Nonpoint Pollution Control Schemes - Making Sense of Experimental Results

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Schemes to Regulate Non-Point Water Pollution:

Making Sense of Experimental Results

Introduction

Three theoretical non-point water pollution (NPS) control schemes were tested repeatedly in experimental studies – tax-subsidy scheme (K. Segerson, 1988), collective fining (Xepapadeas, 1991) and random fining (Xepapadeas, 1991). Camacho and Requate (2004) summarized results reported by Spraggon (2002), Vossler et al (2002), Cochard et al (2002), and Alpizar et al (2004) and replicated their experiments. In this paper I will discuss similarity and differences among all the reported results and in particular the following two. First, both collective fining and random fining induce abatement under the target, their performance deteriorates over time and are relatively consistent over the replications. Second, tax-subsidy scheme induced abatement over the target, its performance is consistent over periods, but not over the replications.

Three different theories offer an explanation of how individuals behave as members of a group: non-cooperative game theory (individuals choose to maximize their individual profits), cooperative game theory (individuals within a group choose a coalition that would maximize profit of each member of the coalition), evolutionary game theory (individuals choose to maximize their relative profits – difference between individual profit and average profit in the group). Each of these theories suggests a specific equilibrium for each of the nonpoint control schemes mentioned above, but individually does not explain experimental results.

I will demonstrate that multi-objective optimization, where individuals are interested in maximizing a bundle (individual profit; payoff from a coalition, relative profit), is consistent with experimental data and accounts for recognized individual differences in players within a group (i.e. Kurzban & Houser, 2005).

Theoretical NPS Schemes

Tax-subsidy

The tax-subsidy mechanism suggested by Segerson (1988) imposes equal tax on all the firms if abatement level is below the target level and pays equal subsidies to all the firms if total abatement exceeds the target level. In mathematical form it can be written the following way:

$$p_i(a_i, a_{-i}) = p^0 - C(a_i) - s\left[A^* - \sum_i^n a_i\right],$$

where s is the tax or subsidy rate and by a_{-i} the vector of decisions of the other firms except i.

Collective Fining

Collective fining mechanism suggested by Xepapadeas' (1991) combines a subsidy proportional to total abatement and a penalty in case that actual aggregate abatement falls short of the optimal level. In mathematical form it can be written the following way:

$$p_i(a_i, a_{-i}) = \begin{cases} p^0 - C(a_i) - \dfrac{s}{n}\left[\sum_i^n a_i\right], & \text{if } \sum_i^n a_i \geq A^* \\ p^0 - C(a_i) - \dfrac{s}{n}\left[\sum_i^n a_i\right] - f, & \text{if } \sum_i^n a_i < A^* \end{cases},$$

where $\dfrac{s}{n}$ is the share of the total subsidy rate s paid to firms per unit of pollution abated

by the whole industry, and f denotes the individual fine the regulator charges each firm.

<u>Random Fining</u>

Random fining is very similar to the collective fining mechanism with the exception that

in case of non-compliance only one of the firms is picked randomly with probability 1/n

and is charged a total fine of $F = fn$. In mathematical form it can be written the following

$$\text{way: } p_i(a_i, a_{-i}) = \begin{cases} p^0 - C(a_i) - s\left[\sum_i^n a_i\right], & \text{if } \sum_i^n a_i \geq A^* \\ p^0 - C(a_i) - s\left[\sum_i^n a_i\right], & \text{if } \sum_i^n a_i < A^*, prob = \dfrac{n-1}{n} \\ p^0 - C(a_i) - s\left[\sum_i^n a_i\right] - F, & \text{if } \sum_i^n a_i < A^*, prob = \dfrac{1}{n} \end{cases}.$$

Theories describing behavior of individuals within a group

<u>Non-cooperative game theory</u>

In the non-cooperative theory, a game is a detailed model of all the moves available to

the players. It suggests, for example, that each player chooses from strategies available to

him the one that maximizes his individual profit $E[p_i]$.

<u>Cooperative game theory</u>

The cooperative game theory describes the outcomes that result when the players come

together in different combinations (coalitions). It suggests that each player is choosing

what coalition to join to maximize his own payoff and payoffs of other members of the

coalition, r_i - set of payoffs to player i and other members of any coalition that contains

player i.

Evolutionary game theory

Evolutionary game theory studies equilibria of games played by populations of players, where the "fitness" of the players derives from the success each player has in playing the game. For instance, evolutionary theory suggests that players are concerned with their relative payoffs, $E\left[p_i - \bar{p}\right]$.

Predictions of how tax-subsidy, collective and random fini ng schemes would perform made by non-cooperative, cooperative and evolutionary game theories

Let's examine how each NPS control scheme will perform based on non-cooperative, cooperative and evolutionary game theories.

Non-cooperative game theory predicts that all schemes create incentives for profit maximizing players to choose a strategy a_{nc} such that $MC(a_{nc}) = s$.[1]

Cooperative game theory predicts that under tax-subsidy schemes each player will choose a strategy a_c such that $MC(a_c) = sn$, where n is a number of players; under both collective and random fining in equilibrium players will choose a strategy a_c such that $MC(a_c) = s$, the same strategy as non-cooperative game theory predicts.[2]

Evolutionary game theory predicts that all schemes will perform similarly and in equilibrium each player will choose a strategy $a_e = 0$. (For the detailed proof see appendix.)

Table below summarizes the predictions.

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[1] See for example Camacho and Requate (2004)
[2] See for example Camacho and Requate (2004)

	tax-subsidy	collective fining	random fining
<u>Non-cooperative game theory</u>	$MC(a_{nc}^{ts}) = s$	$MC(a_{nc}^{cf}) = s$	$MC(a_{nc}^{rf}) = s$
<u>Cooperative game theory</u>	$MC(a_{c}^{ts}) = sn$	$MC(a_{c}^{cf}) = s$	$MC(a_{c}^{rf}) = s$
<u>Evolutionary game theory</u>	$a_{e}^{ts} = 0$	$a_{e}^{cf} = 0$	$a_{e}^{rf} = 0$

Note that $a_{nc}^{ts} = a_{nc}^{cf} = a_{nc}^{rf} = a_{c}^{cf} = a_{c}^{rf} < a_{c}^{ts}$.

Experimental results

Camacho and Requate (2004) provide an excellent summary of the previous and their own experimental results. Below are graphs and tables adopted from their work.

These figures and table suggest the following overall results.

<u>Result 1</u>

Tax-subsidy scheme on average outperforms collective and random scheme.

<u>Result 2</u>

Under tax-subsidy scheme some subjects consistently choose to over abate between 20% (for inexperienced subjects) and 35% (for experienced subjects). Under random and collective fining less then 15% of inexperienced and experienced subjects over abate.
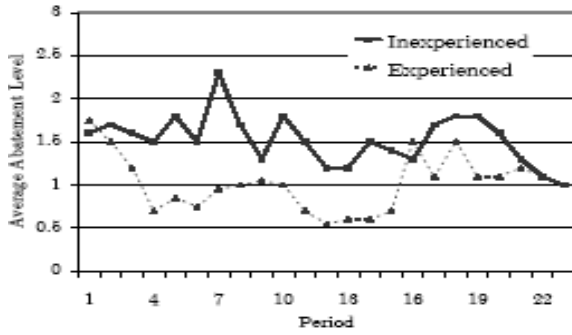
<u>Result 3</u>

Under tax-subsidy scheme some subjects less then 10% choose to deliver nothing; under collective and random schemes up to 35% inexperienced subjects and up to 50% experienced subjects choose to deliver nothing.
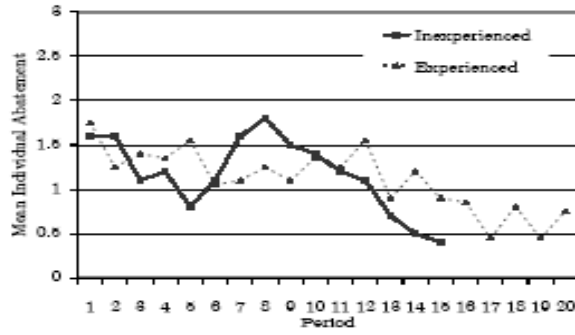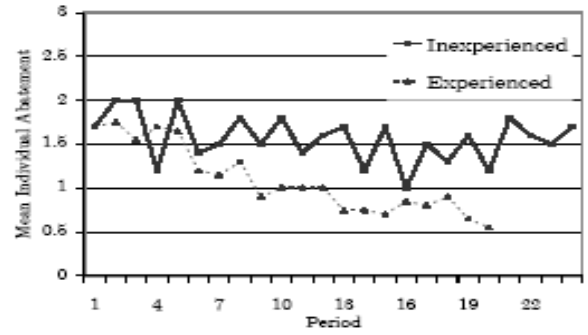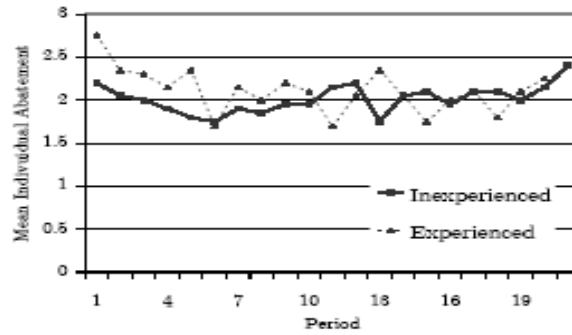
(a) Collective 60
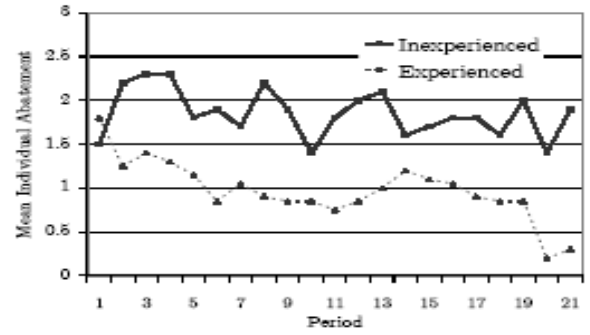
(b) Collective 90

(c) Random 300

(d) Random 450

(e) Tax-Subsidy

Figure 1: Mean individual abatement level per period for each treatment.

Figure 1: Mean individual abatement level per period for each treatment (adopted).

Socially optimal level of abatement is 2 units.
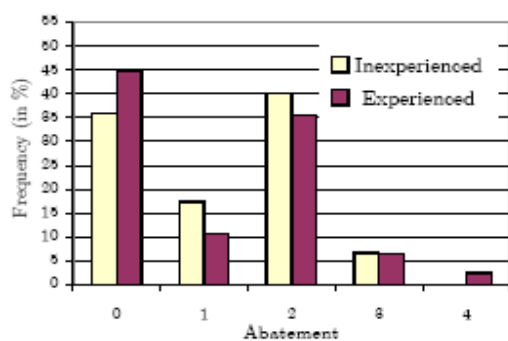
(a) Collective 60

(b) Collective 90

(c) Random 300
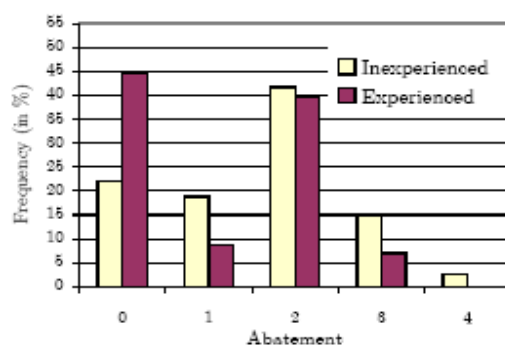
(d) Random 450
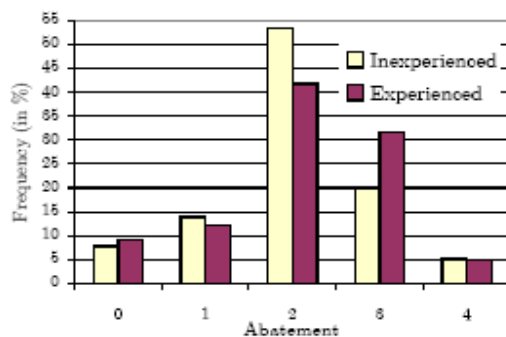
(e) Tax-Subsidy

Figure 2: Frequency distribution of individual abatement levels per treatment.

Figure 2: Frequency distribution of individual abatement levels per treatment (adopted).

Efficiency (in %)

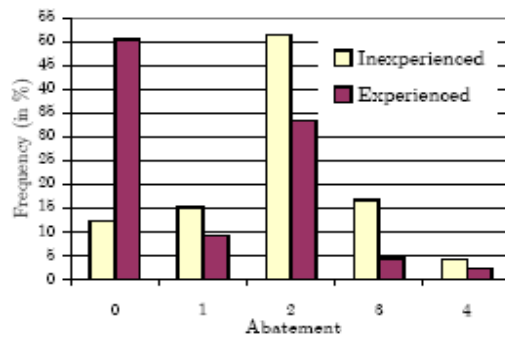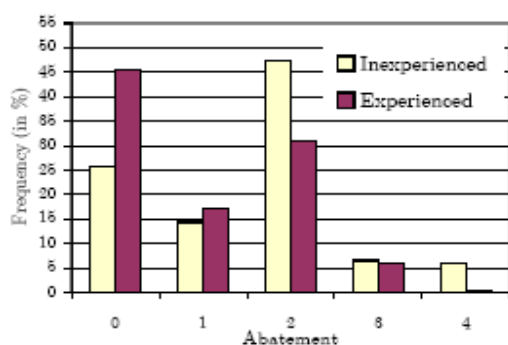| Instrument	Our results		Alpízar et al.[1]		Spraggon[2]		Cochard et al.[3]	Vossler et al.[4]
	Inexp.	Exp.	Inexp.	Exp.	Inexp.	Exp.	(Inexp.)	(Inexp.)
Collective 60	58	68	62	48				
Collective 90	76	44			54	78	60	42
Random 300	63	49	59	58				
Random 450	67	52						
Tax-Subsidy	79	75			98	96	-41	56

[1] Alpízar, Requate and Schramm (2004).
[2] Spraggon (2002).
[3] Cochard, Willinger and Xepapadeas (2002).
[4] Vossler, Poe, Segerson and Schulze (2002).

Table V: Efficiency comparison.

Table V: Efficiency comparison (adopted).

Result 4

Tax-subsidy scheme performs consistently over periods for both experienced and inexperienced subjects. Performance of collective and random fining mechanisms deteriorates over periods and more so for experience subjects.

Result 5

Tax-subsidy scheme performs less consistently over replications then collective and random fining schemes.

Result 2 can be predicted by cooperative game theory, and therefore indirectly implies result 1. However result 3-5 could not be explained by any of the described above game theories.

Multi attribute optimization approach

Most realistic optimization problems require the simultaneous optimization of more than one objective function, and it is unlikely that the different objectives would be optimized by the same alternative parameter choices. Hence, some trade-off between the criteria is needed to ensure a satisfactory design. In economics multi attribute optimization has its roots in late-nineteenth-century welfare economics, in the works of Edgeworth and Pareto (Das, 1997).

For example, an individual member of a group could be concern with optimizing a bundle that consists of three separate objectives: individual profit, payoff to the optimal coalition, and relative profit.

The scalar concept of ``optimality'' does not apply directly in the multiobjective setting. A useful replacement is the notion of *Pareto optimality*, where a vector x is said to be Pareto optimal for (MOP) if all other vectors have a lower value for at least one of the objective functions, or else have the same value for all objectives.

Weighted sum

One of the simplest techniques to solve multi attributes optimization problem is to maximize the weighted sum of all objective functions.

For example in our case the optimization problem will have the following form

$Max\ S_i = a_i p_i + b_i r_i + g_i(p_i - \bar{p})$, where parameters $a_i, b_i\ \& g_i$ are different for different players.

Lexicographic preferences

Another way to deal with three objectives simultaneously is to assume that individuals have lexicographic preferences over the objectives.

Lexicographic preferences are concerned with the ordering of the objectives and then evaluating each objective in the order they have been placed. For example, an individual member of the group could put on the first place a coalition payoff, on the second individual profit, and on the third his relative profit. In this case this individual member first will choose strategies that maximize a payoff for the optimal for his coalition, then from the set of these strategies he will choose those that maximize his profit, and finally if he has more then one strategy left, he will choose the one that guarantees him the highest relative profit. Obviously, players who have the same cost of abatement but different order of objectives could choose different strategies.

Connection to individual differences

Any form of multi attribute optimization requires additional parameters that express players' attitudes toward each objective: in the case of lexicographic preferences that would be the order of objectives; in the case of weighted sum that would be relative weights.

The laboratory experiment in public good settings reported three stable types of players: (i) cooperators, (ii) free-riders, and (iii) reciprocators, who respond to others' behavior by using a conditional strategy (i.e. Kurzban & Houser, 2005). Multi attribute optimization potentially might explain cooperators as players who weigh coalition payoffs much higher then other objectives, free-riders as players who value their relative payoff higher, and reciprocators as players who assign similar values to all the objectives.

Predictions based on multi attribute optimization

Let's assume that we have three kinds of people in the group. One kind is those who value individual profits higher then other objectives, the second kind is those who value collusive payoffs higher, and the third is those who value their relative payoff higher.

Then, under tax subsidy scheme those who value collusive payoffs higher, if they believe that at least one other person in the group is willing to collide, will over abate. Those who are interested in their individual profit will chose strategy a_{nc}^{ts} that maximizes it. And those who are interested mostly in their relative profit can choose the strategy a_{nc}^{ts} and still have positive relative profit, since they would be able to free ride on players who have over abated.

Under both collective and random schemes no one has any incentives to over abate, therefore spiteful players (who value the relative profits higher then they value other objectives) can keep their relative profits only if they under abate. But in this case they have to compete with other spiteful players, and will decrease their abatement contributions in each successive period. At some point if spiteful players would significantly under abate, then players who value individual and/or collusive profits higher will be forced to switch to strategy $a_i = 0$. In groups with experienced players the same process will occur more quickly. Note that spiteful players will not start from the strategy $a_i = 0$, since they are interested not only in relative but also in absolute profits.

Therefore, we would expect that tax subsidy will perform better and more consistently over periods then both collective and random fining, that would perform similarly. These predictions are consistent with results 1-4.

In addition, note that under tax subsidy schemes all three objectives are maximized by different strategy, therefore this scheme should be more sensitive to individual differences across subjects then collective and random fining, and this will suggest that the scheme will be less consistent over the replications than collective and random fining. This prediction is consistent with the result 5.

Implications for policy development

The most obvious implication of this hypothesis to the policy development is to that all three objectives have to be taken into account. Optimal policy would be such that allows the same strategy is optimal for all of three objectives. Then a policy will work more predictably and consistently across the environments.

Further tests

Of course, whether a multi attribute approach to the question of how individuals make

decisions within a group is only a testable hypothesis at this point.

One way to examine it would be to design a contract such that each of the three

objectives is maximized by the same strategy and experimentally test it. Multi attributes

hypothesis would be supported if under this contract players would choose the predicted

strategy more often, and if the performance of such a contract is more consistent over the

replications.

Predictions of Evolutionary Game Theory

Tax-subsidy scheme

$$Max_{a_i}\left(p_i(a_i,a_{-i})-\overline{p_i}(a_i,a_{-i})\right)= Max_{a_i}\left(p_i(a_i,a_{-i})-\frac{1}{n}\sum_j p_j(a_j,a_{-j})\right)=$$

$$= Max_{a_i}\left(-C(a_i)+\frac{1}{n}\sum_j^n C(a_j)\right)\Rightarrow\quad a_i=0$$

Collective fining

$$Max_{a_i}\left(p_i(a_i,a_{-i})-\overline{p_i}(a_i,a_{-i})\right)= Max_{a_i}\begin{cases}\frac{1}{n}\sum_j^n C(a_j)-C(a_i),\ if\ \sum_i^n a_i\geq A^* \\ \frac{1}{n}\sum_j^n C(a_j)-C(a_i),\ if\ \sum_i^n a_i< A^*\end{cases}\Rightarrow$$

$$\Rightarrow\quad a_i=0$$

Random fining

$$Max_{a_i}\left(p_i(a_i,a_{-i})-\overline{p_i}(a_i,a_{-i})\right)=\begin{cases}\frac{1}{n}\sum_j^n C(a_j)-C(a_i), & if\ \sum_i^n a_i\geq A^* \\ \frac{1}{n}\sum_j^n C(a_j)-C(a_i)+\frac{F}{n}, & if\ \sum_i^n a_i< A^*,prob=\frac{n-1}{n} \\ \frac{1}{n}\sum_j^n C(a_j)-C(a_i)+\frac{(1-n)F}{n}, & if\ \sum_i^n a_i< A^*,prob=\frac{1}{n}\end{cases}\Rightarrow$$

$$\Rightarrow\quad a_i=0$$

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