Uncertain Penalties and Compliance

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Abstract: We present the results of a series of laboratory economic experiments designed to study compliance behavior of polluting firms when information on the penalty is uncertain. The experiments consist of a regulatory environment in which university students face emission standards and an enforcement mechanism composed of audit probabilities and penalties (conditional on detection of a violation). We examine how uncertainty on the penalty affects the compliance decision and the extent of violation under two enforcement levels: one in which the regulator induces perfect compliance and another one in which it does not. Our results suggest that in the first case, uncertain penalties increase the extent of the violations of those firms with higher marginal benefits. When enforcement is not sufficient to induce compliance, the uncertain penalties do not have any statistically significant effect on compliance behavior. Overall, the results suggest that a cost-effective design of emission standards should consider including public and complete information on the penalties for violations.

Keywords: uncertainty, penalty, emission standard, economic experiment

JEL Classification: C91, L51, Q58, K42

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1. Introduction

Enforcement to induce compliance is a key element of the regulatory process. In the conventional model of enforcement (Becker, 1968), the regulated entity is an expected profit maximizer who, when deciding whether to comply with a norm, compares the marginal costs of complying with the marginal expected benefit of not complying. In this model, the regulator has two instruments to induce deterrence: inspections (to detect violations) and penalties (to sanction discovered violations). The regulated population, on the other side, has perfect information on the probability of being inspected, the penalties associated with every offense and responds accordingly. In the case of the classical models of enforcement of emission standards, which is our motivation, there is a one-to-one correspondence between the level of emissions in excess of the standard (the violation) and the amount of the fine, and the polluting firms know this correspondence (Harford, 1978; Heyes (2000); Stranlund et. al., 2002).

In the real world, this one-to-one correspondence between a given level of violation and the amount of the fine is not always observed. For example, in the Emissions Compensation Program of Santiago, Chile, the consequences of being found out of compliance vary between a written warning, a monetary penalty or a temporary closure. At the same time, the amount of the monetary penalties may fluctuate over a wide range, with the amount finally imposed depending, rather idiosyncratically, on characteristics of the offense and the offender (Palacios and Chávez 2002). In Uruguay, the Decree 253/79, which contains guidelines for water pollution control, imposes sanctions that vary according to the type of offense and its recurrence. The types of offenses are determined by specific causes behind the discovered illegal level of pollution: not having a treatment plant, not operating the treatment plant correctly, etc. Moreover, the type of offense and the recurrence do not define a given level of a penalty, but rather define the range, while the actual penalty within this range is left to the discretion of the inspector and the political will of officials. The situation is not apparently characteristic only of developing countries. In the US for example, while under SO2 program EPA automatically sanctions any excess emissions above the level of permits holdings with a known and predetermined fixed amount of money per excess tone, under the RECLAIM program facilities detected violating their emissions permits may face a financial penalty which depends on several specific circumstances, including, extent of violation, reasons for exceedance, and even effort of the facility to correct its violation (Stranlund et. al., 2002). More generally, it has been argued that "the legal system does not persistently pursues predictability in sanctioning" (Baker et al, 2003, p. 447). Taken together, these examples suggest that the consequences of committing an offense if detected are far from being completely known by the polluting sources when making the decision regarding their compliance status.[1] We refer to this situation as one in which penalties are uncertain. Certain penalties, on the other hand, are those in which there is a known one-to-one correspondence between every possible level of violation and the penalty.

In this work we present the results of a series of laboratory economic experiments designed to study the compliance behavior of polluting firms when information on the penalty for noncompliance is uncertain.[2] We examine how uncertainty on the penalty affects the compliance decision and the extent of violation under two regulatory schemes: one in which the regulator induces perfect compliance and another one in which it does not. This is an important matter because if uncertain

[1] An additional example is provided by Escobar and Chávez (2013) with respect to Mexico. In the event of detection of noncompliance with environmental regulations on emission discharges from companies operating in Mexico City, the authors note that, according to the current environmental legislation, the amount of the penalty that may be imposed by the responsible regulatory agency should consider several criteria, including the severity of the offense, financial situation of the offender, intention and negligence, and the economic benefits of noncomplying, among others.

[2] Whenever we refer to uncertainty, we refer to the uncertainty that can be measured. We are aware of Knight's distinction between risk (measurable uncertainty) and uncertainty (not measurable uncertainty). However, it seems better to talk about penalties of certain amounts versus penalties of uncertain amounts, rather than penalties of certain amounts versus penalties of risky amounts to differentiate the treatments of our experiments.

penalties decrease compliance, a regulator could increase compliance simply by making more transparent and clear the consequences of violations.

We found evidence that violations increase when penalties are uncertain, relatively to when they are certain, but only when the regulatory design induces compliance. When enforcement is weak (i.e.: not sufficient to induce compliance on risk-neutral individuals), violations do not vary in a statistically significant way between certain and uncertain penalties. The results suggest that a cost-effective regulation design should provide full information concerning the consequences of a violation.

2. Overview of the literature

The environmental enforcement literature was built upon theoretical models that in almost all cases assume both a known penalty for non-compliance and risk neutrality on the part of the polluting firms. In the tax compliance literature, Alm et al. (1992) argue that a subject will respond to an increase in risk in the penalty with an increase in declared income, if it exhibits non-decreasing absolute risk-aversion. On the other hand, Harel (1999) argues that criminals would prefer a scheme in which the degree of the sentence is uncertain.

De Angelo and Charness (2012) find that uncertainty in the probability of detection results in a significant reduction in detected offenses to a speed limit in a framed laboratory experiment. In contrast to De Angelo and Charness´s, our analysis investigates the effect of uncertainty on the level of the penalty for detected violations, not on the probability of being detected. In De Angelo and Charness's (2012) design, the penalty imposed on detected violators is well known by the regulated population.

The only experimental investigations of the effect of the uncertainty in the penalty on compliance behavior that we are aware of are Alm et. al. (1992) and Baker et. al. (2003). Using an income tax declaration framework, Alm et. al. (1992) find that an increase in measurable uncertainty (risk) in the penalty increases compliance. Using a frame in which subjects choose between lotteries through which they could gain additional money but being fined if caught playing, Baker et al (2003) found that an increase in risk in the penalty for playing the lottery decreases the percentage of subjects playing it. The literature does not distinguish between situations in which the enforcement regime induces perfect compliance and those in which there is noncompliance. Moreover, we are not aware of any work exploring the effect of uncertain penalties on the level of compliance of polluters with emission standards.

The paper is organized as follows. In the next section, we present the main hypotheses to be evaluated with our experimental design. In section 3, we describe the experimental design of our experiments and the procedures we used to implement them. Section 4 presents the results of our work. We conclude in section 5.

2. Hypotheses

In this section, we present the hypotheses we test. These hypotheses are based on the positive theoretical literature on behavior of polluting firms under emission standards (Harford 1978; Stranlund 2013; Arguedas 2008; Caffera and Chávez 2011). In this literature, typically, a regulatory agency conducts random inspections to control the level of compliance of a set of n polluting firms. If the agency detects a violation to the emission standard in an inspection, it imposes a fine. Firms are assumed to be risk-neutral. Each firm is completely described by a function of abatement costs $c(q)$ that is strictly decreasing and convex in the level of emissions q [$c'(q) < 0$ and $c''(q) > 0$]. The environmental target is a fixed aggregate level of emissions, denoted as Q, which is exogenously determined by the regulatory authority.

Each firm faces an emission standard s. The standard represents the maximum (legal) level of emissions that the firm can discharge, such that $\sum_i s_i = Q$. In this context, a violation of the standard, denoted as v, occurs when the emissions level of the firm exceeds the standard, $v = q - s > 0$. The firm is audited with an exogenously determined probability, π. An audit provides the regulator with perfect information about the firm's compliance status. If the regulator audits a firm and finds it violating the standard, it imposes the firm a penalty $f(v)$. Following Stranlund (2007), the structure of the penalty is given by $f\ (q - s)\ =\ \varphi(q - s)\ +\ (\gamma/2)(q - s)^2$, where $\varphi > 0$ and $\gamma > 0$.

Under the described regulatory scheme, and assuming that the penalty is known with certainty, a firm selects the level of emission to minimize its expected compliance costs. These are the sum of the abatement costs and the expected penalty. A risk neutral firm will choose to comply with the standard ($q\ =\ s$) if and only if $-c'(s) \leq \pi\varphi$ (Heyes 2000; Malik 1992; Harford 1978). That is, a firm will comply with the standard if the expected penalty for marginally violating the standard is higher than the marginal benefit (the marginal decrease in abatement costs). We say that a regulatory scheme induces compliance when this compliance condition holds for every firm. When the condition does not hold for at least one firm, we say the regulatory scheme allows violations. In the case, the violating firms will select a level of emission $q(s, \pi) > s$, where $q(s, \pi, \varphi, \gamma)$ is the solution to the equation $-c'(q) = \pi[\varphi + \gamma(q - s)]$.

Moreover, it is possible to show that a risk-neutral firm will not alter the level of emissions that choses with a given audit probability and non-random penalty, if confronted to a mean preserving spread of the penalty (a simple lottery or a compound lottery).[3] Accordingly, the hypotheses to be evaluated herein are as follows.

[3] This result is presented on Section 1 of the Appendix.

Hypothesis 1: *A mean preserving spread of a penalty function does not alter the firms' choice of emissions in a system of emission standards, under a regulation scheme that induces compliance.*

Hypothesis 2: *A mean preserving spread of a penalty function does not alter the firms' choice of emissions in a system of emission standards, under a regulation scheme that allows non-compliance.*

3. Experimental Design and Procedure

In this section, we present the experimental design and the procedures we used to implement our experiments.

3.1. Design

We framed the experiment as a neutral production decision of an unspecified good. Individuals take the role of a producer of a fictitious good from which each of them receive benefits per unit produced. The units produced can take values from 1 to 10. The marginal benefits obtained from the production of this good differ among individuals, creating four types of subjects: two with "high" marginal benefits from production and two with "low" marginal benefits (see Annex 1). These schedules of marginal benefits are the same through all the experiments and are randomly assigned across subjects. Production is subject to type-specific legal maximum levels (standards). A regulatory authority controls compliance to these maximum levels by conducting random inspections and imposing penalties on those detected producing more thatn the standard.

The design of the experiment considers two regulatory schemes. The first one induces perfect compliance. The second scheme allows violations of the standards by reducing the inspection rate and the emissions standards in amounts such that an expected profit maximizer firm would produce the same level of output in both regulatory schemes.

We construct six different treatments for this experiment (see Table 1) by varying the stringency of enforcement (strong and weak enforcement) and the (un)certainty subjects face with respect to the value of the penalty corresponding to a given level of violation (deterministic penalty, random penalty with simple lottery and random penalty with compound lottery), such that the expected value of the fine is the same in the three cases. All treatments consider an increasing marginal penalty. In the case of the deterministic penalty function, there is a one-to-one correspondence between each level of violation and the value of the fine. The simple lottery is mean-preserving spread of the deterministic penalty, in which the amount of the penalty may take a high value with a 50% probability or take a low value with 50% probability. Finally, in the case of a compound lottery penalty, subjects face a 33% chance of being penalized with the low value of the penalty, a 33% chance of being penalized with the high one, and a 33% chance that the penalty is determined with the previously described simple lottery (high/low value with 50%).

3.2. Procedure

The experiments were implemented using z-tree (Fishbacher (2007)) software in the laboratories of the Center for Training and Learning Resources at Universidad de Concepción, Chile. We recruited undergraduate students from the city of Concepción majoring in business and economics, civil industrial engineering, and auditing at the following institutions: Universidad de Concepción, Universidad Católica de la Santísima Concepción and Universidad del Bio-Bio. The students participating in the experiments were sophomores or above.

Table 1.Parameters per treatment

Treatment	Probability of monitoring per type of firm				Probability per type of penalty	Parameters value						Policy induces	Aggregated standards	Standard	Expected aggregated level of emissions
						Penalty		Low penalty		High penalty					
	Type 1	Type 2	Type 3	Type 4		Phi	Gamma	Phi	Gamma	Phi	Gamma				
T1	0.6	0.65	0.63	0.66	1	100	66.67					Compliance	40	Type 1=7 Type 2=6 Type 3=4 Type 4=3	40
T2	0.6	0.65	0.63	0.66	0.5 (Simple lottery)			50	33.37	150	99.9				
T3	0.6	0.65	0.63	0.66	0.5 (Compund lottery)			50	33.37	150	99.9				
T4	0.24	0.26	0.32	0.32	1	100	66.67					Violations	20	Type 1=4 Type 2=3 Type 3=2 Type 4=1	
T5	0.24	0.26	0.32	0.32	0.5 (Simple lottery)			50	33.37	150	99.9				
T6	0.24	0.26	0.32	0.32	0.5 (Compund lottery)			50	33.37	150	99.9				

Subjects participating in a session were randomly assigned into groups of eight individuals. The number of subjects showing up for a session was not always multiple of eight. This was not a problem because in these standards experiments the subjects do not relate with each other in any form. Each eight-subject group comprised a group of firms regulated by a set of the emissions standards. A maximum of four groups of eight participated in a particular session.

The experiment consisted of six different treatments performed over nine experimental sessions.[4] The subjects participated in only one experimental session. In each session, they were exposed to two different treatments. We reversed the order of application of the treatments to control for potential order effects. Each treatment had two initial test periods and ten actual periods. At the beginning of each session, the experimenter read the instructions aloud with PowerPoint slides highlighting the key points. Two practice rounds were then allowed and subjects' questions were answered.[5] At the beginning of each treatment, the subjects had an initial working capital of 1,050 experimental pesos. In their personal screen, each subject had information on the profits obtained per each unit produced, the limit of production, the fine for each level of violation and the probability of inspection. In each period, the subjects had two minutes to make the production decision. After all subjects in the group had made their decision, the computer program produced a random number between 0 and 1 for each subject. If this number was below the informed probability of being monitored, the subject was inspected. Subjects were informed in their screen whether they had been selected for inspection or not, and the result of the inspection (violation level, total fine and net profits after inspection). After this, subjects were informed in their screen the history of

[4] The detail of the treatments conducted in each session is presented in Table A.2 in Annex 2.
[5] The English version of the instructions is available in section 2 of the Appendix.

their decisions in the game, the history of inspections and the history of profits, up to the last period just played. After 20 seconds in this screen, the next period began automatically.

After completing the ten periods, the first treatment results were informed before beginning the second treatment. Finally, at the end of the second treatment, the personal screen informed subject the total amount of profits generated from both treatments. Finally, subjects answered an online survey to complete to gather socio-economic information and to elicit risk preferences.[6] Each session lasted about two hours. At the end of the experiment, participants were paid their accumulated earnings in cash. Subjects were paid the equivalent to US$ 4 for showing up on time, plus what they earned from their participation in the experiment. The exchange rate between the experimental and Chilean pesos was set in order to produce an average expected payment for the participation in the experiment that was similar to what an advanced student could earn in the market for 2 hours of work. Total payments ranged between US$ 5.7 and US$ 22.8, with a mean value of US$ 14.9, a median of US$ 14.9 and a standard deviation of US$ 4.4.

A total of 225 students participated in the experiment. We ran a total number of 3 T1 treatments (11 groups), 3 T2 treatments (9 groups), 3 T3 treatments (9 groups), 3 T4 treatments (11 groups), 3 T5 treatments (10 groups), and 3 T6 treatments (10

[6] To elicit subjects' level of risk aversion we conducted a Holt and Laury (Holt and Laury 2002) type of test. The subjects were confronted to 10 choices between a certain amount of money (labeled Option A and equal to US$38.2 and fixed across the 10 choices) and a lottery (labeled Option B). In the lottery, subjects could earn either US$ 14.3 or US$ 62.0. The probability of winning the higher prize varied from 0.1 to 1 between choices 1 and 10. Our measure of risk aversion is the number of the choice in which the subject switches to Option B. It then varies between 1 and 10, with 10 being the highest value of risk aversion. (In the tenth choice the higher prize of the lottery, higher than the certain amount in option A, has a probability equal to 1, so every subject should choose the lottery in the 10th choice). A risk-neutral subject should switch from option A (the certain amount) to option B (the lottery) in the fifth or sixth choice. We informed the subjects that after completing the questionnaire, one subject was going to be chosen from the pool of subjects in the room and that she was going to be paid according to her decisions in the Holt and Laury choices by drawing a number between 1 and 10 from an urn. If the subject selected the lottery in the drawn choice, the lottery was conducted with the corresponding probabilities in the form of colored balls in an urn.

groups). Twenty four subjects went bankrupt in the experiment. Most of bankruptcies were concentrated in those treatments with incomplete enforcement where individuals had a level of production above the level predicted by the theory.[7]

4. Results

In this section, we present the results of our work. First, we present the descriptive analysis of the overall results. Second, we present the results of hypotheses tests.

4.1. Overall Results-Descriptive analysis

Table 2 presents the descriptive statistics for the level of emissions and violations observed in the perfect compliance treatments (T1, T2, and T3) by firm's type. Modal behaviors in the compliance treatments are those predicted by theory. However, this is not the case with average behaviors. We note that the average violation is positive for all types of subjects in all perfect enforcement treatments. Average positive levels of violations in enforcement regimes that induce compliance in the margin have previously been observed in the literature (see, for example, Murphy and Stranlund (2006 and 2007) and Stranlund et al. (2011 and 2013) and Caffera and Chávez (2016). Our results, however, show that as an addition to the literature, this result does not depend on the level of certainty regarding the amount of the penalties.

An additional result that can be observed in Table 2 is that the mean level of violation increases for almost all types of firms under a random penalty with simple lottery (T2) with respect to a deterministic penalty (T1). The only exception is observed in the case of the lowest marginal abatement cost firms (firms Type 4). A similar

[7] In order not to lose the total number of observations in which a subject went bankrupt, we use the observations in the periods during which the subjects were active. The results that we present do not change qualitatively if we use only cases in which no subject went bankrupt.

qualitative result is observed also for the mean level of violation for high marginal abatement costs firms types under a random penalty with a compound lottery (T3) with respect of the baseline (T1).

Table 2: Descriptive statistics for perfect compliance treatments

		Type 1 (s=7)		Type 2 (s=6)		Type 3 (s=4)		Type 4 (s=3)	
		q	v	q	V	q	v	q	v
Theory		**7.00**	**0.00**	**6.00**	**0.00**	**4.00**	**0.00**	**3.00**	**0.00**
Treatment 1 Deterministic Penalty	Mean	7.42	0.42	6.53	0.53	4.63	0.63	4.31	1.31
	Std. Dev.	0.87	0.87	0.89	0.89	0.89	0.89	1.11	1.11
	Mode	7	0	6	0	4	0	5	2
	Median	7	0	6	0	4	0	4.5	1.5
	# Obs.	130	130	127	127	110	110	100	100
		Type 1 (s=7)		**Type 2 (s=6)**		**Type 3 (s=4)**		**Type 4 (s=3)**	
		q	**v**	**q**	**V**	**q**	**v**	**q**	**v**
Theory		**7.00**	**0.00**	**6.00**	**0.00**	**4.00**	**0.00**	**3.00**	**0.00**
Treatment 2 Random Penalty simple lottery	Mean	7.72	0.72	6.89	0.89	4.88	0.88	3.88	0.88
	Std. Dev.	1.07	1.07	1.14	1.14	1.36	1.36	1	1
	Mode	7	0	6	0	4	0	3	0
	Median	7	0	7	1	4	0	4	1
	# Obs.	100	100	140	140	129	129	99	99
		Type 1 (s=7)		**Type 2 (s=6)**		**Type 3 (s=4)**		**Type 4 (s=3)**	
		q	**v**	**q**	**V**	**q**	**v**	**q**	**v**
Theory		**7.00**	**0.00**	**6.00**	**0.00**	**4.00**	**0.00**	**3.00**	**0.00**
Treatment 3 Random Penalty compound lottery	Mean	7.52	0.52	6.66	0.66	4.62	0.62	3.84	0.84
	Std. Dev.	0.80	0.80	0.96	0.96	1.01	1.01	1.02	1.02
	Mode	7	0	6	0	4	0	3	0
	Median	7	0	6	0	4	0	4	1
	# Obs.	108	108	138	138	130	130	100	100

The table shows the average, the standard deviation, the mode, the median, and the number of observations for (q) emissions and (v) violations.

Table 3 shows the descriptive statistics for the case of the treatments that induce violations, by firms' type. In this case, average violations are lower than the ones predicted for expected profit maximizers in the case of Type-1 firms (those with high marginal benefits and laxer standards), in all treatments. On the contrary, violations are almost equal or higher than those predicted by the model in the case of Type-3 and

Type-4 firms (those with lower marginal benefits but stricter standards). Meanwhile, Type-2 firms behave as predicted, on average, in the case of known penalties, but they show lower than predicted violations in the case of uncertain penalties (treatments 5 and 6).

In Caffera and Chávez (2016), we observe that in general, the level of emissions achieved in the imperfect compliance treatments are lower than the level achieved in the case of perfect compliance treatments, although both were designed to induce the same levels of emissions in an expected profit maximizer subject. We see here that this result does not change with uncertain penalties.

Moreover, as it can be seen in Table 3, the mean level of violation under a random penalty with simple lottery (T5) does not differ much with respect to the level observed under deterministic penalty (T4). A similar qualitative result is observed also for the mean level of violation for high marginal abatement costs firms types under a random penalty with a compound lottery (T6) with respect of the baseline (T4).

Table 3: Descriptive statistics for violation treatments

Treatment 4		Type 1 (s=4)		Type 2 (s=3)		Type 3 (s=2)		Type 4 (s=1)	
		q	V	q	V	q	v	q	v
Theory		**7**	**3**	**6**	**3**	**4**	**2**	**3**	**2**
Deterministic Penalty	Mean	6.09	2.09	5.93	2.93	3.99	1.99	3.76	2.76
	Std. Dev.	1.97	1.97	1.91	1.91	1.23	1.23	2.07	2.07
	Mode	5	1	6	3	4	2	2	1
	Median	5	1	6	3	4	2	4	3
	# Obs.	129	129	130	130	110	110	100	100
Treatment 5		**Type 1 (s=4)**		**Type 2 (s=3)**		**Type 3 (s=2)**		**Type 4 (s=1)**	
		q	V	q	V	q	v	q	v
Theory		**7**	**3**	**6**	**3**	**4**	**2**	**3**	**2**
Random Penalty simple lottery form	Mean	6.36	2.36	6.1	3.1	4.04	2.04	2.63	1.63
	Std. Dev.	1.61	1.61	2.28	2.28	1.77	1.77	1.66	1.66
	Mode	6	2	5	2	4	2	3	2
	Median	6	2	6	3	4	2	2.5	1.5
	# Obs.	110	110	90	90	120	120	40	40
Treatment 6		**Type 1 (s=4)**		**Type 2 (s=3)**		**Type 3 (s=2)**		**Type 4 (s=1)**	
		q	V	q	V	q	v	q	v
Theory		**7**	**3**	**6**	**3**	**4**	**2**	**3**	**2**
Random Penalty compound lottery form	Mean	6.45	2.45	5.73	2.73	3.7	1.7	3.43	2.43
	Std. Dev.	1.64	1.64	2.03	2.03	1.61	1.61	2.4	2.4
	Mode	6	2	5-6	1-2	3	1	3	2
	Median	6	2	5.5	2.5	3	1	3	2
	# Obs.	110	110	90	90	120	120	40	40

The table shows the average, the standard deviation, the mean, the median, and the number of observations for (q) emission and (v) violation. Descriptive statistics calculated for the last 10 periods and positive levels of violations from subjects making consistent choices in the Holt and Laury lottery activity

4.2. Hypotheses tests

4.2.1 Nonparametric Tests

We are interested in comparing: (i) *violations under a deterministic penalty vs. violations under a simple lottery form of penalty*, (ii) *violations under a deterministic* *penalty vs. violations under a compound lottery form of penalty* and (iii) *violations under a simple lottery form of penalty vs. violations under a compound lottery form of penalty.* The null hypothesis is that there are no differences between average individual violations across penalties by firms' type.

Table 4 presents the results of the Mann-Whitney tests for each comparison. The overall result is fairly clear. In the cases where the treatments induce compliance the differences in the certainty in the value of the penalty appears to affect the level of individual violation. This is not the case in treatments that allow for violations. Specifically, in the case of perfect compliance treatments, the level of violation under a simple lottery form of penalty (v_s) is higher than the level of violation under a deterministic penalty (v_k) and the level of violation under a compound lottery penalty (v_c). Meanwhile, the level of violation under a certain penalty (v_k) is not different from the level of violation under a compound lottery penalty (v_c).

Table 4: Mann Whitney Test by enforcement system and risk preferences

Enforcement System		Deterministic penalty vs. Random penalty-Simple lottery			Deterministic penalty vs. Random penalty-Compound lottery			Random penalty-Simple lottery vs. Random penalty-Compound lottery		
		H_0: v_k=v_{sl} H_1:$v_k \neq v_{sl}$			H_0: v_k=v_{cl} H_1:$v_k \neq v_{cl}$			H_0: v_{sl}=v_{cl} H_1:$v_{sl} \neq v_{cl}$		
		Rejected	Dif V_k-v_{sl}	Obs	Rejected	Dif V_k-v_{cl}	Obs	Rejected	Dif v_{sl}-v_{cl}	Obs
All firms	Induces perfect compliance	**5%**	**-**	**935**	**No**		**943**	**5%**	**+**	**944**
Risk lover		1%	-	70	1%	-	70	No		40
Risk Neutral		No		399	1%	+	408	1%	+	427
Risk averse		10%	-	466	No		465	No		477
All firms	Induces violations	**No**		**829**	**No**		**829**	**No**		**720**
Risk lover		No		90	No		90	No		80
Risk Neutral		No		320	No		320	No		260
Risk averse		No		419	No		419	No		380

Note: Tests were performed using positive levels of violations from subjects making consistent choices in the Holt and Laury lottery activity. v_k= violation with deterministic penalty; v_{ls}= violation under random penalty- simple lottery form; v_{lc}= violation under random penalty- compound lottery form.

We also test for differences in the individual levels of violation dividing the subjects by firms' types. To perform these tests we divided the subjects into two groups, high costs subjects (Types 1 and 2) and low costs subjects (Types 3 and 4). The general results remain. We observe now that for the perfect compliance treatments, the level of violation under simple lottery penalty is higher than the level of violation under a compound lottery penalty for the high costs firms (see Table 5). Overall, violations of high cost firms are higher with random penalties than with deterministic penalties. Also, the results in Table 5 suggest that the results that we obtain for the case of treatments that allow for non-compliance are mainly driven by high cost firms, as the uncertainty of the penalty does seem to affect the level of violation for low cost firms.

Table 5: Mann Whitney Test by enforcement system and firms' type

Enforcement System/Firms' Type		Deterministic penalty vs. Random penalty-Simple lottery			Deterministic penalty vs. Random penalty-Compound lottery			Random penalty-Simple lottery vs. Random penalty-Compound lottery		
		H_0: $v_k=v_{ls}$ H_1: $v_k \neq v_{ls}$			H_0: $v_k=v_{lc}$ H_1: $v_k \neq v_{lc}$			H_0: $v_{ls}=v_{lc}$ H_1: $v_{ls} \neq v_{lc}$		
		Rejected	Dif V_k-v_{ls}	Obs	Rejected	Dif V_k-v_{lc}	Obs	Rejected	Dif V_{ls}-v_{lc}	Obs
Complete	High (types 1y 2)	1%	-	497	5%	-	503	10%	+	486
	Low (types 3 y 4)	No		438	1%		440	No		458
Incomplete	High (types 1y 2)	No		459	No		459	No		400
	Low (types 3 y 4)	1%	+	370	1%	+	370	No		320

The observations consider the 10 periods, $v \geq 0$ and subjects making consistent choices in the Holt and Laury lottery activity, v_k= violation under deterministic penalty; v_{ls}= violation under random penalty-simple lottery form; v_{lc}= violation under random penalty compound lottery form.

4.2.2 Regressions

To complement the results of the non-parametric tests presented in the previous tables, we perform a regression analysis. In this regressions, the unit of analysis is the individual level of violation. The general specification of the estimated equations is the following:

$v_{it} = f$ (*SIMPLE*$_i$, *COMPOUND*$_i$, *FIRM-TYPE*$_i$, *RISK PREFERENCES*$_i$, *OTHERCONTROLS*) [1]

where v_{it} is the level of violation of subject i in round t; *SIMPLE* is a dummy variable indicating whether the subject faces a simple lottery penalty; *COMPOUND* is a similar variable for the case of a compound lottery penalty; *FIRMTYPE* is a set of three dummy variables to control for firms' type, *RISK PREFERENCES* is a set of two dummy variables, each variable is equal to 1 if the subject is risk averse or risk lover. The risk preference indicator was constructed using the results of the Holt and Laury test as previously explained in Section 3.2. The other controls employed in the regressions depend on the specification. We consider interacting variables between treatment and firm type. Finally, we included random individual effects, and we clustered errors by groups.[8]

The results of our regression analysis are presented in Table 6. Consistent with the nonparametric tests, we observe that high-benefit firms seems to be the ones that violate more with uncertain penalties in "high" enforcement environments, with the effect being more statistically significant for firms of type 1 (higher benefits of polluting). On the other hand, we only observe a statistically weak effect for firms type 1 in the case of enforcement regimes that allow non-compliance.

[8] We also consider interacting variables between treatments and risk preferences and ran the specifications with and without controlling for the possibility that the subject could have been inspected in the previous round to explore the potential effect of being inspected in the previous period on the violation decision in the current period. The results regarding treatment effects were robust to these different specifications.

Table 6. Linear random effects models-Level of violations

Treatments induce compliance		Treatments allows violations	
Trat2	-0.436	Trat5	-1.161*
	(0.330)		(0.594)
Trat3	-0.469*	Trat6	-0.361
	(0.285)		(0.854)
RiskAverse	0.010	RiskAverse	-0.064
	(0.126)		(0.300)
Risklover	0.073	Risklover	0.064
	(0.224)		(0.664)
Type1	-0.891***	Type1	-0.679
	(0.253)		(0.492)
Type2	-0.791***	Type2	0.165
	(0.265)		(0.510)
Type3	-0.675**	Type3	-0.766*
	(0.295)		(0.399)
Trat2xType1	0.742***	Trat5xType1	1.447*
	(0.272)		(0.756)
Trat2xType2	0.813*	Trat5xType2	1.324
	(0.435)		(1.163)
Trat2xType3	0.693	Trat5xType3	1.225
	(0.489)		(0.747)
Trat3xType1	0.580**	Trat6xType1	0.738
	(0.274)		(0.919)
Trat3xType2	0.605*	Trat6xType2	0.158
	(0.338)		(1.177)
Trat3xType3	0.463	Trat6xType3	0.083
	(0.388)		(1.018)
Constant	1.298***	Constant	2.785***
	(0.228)		(0.307)
N	1411	N	1189

* p<0.1, ** p<.05, *** p<.01

5. Conclusions

In this study, we used a laboratory economic experiment to analyze compliance behavior of individual firms subject to emissions standards. The design considered exogenous variations in the stringency of enforcement to induce compliance under different degrees of information regarding the severity of the penalty.

Based on our findings, the general conclusion is that uncertain penalties affects the level of violations of those polluting firms that have the most to profit with violations. But this result is only observed when the marginal expected penalty is high enough to induce compliance in risk-neutral firms. On the contrary, when the marginal expected penalty is low enough to induce risk-neutral firms to violate their standards, the level of uncertainty in the penalty does not affect the level of emissions of any type of firm. A possible interpretation is that once the enforcement level is perceived as lax, the information regarding the penalty neither adds nor detracts from the incentives affecting the decision to comply. It is only if the control system is not lax and the severity of the penalty is known and certain that a difference in the level of infringement of companies is observed, especially in companies with high marginal costs.

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Annex 1

Table A1. Production marginal benefits of the fictitious good per type of firm

Produced Units	Production marginal benefits			
	Type 1	Type 2	Type 3	Type 4
1	161	151	129	125
2	145	134	113	105
3	130	119	98	88
4	116	106	84	74
5	103	95	73	63
6	91	86	63	54
7	80	79	53	47
8	70	74	44	42
9	61	70	35	38
10	53	67	27	35

Source: Cason and Gangadharan (2006).

Annex 2

Table A.2. Detail of treatments conducted in each session

Session	Treatment	Compliance	Penalty
1	2	Perfect	Random-Simple lottery
	3	Perfect	Random-Compound lottery
2	5	Violations	Random-Simple lottery
	6	Violations	Random-Compound lottery
3	3	Perfect	Random-Compound lottery
	2	Perfect	Random-Simple lottery
4	6	Violations	Random-Compound lottery
	5	Violations	Random-Simple lottery
5	1	Perfect	Deterministic
	4	Violations	Deterministic
6	4	Violations	Deterministic
	1	Perfect	Deterministic
7	1	Perfect	Deterministic
	4	Violations	Deterministic
8	5	Violations	Random-Simple lottery
	6	Violations	Random-Compound lottery
9	2	Perfect	Random-Simple lottery
	3	Perfect	Random-Compound lottery