Regulation of Nonpoint Emissions under Limited Information: A Stress Experimental Test of the Ambient Tax Mechanism

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Abstract

We provide a stress experimental test of the ability of (a damaged based version) the ambient tax mechanism to induce socially optimal outcomes in a nonpoint pollution context. To mirror the features of naturally occurring environments, we consider a convex damage function, uncertainty in measuring the ambient level of pollution, polluters with heterogeneous profit functions competing against the same opponents for the duration of the experiment (which runs for an indeterminate length), and in half of our treatments polluters do not know others profit functions. In almost all implemented conditions, the observed total pollution level is not significantly different from the socially optimal level whereas, in none of the conditions, compliance at the individual level is observed. The efficiency performance of the ambient tax mechanism is higher (though not significantly) under limited information than under complete information as subjects comply more with the socially optimal level the less information about the profit functions of others they have.

1 Introduction

Regulation of nonpoint emission problems such as pesticide, and nitrogen pollution of lakes and ground water is a major policy challenge. The emissions-based instruments that economists usually advocate for cost-effective pollution control are not feasible since individual emissions are unobservable. Among the policy instruments suggested by the theoretical literature on nonpoint management, the tax/subsidy schemes applied to ambient concentrations have drawn particular interest.[1]

Segerson (1988) first proposed an ambient tax/subsidy scheme which implements an economically efficient allocation of pollution control among nonpoint sources. Under such a fiscal instrument, each polluter pays a marginal tax corresponding to total marginal environmental damage caused by changes in the ambient concentration. When the damage function is linear, the social optimum is implemented in dominant strategies and the correct specification of the mechanism only requires the regulator to have knowledge of the damage function.[2]

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[1]Shortle and Horan (2001) provides an exhaustive review of the nonpoint source pollution control literature.

[2]Social optimality in dominant strategies relies on the additional assumption that the ambient pollution is the sum of the individual emissions.

When the damage function is strictly convex, the regulator cannot introduce a linear ambient tax if he does not observe each polluter's profit function. Hansen (1998) has proposed a damaged based version of the ambient tax that eliminates the need of additional information as the planning problem is decentralized to polluters. The damage based mechanism was independently introduced by Horan, Shortle, and Abler (1998) to handle the multiple dimensionality of polluters' choice set. Shifting the base of the mechanism from ambient concentrations to environmental damage weakens the solution concept since the social optimum is only implemented in non-dominant Nash strategies. Polluters' optimal emissions become interdependent which implies that if polluters have limited information about their strategic environment (e.g., if the other polluters' profit functions are unknown) then the efficiency of the mechanism becomes questionable.

As far as we know, no real world implementation of an ambient tax/subsidy scheme to regulate nonpoint source pollution has been reported on till now.[3] The only available empirical evaluation of the ambient tax scheme has been carried out in the laboratory. Spraggon (2002a) investigates the ability of four variants of the ambient tax instrument to effectively control the nonpoint source pollution problem: a tax/subsidy scheme which combines a tax and a subsidy depending upon whether the total pollution level is above or below the optimal level; a tax scheme which involves only a tax if the optimal level is exceeded; a subsidy scheme which involves a subsidy and a bonus in case the total pollution level is below the optimal level; and a group fine scheme which involves a lump-sum fine if the total pollution level exceeds the optimal level. Contrary to the subsidy and group fine schemes, the two first variants of the fiscal scheme applied to ambient concentrations are effective in enforcing the socially optimal level, this result being robust to both uncertainty in measuring the ambient level of pollution and experience of the subjects with the environment. However, the data show that these schemes do not ensure individual compliance. As an extension of the previous study, Spraggon (2003) investigates the ability of the tax/subsidy and the group fine schemes to induce a group of heterogeneous polluters to choose a target pollution level. At the aggregate level, the group fine scheme is not effective in enforcing the socially optimal level whereas the tax/subsidy scheme is but there are significant reductions in efficiency when the group is composed of polluters who have different unconstrained emission levels. Additional experimental evidence on the ability of the ambient tax mechanism to induce socially optimal outcomes in a nonpoint pollution context is provided by Cochard, Willinger, and Xepapadeas (2002), Alpizar, Requate, and Schram (2002), and Vossler, Poe, Schulze, and Segerson (2002) among others. Broadly speaking, the existing controlled laboratory experiments on the ambient tax/subsidy scheme conclude that though the polluters' emissions do not maximize the social net benefit, a second-best level of social welfare is achieved as the observed total pollution level matches the specified target.

In this paper we experimentally investigate the ability of the damage based tax mechanism to induce socially optimal outcomes in a nonpoint pollution context outside the domain of its theoretical validity. Contrary to the previous laboratory studies which focused more on the internal validity of the experiment by considering 'stylized' environments, our experimental setting has been specifically designed to incorporate important aspects of nonpoint pollution problems. To reflect on external validity, we combine a strictly convex damage function with uncertainty in measuring the ambient level of pollution, heterogeneity in polluters' profit functions, an indeterminate length of the time horizon, and limited information about the strategic environment as polluters only know their own payoff function and maximal emission level. The first aspect of our experimental design derives from the empirical observation that in many potential practical applications of the ambient tax mechanism (like pollution of lakes, streams and ground water reservoirs) damage functions are notoriously nonlinear –with sharply rising damage from concentrations above a critical level. By considering an indeterminate length of the time during which polluters interact, we evaluate the costs to the regulator of implementing the ambient tax/subsidy scheme when polluters have

[3]Ribaudo, Horan, and Smith (1999) discusses several fiscal schemes sharing strong similarities with ambient taxes that have been introduced in the United States to regulate nonpoint source pollution.

strong incentives to collude. The last aspect of our setting is particularly relevant for practical application of mechanisms based on ambient pollution concentrations as the solution of the planning problem under the damage based tax mechanism is decentralized to polluters.[4] More precisely, by comparing an experimental condition where polluters have no information about the other polluters' profit functions with an experimental condition where profit functions are common knowledge, we investigate whether shifting the burden of information from regulators to polluters severely limits what the ambient tax scheme can accomplish in practice.[5]

In our attempt to implement a setting which captures the uncertainties of the real world, we also consider limited information on the regulator's side. Under a damage based tax/subsidy scheme, polluters pay taxes if the social damage is greater than the lump-sum subsidy and they get subsidies if the social damage is smaller than the lump-sum subsidy. Neglecting entry/exit problems, the "*ideal*" lump-sum subsidy is equal to the expected damage level at the social optimum meaning that no taxes are collected from polluters and no subsidies are distributed to them in case of full compliance. Computation of the *ideal* lump-sum subsidy level requires perfect information on the regulator side about the distribution of the polluters' profit functions. In the more realistic case of imperfect information, the regulator would either under- or over-estimate the *ideal* lump-sum subsidy value. If the *ideal* lump-sum subsidy level is under-estimated then polluters pay taxes under full compliance whereas if the *ideal* lump-sum subsidy is over-estimated they get subsidies at the social optimum. We test the efficacy of the ambient tax mechanism in case of limited information on the regulator's side by comparing an experimental condition where the lump-sum subsidy is under-evaluated with an experimental condition where the lump-sum subsidy is over-evaluated.

In addition to evaluating what the ambient tax scheme can accomplish in informationally limited settings, we study whether the relative position of the social optimum in the polluters' emission space has an impact on the efficiency of the fiscal instrument. Considering this additional treatment variable is justified by the fact that reducing pollution might sometimes require a severe changing and other times only a small adjustment in the polluters' behavior. It should be noticed that existing laboratory studies on nonpoint management did not pay attention to this feature of the environment even though it led to strikingly dissimilar findings. Thus, while the ambient tax/subsidy mechanism reaches high efficiency levels in Spraggon's (2002a) experiment where the social optimum is relatively low in the polluters' emission space, much lower efficiency levels are observed in Cochard, Willinger, and Xepapadeas's (2002) setting where the social optimum is relatively high in the polluters' emission space.[6] Related experimental evidence on public goods also shows the impact of the position of the equilibrium (the social optimum in the present study) on the participants' behavior. Roughly speaking, moving the equilibrium closer to the collusive outcome has been found to decrease collusion (see, e.g., Willinger and Ziegelmeyer, 2001). To study this issue, we evaluate the efficiency of the ambient tax/subsidy scheme both in an experimental condition where the social optimum is below the middle of the emission space and where it is above the middle of the emission space.

[4] Spraggon (2002b) considers three different information conditions in an experimental tax/subsidy setting with both homogeneous and heterogeneous profit functions, perfect observation of the ambient pollution level, and a finite time horizon. Under the *full information condition*, the number of interacting participants in each group as well as their profit functions are common knowledge. Under the *partial information condition*, participants have no information about the payoff functions of their opponents whereas in the *no information condition* participants neither know the size of their group nor their opponents' profit functions. Information has no significant effect on the total pollution level but efficiency tends to increase with the level of information. Theoretically, due to the linearity of the setting, the level of information should have no impact as the social optimum is implemented in dominant strategies. Other less related experiments show that decreasing the subjects' level of information has no significant effect on behavior (Isaac and Walker, 1998; Marks and Croson, 1999), or can even decrease collusion, thereby increasing the frequency of Nash equilibrium play (Mason and Phillips, 1997; Huck, Normann, and Oechssler, 1999).

[5] Several authors expressed concern about this issue in the theoretical literature on nonpoint management (see, among others, Hansen, 1998).

[6] The two experimental settings differ in additional aspects but we hypothesize that the relative position of the social optimum in the polluters' emission space is the one driving the dissimilarity in the results.

The remainder of the paper is structured as follows. Section 2 presents the decision setting for our experimental study. The experimental design is described in section 3. Section 4 is devoted to the results and section 5 concludes.

2 Regulation of nonpoint emissions

In this section, we first consider a static model of pollution in which a particular resource is damaged from nonpoint sources of emissions, and where polluters have complete information about their strategic environment. We define complete information as common knowledge of the number of polluters interacting on the market, the distribution of the stochastic variables, and polluters' profit functions. Next we consider the implications of dropping the assumption that polluters know other polluters' profit functions. Finally, we discuss the implications of an infinite interaction between polluters.

2.1 Regulation of one-shot nonpoint emissions under polluters' complete information

We consider a market that consists of $i = 1, \ldots, n$ polluters emitting a pollutant to the same recipient where interaction between polluters is assumed to take place only once. Emissions cannot be observed by the environmental regulator (at least not at an acceptable cost). Environmental damage in the recipient is a function of the ambient pollution level at one given measuring point.

The profit function of each polluter is defined as a function of emission levels which are a by-product of the polluter's production: $B_i(e_i) = \gamma_i - \alpha_i(e_i - e_i^{max})^2$ where $e_i \in \{0, \ldots, e_i^{max}\}$ denotes the emissions of the ith polluter and e_i^{max} denotes polluter i's maximal amount of emissions. In the absence of any environmental control, polluter i will release pollution up to e_i^{max} which we refer to as the uncontrolled level of emissions. In that case, the total emissions would be equal to $\sum_i e_i^{max}$. We assume that the number of polluters and the polluters' profit functions are common knowledge.

For simplicity, the ambient concentration of the pollutant is given by $\sum_i e_i + \epsilon$, where ϵ is a stochastic environmental variable. We assume that the distribution of the stochastic environmental variable is common knowledge with null expectation. The economic costs of damages caused by pollution are given by $(\sum_i e_i + \epsilon)^2$, meaning that damages from total emissions are a convex function of total emissions.

The environmental regulator or social planner seeks to maximize total profit less expected environmental damages, i.e., he will choose the socially optimum emission level for each polluter such that the expected net profit is maximized. The expected net profit of resource allocation decisions by nonpoint sources is given by $NB = \sum_i B_i(e_i) - E\left[(\sum_i e_i + \epsilon)^2\right]$ where E denotes the expectations operator over the stochastic environmental variable. Assuming that polluters and the environmental regulator are risk-neutral, the socially optimal level of emissions for each polluter is found by solving

$$\max_{\{e_1, \ldots, e_n\}} \quad \sum_{i=1}^{n} B_i(e_i) - E\left[(\sum_i e_i + \epsilon)^2\right]$$

which we refer to as the environmental regulator's problem.

We assume that the regulator relies on a fiscal instrument in order to implement the optimum as a unique Nash equilibrium. More precisely, the environmental regulator imposes a tax-subsidy mechanism on each polluter, based on the level of expected social damages due to the ambient pollution, as first suggested by Hansen (1998) and Horan, Shortle, and Abler (1998). After the mechanism has been introduced, polluters choose e_i so as to maximize $B_i(e_i) - E\left[(\sum_i e_i + \epsilon)^2\right] + K$, where K is a lump-sum subsidy determined by the regulator. It is straightforward to see that the Nash equilibrium emission levels are solutions to the environmental regulator's problem.

Optimal Nash equilibrium first order conditions are given by $-2\alpha_i e_i^* + 2\alpha_i e_i^{max} - 2\sum_i e_i^* = 0$, for $i = 1, \ldots, n$ leading to $e_i^* = (\alpha_i e_i^{max} - \sum_{j \neq i} e_j^*)/(1 + \alpha_i)$, for $i = 1, \ldots, n$.[7] Notice that for specification of the mechanism the environmental regulator does not require knowledge of polluters' profit functions, it is sufficient for him to know the damage function. By knowing the distribution of the polluters' profit functions, the regulator could determine a level of the lump-sum subsidy K^* so that polluters would not incur expected taxes at the social optimum, i.e., $K^* = (\sum_i e_i^*)^2 + \mathrm{Var}[\epsilon]$.

2.2 Regulation of one-shot nonpoint emissions under polluters' limited information

As already mentioned, for specification of the damage based mechanism introduced above, the environmental regulator does not require knowledge of polluters' profit functions, i.e., the solution of the planning problem is decentralized to polluters. Theorists like Hansen who suggested damage based tax mechanisms recognized that though decentralization reduces the regulator's information problem it also introduces the possibility that the optimal Nash equilibrium becomes unstable. Indeed, if we assume that each polluter only knows its own profit function, without even knowing the distribution of other polluters' profit functions,[8] then any emission level can be rationalized as polluter i's expectations concerning the other polluters total emissions $\left(\sum_{j \neq i} e_j\right)$ are not constrained. Therefore, no precise predictions can be formulated in the above framework once we drop the assumption that the polluters' profit functions are common knowledge.

2.3 Regulation of nonpoint emissions under infinite interactions between polluters

In the above analysis, we considered a single interaction between the polluters. By assuming that polluter's preferences and rationality are common knowledge, we could extend our theoretical analysis under complete information to a finite number of interactions by relying on the concept of subgame-perfect equilibrium. As there is a unique Nash equilibrium of our stage game, the unique subgame-perfect equilibrium of the finitely repeated game implies that polluters choose the socially optimal level in every repetition.

It is however clear that in reality interactions are likely to be better represented as an infinitely repeated game. Considering an infinite number of interactions between polluters as an impact on the possible outcomes. Indeed, outcomes more collusive than the optimal Nash equilibrium in the underlying one-stage interaction can be supported as a subgame-perfect equilibrium in infinitely repeated interactions, or in interactions with unknown and randomly determined end points (see, among others, Fudenberg and Tirole, 1991, for more details).[9] Actually, every outcome between the collusive solution and the optimal Nash solution can be supported as a subgame-perfect equilibrium in an infinite sequence of interactions between polluters. The collusive outcome is obtained if each polluter i maximizes $\sum_i B_i(e_i) - E\left[(\sum_i e_i + \epsilon)^2\right] + K$, which leads to $e_i^C = (\alpha_i e_i^{max} - 6\sum_{j \neq i} e_j^C)/(6 + \alpha_i)$. Collusive emissions are clearly lower than the optimal Nash emissions which, of course, reduces the efficiency of the damage based mechanism.

Common knowledge of profit functions is fundamental in this context,[10] since it reveals emission combinations that can be supported as an equilibrium, and because it permits the determination of each polluter's incentives to participate in a collusive agreement. Therefore, polluters have

[7]Due to our convexity assumptions, second order conditions are trivially satisfied.

[8]Meaning that we cannot rely on the concept of Bayesian Nash equilibrium to derive a solution.

[9]Subgame-perfect equilibria in infinitely repeated games are based on *trigger* strategies. Polluters select a collusive emission level until defection is detected; if defection occurs, a "punishment" phase ensues (see Abreu, 1986, for more details).

[10]Green and Porter (1984) show that in a duopoly market some collusion can result when payoffs to both agents are random. However, polluters share minimal knowledge about their profit functions.

less incentive to play cooperatively under limited information meaning that the efficiency of the mechanism could be higher under limited information than under complete information. Clearly, there are welfare ambiguities associated with the amount of information available to polluters about their strategic environment and resolving policy these concerns becomes an empirical question.

3 Experimental design

In our laboratory environment, subjects in groups of six take the role of polluters whose decisions correspond to the level of emissions. The larger the decision number the more emissions that the polluter releases up to some maximum decision number which corresponds to the polluters uncontrolled level of emission, i.e., to the subject's endowment (in tokens).[11] In each group, one subject was endowed with 23 tokens, four subjects were endowed with 31 tokens and the last subject was endowed with 45 tokens. From now on, we will refer to the subject whose endowment is the lowest as the small polluter, the subject whose endowment is the highest as the large polluter and the four remaining subjects in the group as the medium polluters. Subjects were told that their total payoff in each period was the sum of a private payoff and a group payoff. The private payoff was found by looking up their decision number on a payoff table. A different payoff table was associated to each polluter's type, small, medium or large, as the private component of the payoff function differs (see table 2 below). The group payoff depended on the group total. Subjects were informed that the group total was the sum of the decision numbers of all of the subjects and a random variable which follows a triangular distribution.[12] The group total is analogous to the ambient level of pollution in the nonpoint source pollution case. Adding a random variable to the sum of the decision numbers allows us to investigate the effects of the ambient level pollution being observed with error.

The number of periods and the exact time an experiment would run were not known by any of the participants during a session. Subjects were only informed that they would interact for at least 12 periods. At the end of the session, subjects were paid their accumulated payoffs, converted from laboratory points to euros. Conversion rates differed between sessions and polluters' types so that in case of perfect individual compliance with the social optimum, payoffs would be identical.

Two information conditions were used. In the *limited information* condition subjects had no information about the endowments and private payoff tables of other group members. They were only informed that not all group members had been provided with the same endowment and private payoff table than themselves. In the *complete information* condition they knew both the endowments and private payoff tables of the other people in their group. In both information conditions subjects knew their own endowments and private payoff tables.

Two positions of the socially optimal level in the strategy space were considered. In the *low position of the social optimum* condition each polluter's socially optimal level of emission is between 1/3 and 40% of its endowment depending on its type. In the *high position of the social optimum* condition each polluter's socially optimal level of emission is between 60% and 2/3 of its endowment depending on its type (see table 2 and table 3 below for more details). Recent experimental literature on public good games has shown that the level of the equilibrium in the strategy space has an impact on the subjects' contributions as moving the equilibrium level of contribution closer to the Pareto optimum, leads to a decrease in average over-contribution (see, among others, Isaac and Walker, 1998 and Willinger and Ziegelmeyer, 2001). By considering two different levels of the social optimum, we study whether these findings can be confirmed in a "public bad" setting.

There were two levels of the lump-sum subsidy. Indeed, instead of assuming that the regulator can determine the level of the lump-sum subsidy which corresponds to no tax/subsidy at the social optimum, we investigate whether a miscalculation has an impact on the subjects' behavior. In the

[11] Emissions were restricted to integer values.

[12] The triangular distribution is a good approximation of the normal distribution and it is easy to explain to subjects.

Kinf condition the regulator has under-evaluated the level of the lump-sum subsidy which implies that polluters pay taxes at the social optimum whereas in the *Ksup* condition the regulator has over-evaluated the level of the lump-sum subsidy which implies that polluters are subsided at the social optimum.

The two information conditions were combined with the position of the socially optimal level factor and the level of the lump-sum subsidy factor in a complete 2x2x2 factorial design. Table 1 summarizes our experimental design and table 2 provides the parameters chosen for each treatment.

Amount of information	Limited				Complete			
Social optimum's position	Low		High		Low		High	
Lump-sum subsidy	Kinf	Ksup	Kinf	Ksup	Kinf	Ksup	Kinf	Ksup
Treatment	*Lim Low Kinf*	*Lim Low Ksup*	*Lim High Kinf*	*Lim High Ksup*	*Com Low Kinf*	*Com Low Ksup*	*Com High Kinf*	*Com High Ksup*

Table 1: Experimental design.

Social optimum's position	Low			High		
Under-evaluated lump-sum subsidy (*Kinf*)	4200 (85% of 4922.5)			12300 (85% of 14462.5)		
Over-evaluated lump-sum subsidy (*Ksup*)	5700 (115% of 4922.5)			16700 (115% of 14462.5)		
Random variable's support	{-9,-6,-3,0,3,6,9}			{-15,-10,-5,0,5,10,15}		
Polluter's type	Small	Medium	Large	Small	Medium	Large
Endowment	23	31	45	23	31	45
Value of γ	2645	3363.5	5062.5	7935	9610	15187.5
Value of α	5	3.5	2.5	15	10	7.5

Table 2: Parameters of the design.

As already mentioned in Section 2, according to non-cooperative game theory, there is no unique prediction neither in the complete nor in the limited information condition. Because we are mainly interested in evaluating the efficiency of the ambient-tax mechanism, we consider as a first benchmark the socially optimal decision. Moreover, we would like to measure the degree of collusion which takes place in our laboratory environment between the polluters. We therefore consider as a second benchmark the collusive decision. Table 3 summarizes our theoretical predictions for the two positions of the socially optimal level in the strategy space.

Social optimum's position	Low			High		
Polluter's type	Small	Medium	Large	Small	Medium	Large
Socially optimal decision	9	11	17	15	19	29
Collusive decision	2.9	2.3	4.8	6.3	6.0	11.6

Table 3: Theoretical predictions.

Practical procedures

The experiment was run on a computer network[13] between July and September 2003 using 192 inexperienced students at the BETA laboratory of experimental economics (LEES) at the University of Strasbourg. Sixteen sessions were organized, with 2 groups of 6 subjects per session.[14] A total of 4 independent observations per treatment was collected. Subjects were randomly assigned to a group of 6 players on a computer terminal, which was physically isolated from other terminals. Communication, other than through the decisions made, was not allowed. The subjects were instructed about the rules of the game and the use of the computer program through written instructions, which were framed in neutral language and read aloud by a monitor (who was chosen at random from the group of subjects at the beginning of the session). A short questionnaire and one dry run followed.[15] Each session took between $1\frac{1}{2}$ and $2\frac{1}{4}$ hours. Table 4 summarizes the subjects' earnings in each treatment. In addition to the earnings related to their performance, subjects received a participation fee of 3 euros.[16]

	Treatment							
Amount of information	Complete				Limited			
Social optimum's position	Low		High		Low		High	
Lump-sum subsidy	Kinf	Ksup	Kinf	Ksup	Kinf	Ksup	Kinf	Ksup
Total	364.16	137.62	212.05	181.95	155.84	112.80	199.28	162.52
Mean	15.17	5.73	8.84	7.58	6.49	4.70	8.30	6.77
Maximum	25.62	14.23	16.59	10.48	15.70	9.77	12.44	11.27
Minimum	3.82	-0.20	2.51	4.82	-1.82	1.07	4.08	2.54

Table 4: Subjects' earnings in euros.

4 Results

In this section we describe the results from the eight treatments. We first compare the observed total pollution level to the socially optimal level in each treatment and discuss the impact of each treatment variable on the group totals. We then evaluate the ability of the ambient tax-subsidy mechanism to induce socially optimal outcomes by computing the efficiency in each treatment. Finally, we analyze the individual decisions and we look at the subjects' payoffs. Acceptance or rejection of the null hypothesis is always based on a 5 percent level of significance, and only the first twelve periods of the time horizon have been considered for the analyses.

4.1 Analyses at the aggregate level

The two first results presented here are primarily based on the means of the group totals over the two sessions in each treatment.

Result 1. The mean group totals are close to the socially optimal level in all treatments but the *ComLowKinf* one.

[13] Based on an application developed by Boun My (2003) designed for Visual Basic.

[14] Around 15 subjects were invited for each session to be able to select subjects and make sure all of the participating subjects had understood the game.

[15] Subjects did not take decisions in this dry run. Practice rounds were excluded in order to check for subjects' learning during a session.

[16] We did not endow subjects with a starting cash balance to cover potential losses. In case of negative payoffs at the end of a session the subject's earnings were only made of the participation fee.

Support. Figure 1 shows the mean group totals in each period for each treatment. Figure 11 and figure 12 in the Appendix show respectively the group totals under limited information and under complete information.

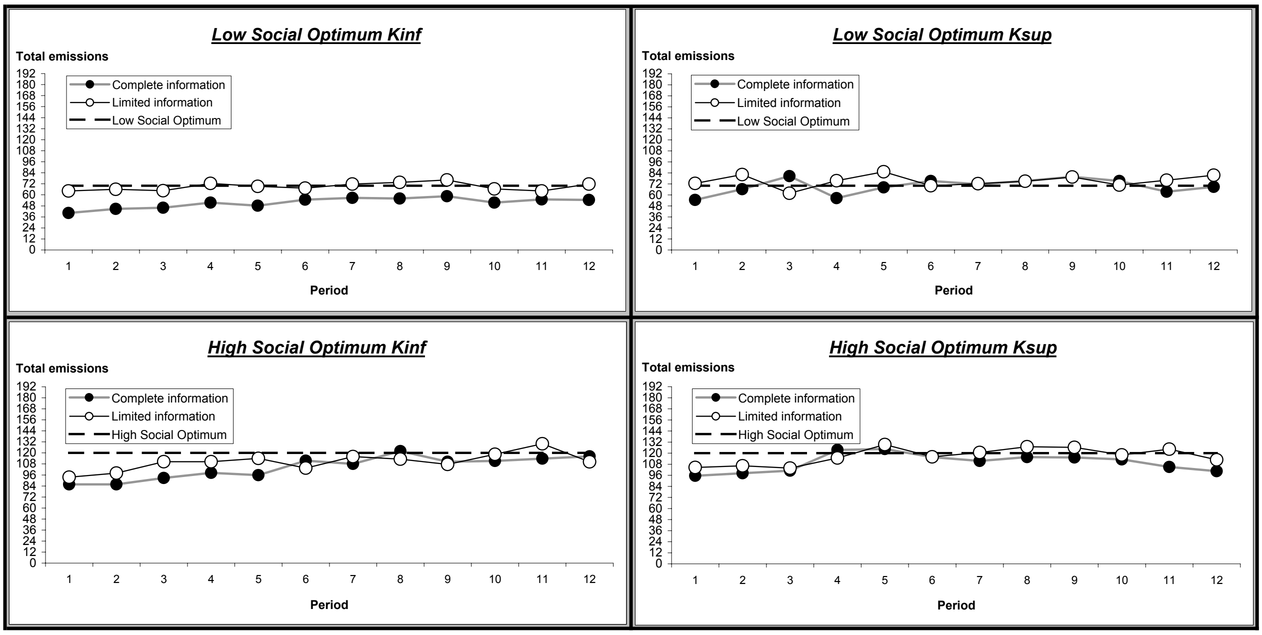

Figure 1: Mean group totals in each period.

In all treatments but the *ComLowKinf* treatment, the group total is close to the socially optimal level either from the beginning or it is in the second half of the time horizon (periods 7 to 12). To see this, we ran a two-factor random effects generalized least squares (GLS) regression with the group total as the dependent variable and the inverse of the period as an independent one (the regression was stratified by groups). Table 5 describes the results of the regression. According to the regression results, the "asymptotic" value of the group total in the *ComLowKinf* treatment, which equals 56.17, is significantly different from the socially optimal level. Similar regressions for the other treatments enable us to conclude that the "asymptotic" value of the group total is not significantly different from the socially optimal level.

Group total	Coefficient	Std. Err.	t-stat	$p >\mid t \mid$	[95% confidence interval]
Constant	56.17	6.49	8.66	0.00	[43.46 , 68.89]
(1/time)	-18.16	4.88	-3.72	0.00	[-27.72 , -8.59]

Table 5: Two-factor random effects GLS regression: asymptotic value of the group total in the *ComLowKinf* treatment.

Additional support is given to our first result by looking at table 12 and table 13 in the Appendix which show the means and standard deviations[17] of the group totals across all four 12 period phases. The standard deviations of the group totals are lower under limited information than under complete information except in case of both a high position of the socially optimal level in the strategy space and an over-evaluated lump-sum subsidy. The mean group totals are closer to the socially optimal level in the second part of the time horizon than in the first part except under

[17] These are the standard deviations of the mean group totals.

limited information in case of both a low position of the socially optimal level in the strategy space and an over-evaluated lump-sum subsidy. □

Next we study the impact of each treatment variable on the absolute difference (distance) between the group total and the socially optimal group total level (respectively 70 in the low social optimum treatments and 120 in the high social optimum treatments).

Result 2. Pooling the data over all treatments, the distance between the group total and the social target is significantly smaller in the last 6 periods than in the first 6 periods and significantly smaller under limited than under complete information.

Support. Tables 14-17 in the Appendix provide the supportive results of two-factor random effects GLS regressions where the dependent variable is always the absolute difference between the group total and the social target[18] whereas the independent variables are: a dummy for the complete information treatments in the first regression, a dummy for the high position of the social optimum in the strategy space treatments in the second regression, a dummy for the high level of the lump-sum subsidy in the third regression, and a dummy for the second half of the time horizon (periods 7 to 12) in the last regression. The absolute difference between the group total and the socially optimal level is significantly smaller under limited than under complete information (table 14), and in the second half than in the first half of the considered time horizon (table 17) which reveals a significant convergence towards the social target. The distance between the actual group total and the socially optimal group total level is also smaller, though non significantly, under a low position than under a high position of the social optimum, and when the lump-sum subsidy is over-evaluated than when it is under-evaluated. □

Our two first results, which state that the group totals are close to the social targets does not establish the ability of the ambient tax-subsidy instrument to induce socially optimal outcomes. Indeed, the mean group totals can be very close to the socially optimal level with the achieved efficiency being very low as the latter is strongly affected by the distribution of the emissions in the group. To evaluate the ability of the ambient tax-subsidy mechanism to induce socially optimal outcomes, we compute the efficiency rate in each period for each group. The efficiency rate is the ratio of the difference between the actual efficiency level and the minimal efficiency level to the difference between the maximal efficiency level and the minimal one. Of course, the maximal efficiency level is obtained when each polluter emits at his socially optimal level. But depending on the position of the socially optimal level in the strategy space, the minimal efficiency level is either obtained if the polluters emit as much as possible (low position) or if they do not emit at all (high position).[19] Recall that in all cases the *uncontrolled* efficiency level is achieved when all polluters emit as much as possible. This implies that the uncontrolled efficiency level is different in the low and the high social optimum conditions. In the former, it is equal to 0%, while in the latter, it is equal to 64.11%.

Result 3. Pooling the data over all treatments, the efficiency rate is found to be significantly higher under a low position than under a high position of the socially optimal level, and in the last six periods than in the first six ones. Though the average efficiency rate is always higher under limited information than under complete information, this difference is not statistically significant. The level of the lump-sum subsidy has no clear impact on the efficiency rate.

[18] The data are stratified by groups.

[19] Alternatively one can define the efficiency rate as the ratio of the difference between the actual efficiency level and the efficiency level in the status quo state to the difference between the maximal efficiency level and the efficiency level in the status quo state. In the status quo state polluters emit at their maximal level. Our qualitative statements would remain unchanged but the difference between the efficiency rate under a low position of the socially optimal level in the strategy space and the efficiency rate under a high position would be strengthened.

Support. Figure 2 shows the mean efficiency rates in each period for each treatment. Figure 13 and figure 14 in the Appendix show respectively the efficiency rates under limited information and under complete information. Table 6 and table 7 on the next page show the mean efficiency rates across all four 12 period phases. We first carry out a descriptive analysis on the average efficiency rates, and observe that they are always higher under limited information than under complete information, they are always higher under a low position than under a high position of the socially optimal level in the strategy space, and they are always higher in the last six periods than in the first six ones. On the contrary, the level of the lump-sum subsidy has no clear impact on the efficiency rates. In order to capture the observed tendencies, we run two-factor random effects GLS regressions on the pooled data. In all regressions, the dependent variable is the efficiency rate, and the data are stratified by groups. The independent variable in the first regression is a dummy for the complete information treatments. The independent variable in the second regression is a dummy for the high position of the social optimum in the strategy space treatments. The independent variable in the third regression is a dummy for the high level of the lump-sum subsidy. In the last regression, the independent variable is a dummy for the second half of the time horizon (periods 7 to 12). Tables 18- 21 in the Appendix summarize the results of the regressions.

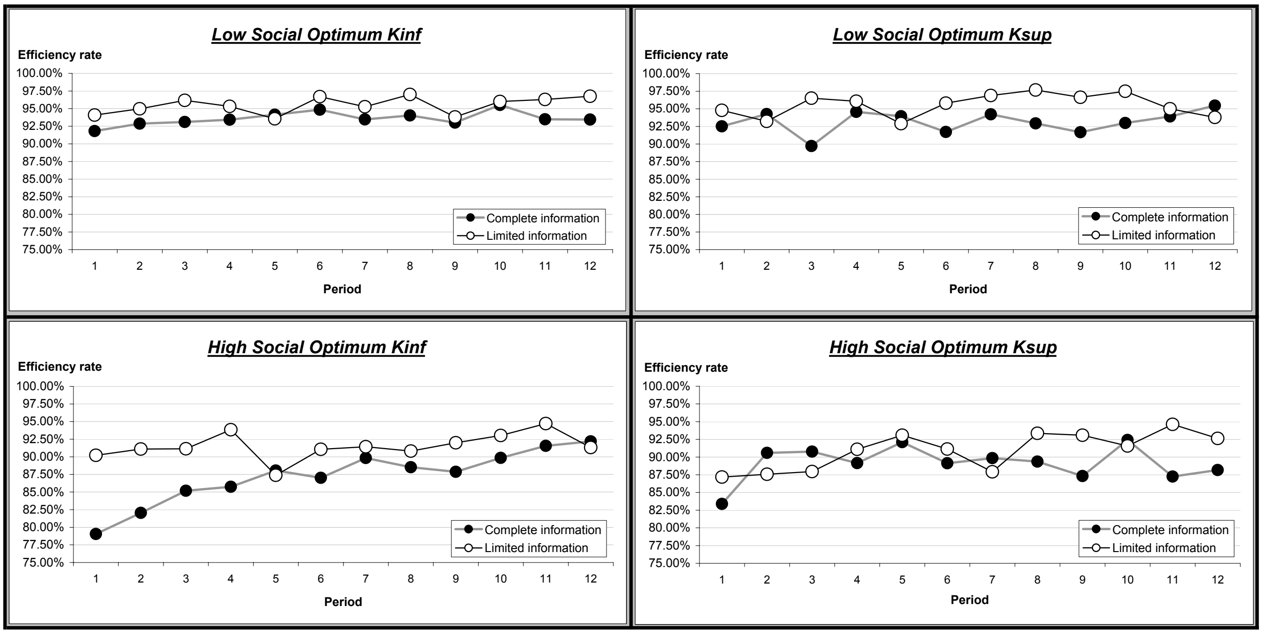

Figure 2: Mean efficiency rates in each period.

	Treatment			
	ComLowKinf	*ComLowKsup*	*ComHighKinf*	*ComHighKsup*
Mean over the 12 periods	93.60%	93.16%	87.25%	89.12%
Mean over the first 6 periods	93.37%	92.79%	84.52%	89.06%
Mean over the last 6 periods	93.83%	93.53%	89.97%	89.19%

Table 6: Mean efficiency rates under complete information.

According to the random effects GLS regressions, there are two significant results: efficiency rates are 4.75% greater under a low position than under a high position of the socially optimal level

	Treatment			
	LimLowKinf	*LimLowKsup*	*LimHighKinf*	*LimHighKsup*
Mean over the 12 periods	95.50%	95.57%	91.51%	90.93%
Mean over the first 6 periods	95.14%	94.88%	90.79%	89.67%
Mean over the last 6 periods	95.86%	96.25%	92.22%	92.19%

Table 7: Mean efficiency rates under limited information.

in the strategy space, and they are 1.57% greater in the second half of the periods than in the first one. No other significant effects are found.[20] □

4.2 Analyses at the individual level

Though the ability of the ambient tax-subsidy instrument to achieve aggregate compliance on the socially optimal group total level has been established, the relatively low observed efficiency rates seem to indicate that the fiscal instrument does not insure compliance at the individual level. Our next result confirms this intuition.

Result 4. The ambient tax-subsidy instrument does not induce individuals to choose the socially optimal action though more (almost) optimal decisions are observed under limited information than under complete information.

Support. Figure 3-10 present the distributions of individual emissions for each type of polluter in each treatment. In all treatments, a negligible percentage of the large and medium polluter's individual decisions coincide exactly with the socially optimal decision. Though this is also true in most treatments for the small polluter's individual decisions, there are two exceptions: treatments *ComHighKsup* and *LimHighKsup* where, respectively, 29% and 19% of the individual decisions coincide exactly with the socially optimal one. By averaging over all treatments, slightly less than a quarter of the small polluter's individual decisions are within three decision numbers of the socially optimal decision (23%), slightly more than a quarter of the medium polluter's individual decisions are within three decision numbers of the socially optimal decision (26%), and 13.50% of the large polluter's individual decisions are within five decision numbers of the socially optimal decision.[21]

[20]Interestingly enough, the test of significance for the complete information dummy just fails the 5% level (p = 0.054), and it is significant if we regress only on the second half of the time horizon (p = 0.039). This suggests that efficiency could reasonably be regarded as significantly higher under limited than under complete information.

[21]To take into account the size of the strategy space we considered a wider interval for the large polluter than for the small and medium polluters. By considering the same interval for the medium polluter as for the large polluter we get that 33.50% of the medium polluter's individual decisions are within five decision numbers of the socially optimal decision.

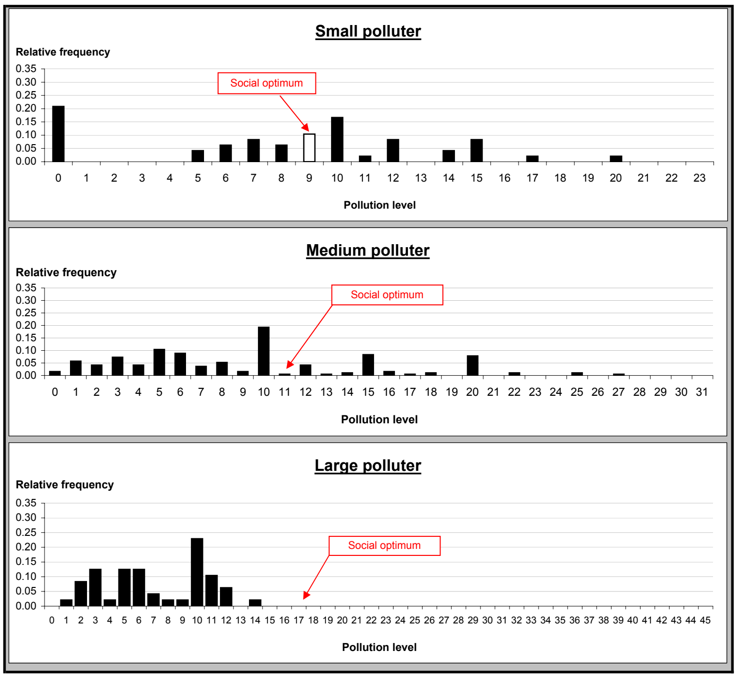

Figure 3: Distributions of individual decisions in treatment *ComLowKinf*.

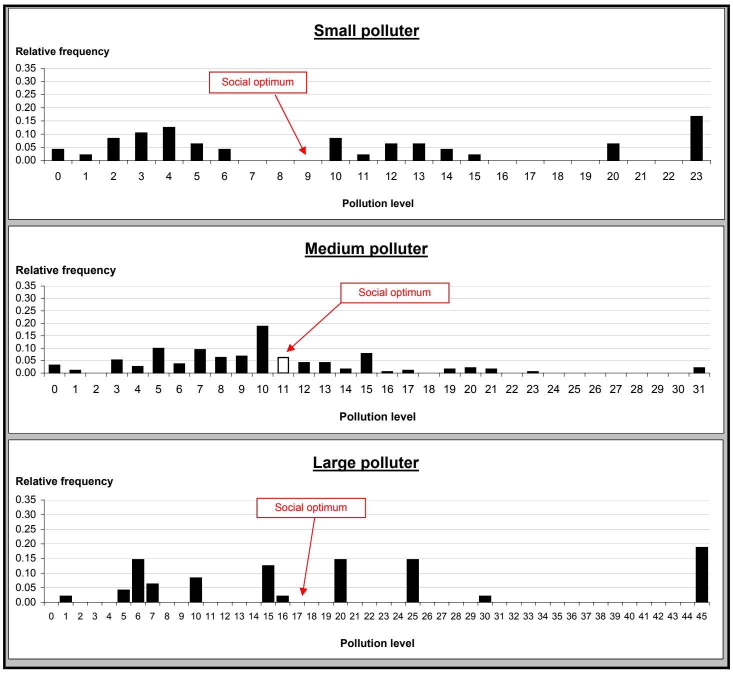

Figure 4: Distributions of individual decisions in treatment *ComLowKsup*.

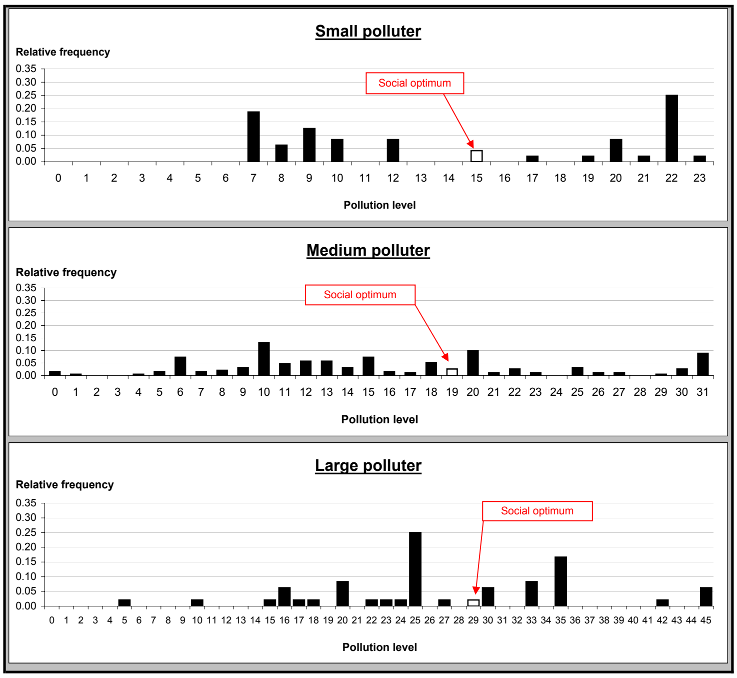

Figure 5: Distributions of individual decisions in treatment *ComHighKinf*.

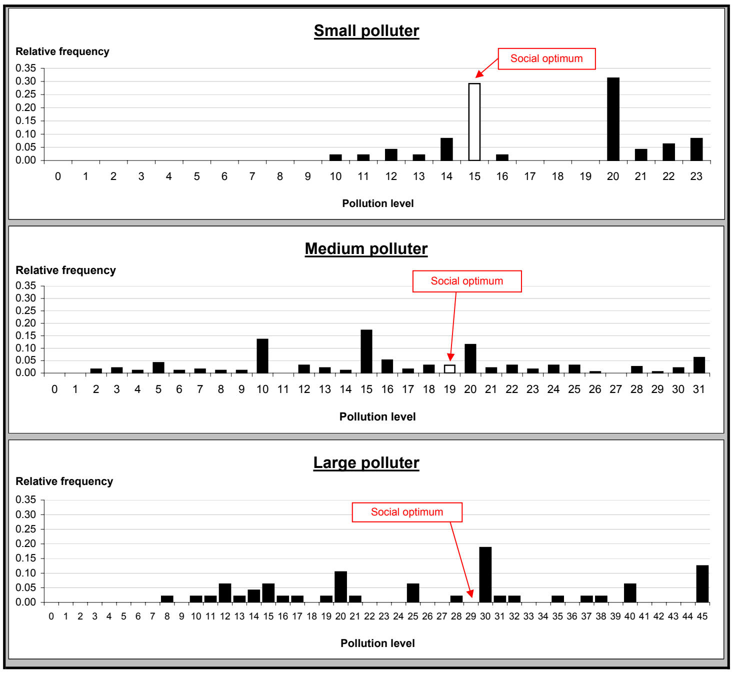

Figure 6: Distributions of individual decisions in treatment *ComHighKsup*.

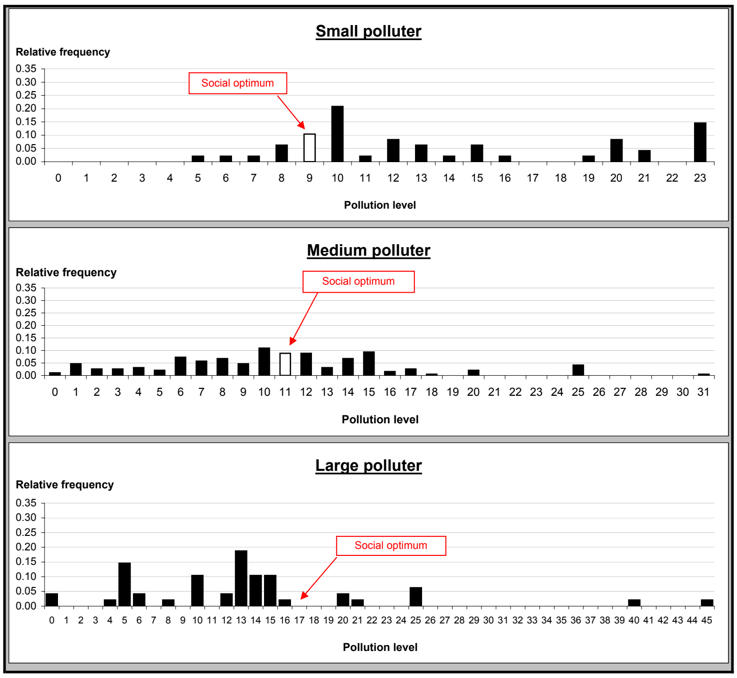

Figure 7: Distributions of individual decisions in treatment *LimLowKinf*.

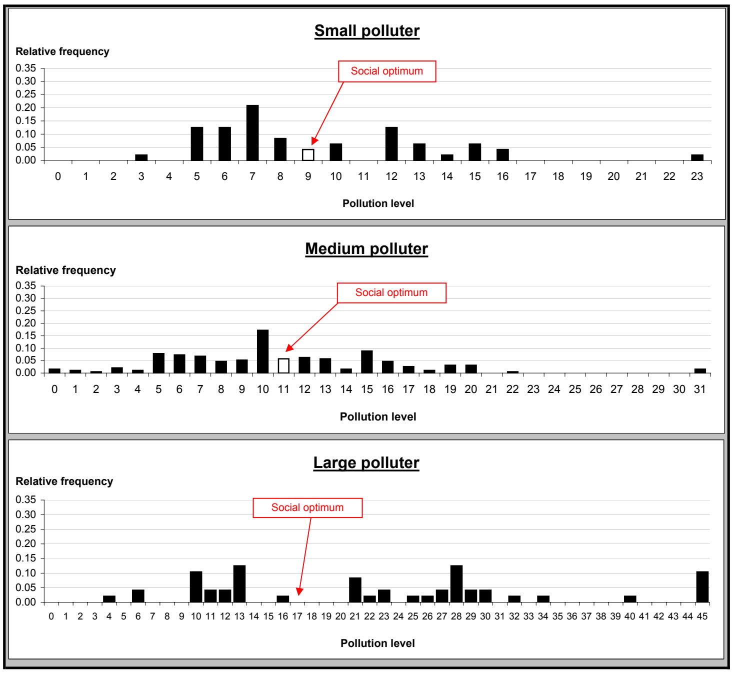

Figure 8: Distributions of individual decisions in treatment *LimLowKsup*.

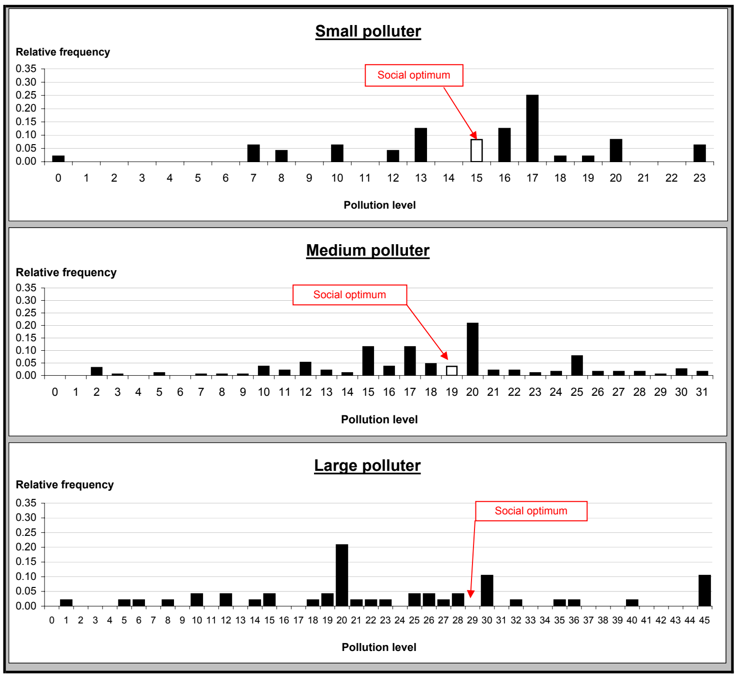

Figure 9: Distributions of individual decisions in treatment *LimHighKinf*.

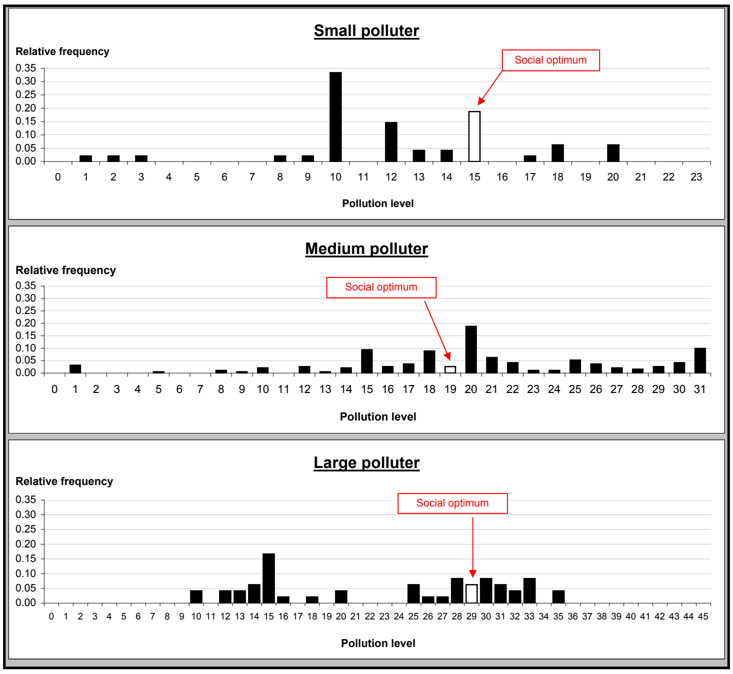

Figure 10: Distributions of individual decisions in treatment *LimHighKsup*.

Table 8 shows the percentage of individual decisions which coincide with the socially optimal action for each polluter's type under complete information, and table 9 shows the percentage of individual decisions which coincide with the socially optimal action for each polluter's type under limited information.

	Treatment											
	ComLowKinf			*ComLowKsup*			*ComHighKinf*			*ComHighKsup*		
Polluter's type	S	M	L	S	M	L	S	M	L	S	M	L
Perfect adequacy	10%	1%	0%	0%	6%	0%	4%	3%	2%	29%	3%	0%
Within three	33%	24%	—	8%	29%	—	4%	18%	—	39%	17%	—
Within five	—	27%	0%	—	40%	15%	—	20%	10%	—	21%	23%

Table 8: Percentage of individual decisions coinciding with the socially optimal decision under complete information.

	Treatment											
	LimLowKinf			*LimLowKsup*			*LimHighKinf*			*LimHighKsup*		
Polluter's type	S	M	L	S	M	L	S	M	L	S	M	L
Perfect adequacy	10%	9%	0%	4%	6%	0%	8%	4%	0%	19%	3%	6%
Within three	37%	29%	—	18%	29%	—	21%	30%	—	23%	31%	—
Within five	—	37%	12%	—	40%	2%	—	43%	16%	—	41%	30%

Table 9: Percentage of individual decisions coinciding with the socially optimal decision under limited information.

Whether the level of lump-sum subsidy has been under-evaluated or over-evaluated has almost no impact on the adequacy of the small polluter's individual decisions to the socially optimal decision, and concerning the small and large polluters it has some impact but no systematic one. Whether the position of the social optimum is high or low has no systematic impact on the adequacy of the small and medium polluter's individual decisions to the socially optimal decision while the large polluter's individual decisions are closer to the socially optimal decision in case of a high position than in case of a low one. The most influential treatment variable on the adequacy of the individual decisions to the socially optimal decision is the amount of information available to the subjects. Indeed, it is almost always true that for each polluter's type, the *less* information the *closer* the individual decisions to the socially optimal action (the two exceptions are the combination of a high position and an over-evaluated lump-sum subsidy for the small polluter and the combination of a low position and an over-evaluated lump-sum subsidy for the large polluter). To summarize, under complete information, the average percentage of individual decisions which almost coincide with the socially optimal action for the small, medium, and large polluter is respectively 21%, 22% (27%), and 12%. Under limited information, the average percentage of individual decisions which almost coincide with the socially optimal action for the small, medium, and large polluter is respectively 25%, 30% (40%), and 15%. □

Subjects' earnings

We conclude this section by looking at the subjects' payoffs. Table 10 and table 11 on the following page show the average payoffs in euros per polluter's type (if in a given period each polluter complies with the social optimum, a polluter's payoff, whatever his type, equals about 0.58 euros). In accordance with our previous results, higher payoffs are observed in the complete information condition than in the limited information condition[22] and in almost each treatment, whatever the polluter's type, the average payoff decreases over time, meaning that the average payoff in the first six periods is higher than the average payoff in the last six periods.[23] The actual earnings confirm that collusion among subjects is easier to achieve in the complete information condition (especially in the first half of the twelve periods) than in the limited information condition.

	Treatment											
	ComLowKinf			*ComLowKsup*			*ComHighKinf*			*ComHighKsup*		
Polluter's type	S	M	L	S	M	L	S	M	L	S	M	L
All 12 periods	1.65	1.31	0.70	0.49	0.46	0.53	0.85	0.72	0.69	0.73	0.62	0.60
First 6 periods	1.93	1.48	0.79	0.58	0.52	0.57	1.09	0.87	0.72	0.72	0.61	0.61
Last 6 periods	1.37	1.13	0.62	0.40	0.41	0.49	0.61	0.57	0.60	0.73	0.62	0.59

Table 10: Average payoffs in euros under complete information.

	Treatment											
	LimLowKinf			*LimLowKsup*			*LimHighKinf*			*LimHighKsup*		
Polluter's type	S	M	L	S	M	L	S	M	L	S	M	L
All 12 periods	0.84	0.50	0.42	0.37	0.37	0.51	0.78	0.70	0.57	0.54	0.58	0.52
First 6 periods	1.05	0.57	0.46	0.39	0.38	0.50	0.91	0.82	0.58	0.58	0.63	0.55
Last 6 periods	0.62	0.42	0.38	0.35	0.35	0.51	0.64	0.59	0.55	0.49	0.54	0.49

Table 11: Average payoffs in euros under limited information.

5 Conclusion

This paper presents the results of an experiment intended to test the efficiency of an ambient tax/subsidy under more natural conditions than in previous experiments. Since the damage function is strictly convex, the regulator cannot introduce a linear ambient tax if he is uninformed of polluters' types. Instead, he can introduce a damage based mechanism, but this decentralizes the planning problem to polluters. However, under real-world conditions, polluters are likely to have limited information on the other polluters' types, so that they cannot calculate their optimal Nash strategies. Thus, our first objective is to study the ability of the instrument to implement the social optimum both under limited and full information. Second, since the instrument is an ambient tax/subsidy, we investigate the effect of an under- or an over-evaluation of the lump-sum subsidy on behaviors. Third, we test whether the conjecture that efficiency will be greater when the social optimum is in a "low" position than when it is in a "high" position is verified in our public bad environment.

By establishing that the observed total pollution level matches the specified environmental target whatever the experimental condition (at least in the second half of the time horizon), our findings confirm the results of the previous experimental studies on the ambient tax/subsidy scheme. Also in line with the early experimental evidence, we found that that the fiscal instrument does not insure compliance at the individual level indicating that only a second-best level of social welfare can be achieved.

[22]See, e.g., figure 1 on page 9.

[23]The average payoff increases in three cases but then the difference between the average payoff over the first half of the time horizon and the second half of the time horizon is negligible.

More interestingly, our experimental results show that the efficiency performance of the ambient scheme is significantly higher under a low position than under a high position of the socially optimal level, that it is always higher (though not significantly) under limited information than under complete information, and that the level of the lump-sum subsidy has no clear impact on the efficiency rate. This last observation is good news for the environmental regulator. Indeed, even if the regulator has limited information and cannot compute the socially optimal level of ambient pollution, he can resort to proxies to set lump-sum subsidies. The effect of the position of the social optimum in the strategy space is also of interest. It implies that the experimental parameters chosen in an experiment can have a significant effect on the conclusions. The next question is of course whether a given situation in reality corresponds to a low or to a high social optimum condition. This depends on the damage and profit functions, and on the size of the strategy space.

The effect of information is the most striking result of this paper. Theorists have traditionally been uneasy concerning the behavioral relevance and hence the actual power of the policy instruments they suggested. The reason for this is that the suggested instruments crucially rely on Nash expectations on the part of the agents and thus on cognitively highly demanding reasoning processes. According to the experimental evidence we provided in this paper, concerns are without substance when it comes to the instruments' actual efficiency performance. As it turns out, the specific ambient tax/subsidy mechanism does partly achieve the goal it has been designed for, i.e., it induces a quite high level of efficiency and the actual total pollution level matches the specified environmental target. Our experimental study shows that the suggested mechanism works efficiently even where subjects in fact cannot apply the reasoning the mechanism is based on theoretically. Additionally, our experimental results confirm that polluters have less incentive to play cooperatively under limited information than under complete information, which corroborates that less amount of information available to polluters about their strategic environment is beneficial from a social point of view.

Appendix

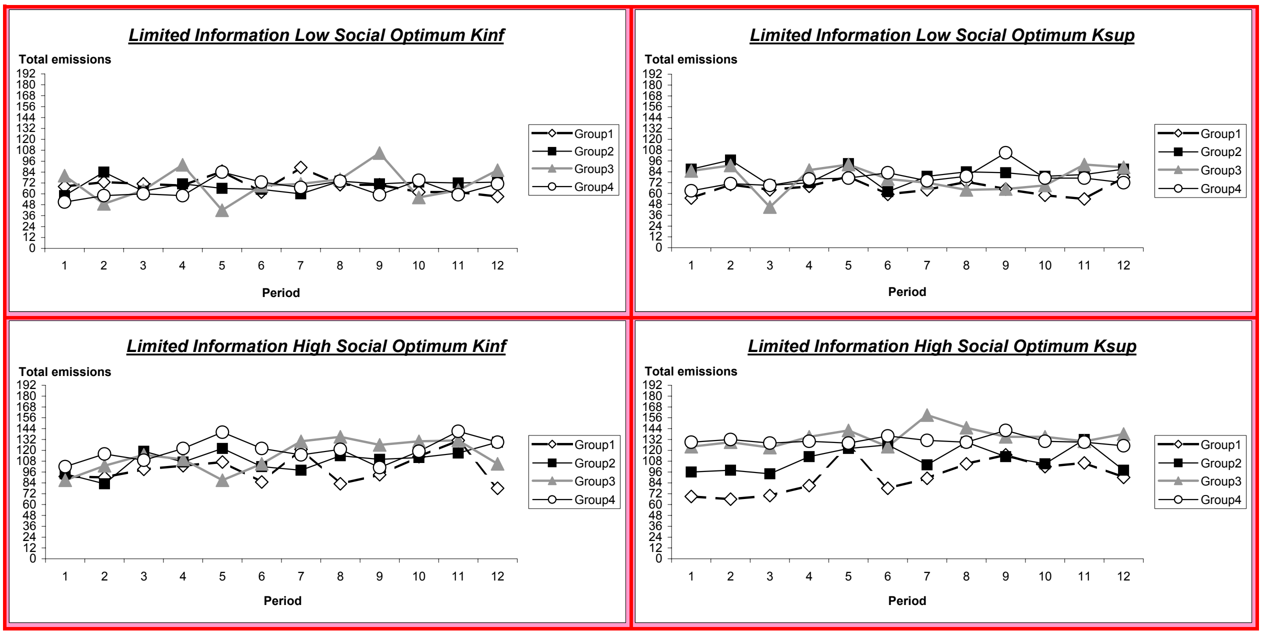

Figure 11: Group totals by period under limited information.

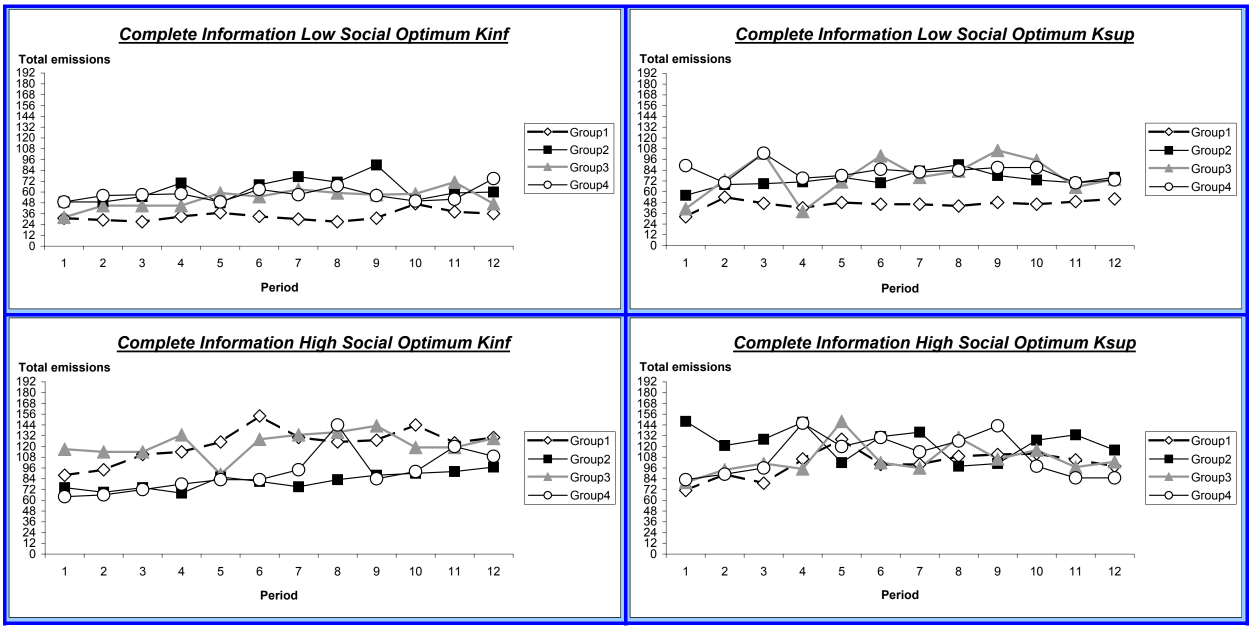

Figure 12: Group totals by period under complete information.

	Treatment			
	ComLowKinf	*ComLowKsup*	*ComHighKinf*	*ComHighKsup*
Mean over the 12 periods	51.48	69.63	104.29	109.98
Mean over the first 6 periods	47.58	66.88	94.96	109.75
Mean over the last 6 periods	55.38	72.38	113.63	110.21
Standard deviation	12.73	16.03	21.37	10.03

Table 12: Mean and standard deviations of the group totals under complete information.

	Treatment			
	LimLowKinf	*LimLowKsup*	*LimHighKinf*	*LimHighKsup*
Mean over the 12 periods	68.98	75.19	110.46	116.96
Mean over the first 6 periods	67.29	74.54	105.00	112.42
Mean over the last 6 periods	70.67	75.83	115.92	121.50
Standard deviation	2.39	6.68	8.55	20.06

Table 13: Mean and standard deviations of the group totals under limited information.

Table 14: Two-factor random effects GLS regression: impact of the amount of information available to the subjects on the distance to the socially optimal group total.

Distance to the socially optimal group total	Coefficient	Std. Err.	t-stat	$p >\mid t \mid$
Constant	12.84	1.98	6.48	0.000
Complete information dummy	6.77	2.80	2.41	0.016

Table 15: Two-factor random effects GLS regression: impact of the position of the social optimum in the strategy space on the distance to the socially optimal group total.

Distance to the socially optimal group total	Coefficient	Std. Err.	t-stat	$p >\mid t \mid$
Constant	13.52	2.05	6.59	0.000
High position of the social optimum dummy	5.43	2.90	1.87	0.061

Table 16: Two-factor random effects GLS regression: impact of the value of the lump-sum subsidy on the distance to the socially optimal group total.

Distance to the socially optimal group total	Coefficient	Std. Err.	t-stat	$p >\mid t \mid$
Constant	16.95	2.16	7.85	0.000
Over evaluated lump-sum subsidy dummy	-1.44	3.05	-0.47	0.638

Table 17: Two-factor random effects GLS regression: impact of time on the distance to the socially optimal group total.

Distance to the socially optimal group total	Coefficient	Std. Err.	t-stat	$p >\| t \|$
Constant	18.41	1.58	11.62	0.000
Second half of the time horizon dummy	-4.35	0.97	-4.47	0.000

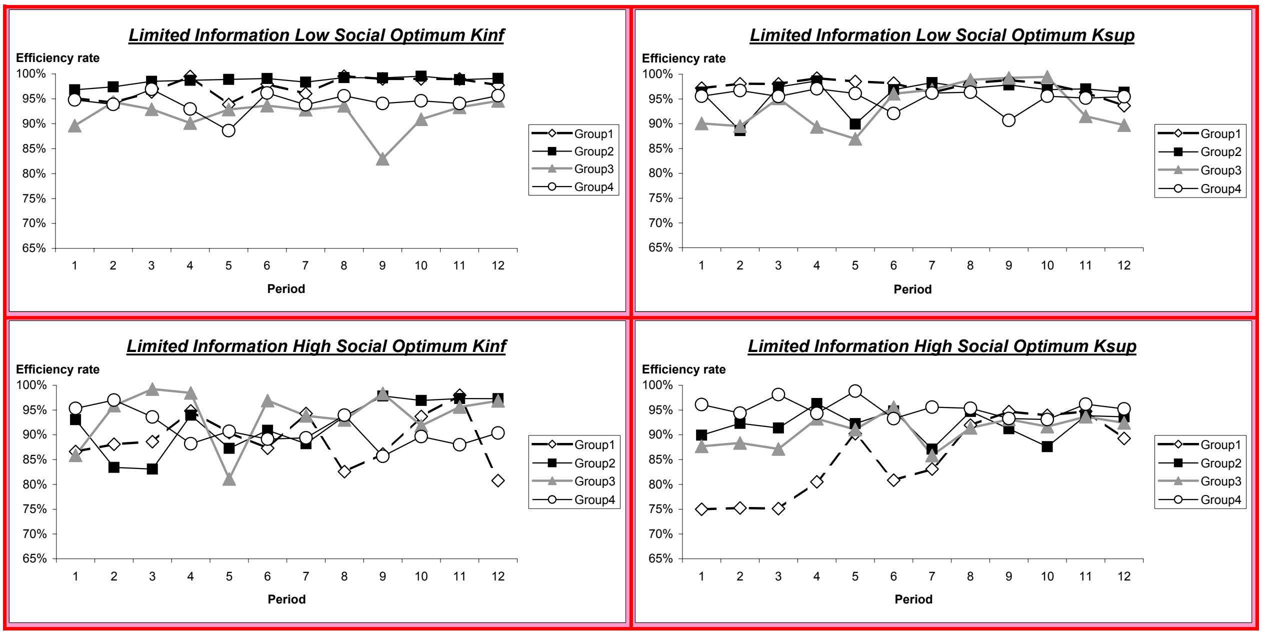

Figure 13: Efficiency rates by period under limited information.

Efficiency rate	Coefficient	Std. Err.	t-stat	$p >\| t \|$
Constant	93.37%	0.0095	98.22	0.000
Complete information dummy	-2.59%	0.0134	-1.93	0.054

Table 18: Two-factor random effects GLS regression: impact of the amount of information available to the subjects on the efficiency rate.

Efficiency rate	Coefficient	Std. Err.	t-stat	$p >\| t \|$
Constant	94.45%	0.0080	118.14	0.000
High position of the social optimum dummy	-4.75%	0.0113	-4.20	0.000

Table 19: Two-factor random effects GLS regression: impact of the position of the social optimum in the strategy space on the efficiency rate.

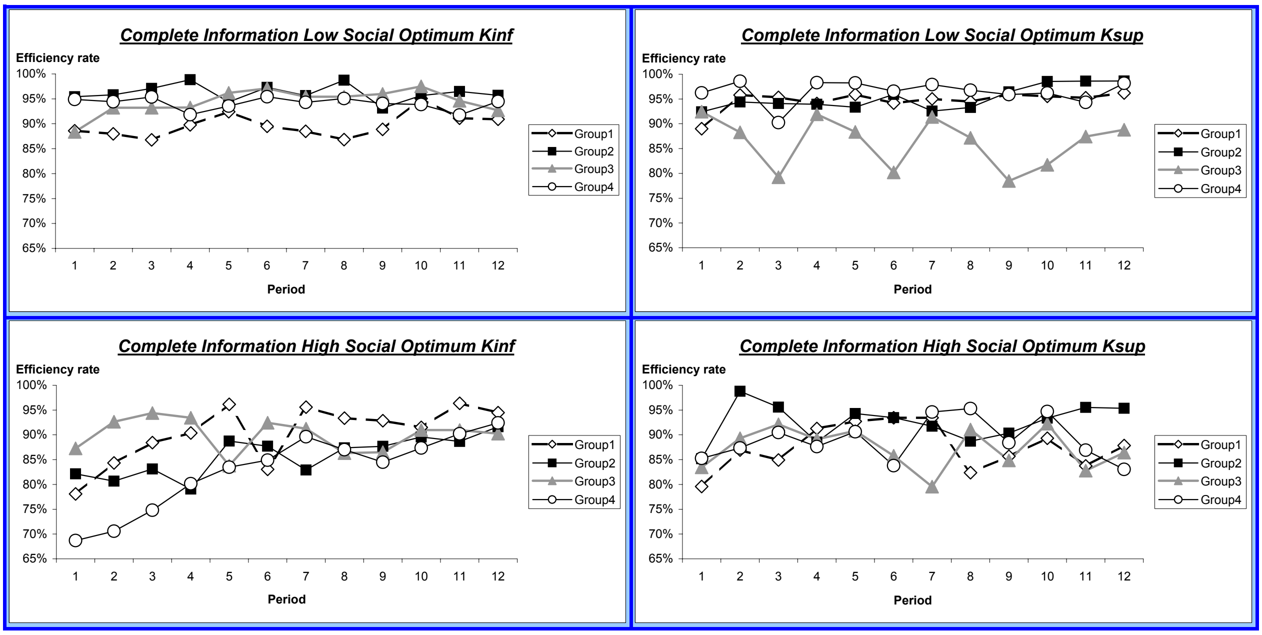

Figure 14: Efficiency rates by period under complete information.

Efficiency rate	Coefficient	Std. Err.	t-stat	$p >\mid t \mid$
Constant	91.96%	0.0101	91.28	0.000
Over evaluated lump-sum subsidy dummy	0.23%	0.0142	0.16	0.871

Table 20: Two-factor random effects GLS regression: impact of the value of the lump-sum subsidy on the efficiency rate.

Efficiency rate	Coefficient	Std. Err.	t-stat	$p >\mid t \mid$
Constant	91.29%	0.0073	125.5	0.000
Second half of the time horizon dummy	1.57%	0.0039	4.05	0.000

Table 21: Two-factor random effects GLS regression: impact of time on the efficiency rate.

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