (T2)

In this treatment, we included a new factor in the PC decision, which is the possibility for the PC to corrupt the PO with a bribe. In fact, the PO could decide to be corrupted by under-reporting the level of illegal waste detected. In particular, he or she could decide whether to be honest (declaring 100% of the illegal waste detected), so that the PC would pay the entire sanction, or to be corrupted by declaring just a percentage of the detected waste.

Prior to asking the Private Citizen how much to pollute illegally for each level of the fine, we provided PC the with information about the determinants of the PO's willingness to be corrupted. In particular, according to the theoretical framework, we proposed the following scheme.

As a bribe, the PO will ask PC to divide at 50% with him/her the amount of the fine unpaid, which is proportional to the fine (f) and waste disposed illegally (x^*). In fact, under certain conditions and in case of possible corruption, given a 50% split of the unpaid fine, it may be convenient for the PC to increase the illegal waste, and for the PO to under-report it. For the PC, the level of economic discount over the fine is uncertain, but the subjects knew that PO's decision of under-reporting – hence to accept a bribe – was affected by two factors: (i) the PO has to cover a cost (e.g., falsifying documents which increase with the quantity of illegal waste disposed (or also moral and psychological costs); (ii) the PO shall be subject to supervision by the anti-corruption authority, IAD, which we assume to discover the 50% of the auditors' corruption cases. Since PO inspects 10% of companies, then the probability that the PC's company is controlled by the anti-corruption authority is $\hat{p} = 50\% * 10\% = 5\%$. The PO's expected payoff is increasing in the fine rate, because the bribe offered by the PC is a percentage of the penalty that PC is supposed to pay.

Once provided all this information, we invite the PC to report his/her amount of waste to disposal illegally, for each level of the fine. In conclusion, differently from Treatment 1, in T2, participants know that the PO could be corrupted. The second set of decisions was displayed as follows:

"Indicate (with a number from 0 to 100) how many tons (X) you dispose of illegally, knowing that the controller can be corrupted, when the fine (f) is fixed at"

	0	25	50	75	100
(f) = 0.1					
(f) = 2					
(f) = 4					
(f) = 6					

In this treatment, we expected the following results/hypotheses.

Hp. 1 - Dilution of crime deterrence: for each level of the fine, the average illegal waste disposal should be greater in the case of corruption than in the case without corruption. This is because corruption may allow the criminal to obtain some "discount" on the fine, if caught.

Hp. 2 - The possibility of crime-encouraging or, at least, non-discouraging reactions to fine increments: provided that some of the parameters of the theoretical model are not monetized in the experiment, subjects may rationally react to marginal increases in the fine by monotonically reducing the crime. However, according to our model, this is not necessarily the case, since the fine may lose its crime-discouraging effect, and become ineffective or even encouraging in some cases for excessively high fine rates.

At the end of the experiment, we propose several control questions in order to elicit the attitudes of individuals towards the environment, trust and honest/corrupting behavior.[17] In particular, we consider

[17] The control questions were inspired by the European Social Survey, ESS8 2016 (https://ess-search.nsd.no/en/study/f8e11f55-0c14-4ab3-abde-96d3f14d3c76), accessed 5 January, 2023.

their attitude in terms of: Honesty ("*If you want to make money, you can't always act honestly*"); Respect of the law ("*You should always strictly obey the law even if it means missing good opportunities*"); Climate responsibility ("*To what extent do you feel a personal responsibility to try to reduce climate change?*"); Trust ("*To what extent do you think that most people can be trusted?*".

We also included questions regarding socio-demographic characteristics of participants, such as age, gender and the average family monthly income. All the instructions and the structure of the experiment are reported in appendix A.1.

All-in-all, we expect that the introduction of corruption opportunities significantly alters the behavior of subjects for any fixed level of the fine rate. In addition, provided that corruption of PO is allowed, it may be the case that a part of the subject pool deviates from the standard behavior according to which a higher fine rate reduces illegal behavior. As such, a U-shaped relationship between an increase in the fine and the level of illegal waste may be observed on average.

3.2 Results

Table 1 describes the experimental outcomes.

Table 1. Distribution of results - absolute values and percentage - (N=148)

			Illegal Waste					
			0	**25**	**50**	**75**	**100**	**total**
Fine	**0.1**	Without corruption	19 (12.84)	10 (6.76)	34 (22.97)	13 (8.78)	72 (48.65)	*148 (100)*
		With corruption	13 (8.78)	9 (6.08)	18 (12.16)	20 (13.51)	88 (59.46)	*148 (100)*
		Total	*32 (10.81)*	*19 (6.42)*	*52 (17.57)*	*33 (11.15)*	*160 (54.05)*	*296 (100)*
		Wilcoxon signed rank test $z = -4.435$ Pr = 0.000						
	2	Without corruption	39 (26.35)	31 (20.95)	44 (29.73)	16 (10.81)	18 (12.16)	*148 (100)*
		With corruption	20 (13.51)	16 (10.81)	53 (35.81)	31 (20.95)	28 (18.92)	*148 (100)*
		Total	*59 (19.93)*	*47 (15.88)*	*97 (32.77)*	*47 (15.88)*	*46 (15.54)*	*296 (100)*
		Wilcoxon signed rank test $z = -5.784$ Pr = 0.000						
	4	Without corruption	72 (48.65)	33 (22.3)	31 (20.95)	1 (0.68)	11 (7.43)	*148 (100)*
		With corruption	32 (21.62)	37 (25)	51 (34.46)	15 (10.14)	13 (8.78)	*148 (100)*
		Total	*104 (35.14)*	*70 (23.65)*	*82 (27.7)*	*16 (5.41)*	*24 (8.11)*	*296 (100)*
		Wilcoxon signed rank test $z = -6.767$ Pr = 0.000						
	6	Without corruption	105 (70.95)	19 (12.84)	12 (8.11)	1 (0.68)	11 (7.43)	*148 (100)*
		With corruption	72 (48.65)	29 (19.59)	22 (14.86)	6 (4.05)	19 (12.84)	*148 (100)*
		Total	*177 (59.8)*	*48 (16.22)*	*34 (11.49)*	*7 (2.36)*	*30 (10.14)*	*296 (100)*
		Wilcoxon signed rank test $z = -5.447$ Pr = 0.000						
	Total	Without corruption	235 (39.7)	93 (15.71)	121 (20.44)	31 (5.24)	112 (18.92)	*592 (100)*
		With corruption	137 (23.14)	91 (15.37)	144 (24.32)	72 (12.16)	148 (25)	*592 (100)*
		Total	*372 (31.42)*	*184 (15.54)*	*265 (22.38)*	*103 (8.7)*	*260 (21.96)*	*1184 (100)*
		Wilcoxon signed rank test $z = -11.266$ Pr = 0.000						

Note: The number at the top of each cell is the frequency count. The number in parentheses is the row percentage. Because of the small sample size, for the Wilcoxon signed rank test, we report the "exact" p-value based on actual randomization distribution of the test statistic.

Preliminarily, taking into account the ordinal/categorical nature of variables and that we use repeated measures (i.e. paired sample), we run *Wilcoxon Signed Rank* Tests to check whether there is a statistically significant difference in illegal dumping between the two experimental settings (with and without corruption) for each level of fine. These results indicate that the treatment (corruption) had a significant effect on the distributions of illegal disposal for each level of fine rate.

3.3 Econometric Analysis

This section deals with the empirical analysis of two main hypotheses of this research. We are interested in looking for the relationship between the level of illegal waste and the fine. Hence, we estimate this relationship according to the following econometric specification:

$$x_i^* = \beta_0 + \beta_1 f_i + \beta_2 f_i^2 + \beta_3 Corrup_i + \beta_4 (Corrup_i * f_i) + \beta_5 (Corrup_i * f_i^2) + X_i'\gamma + \mu_i \quad (8)$$

where x_i^* represents an unobservable latent variable underlying the measure of illegal waste x_i of each individual i; f represents the fine rate associated with each level of illegal waste; f^2 is the squared fine rate, which we include in order to control for the presence of a potential quadratic relationship;[18] $Corrup$ is a dummy variable identifying the treatment with the possibility of corrupting the PO; β_4 and β_5 account for the marginal effects of potential interaction between corruption and the severity of the fine; X_i' is a vector including control variables for individual characteristics and attitudes towards the environment, trust and corrupting behavior; finally, u_i represents the error term. We estimate equation (8) by three estimation approaches: the ordinary least squares (OLS) method, assuming that the illegal waste is a cardinal measure ranging from 0 to 100;[19] Ordered logistic regression (Olog) to take into account the ordinal nature of dependent variable and (3) by generalized ordinal logistic regression (G-OLog) to account for the violation of the assumption that the estimated coefficients of independent variables do not vary across the five categories of dependent variables (parallel-lines assumption, (e.g., McCullagh and Nelder, 1989; Peterson and Harrell, 1990).[20]

We run all regressions by excluding from the sample "irrational" subjects (i.e., 10 subjects). We define a subject as "irrational" if he or she does not reduce the illegal activity as deterrence increases (i.e. fine rate) in the scenario without corruption; this behavior, indeed, is inconsistent with the standard effect of

[18] We also controlled for the presence of a cubic effect of the fine, including the term f^3. The respective coefficient turned out to be not statistically significant; hence we did not include it in the following analysis.

[19] This assumption of continuity of illegal waste variable is regarded as acceptable because the four categories of dependent variable are equally spaced (i.e. 0, 25, 50, 75 and 100).

[20] As robustness checks we also estimate the models with control variables treated as ordinal instead of continuous variables. and including all the respondents instead of the only "rational" agent. Results are qualitatively the same (see Appendix A.4 for a sample of these robustness checks).

deterrence on utility maximizers according to very basic corruption models (since Becker 1968). This ex-post sample selection aims to control for participants' lack of attention or miscomprehension of the experiment so as to increase the external validity of our empirical results.

As for Treatment 2 (i.e. with corruption), by focusing on the sole rational set of the subject pool, we observe a strictly decreasing pattern of effort in crime with respect to the fine level for 56% of subjects. In the rest of the population, for 28% of subjects, we observe an initially decreasing pattern of effort in crime for low levels of the fine, which becomes flat or even increasing for high levels of the fine, while for 16% of the population the fine does not affect the level of crime.

3.3.1 Ordinary Least Square Regressions

Table 2 reports eleven model specifications based on eq. (8) based on "rational" participants. In order to evaluate the goodness of fit, we report the *Adjusted-R^2*, Akaike information criterion (*AIC*) and the p-value of Ramsey Regression Equation Specification Error Test (*RESET pv*) to detect the general form misspecification (where the null hypothesis is that the functional form of the model is correctly specified).

Table 2. *OLS regressions (Dep. Var.: Illegal waste; N=148)*

	(I)	(II)	(III)	(IV)	(II_r)	(III_r)	(IV_r)	(V)	(VI)	(VII)	(VIII)
Fine	-8.566***	-8.907***	-14.755***	-16.883***	-8.907***	-14.755***	-16.883***	-15.096***	-14.755***	-16.883***	-12.627***
	(-16.86)	(-16.16)	(-12.34)	(-11.94)	(-16.21)	(-12.37)	(-11.98)	(-12.52)	(-12.37)	(-11.98)	(-9.22)
Fine^2			1.013***	1.305***		1.013***	1.305***	1.013***	0.983***	1.305***	0.720***
			(7.02)	(7.46)		(7.04)	(7.49)	(7.03)	(6.43)	(7.49)	(4.21)
Corruption	13.133***	11.069***	13.133***	8.448**	11.069***	13.133***	8.448**	11.069***	12.307***		
	(7.16)	(4.18)	(7.16)	(3.12)	(4.20)	(7.18)	(3.13)	(4.19)	(5.36)		
Corr.#Fine		0.683		4.257**	0.683		4.257**	0.683			
		(1.06)		(2.98)	(1.07)		(2.99)	(1.07)			
Corr.#Fine^2				-0.585**			-0.585**		0.059		
				(-3.05)			(-3.06)		(0.62)		
Control Variables											
Male	3.893	3.893	3.893	3.893							
	(0.95)	(0.95)	(0.95)	(0.95)							
Age	0.470	0.470	0.470	0.470							
	(1.14)	(1.13)	(1.13)	(1.13)							
Honesty	1.775	1.775	1.775	1.775							
	(0.94)	(0.94)	(0.94)	(0.93)							
Law_Resp	-2.410	-2.410	-2.410	-2.410							
	(-1.18)	(-1.18)	(-1.18)	(-1.18)							
Clim_resp	-1.661	-1.661	-1.661	-1.661							
	(-0.64)	(-0.63)	(-0.63)	(-0.63)							
Trust	-3.373	-3.373	-3.373	-3.373							
	(-1.57)	(-1.57)	(-1.57)	(-1.57)							
Inc_class	-0.813	-0.813	-0.813	-0.813							
	(-0.37)	(-0.37)	(-0.37)	(-0.37)							
constant	71.493***	72.525***	76.029***	78.372***	63.938***	67.443***	69.785***	68.475***	67.856***	69.785***	78.234***
	(4.54)	(4.54)	(4.83)	(4.89)	(22.32)	(24.29)	(22.91)	(22.93)	(23.50)	(22.92)	(27.95)
N	1184	1184	1184	1184	1184	1184	1184	1184	1184	592	592
adj. R^2	0.291	0.291	0.301	0.301	0.275	0.285	0.285	0.285	0.285	0.285	0.242
AIC	11578.2	11579.6	**11562.4**	11564.2	11598.7	11582.0	11583.9	11583.3	11583.8	5785.3	5798.5
BIC	11629.0	11635.4	11618.2	11630.2	11619.0	**11602.3**	11614.3	11608.7	11609.2	5798.5	5811.6
Ramsey_pv	0.0423	0.002	0.836	0.951	0.000	0.739	0.613	0.613	0.521	0.626	0.729

Note: t-stat is reported in parentheses. We employ Cluster-robust standard errors (at individual level). *, **, *and* *** *to denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

The empirical findings show that the fine rate and the possibility to corrupt public officials are the main determinants of the subject's behavior. Indeed, control variables for individual characteristics and attitudes towards the environment, trust and corrupting behavior have no statistically significant effects.

Looking at the goodness-of-fit statistics shown in Table 2, model III is the best specification according to the AIC and Adjusted-R^2, the restricted version (III_r) is the best model according to BIC. Adjusted-R^2 is higher in models III than III_r, however, since the marginal effects of the fine (β_1 and β_2) and corruption (β_3) on illegal waste disposal do not change between these two models, thus this divergence among goodness-of-fit statistics is inconsequential to the aims of this analysis. To further confirm model selection, we observe that the p-value for the F-stat of the Ramsey RESET test fails to reject the null hypothesis of correct specification at the 5% significance level for the linear models (I, II, and II_r). As the interaction terms concern, in models IV and IV_r they are statistically significant at 5% but the overall goodness of fitting is inferior to the more parsimonious specification models III and III_r.

3.3.2 Generalized Ordered logistic Regressions

Table 3 reports six model specifications based on eq. (8) where, for the sake of comparability with OLS estimates, we use the same labels of Table 2. Accordingly, models (I.a, III.a and III_r.a) were estimated by Ordered logistic regression (Olog). Taking into account that the parallel lines assumption does not hold, we estimate the best model specification (i.e. III_r) by G-Olog.[21] This estimation

[21] We test this assumption by different approaches (e.g. Brant 1990) that suggest to reject the parallel-lines assumption. These tests are available on request from the corresponding author. See Long (1997) and Williams (2016) for a discussion of Generilized Ordered logistic regression.

approach allows for heterogeneity of β and γ coefficients across the categories of the dependent variable.

This approach leads to the estimation of three binary logit models. The first model estimates the first category, *Illegal Waste*=0, versus *Illegal Waste* $\geq$ 25 (model III_r.1); the second model does the same regarding categories *Illegal Waste* $\leq$ 25 versus *Illegal Waste* $\geq$ 50 (model III_r.2); the third model compares the choice between categories *Illegal Waste* $\leq$ 50 versus *Illegal Waste* $\geq$ 75 (model III_r.3) and *Illegal Waste* $\leq$ 75 versus *Illegal Waste* = 100 (model III_r.4).

To evaluate the goodness of fit, we report the *Pseudo-R^2*, *Wald χ^2 test,* and, for comparing models, the *Log-pseudolikelihood* (where the model with the highest value offers a better fit to the data).

Table 3. *Generalized Ordered Logistic regressions (Dep. Variable_ Illegal waste; N=148)*

	(I.a)	(III.a)	(III_r.a)	(III_r.1)	(III_r.2)	(III_r.3)	(III_r.4)
Fine	-0.519***	-0.781***	-0.766***	-0.311**	-0.578***	-1.025***	-1.265***
	(-11.78)	(-9.76)	(-9.70)	(-3.03)	(-5.36)	(-9.96)	(-9.58)
Fine^2		0.043***	0.042***	-0.021	0.015	0.092***	0.140***
		(5.01)	(5.04)	(-1.54)	(1.07)	(6.42)	(8.07)
Corruption	0.816***	0.823***	0.803***	0.955***	0.884***	0.861***	0.544***
	(6.57)	(6.63)	(6.80)	(6.65)	(6.40)	(5.61)	(3.60)
Control variables							
Male	0.242	0.242					
	(0.99)	(0.99)					
Age	0.028	0.028					
	(1.21)	(1.20)					
Honesty	0.122	0.122					
	(1.14)	(1.13)					
Law_Resp	-0.162	-0.163					
	(-1.42)	(-1.42)					
Clim_resp	-0.118	-0.119					
	(-0.78)	(-0.78)					
Trust	-0.188	-0.187					
	(-1.53)	(-1.51)					
Inc_class	-0.056	-0.059					
	(-0.44)	(-0.46)					
cut1 / costant	-2.730**	-2.955***	-2.363***	1.732***			
	(-3.15)	(-3.37)	(-10.15)	(7.44)			
cut2 / costant	-1.851*	-2.084*	-1.519***		1.258***		
	(-2.15)	(-2.39)	(-7.70)		(6.46)		
cut3 / costant	-0.592	-0.811	-0.275			0.362*	
	(-0.69)	(-0.93)	(-1.66)			(2.15)	
cut4 / costant	-0.019	-0.223	0.306				0.027
	(-0.02)	(-0.26)	(1.72)				(0.16)
N	1184	1184	1184	1184			
Pseudo- R^2	0.120	0.123	0.112	0.129			
Wald χ^2 stat (df)	155.2 (9)	154.9 (10)	143.7 (3)	182.8 (12)			
χ^2 (p-value)	0.000	0.000	0.000	0.000			
Log-pseudo-Lik.	-1597.0	-1592.5	-1612.3	-1581.9			

Note: We report coefficients in log-odds units; t-stat is reported in parentheses. We employ Cluster-robust standard errors (at individual level). *, **, *and* *** *to denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

The empirical findings of Table 3 confirm the results of the OLS estimator (i.e. the fine rate and the possibility of bribing public officials are the main determinants of the subject's behavior, there is a quadratic relation between sanctions and *Illegal waste* disposal, control variables have not statistically significant effects). Because coefficients in log-odds units are difficult to interpret and considering that parallel-lines assumption does not hold, we report in Table 4 the marginal effects of discrete change in treatment (i.e. scenario without corruption versus scenario with corruption) for each level of fine rate and each category of the ordinal dependent variable (*Illegal waste)*.

Table 4. *Marginal Effects - Model V (G-OLog)*

		Illegal Waste				
		0	25	50	75	100
Fine	0.1	-0.089^{***}	-0.032^{**}	-0.069^{***}	0.055^{**}	0.134^{***}
	2	-0.143^{***}	-0.057^{***}	0.023	0.104^{***}	0.073^{***}
	4	-0.214^{***}	0.003	0.107^{***}	0.066^{***}	0.038^{***}
	6	-0.225^{***}	0.069^{***}	0.067^{***}	0.042^{***}	0.047^{***}

Table 4 shows that, for instance, when corruption becomes possible ($Corrup = 1$), with a fine rate equal to 6, the probability that an individual disposes of all waste properly (Illegal Waste=0) is 22.5 percentage points lower than the treatment without corruption ($Corrup = 0$). Again, with a fine rate equal to 0.1, completely illegal dumping (*Illegal Waste=100*) is 13.4 percentage points more likely when corruption is a feasible option rather than if $Corrup = 0$.

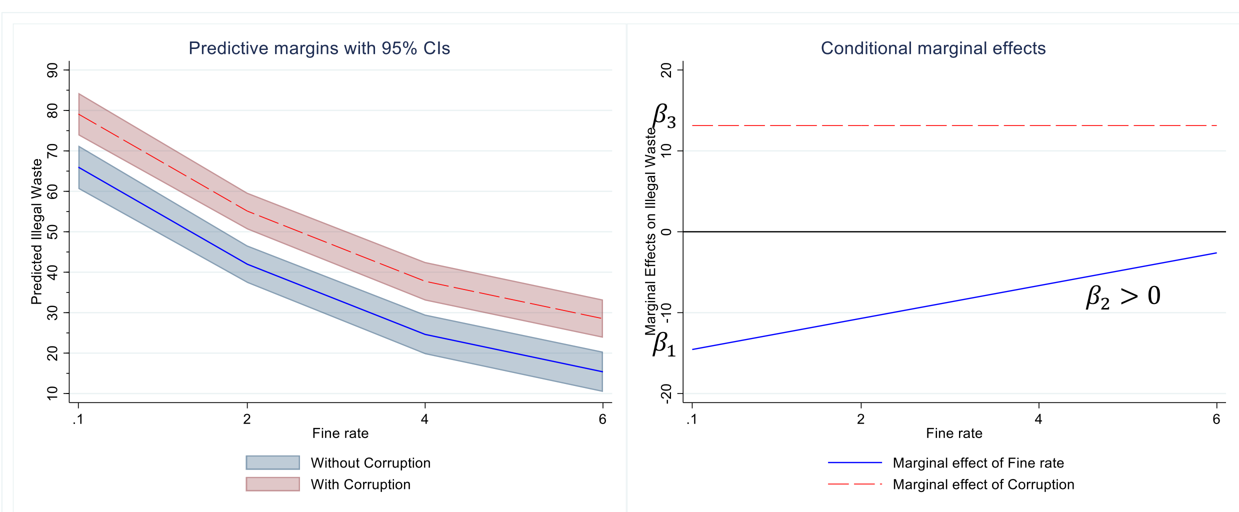
3.4 Discussion

Taking into account that OLS, Olog and G-Log estimators provide the same qualitative results, in this section we report conclusions on the hypotheses *Hp. 1* and *Hp. 2* using OLS coefficients (Table 2) because of simpler interpretation of coefficients. Accordingly, with regards to the first of the expected result/hypothesis, the empirical analysis proves that agents significantly increase illegal waste disposal for each level of deterrence when corruption is possible (i.e. *Hp. 1 - Dilution of crime deterrence*).

As for the second of the two expected result/hypothesis concerns - *Hp. 2 - The possibility of crime-encouraging or, at least, non-discouraging reactions to fine increments* - , findings for both model III and III_r validate the theoretical proposition according to which a U-shaped relationship (on average) exists between the level of the fine and illegal waste disposal (i.e. $\beta_1 < 0$ and $\beta_2 > 0$). Our results prove a crime non-discouraging fine rate, that for values of *f* larger than six may be also crime-encouraging.

Figure 1 (left-side) shows predicted illegal waste as a function of the fine $\hat{x}^*(f)$ in two scenarios (with and without corruption) according to the best specifications in the whole sample (model III_r) and the subsample of rational subjects (i.e. *Hp. 1*). On the right-hand-side of Figure 1, we show the marginal effects of change in fine levels and corruption on illegal waste (i.e. *Hp. 2*). Formally, the conditional marginal effects are derived from Model V as: $\frac{\partial \hat{x}^*}{\partial f} = \beta_1 + 2\beta_2 \times f = -14.76 + 2.26 \times f$ and $\frac{\partial \hat{x}^*}{\partial Corrup} = \beta_3 = 13.13$.

***Figure 1**. Predictive margins and conditional marginal effects*



4 Concluding remarks

Deterrence theory, based on a rational choice paradigm of decision-making, proposes that an offender will engage in criminal behavior if they believe that the expected payoff from criminal activity is larger than the costs associated with legal sanctioning if caught. A vast number of studies test hypotheses generated by deterrence theory. In this latter regard, our findings suggest that higher fines are indeed likely to be less effective than expected for the interaction with corruption.

We find that: (1) the possibility of corrupting public officials incentives illegal waste activity, and (2) a higher fine rate decreases illegal activity at a decreasing rate. In particular, this relationship may follow a U-shaped curve (given that $\beta_1 < 0$ and $\beta_2 > 0$).

The economic interpretation of these findings is that when the fine rate increases two effects co-exist: a first-order (negative) direct effect (i.e. higher fine rate decreases illegal waste due to the deterrence effect of a larger expected sanction) and a second-order indirect effect that appears only in presence of corruption. It supposes that corruption reduces the deterrence effect of higher fines on illegal waste. As conjectured by our theoretical model, the second-order effect may depend on the agent's conjecture that a higher fine makes corruption more profitable for the public official. Hence, while the dilution of crime deterrence of fines is originating from the presence of corruption (β_3), only for "cleverer" PC the possibility of a crime-encouraging fine is motivated by the higher likelihood that higher bribes incentive public officials to cheat.

As concern the lack of experimental evidence on a positive correlation between crime and sanction (as predicted by the U-shaped curve), two potential explanations are possible. The first hypothesis is that it depends on the maximum value of the fine fixed in the experimental setting (i.e. *f=6)* which is lower than the turning (minimum) point of the estimated quadratic relation between fine and illegal waste disposal ($f|_{Min(x^*)} = 7.6$). The second preferred hypothesis is that this result depends on the complex incentive mechanism linking the fine rate and corruption. Specifically, a higher fine rate is an effective incentive only for PCs that conjecture in their profit function the PO's likelihood to accept a bribe as illegal waste increases. This participant's ability to understand the incentive mechanism of PO, as explained in the instructions of the experiment, may be considered a proxy of PC's know-how and/or his familiarity with PO (Kugler et al. 2005). In our experiment, such a degree of PC's skills has not been achieved, therefore a fine rate greater than the maximum one used in our experiment would be required.

From a policy perspective, it is worth observing that our study sheds some light on the interaction between crime and corruption, in a way that highlights the key role of the optimal balance between anti-crime and anti-corruption policies. Indeed, public spending for anti-crime policies may be more or less effective than public spending for anti-corruption policies depending on context-specific benefits and costs associated to crime and corruption. This aspect cannot be ignored in the attempt to obtain an optimal crime-deterring sanctioning system by which effort in crime is effectively minimized.

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ONLINE APPENDIX
Appendix A. Experiment instructions

Welcome/a to the experiment,
You're playing a sequential group game.
Each group consists of two types of players: 10 PC (entrepreneurs) and 1 PO (controller).
There will be two phases: in each of these you will have to take a choice based on the role you will be assigned.
It is an incentive experiment: before making your choices, you will find instructions to participate in the winner draw with the respective payout (calculated according to the choices you will make).
All figures are expressed in ECU (Experimental Currency Units).
The exchange rate for payment is set at ECU100 = 1€.

You have been assigned the role of entrepreneur (PC).
Below you will find the information to make your choices.
"*You are an entrepreneur and have the opportunity to dispose of your company's illegal waste (X) in a landfill of 100 tons. Illegal disposal consists of transporting waste to another region with containers with a capacity of 50 tons each in an illegal landfill (or max 2 containers)*."

The profit from illegal disposal
Revenue: Every ton disposed of illegally allows you to save (gross gain) ECU 200.
Costs: The first 50 tons (1 container) can be transported illegally with a truck at a cost of ECU 800. If you dispose of more than 50 tons, you will have to take both containers on board a vessel for ECU 7500.
Your profit (π) is therefore given by:

$$\pi = 200ECU * X - 800ECU \; if \; x \leq 50tons$$
$$\pi = 200ECU * X - 7500ECU \; if \; x > 50tons$$

The activity of combating illegal disposal
The controller (PO) inspects 10% of the companies and sanctions illegal disposal with a fine of "f" times ECU 200 per ton illegally disposed.
For example:
- if it turns out that you have illegally disposed of 50 tons and the fine is ECU 20 per ton (f=0.1), you will have to pay: ECU 1000 fine. If f doubles (ECU 40 per ton illegally disposed of, f=0.2) the fine doubles (ECU 2000).
- if you have been illegally disposed of but not inspected, you will not be fined.

Winner's draw and payout
Remember, if you are checked out, your payment in euros will depend on the ECU earned with this choice.
The payoff will be calculated based on the choices made in this experiment, extracting a random scenario among those proposed (f=0.1, 2, 4, 6).
You will receive the result (winner/non-winner) and the payment collection process by email within 72 hours.

Enter your e-mail and start the experiment:

(Example: You are a person who has been assigned the role of Entrepreneur. The scenario with a fine (f) of 2 is drawn randomly. The controller has not inspected your company.
In the respective scenario you have chosen to dispose of X=50 tons, so your payoff is equal to:
Π = ECU 200 * 50 tonnes - ECU 800 = ECU 9200
Considering the exchange rate 100 ECU = 1€ -> The extracted party will receive a payment of 92€.)

YOUR CHOICE (STEP 1)
"Indicate (with a number from 0 to 100) how many tons (x) you dispose of illegally when the fine (f) is fixed at:"

	0	25	50	75	100
(f) = 0.1	○	○	○	○	○
(f) = 2	○	○	○	○	○
(f) = 4	○	○	○	○	○
(f) = 6	○	○	○	○	○

STEP 2: possibility to corrupt the controller

In this second phase of the experiment, we add a new variable to your decision:
The possibility of bribing the controller.
Without prejudice to the costs and revenues indicated in Phase 1, now both you and the anti-corruption authority know that some controllers let themselves be bribed with a bribe.

The corruption of the controller
The controller will ask you as a bribe to divide 50% with him the penalty not paid (which I remind you is proportional to the fine and therefore also to waste disposed of illegally).
Obviously, you do not know how much "discount" will make you on the sanction, but you know that the controller will have to evaluate whether or not to accept a bribe based on these two factors:

- the controller has a cost of falsifying documents which increases with the quantity of illegal waste disposed of.
- The controller shall be subject to supervision by the anti-corruption authority.
It discovers 50% of the auditors' corruption cases (remember that since controllers inspect 10% of companies, then the probability that your company is controlled by the anti-corruption authority is 5%, or 50%*10%).

The bribe you may offer is directly proportional to the amount of tons you illegally dispose of, and the controller's propensity to be bribed increases with the bribe offered.

When you decide how much to dispose of illegally you also assess that the controller, (another player selected by lot among the participants in the experiment) will be affected by the value of the bribe you can offer.
In particular, remember that he will or will not accept the bribe for his own personal gain.

His expected income is reduced by increasing the amount of waste that you dispose of illegally (because they increase his costs of counterfeiting) but will increase with the increase of the fine, f (because the bribe you offer him will be a percentage of the fine you will have to pay).

For example: if you illegally dispose of 50 tons and the fine f=0.1 (that is ECU 20 per ton) then the bribe you offer is ECU 500, but if f=6 (that is ECU 600 per ton) then you can offer the controller ECU 30,000.

The controller can choose after your bribe offer if:
1) Be honest (or denounce 100% of illegal waste): You do not pay any bribes but will pay the fine in full.
2) To partially denounce illegal waste disposal.

If in this control activity it is discovered that the controller (PO) has taken a bribe, the controller will be penalized with the dismissal (that is, any bribe received).

For example, if the controller:
(a) Report 100%: you will pay the entire penalty, and the controller gets no bribes.
(b) Report 50%: you will pay half of the penalty and the other half "saved" will be shared with the controller (i.e., you are paying 75% of the penalty due).
(c) Report 0%: you do not pay the penalty but pay the controller a bribe equal to half the fine "saved" (i.e., you are paying 50% of the penalty due).

If the controller is discovered, the bribe paid will be confiscated and you will also pay the remainder of the penalty (25% in the case (b), 50% in the case (c)), for a total of 100% of the fine, in addition to the costs of illegal disposal mentioned above.

YOUR CHOICE (STEP 2)

“Indicate (with a number from 0 to 100) how many tons (X) you dispose of illegally, knowing that the controller can be corrupted, when the fine (f) is fixed at”

	0	25	50	75	100
(f) = 0.1	○	○	○	○	○
(f) = 2	○	○	○	○	○
(f) = 4	○	○	○	○	○
(f) = 6	○	○	○	○	○

Socio-demographic information and personal preferences

- Age: _______

- Gender:
  - M
  - F
  - Other

- Net monthly family income:

  - less than 1,500€
  - between 1,500€ and 3,500€
  - between 3,500 and 4,500€
  - more than 4,500€

State how you agree with the following statements:

- "*If you want to make money, you can't always act honestly*"
  - 1 strongly disagree
  - 2
  - 3
  - 4
  - 5 strongly agree

- *"You should always strictly obey the law even if it means missing good opportunities*"
  - 1 strongly disagree
  - 2
  - 3
  - 4
  - 5 strongly agree

- *"To what extent do you feel a personal responsibility to try to reduce climate change?*"
  - 1 not at all
  - 2
  - 3
  - 4
  - 5 a great deal

- "*To what extent do you think that most people can be trusted?*"
  - 1 not at all
  - 2
  - 3
  - 4
  - 5 a great deal

Appendix A.2 - Proof of Proposition

From (7), $x_i^*|_{f=0} = \frac{(1-p)b}{c_c} > 0$ and $\frac{\partial x^*(f)}{\partial f}\Big|_{f=0} = \frac{bp[-2c_\rho - (1-\hat{p})\hat{p}S]}{2c_c c_\rho} < 0$. This proves that $x^*(f)$ is positive and decreasing at $f = 0$. Notice that $x^*(f)$ presents a vertical asymptote in the domain $f \in (0, +\infty)$ at $f_a = \left(\sqrt{2}\sqrt{c_c}\sqrt{c_\rho}\right)/\sqrt{b^2 p - 2b^2 p\hat{p} + b^2 p\hat{p}^2}$. Provided that, for $x^*(f)$ to be a maximum, the second-order condition must holds, meaning that the denominator in eq. (7) must be positive, $x^*(f)$ is positive when the numerator in eq. (7) is positive, that is, if $f > 2c_\rho(1-p)/\left[2c_\rho p + p\hat{p}S(1-\hat{p})\right] = \hat{f}$. Given the asymptote at $f = f_a$ and the positivity condition for the maximium $x^*(f)$, i.e. $f > \hat{f}$, it must be $\lim_{f \to f_a} x^*(f) = +\infty \; if \; f_a > \hat{f}$ and $\lim_{f \to f_a} x^*(f) = -\infty \; if \; f_a \leq \hat{f}$. Provided that $x^*(f)$ cannot admit more than two zeros, by continuity, if $f_a > \hat{f}$ then $x^*(f)$ is U-shaped in $f \in (0, f_a)$, whereas it is strictly decreasing in $f \in (0, f_a)$ if $f_a \leq \hat{f}$. In addition, from first and second-order conditions on $x^*(f)$, if a minimum exists, then it must be

$$f^* = \frac{2bc_\rho(1-p)(1-\hat{p}) + \sqrt{2c_\rho\left[2b^2 c_\rho(1-p)^2(1-\hat{p})^2 + pc_c\left(2c_\rho + (1-\hat{p})\hat{p}S\right)^2\right]}}{bp(1-\hat{p})\left[2c_\rho + (1-\hat{p})\hat{p}S\right]}$$

Appendix A.3 - Descriptive statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
Illegal Waste	1264	44.383	37.635	0	100
Fine	1264	3.025	2.204	.1	6
Corruption	1264	0.5	0.5	0	1
Male	1264	0.665	0.472	0	1
Age	1264	22.506	4.111	17	43
Inc_class	1264	2.266	.984	1	4
Honesty	1264	2.5	1.211	1	5
Law_Resp	1264	3.538	.998	1	5
Clim_resp	1264	1.956	.852	1	4
Trust	1264	3.677	.844	1	5

Appendix A.4 -Robustness checks

Table A.4.1 *OLS regression (Dep. Variable_ Illegal waste - All respondents, N=158)*

	(I)	(II)	(III)	(IV)	(II_r)	(III_r)	(IV_r)	(V)	(VI)	(VII)	(VIII)
Fine	-7.579***	-7.741***	-13.263***	-15.249***	-7.741***	-13.263***	-15.249***	-13.426***	-13.263***	-15.249***	-11.278***
	(-13.26)	(-12.23)	(-10.80)	(-10.65)	(-12.26)	(-10.83)	(-10.68)	(-10.71)	(-10.83)	(-10.69)	(-8.13)
Fine^2			0.930***	1.229***		0.930***	1.229***	0.930***	0.928***	1.229***	0.632***
			(6.56)	(7.27)		(6.58)	(7.29)	(6.58)	(6.21)	(7.30)	(3.70)
Corruption	12.579***	11.596***	12.579***	8.924***	11.596***	12.579***	8.924***	11.596***	12.523***		
	(7.06)	(4.54)	(7.05)	(3.39)	(4.55)	(7.07)	(3.40)	(4.55)	(5.67)		
Corr.#Fine		0.325		3.971**	0.325		3.971**	0.325			
		(0.51)		(2.86)	(0.51)		(2.86)	(0.51)			
Corr.#Fine^2				-0.597**			-0.597**		0.004		
				(-3.17)			(-3.18)		(0.04)		
Control Variables											
Male	4.477	4.477	4.477	4.477							
	(1.17)	(1.17)	(1.17)	(1.17)							
Age	0.483	0.483	0.483	0.483							
	(1.24)	(1.24)	(1.24)	(1.24)							
Honesty	1.415	1.415	1.415	1.415							
	(0.79)	(0.79)	(0.79)	(0.79)							
Law_Resp	-2.630	-2.630	-2.630	-2.630							
	(-1.31)	(-1.31)	(-1.31)	(-1.31)							
Clim_resp	-2.277	-2.277	-2.277	-2.277							
	(-0.92)	(-0.92)	(-0.92)	(-0.92)							
Trust	-3.193	-3.193	-3.193	-3.193							
	(-1.64)	(-1.63)	(-1.63)	(-1.63)							
Inc_class	-1.268	-1.268	-1.268	-1.268							
	(-0.61)	(-0.61)	(-0.61)	(-0.61)							
constant	72.008***	72.500***	76.176***	78.004***	61.510***	65.186***	67.014***	65.677***	65.214***	67.014***	75.937***
	(4.93)	(4.90)	(5.21)	(5.25)	(21.93)	(23.88)	(22.30)	(22.26)	(22.89)	(22.31)	(27.55)
N	1264	1264	1264	1264	1264	1264	1264	1264	1264	632	632
adj. R^2	0.240	0.240	0.249	0.249	0.223	0.232	0.232	0.232	0.231	0.220	0.201
AIC	12421.0	12422.9	**12407.7**	12410.0	12443.4	12428.6	12431.0	12430.5	12430.6	6223.6	6207.3
BIC	12472.5	12479.4	12464.3	12476.9	12463.9	**12449.2**	12461.8	12456.2	12456.4	6236.9	6220.6
Ramsey_pv	0.207	0.0620	0.703	0.923	0.00133	0.795	0.596	0.596	0.565	0.606	0.765

Note: t-stat is reported in parentheses. We employ Cluster-robust standard errors (at individual level). *, **, *and* *** *to denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table A.4.2 - *OLS regression (Dep. Var: Illegal waste; Ordinal control var. - All respondents, N=158)*

	(I)	(II)	(III)	(IV)	(II_r)	(III_r)	(IV_r)
Fine	-7.579***	-7.741***	-13.263***	-15.249***	-7.741***	-13.263***	-15.249***
	(-13.20)	(-12.16)	(-10.75)	(-10.60)	(-12.26)	(-10.83)	(-10.68)
Fine²			0.930***	1.229***		0.930***	1.229***
			(6.53)	(7.24)		(6.58)	(7.29)
Corruption	12.579***	11.596***	12.579***	8.924***	11.596***	12.579***	8.924***
	(7.02)	(4.51)	(7.02)	(3.38)	(4.55)	(7.07)	(3.40)
Corr.#Fine		0.325		3.971**	0.325		3.971**
		(0.51)		(2.84)	(0.51)		(2.86)
Corr.#Fine²				-0.597**			-0.597**
				(-3.16)			(-3.18)
Male	3.796	3.796	3.796	3.796			
	(0.94)	(0.94)	(0.94)	(0.94)			
Age	0.794*	0.794*	0.794*	0.794*			
	(2.18)	(2.18)	(2.18)	(2.18)			
2.Inc_class	-5.539	-5.539	-5.539	-5.539			
	(-1.12)	(-1.12)	(-1.12)	(-1.12)			
3.Inc_class	-7.879	-7.879	-7.879	-7.879			
	(-1.32)	(-1.32)	(-1.32)	(-1.32)			
4.Inc_class	-4.146	-4.146	-4.146	-4.146			
	(-0.63)	(-0.63)	(-0.63)	(-0.63)			
2.Honesty	-7.478	-7.478	-7.478	-7.478			
	(-1.51)	(-1.51)	(-1.51)	(-1.51)			
3.Honesty	-8.387	-8.387	-8.387	-8.387			
	(-1.22)	(-1.21)	(-1.21)	(-1.21)			
4.Honesty	1.139	1.139	1.139	1.139			
	(0.19)	(0.19)	(0.19)	(0.19)			
5.Honesty	6.566	6.566	6.566	6.566			
	(0.56)	(0.56)	(0.56)	(0.56)			
2.Law_Resp	-5.511	-5.511	-5.511	-5.511			
	(-0.78)	(-0.77)	(-0.77)	(-0.77)			
3.Law_Resp	0.464	0.464	0.464	0.464			
	(0.07)	(0.07)	(0.07)	(0.07)			
4.Law_Resp	-7.316	-7.316	-7.316	-7.316			
	(-1.22)	(-1.22)	(-1.22)	(-1.22)			
5.Law_Resp	-17.435*	-17.435*	-17.435*	-17.435*			
	(-2.08)	(-2.08)	(-2.08)	(-2.08)			
2.Clim_resp	-1.236	-1.236	-1.236	-1.236			
	(-0.29)	(-0.29)	(-0.29)	(-0.29)			
3.Clim_resp	-8.633	-8.633	-8.633	-8.633			
	(-1.93)	(-1.93)	(-1.93)	(-1.93)			
4.Clim_resp	18.967	18.967	18.967	18.967			
	(1.76)	(1.76)	(1.76)	(1.76)			
2.Trust	-0.851	-0.851	-0.851	-0.851			
	(-0.09)	(-0.09)	(-0.09)	(-0.09)			
3.Trust	7.386	7.386	7.386	7.386			
	(0.75)	(0.75)	(0.75)	(0.75)			
4.Trust	-5.823	-5.823	-5.823	-5.823			
	(-0.63)	(-0.63)	(-0.63)	(-0.63)			
5.Trust	-0.955	-0.955	-0.955	-0.955			
	(-0.10)	(-0.10)	(-0.10)	(-0.10)			
constant	57.581***	58.072***	61.748***	63.576***	61.510***	65.186***	67.014***
	(4.40)	(4.41)	(4.69)	(4.79)	(21.93)	(23.88)	(22.30)
N	1264	1264	1264	1264	1264	1264	1264
adj. R^2	0.287	0.287	0.296	0.296	0.223	0.232	0.232
AIC	12351.1	12352.9	**12336.6**	12338.7	12443.4	12428.6	12431.0
BIC	12464.2	12471.2	12454.8	12467.3	12463.9	**12449.2**	12461.8
Ramsey_pv	0.762	0.659	0.214	0.270	0.00133	0.795	0.596

*Note: t-stat is reported in parentheses. We employ Cluster-robust standard errors (at individual level). *, **, and *** to denote statistical significance at the 10%, 5%, and 1% levels, respectively. Outputs of models V, VI, VII, VIII are equal to Table A.4.1*

Table A.4.3 *OLS (Dep. Var.: Illegal waste; Ordinal control var. - Only Rational Respondents, N=148)*

	(I)	(II)	(III)	(IV)	(II_r)	(III_r)	(IV_r)
Fine	-8.566***	-8.907***	-14.755***	-16.883***	-8.907***	-14.755***	-16.883***
	(-16.77)	(-16.07)	(-12.27)	(-11.87)	(-16.21)	(-12.37)	(-11.98)
Fine²			1.013***	1.305***		1.013***	1.305***
			(6.98)	(7.42)		(7.04)	(7.49)
Corruption	13.133***	11.069***	13.133***	8.448**	11.069***	13.133***	8.448**
	(7.12)	(4.16)	(7.12)	(3.10)	(4.20)	(7.18)	(3.13)
Corr.#Fine		0.683		4.257**	0.683		4.257**
		(1.06)		(2.96)	(1.07)		(2.99)
Corr.#Fine²				-0.585**			-0.585**
				(-3.04)			(-3.06)
Male	3.647	3.647	3.647	3.647			
	(0.87)	(0.87)	(0.87)	(0.87)			
Age	0.837*	0.837*	0.837*	0.837*			
	(2.19)	(2.19)	(2.19)	(2.18)			
2.Inc_class	-5.132	-5.132	-5.132	-5.132			
	(-0.98)	(-0.98)	(-0.98)	(-0.98)			
3.Inc_class	-6.582	-6.582	-6.582	-6.582			
	(-1.04)	(-1.04)	(-1.04)	(-1.04)			
4.Inc_class	-2.458	-2.458	-2.458	-2.458			
	(-0.35)	(-0.35)	(-0.35)	(-0.35)			
2.Honesty	-6.355	-6.355	-6.355	-6.355			
	(-1.20)	(-1.20)	(-1.20)	(-1.20)			
3.Honesty	-8.837	-8.837	-8.837	-8.837			
	(-1.16)	(-1.16)	(-1.16)	(-1.16)			
4.Honesty	2.776	2.776	2.776	2.776			
	(0.45)	(0.45)	(0.45)	(0.45)			
5.Honesty	6.704	6.704	6.704	6.704			
	(0.54)	(0.54)	(0.54)	(0.54)			
2.Law_Resp	-6.841	-6.841	-6.841	-6.841			
	(-0.96)	(-0.96)	(-0.96)	(-0.96)			
3.Law_Resp	1.159	1.159	1.159	1.159			
	(0.17)	(0.17)	(0.17)	(0.17)			
4.Law_Resp	-7.327	-7.327	-7.327	-7.327			
	(-1.20)	(-1.20)	(-1.20)	(-1.20)			
5.Law_Resp	-16.781*	-16.781*	-16.781*	-16.781*			
	(-2.00)	(-2.00)	(-2.00)	(-1.99)			
2.Clim_resp	0.039	0.039	0.039	0.039			
	(0.01)	(0.01)	(0.01)	(0.01)			
3.Clim_resp	-7.646	-7.646	-7.646	-7.646			
	(-1.62)	(-1.62)	(-1.62)	(-1.62)			
4.Clim_resp	20.699	20.699	20.699	20.699			
	(1.96)	(1.96)	(1.96)	(1.96)			
2.Trust	-2.507	-2.507	-2.507	-2.507			
	(-0.24)	(-0.24)	(-0.24)	(-0.24)			
3.Trust	7.265	7.265	7.265	7.265			
	(0.70)	(0.70)	(0.70)	(0.70)			
4.Trust	-6.099	-6.099	-6.099	-6.099			
	(-0.63)	(-0.63)	(-0.63)	(-0.62)			
5.Trust	-2.166	-2.166	-2.166	-2.166			
	(-0.22)	(-0.22)	(-0.22)	(-0.22)			
constant	57.155***	58.187***	61.692***	64.034***	63.938***	67.443***	69.785***
	(4.08)	(4.14)	(4.38)	(4.51)	(22.32)	(24.29)	(22.91)
N	1184	1184	1184	1184	1184	1184	1184
adj. R^2	0.341	0.341	0.351	0.351	0.275	0.285	0.285
AIC	11502.3	11503.6	**11484.9**	11486.5	11598.7	11582.0	11583.9
BIC	11614.0	11620.3	11601.6	11613.4	11619.0	**11602.3**	11614.3
Ramsey_pv	0.227	0.092	0.202	0.361	0.000	0.739	0.613

Note: t-stat is reported in parentheses. We employ Cluster-robust standard errors (at individual level). *, **, *and* *** *to denote statistical significance at the 10%, 5%, and 1% levels, respectively. Outputs of models V, VI, VII, VIII are equal to Table 2.*