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Research Paper

Maximal fines and corruption: An experimental study on illegal waste disposal

Antonio Abatemarco[a,*], Alessandro Cascavilla[b], Roberto Dell'Anno[a], Andrea Morone[c]

[a] Department of Economics and Statistics, CELPE, University of Salerno, Via Giovanni Paolo II, 132, 84084 Fisciano, SA, Italy
[b] Department of Law and Economics, Unitelma Sapienza University, Italy
[c] Department of Economics, Management and Law, University of Bari "Aldo Moro", Italy

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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. From 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.

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. Levitt, 1998; Haselhuhn et al., 2012; DeAngelo and Charness, 2012; Hansen, 2015; Chalfin and McCrary, 2017).

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 (Stigler, 1970; Polinsky and Shavell, 1979, 1992; Bebchuk and Kaplow, 1992; Feess et al., 2018). Corruption of public officials (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 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.[1]

In this paper, we provide experimental evidence on the impact of corruption – intended as 'corruption with theft' of public officials (Shleifer 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 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.

Our focus on waste management is motivated by recent evidence emphasizing the remarkable impact of corruption and organized crime on illegal transport and disposal of waste (Liddick, 2010; European Commission, 2014; Abrate et al., 2014; Cesi et al., 2019). Not

* Corresponding author.
E-mail addresses: aabatemarco@unisa.it (A. Abatemarco), alessandro.cascavilla@unitelmasapienza.it (A. Cascavilla), rdellanno@unisa.it (R. Dell'Anno).

[1] 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.".

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surprisingly, in December 2019, the Conference of the States Parties (CoSP) to the United Nations Convention adopted resolution 8/12, which "notes with concern the role that corruption can play in crimes that have an impact on the environment, which may constitute a growing source of profits for various criminal activities" (UNODC, 2021). In this scenario, a greater research effort is required for a better understanding of economic mechanisms affecting crime deterrence when the possibility of corruption is opportunely accounted for; this is particularly important as far as corruption can undermine any crime-deterring sanctioning system.

Recent empirical evidence highlighted the impact of corruption on waste management practices. Analyzing data from Italian provinces, Romano et al. (2021) reveal that higher corruption and maladministration levels are associated with increased per capita urban waste production, indicating potential opportunities for illicit activities at the expense of public interests. Furthermore, D'Amato et al. (2018) provide empirical evidence that a stronger waste policy commitment can paradoxically increase illegal waste disposal in Italy, and that a nonlinear relationship exists between inspection frequency and illegal disposal quantity. This evidence supports the complex dynamic between punishment, uncertainty, and deterrence, as suggested by Feess et al. (2018). Specifically, by means of a theoretical model and laboratory experimental evidence, Feess et al. (2018) argue that higher fines reduce the violation and the punishment frequency, while legal uncertainty increases the number of violations and decreases the punishment frequency. Moreover, higher fines are associated with a reduction in the punishment frequency if and only if there is legal uncertainty. Therefore, the role of environmental controls for effective deterrence is found to be crucial.

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 available to the public enforcement agency when an authority is expected to prevent both crimes and public officials' corruption. In their model, any increase in the fine imposed on 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. Even if the indirect effect can never dominate the direct effect in the basic framework, they prove that, if one allows for a third actor, e.g. the policy department that is maximizing social welfare in the presence of a social cost of corruption,[2] then the indirect effect of the fine may become dominating so as to observe a greater supply of crime when the fine is increased.[3]

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[4] hire criminals in the presence of a reservation wage which is decreasing in corruption due to a lower risk premium; hence, when corruption becomes higher due to greater expected fines, 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 (e.g., detection probabilities).

Our theoretical framework shares with Bowles and Garoupa (1997) the application of Becker's 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 of 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, $x \in R_0^+$, at time 1 (e.g. illegal waste disposal), and a public official

[2] In line with Shleifer and Vishny (1993), they assume that corruption is an evil per se, in that it jeopardizes market competition, economic development, democracy, etc., all of these causing efficiency losses in the allocation of resources.

[3] 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.

[4] Corruption indeed is more likely to occur in the case of criminal organizations playing repeated (not one-shot) games with public officials (Cesi et al., 2019).

who may detect and prevent crime with probability p at time 2.[5] 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.[6]

At time 2, corruption may occur. Provided that crime has been detected and prevented (incapacitation[7]), 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. $(1/2)\rho\ fbx$.[8] 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; Shleifer 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 $\widehat{p}$. 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, $(1/2)\rho\ fbx$, with an overall negative payoff equal to fbx.[9] As for the public official, the bribe is confiscated and a proportional sanction, $\rho\ S$, 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

$$\rho^* = \underset{\rho}{argmax}\widehat{EU}(\rho) = \widehat{p}\left(-\rho\ S - \frac{1}{2}c_\rho\rho^2\right) + (1-\widehat{p})\left(\frac{1}{2}\rho\ fbx - \frac{1}{2}c_\rho\rho^2\right) \tag{1}$$

implying

$$\rho^*(x) = \frac{(1-\widehat{p})fbx - 2\widehat{p}S}{2c_\rho} \tag{2}$$

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,

$$\rho^*(x) = \{0 \Leftrightarrow bx \le \frac{\widehat{p}}{1-\widehat{p}}\frac{2S}{f} 1 \Leftrightarrow bx \ge \frac{2c_\rho + 2\widehat{p}S}{(1-\widehat{p})f} \tag{3}$$

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).

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 $p\widehat{p}$; (ii) with probability $p(1-\widehat{p})$, 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:

$$\begin{aligned} x^* &= \underset{x}{argmax}EU(x) = p\widehat{p}\left[-fbx - \frac{1}{2}c_c x^2\right] \\ &+ p(1-\widehat{p})\left[-(1-\rho^*(x))fbx - \frac{1}{2}\rho^*(x)fbx - \frac{1}{2}c_c x^2\right] + (1-p)\left(bx - \frac{1}{2}c_c x^2\right) \end{aligned} \tag{4}$$

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

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

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.[10]

Not surprisingly, if $\widehat{p} = 1$ 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 $f \ge \underline{f}$ such

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

[6] The fine, f, can be intended as a monetization of any kind of punishment cost for crime (e.g. incarceration, social stigma).

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

[8] 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 1) can be generalized for any exogenous value of the sharing rule.

[9] 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).

[10] 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.

that $x^* = 0$. 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:

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

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:

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

with $\left[2c_c c_\rho - b^2 f^2 (1-\hat{p})^2 p\right] > 0$ in (4) for x_i^* to be a finite maximum (Second-Order Condition).[11]

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.[12] Most importantly, as formalized in the following Proposition, effort in crime may not be strictly decreasing with the fine f.

Proposition 1. 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.

Proposition 1 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).

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 generally originates 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 is composed of 158 students, recruited on the social web page of the largest Italian network of economics students in Italy.[13] 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 operative cost to dump waste illegally and it is an opportunity cost associated with 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 are asked to complete a questionnaire, in which they are assigned the role of Private Citizen (PC), while the other roles are played by the nature. We informed the participants that, at the end of the experiment, one of them would have been randomly selected for the monetary payoff (with the exchange rate 100ECU = 1€, where ECU stands for experimental currency units).[14]

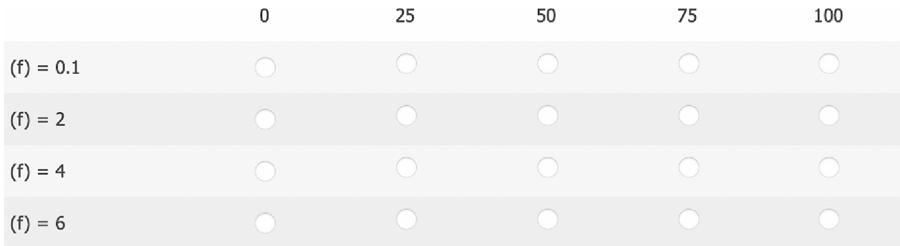
Each subject playing the role of Private Citizen faces the hypothetical opportunity to dispose up to 100 tons of waste illegally ($x_i = 0; 25; 50; 75; 100$), knowing that the marginal benefit for each unit of

[11] 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).

[12] 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.

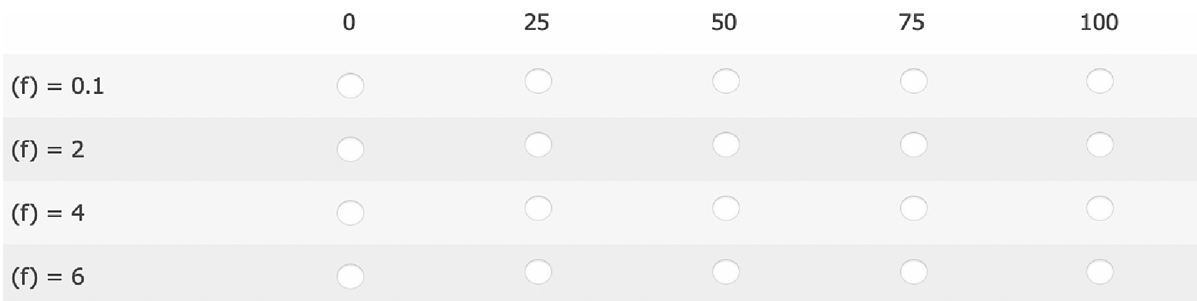
[13] The network is called "Economia del Suicidio", and it counts over 170.000 Italian economics students. We have run a power test before conducting the online experiment to estimate the minimum sample size. According to the proposed parametrization and treatments, at least 120 observations were needed to obtain a statistical power of 95%. Therefore, the survey remained available online to get more than 120 observations, reaching a total number of 158. The additional observations further contribute to the validity of the experimental results.

[14] The survey has been published on the 1st of June 2022, and it remained available until June 2nd, 2022. The average time to complete the survey has been about 12.36 min. The randomly extracted participant received a payoff of 42€ (4200 ECUs) with a time to complete the questionnaire of about 9 min. 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.



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

Fig. 1. T1: "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					

Fig. 2. T2: "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."

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 know that the market is composed of 10 PC and 1 PO, and that the latter is supposed to randomly control and sanction 1 out of 10 ($p = 10\%$) Private Citizens, in case of illegal disposal of waste, with a fine equal to $F = f \times 200ECU \times x_i$. We propose 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).

3.1.1. Treatment 1: No corruption (T1)

In this treatment, subjects know that PO randomly checks 10 % of the market sanctioning on the entire amount of illegal disposal detected, without any possibility of corruption. Then, we ask subjects to choose how much to dispose illegally (x^*), according to each level of the fine (f). The first set of four decisions is displayed as in Fig. 1.

According to the standard theoretical framework for rational expected utility maximizers, we expect an increase in deterrence factors (i.e., an increase in the fine) to monotonically reduce the level of illegal waste, i.e. $\frac{dx^*(.)}{df} < 0$. Once the amount of illegal waste is selected for each level of the fine, each participant moves to the next treatment.

3.1.2. Treatment 2: Possibility of corruption (T2)

In this treatment, we include 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 can decide to under-report 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 provide PC with information about the determinants of the PO's willingness to be corrupted. In particular, according to the theoretical framework, we propose 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 know that PO's decision of under-reporting – hence to accept a bribe – is affected by two factors: (i) 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) PO shall be subject to supervision by the anti-corruption authority, IAD, which we assume to discover the 50 % of auditors' corruption cases. Since PO inspects 10 % of companies, then the probability that PC's company is controlled by the anti-corruption authority is $\hat{p} = 50\% \times 10\% = 5\%$. 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 appears as in Fig. 2:

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 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 the case of 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

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 the actual randomization distribution of the test statistic.

and honest/corrupting behavior.[15] In particular, we consider their attitude in terms of: Honesty ("*If you want to make money, you can't always act honestly*"); Respect for 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 include 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 disposal may be observed on average.

3.2. Results

Table 1 describes the experimental outcomes. These results, such as the econometric findings of Section 3.3 – are based on a sample of 148 respondents because we exclude 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 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 to increase the external validity of our empirical results. As robustness checks, we estimate the econometric regressions including all 158 respondents, and the findings are qualitatively the same (Appendix A.4 reports these robustness checks).

Due to the ordinal/categorical nature of variables and repeated measures (i.e. paired sample), we preliminarily run *Wilcoxon Signed Rank Tests* (Table 1) to verify the statistically significant difference in illegal dumping between the two experimental settings (with and without corruption) for each level of the fine.

3.3. Econometric analysis

In this section, we analyze the relationship between the level of illegal waste disposal and the fine. Specifically, we estimate the following econometric specification:

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

where x_i^* represents an unobservable latent variable underlying the measure of illegal waste 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[16]; *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[17];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

[15] 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 5th January 2023.

[16] 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.

[17] 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).

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.

assumption, e.g., McCullagh and Nelder, 1989; Peterson and Harrell, 1990).[18]

As for Treatment 2 (i.e. with corruption) 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) and "rational" participants. 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).

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-R2, 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 fit 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) are 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.[19] This estimation 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, *IllegalWaste* = 0, versus *IllegalWaste* ≥ 25 (model III_r.1); the second model does the same regarding categories *IllegalWaste* ≤ 25 versus *IllegalWaste* ≥ 50 (model III_r.2); the third model compares the choice between categories *IllegalWaste* ≤ 50 versus *IllegalWaste* ≥ 75 (model III_r.3) and *IllegalWaste* ≤ 75 versus *IllegalWaste* = 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

[18] As robustness checks, we also estimate the models with control variables treated as ordinal instead of continuous variables. Results are qualitatively the same (Appendix A.4 reports these robustness checks).

[19] 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 on Generalized Ordered Logistic regression.

Table 3
Generalized Ordered logistic regressions (Dep. Var.: 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.

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^{***}

with the highest value offers a better fit to the data).

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). Since 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 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 (*IllegalWaste* = 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 (*IllegalWaste* = 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-Olog 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 the existence of a crime non-discouraging fine rate, that for values of f larger than six may be also crime-encouraging.

Fig. 3 (left-side) shows predicted illegal waste as a function of the fine $\widehat{x}^*(f)$ 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 Fig. 3, 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: $\frac{\partial \widehat{x}^*}{\partial f} = \beta_1 + 2\beta_2 \times f = -14.76 + 2.26 \times f$ and $\frac{\partial \widehat{x}^*}{\partial Corrup} = \beta_3 = 13.13$.

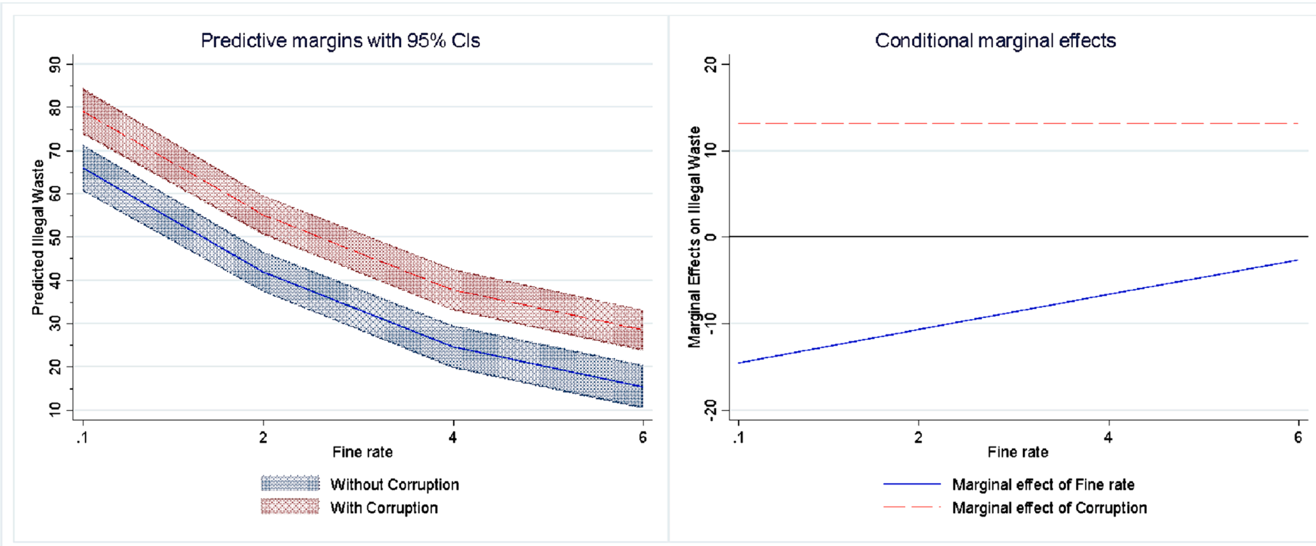


Fig. 3. Predictive margins and conditional marginal effects.

4. Concluding remarks

Our findings suggest that higher fines are likely to be less effective than expected for the interaction with corruption. Specifically, we prove that: (1) corruption enhances illegal waste activity, and (2) higher fines decrease illegal activity at a decreasing rate, with a U-shaped pattern under some circumstances (given that $\beta_1 < 0$ and $\beta_2 > 0$).

These results are driven by two effects: a first-order (negative) direct effect, i.e. higher fine rate decreases illegal waste due to the deterrence effect of a greater expected sanction, and a second-order indirect effect, which 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 encourage 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 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, Cesi et al., 2019). 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 two types of crimes (i.e., illegal waste disposal and corruption), in a way that emphasizes the key role of the optimal balance between the marginal effect of anti-environmental crime (i.e., $\widehat{\frac{\partial x}{\partial f}} = \beta_1 + 2\beta_2 \times f$) and anti-corruption policies (i.e., $\widehat{\frac{\partial x}{\partial Corrup}} = \beta_3$). Indeed, the optimal allocation of public resources to reduce illegal waste disposal can be obtained by equalizing the marginal returns of one extra euro invested in the two policies (i.e., $\widehat{\frac{\partial x^*}{\partial f}} = \widehat{\frac{\partial x^*}{\partial Corrup}}$). From this general rule, we derive that the optimal allocation may be different across local governments, in that influenced by context-specific benefits and costs associated with illegal waste disposal and corruption at the local level. Specifically, provided that the fine rate is the same at the national level, spatial heterogeneities among local jurisdictions in terms of social capital, organized crime, etc. imply that the level of anti-corruption policies should be opportunely diversified in order to equalize the marginal returns weighted by the monetary cost of public policies. To provide some examples, in a perspective of crime minimization, it may be convenient for the policy-maker to increase the fine rate at the national level and transfer these extra revenues from the jurisdictions with higher to those with lower social capital in such a way as to obtain a higher probability of corruption detection where it is more profitable.

Our experimental findings also support theoretical results on the importance of staff rotation to prevent corruption in repeated games (e.g., Abbink, 2004; Cesi et al., 2019). More specifically, in our "one-shot game" experiment – which resembles the idea of a strict staff rotation mechanism – we find that crime deterrence is greater than expected because the criminal is not able to fully anticipate the (expected) gains from corruption.

In our view, these policy implications can enrich the current debate on the optimal design of a crime-deterring sanctioning system for both national and regional policies against environmental crime.

CRediT authorship contribution statement

Antonio Abatemarco: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Alessandro Cascavilla:** Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Roberto Dell'Anno:** Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Andrea Morone:** Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wasman.2024.04.036

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