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

François COCHARD\textsuperscript{a}, Anthony Ziegelmeyer\textsuperscript{b}, Kene Boun My\textsuperscript{c}

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Abstract

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 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. This experimental study tests the efficacy of such a scheme. Contrary to previous experimental studies, we provide a stress-test of the mechanism by considering a convex environmental damage function, uncertainty in measuring the ambient level of pollution, and polluters with heterogeneous profit functions competing against the same opponents for the duration of the experiment, which runs for an indeterminate length. Moreover, to capture the uncertainties of naturally occurring market environments, half of our treatments consider an environment of limited information where polluters do not know others profit functions. We observe that the instrument induces aggregate compliance on the socially optimal level of ambient pollution, but not individual compliance. Surprisingly, individual compliance is better under limited than under complete information.

Keywords: Nonpoint source pollution, Regulation, Ambient tax, Experimental economics.

JEL Classification: C92, D62, H21, H3, Q12, Q18.

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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 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 a linear 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

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

¹Shortle and Horan (2001) provide an exhaustive review of the nonpoint source pollution control literature.
²Optimality in dominant strategies relies on the additional assumption that the ambient pollution is the sum of the individual emissions.
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 instrument since the optimum is only
implemented in non-dominant Nash strategies. Polluters’ optimal emissions become inter-
dependent 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. 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.
Other experimental tests of the ambient tax mechanism are provided by Cochard, Willinger,
and Xepapadeas (2003), Alpizar, Requate, and Schram (2002), Vossler, Poe, Schulze, and
Segerson (2002). Broadly speaking, the existing controlled laboratory experiments on this
scheme conclude that though the polluters’ emissions do not maximize the social net benefit,
the observed total pollution level matches the specified target. In other words, the instrument
is able to induce aggregate compliance but not individual compliance on the socially optimal
level of ambient pollution.
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 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.\footnote{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).}

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.\footnote{Several authors expressed concern about this issue in the theoretical literature on nonpoint management (see, among others, Hansen, 1998).}
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 dam-
age 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 informa-
tion 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 pol-
luters’ 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 some-
times 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 (2003) setting where the social optimum is relatively high in the polluters’
emission space.\footnote{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.} 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
This paper is organized as follows. Section 2 presents the theoretical benchmarks with which our results will be compared. The experimental design is described in section 3. Section 4 is devoted to the results. Section 5 concludes.

2 Theory

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 firms have complete information about their strategic environment. We define complete information as common knowledge of the number of firms interacting on the market, the distribution of the stochastic variables, and firms’ benefit functions. Next we consider the implications of dropping the assumption that firms’ benefit functions are common knowledge. Finally, we discuss the implications of an infinite interaction between firms.

2.1 The static model under complete information

We consider a market that consists of \( i = 1, \ldots, n \) firms emitting a pollutant to the same recipient.\(^6\) 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 benefit (or profit) function of each firm is defined as a function of emission levels which are a by-product of the firm’s production: \( B_i(e_i) = \gamma_i - \alpha_i(e_i - e_i^{\text{max}})^2 \) where \( e_i \in \{0, \ldots, e_i^{\text{max}}\} \) denotes the emissions of the \( i \)th firm and \( e_i^{\text{max}} \) denotes firm \( i \)'s maximal amount of emissions. In the absence of any environmental control, firm \( i \) will release pollution up to \( e_i^{\text{max}} \) which we refer to as the uncontrolled level of emissions. In that case, the total emissions would be equal to \( \sum_i e_i^{\text{max}} \). We assume that the number of firms and the firms’ benefit functions are common knowledge.

For simplicity, the measured ambient concentration of the pollutant is given by \( \sum_i e_i + \epsilon \), where \( \epsilon \) 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.

\(^6\)Interaction between firms is assumed to take place only once.
The environmental regulator or social planner seeks to maximize total benefit less expected environmental damages, i.e., he will choose the socially optimum emission level for each firm such that the expected net benefit is maximized. The expected net benefit 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 firms and the environmental regulator are risk-neutral, the socially optimal level of emissions for each firm is found by solving

\[
\max \sum_{i=1}^{n} B_i(e_i) - E \left[ (\sum_i e_i + \epsilon)^2 \right]
\]

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 firm, 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, firms 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 

\[
-2\alpha_i e_i^* + 2\alpha_i e_i^{\text{max}} - 2 \sum_j e_j^* = 0, \quad \text{for } i = 1, \ldots, n
\]

leading to 

\[
e_i^* = (\alpha_i e_i^{\text{max}} - \sum_{j \neq i} e_j^*)/(1 + \alpha_i), \quad \text{for } i = 1, \ldots, n.
\]

Notice that for specification of the mechanism the environmental regulator does not require knowledge of firms’ benefit functions, it is sufficient for him to know the damage function. By knowing firms’ benefit functions, the regulator could determine a level of the lump-sum subsidy \( K^* \) so that firms would not incur expected taxes at the social optimum, i.e., 

\[
K^* = (\sum_i e_i^*)^2 + \text{Var}[\epsilon].
\]

### 2.2 The static model under limited information

As already mentioned, for specification of the damage based mechanism introduced above, the environmental regulator does not require knowledge of firms’ benefit functions, i.e., the solution of the planning problem is decentralized to firms. Theorists like Hansen who suggested damage based tax mechanisms recognized that though decentralization reduces the

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7Due to our convexity assumptions, second order conditions are trivially satisfied.
regulator’s information problem, it also introduces the possibility that the optimal Nash equilibrium becomes unstable. The reason being that under limited information firms cannot calculate their Nash equilibrium strategies. Indeed, if we assume that each firm only knows its own benefit function, then any emission level can be rationalized as firm $i$’s expectations concerning the other firms 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 firms’ benefit functions are common knowledge.

2.3 Extension to infinite interactions between firms

In the above analysis, we considered a single interaction between the firms. By assuming that firm’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 firms 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 firms 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). Actually, many outcomes can be supported as a subgame-perfect equilibrium in an infinite sequence of interactions between firms, among whose the collusive solution and the static Nash equilibrium. The collusive outcome is obtained if each firm $i$ maximizes $\sum_i B_i(e_i) - E \left[ \left( \sum_i e_i + \epsilon \right)^2 \right] + K$, 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 benefit functions is fundamental in this context, since it reveals emission combinations that can be supported as an equilibrium, and because it permits the determination of each firm’s incentives to participate in a collusive agreement. Therefore, firms have less incentive to play cooperatively under limited information meaning that the

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8Subgame-perfect equilibria in infinitely repeated games are based on trigger strategies. Firms select a collusive emission level until defection is detected; if defection occurs, a “punishment” phase ensues.
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 firms 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 firms whose decisions correspond to the level of emissions. The larger the decision number the more emissions the firm releases up to some maximum decision number which corresponds to the firms uncontrolled level of emission, i.e., to the subject’s endowment (in tokens).\footnote{Emissions were restricted to integer values.} 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 (the firms’ benefit functions) and a group payoff (the ambient tax/subsidy scheme). 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\footnote{The triangular distribution is a good approximation of the normal distribution and it is easy to explain to subjects.}.\footnote{The triangular distribution is a good approximation of the normal distribution and it is easy to explain to subjects.} 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 firm’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 firm’s socially optimal level of emission is between 60% and 2/3 of its endowment depending on its type (see 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’ decisions: moving the equilibrium closer to the collusive outcome leads to a decrease in collusion (see, among others, Isaac and Walker, 1998 and Willinger and Ziegelmeier, 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 $K_{inf}$ condition the regulator has under-evaluated the level of the lump-sum subsidy which implies that firms pay taxes at the social optimum whereas in the $K_{sup}$ condition the regulator has over-evaluated the level of the lump-sum subsidy which implies that firms 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.

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.

### Table 1: Experimental design.

<table>
<thead>
<tr>
<th>Amount of information</th>
<th>Limited</th>
<th>Complete</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social optimum's position</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>Lump-sum subsidy</td>
<td>Kinf</td>
<td>Ksup</td>
</tr>
<tr>
<td>Treatment</td>
<td>Lim</td>
<td>Lim</td>
</tr>
</tbody>
</table>

| Treatment | Low | High | High | Low | Low | High |
| Kinf | Ksup | Kinf | Ksup | Kinf | Ksup | Kinf |

### Table 2: Parameters of the design.

<table>
<thead>
<tr>
<th>Social optimum's position</th>
<th>Low</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Under-evaluated lump-sum subsidy (Kinf)</td>
<td>4200</td>
<td>12300</td>
</tr>
<tr>
<td>(85% of 4922.5) (85% of 14462.5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Over-evaluated lump-sum subsidy (Ksup)</td>
<td>5700</td>
<td>16700</td>
</tr>
<tr>
<td>(115% of 4922.5) (115% of 14462.5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random variable's support</td>
<td>{-9,-6,-3,0,3,6,9}</td>
<td>{-15,-10,-5,0,5,10,15}</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Polluter's type</th>
<th>Small</th>
<th>Medium</th>
<th>Large</th>
<th>Small</th>
<th>Medium</th>
<th>Large</th>
</tr>
</thead>
<tbody>
<tr>
<td>Endowment</td>
<td>23</td>
<td>31</td>
<td>45</td>
<td>23</td>
<td>31</td>
<td>45</td>
</tr>
<tr>
<td>Value of $\gamma$</td>
<td>2645</td>
<td>3363.5</td>
<td>5062.5</td>
<td>7935</td>
<td>9610</td>
<td>15187.5</td>
</tr>
<tr>
<td>Value of $\alpha$</td>
<td>5</td>
<td>3.5</td>
<td>2.5</td>
<td>15</td>
<td>10</td>
<td>7.5</td>
</tr>
</tbody>
</table>

### Table 3: Theoretical predictions.

<table>
<thead>
<tr>
<th>Social optimum's position</th>
<th>Low</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Polluter's type</td>
<td>Small</td>
<td>Medium</td>
</tr>
<tr>
<td>Socially optimal decision</td>
<td>9</td>
<td>11</td>
</tr>
<tr>
<td>Collusive decision</td>
<td>2.9</td>
<td>2.3</td>
</tr>
</tbody>
</table>

### 3.1 Practical procedures

The experiment was run on a computer network\textsuperscript{11} 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.\textsuperscript{12} 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

\textsuperscript{11}Based on an application developed by Bounmy (2003) designed for Visual Basic.

\textsuperscript{12}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.
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.\textsuperscript{13} Each session took between 1\textfrac{1}{2} and 2\textfrac{1}{4} hours. In addition to the earnings related to their performance, subjects received a show-up fee of 3 euros.\textsuperscript{14}

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 then evaluate the ability of the ambient tax-subsidy mechanism to induce socially optimal outcomes by computing the efficiency in each treatment (section 4.1). Finally, we analyze the individual decisions (sections 4.2).

4.1 Analyses at the aggregate level

The first result presented here is based on the means of the group totals in each treatment.

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

\textit{Support.} Figure 1 on the following page shows the mean group totals in each period for each treatment.

In all treatments but the \textit{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 6 on page 14 describes the results of the regression. According to the regression results, the “asymptotic” value of

\textsuperscript{13}Subjects did not take decisions in this dry run. Practice rounds were excluded in order to check for subjects’ learning during a session.

\textsuperscript{14}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.
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 except for the *LimLowKsup* treatment where this value is slightly but significantly higher (75.94).

Table 4 and table 5 on the next page show the means and standard deviations of the group totals across all four 12 period phases. 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 in treatment *LimLowKsup*.

![Figure 1: Mean group totals in each period.](image)

**Table 4: Mean and standard deviations of the group totals under complete information.**

<table>
<thead>
<tr>
<th>Treatment</th>
<th><em>ComLowKinf</em></th>
<th><em>ComLowKsup</em></th>
<th><em>ComHighKinf</em></th>
<th><em>ComHighKsup</em></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean over the 12 periods</td>
<td>51.48</td>
<td>69.63</td>
<td>104.29</td>
<td>109.98</td>
</tr>
<tr>
<td>Mean over the first 6 periods</td>
<td>47.58</td>
<td>66.88</td>
<td>94.96</td>
<td>109.75</td>
</tr>
<tr>
<td>Mean over the last 6 periods</td>
<td>55.38</td>
<td>72.38</td>
<td>113.63</td>
<td>110.21</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>12.73</td>
<td>16.03</td>
<td>21.37</td>
<td>10.03</td>
</tr>
</tbody>
</table>

15These are the standard deviations of the mean group totals.
Table 5: Mean and standard deviations of the group totals under limited information.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>LimLowKinf</th>
<th>LimLowKsup</th>
<th>LimHighKinf</th>
<th>LimHighKsup</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean over the 12 periods</td>
<td>68.98</td>
<td>75.19</td>
<td>110.46</td>
<td>116.96</td>
</tr>
<tr>
<td>Mean over the first 6 periods</td>
<td>67.29</td>
<td>74.54</td>
<td>105.00</td>
<td>112.42</td>
</tr>
<tr>
<td>Mean over the last 6 periods</td>
<td>70.67</td>
<td>75.83</td>
<td>115.92</td>
<td>121.50</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>2.39</td>
<td>6.68</td>
<td>8.55</td>
<td>20.06</td>
</tr>
</tbody>
</table>

Table 6: Two-factor random effects GLS regression: asymptotic value of the group total in the ComLowKinf treatment.

| Group total | Coefficient | Std. Err. | t-stat | p > | $|t$ | 95% confidence interval |
|-------------|-------------|-----------|--------|-----|-----|------------------------|
| Constant    | 56.17       | 2.824365  | 19.89  | 0.00|     | [50.64 61.71]          |
| (1/time)    | -18.16      | 7.820914  | -2.32  | 0.02|     | [-33.48 -2.83]         |

Our first result 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 an “efficiency rate” in each period for each group. The efficiency rate is defined as 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 social optimum 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).\textsuperscript{16} 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%.

\textit{Result 2.} There are four remarkable results: the average efficiency rates are always higher

\textsuperscript{16} 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 firms 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.
under limited information than under complete information, they are always higher under a low position than under a high position of the social optimum 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.

**Support.** Figure 2 on the following page shows the mean efficiency rates in each period for each treatment. Figure 3 on the next page shows the efficiency rates under limited information and figure 4 on page 17 shows the efficiency rates under complete information. Table 7 and table 8 on page 17 show the mean efficiency rates across all four 12 period phases.

In order to compare the effects of treatments variables on efficiency rates, we ran two-factor random effects GLS regressions. In all regressions, the dependent variable is the efficiency rate, and all the regressions were 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 second half of the time horizon (periods 7 to 12). In the last regression, the independent variable is a dummy for the high level of the lump-sum subsidy. Table 9 - 11 on page 17 describe the results of all the regressions but the last one (which is not significant).

According to the random effects GLS regressions, the three differences mentioned above are statistically significant. More precisely, the efficiency rates are 2.59% greater under limited information than under complete information, they are 4.75% greater under a low position than under a high position of the socially optimal level in the strategy space, and they are 1.57% greater in the second half of the periods than in the first one. The two first results are confirmed if we regress only on the second half of the time horizon.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Mean over the 12 periods</th>
<th>Mean over the first 6 periods</th>
<th>Mean over the last 6 periods</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ComLowKinf</strong></td>
<td>93.60%</td>
<td>93.37%</td>
<td>93.83%</td>
</tr>
<tr>
<td><strong>ComLowKsup</strong></td>
<td>93.16%</td>
<td>92.79%</td>
<td>93.53%</td>
</tr>
<tr>
<td><strong>ComHighKinf</strong></td>
<td>87.25%</td>
<td>84.52%</td>
<td>89.97%</td>
</tr>
<tr>
<td><strong>ComHighKsup</strong></td>
<td>89.12%</td>
<td>89.06%</td>
<td>89.19%</td>
</tr>
</tbody>
</table>

Table 7: Mean efficiency rates under complete information.
Figure 2: Mean efficiency rates in each period.

Figure 3: Efficiency rates by period under limited information.
Figure 4: Efficiency rates by period under complete information.

Table 8: Mean efficiency rates under limited information.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>LimLowKinf</th>
<th>LimLowKsup</th>
<th>LimHighKinf</th>
<th>LimHighKsup</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean over the 12 periods</td>
<td>95.50%</td>
<td>95.57%</td>
<td>91.51%</td>
<td>90.93%</td>
</tr>
<tr>
<td>Mean over the first 6 periods</td>
<td>95.14%</td>
<td>94.88%</td>
<td>90.79%</td>
<td>89.67%</td>
</tr>
<tr>
<td>Mean over the last 6 periods</td>
<td>95.86%</td>
<td>96.25%</td>
<td>92.22%</td>
<td>92.19%</td>
</tr>
</tbody>
</table>

Table 9: Two-factor random effects GLS regression: impact of the amount of information available to the subjects on the efficiency rate.

<table>
<thead>
<tr>
<th>Efficiency rate</th>
<th>Coefficient</th>
<th>Std. Err.</th>
<th>t-stat</th>
<th>p &gt;</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>93.37%</td>
<td>0.0037769</td>
<td>247.22</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>Complete information dummy</td>
<td>-2.59%</td>
<td>0.0053414</td>
<td>-4.86</td>
<td>0.00</td>
<td></td>
</tr>
</tbody>
</table>

Table 10: Two-factor random effects GLS regression: impact of the position of the social optimum in the strategy space on the efficiency rate.

<table>
<thead>
<tr>
<th>Efficiency rate</th>
<th>Coefficient</th>
<th>Std. Err.</th>
<th>t-stat</th>
<th>p &gt;</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>94.45%</td>
<td>0.0034927</td>
<td>270.44</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>High position of the social optimum dummy</td>
<td>-4.75%</td>
<td>0.0049394</td>
<td>-9.62</td>
<td>0.00</td>
<td></td>
</tr>
</tbody>
</table>

Table 11: Two-factor random effects GLS regression: impact of time on the efficiency rate.

<table>
<thead>
<tr>
<th>Efficiency rate</th>
<th>Coefficient</th>
<th>Std. Err.</th>
<th>t-stat</th>
<th>p &gt;</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>91.29%</td>
<td>0.0038497</td>
<td>237.14</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>Second half of the time horizon dummy</td>
<td>1.57%</td>
<td>0.0054442</td>
<td>2.89</td>
<td>0.00</td>
<td></td>
</tr>
</tbody>
</table>
4.2 Analyses at the individual level

Though our previous analyzes have established the ability of the ambient tax-subsidy instrument to induce aggregate compliance with the social optimum (result 1), the considered mechanism is not without problems. Indeed, we next show that this fiscal instrument does not insure compliance at the individual level.

**Result 3.** The ambient tax-subsidy instrument does not induce individuals to choose the socially optimal actions though more (almost) optimal decisions are observed under limited information than under complete information.

**Support.** 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 $\text{ComHigh\text{K}sup}$ and $\text{LimHigh\text{K}sup}$ 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.\(^{17}\) Table 12 on the following page shows the percentage of individual decisions which coincide with the socially optimal action for each polluter’s type under complete information, and table 13 shows the percentage of individual decisions which coincide with the socially optimal action for each polluter’s type 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

\(^{17}\text{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.}
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%.

Table 12: Percentage of individual decisions coinciding with the socially optimal decision
under complete information.

<table>
<thead>
<tr>
<th>Polluter’s type</th>
<th>ComLowKInf</th>
<th>ComLowKsup</th>
<th>ComHighKInf</th>
<th>ComHighKsup</th>
</tr>
</thead>
<tbody>
<tr>
<td>S</td>
<td>10%</td>
<td>0%</td>
<td>0%</td>
<td>29%</td>
</tr>
<tr>
<td>M</td>
<td>1%</td>
<td>6%</td>
<td>6%</td>
<td>3%</td>
</tr>
<tr>
<td>L</td>
<td>0%</td>
<td>0%</td>
<td>2%</td>
<td>0%</td>
</tr>
<tr>
<td>Perfect adequacy</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within three</td>
<td>33%</td>
<td>8%</td>
<td>4%</td>
<td>4%</td>
</tr>
<tr>
<td>Within five</td>
<td>27%</td>
<td>40%</td>
<td>20%</td>
<td>21%</td>
</tr>
<tr>
<td>Within five</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 13: Percentage of individual decisions coinciding with the socially optimal decision
under limited information.

<table>
<thead>
<tr>
<th>Polluter’s type</th>
<th>LimLowKInf</th>
<th>LimLowKsup</th>
<th>LimHighKInf</th>
<th>LimHighKsup</th>
</tr>
</thead>
<tbody>
<tr>
<td>S</td>
<td>10%</td>
<td>0%</td>
<td>0%</td>
<td>19%</td>
</tr>
<tr>
<td>M</td>
<td>9%</td>
<td>6%</td>
<td>6%</td>
<td>3%</td>
</tr>
<tr>
<td>L</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>6%</td>
</tr>
<tr>
<td>Perfect adequacy</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within three</td>
<td>37%</td>
<td>18%</td>
<td>21%</td>
<td>23%</td>
</tr>
<tr>
<td>Within five</td>
<td>37%</td>
<td>40%</td>
<td>43%</td>
<td>41%</td>
</tr>
<tr>
<td>Within five</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5 Conclusion

This paper presented 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 firms’ types. Instead, he can introduce a damage based mechanism, but this decentralizes the planning problem to firms. However, under real-world conditions, firms are likely to have limited information on the other firms’ 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.

The instrument is found to be able to induce the socially optimal level of ambient pollution, but not individual compliance. However, efficiency is higher under limited information and when the social optimum is in a low position. The level of the lump-sum subsidy has no significant effect on efficiency.

That the level of the lump-sum subsidy has no significant effect on efficiency is good news for the policymaker. It means that even if he 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 means 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. First, it makes the instrument rather attractive for the policymaker, since real-world conditions are often closer to the limited information case. Second, it clearly calls for further stress tests and new theories to account for the subjects’ observed behavior, which would contribute to extend our knowledge on the regulation of NPSP, and more generally on human behavior.

References


