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# Incentives for Nonpoint Pollution Control

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Abstract

Emissions-based standards and incentives have received considerable attention in the economic literature on pollution control. However, emissions-based instruments are inappropriate for nonpoint pollution. Two input-based incentive structures for nonpoint pollution control are presented. One is incentive compatible and capable of achieving the ex ante efficient outcome. The second economizes on information but with a corresponding loss of efficiency.

## Incentives for Nonpoint Pollution Control

The economic literature on pollution control policy design is focused on emissions incentives and standards. However, emissions-based instruments are inappropriate for nonpoint pollution control. The complex processes by which nonpoint pollutants are formed and pathways by which they are transported to receiving environmental media make identification and monitoring of the pollutants from individual agents on a continuing and widespread basis uneconomic. Furthermore, the formation and transportation of nonpoint pollutants is influenced by climatic events and other stochastic environmental phenomena. Hence, emissions cannot generally be controlled in a deterministic way.

In a recent article, Segerson [8] examined a tax/subsidy scheme based on ambient concentrations designed to shift the distribution of the ambient level of a nonpoint pollutant such that the new distribution dominates the original in the sense of first-order stochastic dominance. However, Segerson assumed that individual firms can observe their own emissions costlessly and regulate the flows deterministically. Random variations in ambient levels are treated only as the consequence of stochastic variations in climatic and topographic conditions influencing the transportation and dilution of pollutants. The more general case is one in which stochastic climatic and topographic conditions are causal factors in determining individual emissions and monitoring is inordinately costly for the firm as well as the pollution control authority. For example, the runoff of pesticides and nitrates from agricultural land cannot be measured with any degree of accuracy at reasonable cost and depends greatly on weather conditions, soil conditions, crop cover, and other factors beyond the farmers control.

This paper presents two incentive structures for nonpoint pollution control for the more general case. Hence, nonpoint flows are unobservable and stochastic at the firm level as well as at the aggregate level. In addition, a differential information structure is assumed under which polluters know more about their individual abatement costs than the regulating agency. One incentive structure is incentive compatible and capable of achieving the ex ante efficient outcome. Incentive compatible planning mechanisms have received considerable attention as a means by which to solve the free rider problem in the allocation of collective goods, including pollution control in the case of nonstochastic emissions that can be costlessly observed by source (Dasgupta et al. [2]). The complexity of these mechanisms is such they are generally considered to be mainly of theoretical interest, although there are also some who argue for the feasibility of their use in solving highly structured small scale problems (e.g., Starrett [10]). In addition to this first-best mechanism, a second-best incentive structure that is less information intensive is also presented. Both the first- and second-best incentives are firm-specific nonlinear taxes on a potentially broad base of inputs used in production and pollution control.

## Analytical Framework and Characterization of the Optimum

For heuristic purposes, consider the problem of an environmental agency that seeks to maximize the expected net benefits from agricultural nonpoint abatement in a specific watershed.[1/] For simplicity, the flow of pollutants from farms to receiving waters is referred to as runoff. The agency is uncertain about the water quality damage resulting from runoff, the effects of input decisions on runoff, forthcoming environmental conditions influencing runoff (e.g., weather), and the effects of changes in input use on farm profits. The farmers are assumed to be price-takers and risk neutral. In addition, the farmers in the watershed as a group exert no significant influence on prices.

The economic cost of water pollution is given by $D(r,\epsilon)$ where r is the aggregate runoff and $\epsilon$ is an unknown parameter representing public uncertainty about the damage resulting from any level of runoff.[2/] The cost function is assumed to be convex in the runoff levels for any value of $\epsilon$.

The agency is to be unable to directly monitor runoff from farms but can formulate expectations conditional upon observations of farm resource allocation and other relevant variables using a probabilistic model of runoff.[3/] The general form of the agency's runoff model is

$$\text{Prob. } [r \leq r^*] = \text{Prob. } [g(x_1,\ldots, x_n, w, \lambda) \leq r^*] \tag{1}$$

where $x_i$ $(i = 1,\ldots, n)$ is a vector of farm input decisions on the ith farm in the watershed, w is a vector of weather conditions that have a causal role in the pollution process, g(.) is a function relating runoff to farm input use and weather, and $\lambda$ is a vector of unknown physical parameters representing public uncertainty about the level of runoff for any given values of $x_1,\ldots,$ $x_n$ and w, due to imperfect knowledge of the physical and chemical processes involved. The agency faces ex ante uncertainty about the effects of input decisions on runoff because of its uncertainty about forthcoming weather and the imperfect knowledge of the runoff function. The imperfect knowledge of the runoff function also implies ex post uncertainty about the effects of changes in farm resource allocation on runoff given that the agency does not monitor runoff by farm.

The maximum profit obtainable by the ith farm for any choice of inputs and weather condition is given by the function $\pi_i(x_i, w, \theta_i)$ where $\theta_i$ represents specialized private knowledge of the farm operation. This function is assumed to be convex in $x_i$ for any values of w and $\theta_i$. Weather is assumed to influence farm profits and runoff but each element of w may not influence each farm.

Farmers must make input decisions before observing the weather and, like the agency, are uncertain about forthcoming weather. Beliefs about the weather by farmers and the agency are assumed to be identical. In contrast, farmers are assumed to have specialized knowledge about their farms when choosing inputs that the agency does not have when choosing a policy.[4/] Hence, the ith farmer knows the true value of $\theta_i$ when making production decisions but $\theta_i$ is a random variable to the agency when making its policy decision. The true value of the ith farmer's specialized knowledge is $\hat{\theta}_i$.

Given the agency's knowledge of the runoff function and the costs of runoff, and the farmers' knowledge of technology, ex ante efficient production in the watershed maximizes

$$J_1 = E[\sum_i \pi_i(x_i, w, \hat{\theta}_i) - D[g(x_1,\ldots, x_n, w, \lambda), \varepsilon]. \tag{2}$$

The first order conditions are:

$$\frac{\partial J_1}{\partial x_{ij}} = E[\partial \pi_i/\partial x_{ij}] - E[\partial D/\partial r)(\partial g/\partial x_{ij})] \leq 0, \tag{3}$$

$(\partial J/\partial x_{ij})x_{ij} = 0$, and $x_{ij} \geq 0$, for all i and j where $x_{ij}$ is the jth element of $x_i$. Since the expected value of the product of two random variables is the product of their expected values plus the covariance, (3) can also be written

$$E[\partial \pi_i/\partial x_{ij}] \leq E[\partial D/\partial r]E[\partial g/\partial x_{ij}] + COV(\partial D/\partial r, \partial g/\partial x_{ij}) \quad (4)$$

for all i and j.

The LHS is the expected gain in profit at the margin for the use of the jth input on the ith farm. In the absence of pollution controls, expected profit maximizing farmers would only choose inputs with nonnegative marginal effects on profits. The RHS is the expected marginal damage cost of the jth input on the ith farm. The first term on the RHS indicates the effect of the input on the expected marginal cost due to its effect on the mean level of runoff. The second term indicates the effect of the input on the expected marginal cost due to its effect on the variability of runoff.

## First-Best Incentives

Let $x^*_{ij}$ denotes the optimal value of $x_{ij}$. The agency could obtain the optimal solution by imposing farm specific design standards requiring each farm to adopt optimal production plan. Alternatively, the agency could obtain the optimal solution by imposing a system of farm specific linear input taxes of the form

$$T_i(x_i) = \sum_j t_{ij}x_{ij} \quad (5)$$

where $t_{ij}$ is the RHS of (4) evaluated at the optimal solution. The RHS of (4) may be negative for some inputs. Hence, the tax rates could be negative for some inputs to encourage their use. Abatement inputs with negative marginal effects on profits would fall into this class but other inputs which are normally used may as well. However, implementing either of these approaches or other conceivable policies that would result in the choice of the optimal production plans would require that the agency have perfect information about the farmers' private knowledge. Hence, the problem is to obtain this knowledge.

A set of firm-specific (in this case farm-specific) taxes that can be used to achieve the first-best solution provided that firms (farms) are risk neutral and do not collude can be identified. The tax structure is an adaptation of an emissions tax scheme developed by Dasgupta et al. [2] for nonstochastic emissions that are readily observable by source. The Dasgupta et al. mechanism is in turn an adaptation of the Groves social choice mechanism. Under the extension developed here, the agency asks farmers to provide their specialized knowledge. The farmers are informed that their reports will be used to formulate farm-specific tax schedules according to guidelines announced to the farmers. The guidelines are such that (a) first-best solution will be attained when all farmers maximize their expected after-tax profits provided that each has given a true report and (b) that truthfulness serves the farmers' economic self-interest. The main distinction between this tax scheme and that of Dasgupta et al. [2] is that the taxes are based directly on the farmer's input decisions rather than on emissions.

Let $\theta_i'$ be the specialized information reported by the ith farmer, $\theta' = [\theta_i']$ and $x_i'(\theta')$, i = 1, 2,.., n, provide the maximum of

$$J_2 = E[\sum_i \pi_i(x_i, w, \theta_i') - D(g(x_1, \ldots, x_n, w, \lambda, \varepsilon)]. \tag{6}$$

Hence, the vectors $x_i'(\theta')$, i = 1, 2,..., n, will be the first-best solution if all farmers make true reports (i.e., $\theta' = \hat{\theta}$). Farmers are informed when reporting their specialized information that their individual taxes will be

$$T_i(x_i, \theta') + c_i = \tag{7}$$

$$E[D[g(x_1'(\theta'), \ldots, x_{i-1}'(\theta'), x_i, x_{i+1}'(\theta)', \ldots, x_n'(\theta'), w, \lambda]]$$

$$-E[\sum_{j \neq i} \pi_j(x_j'(\theta'), w, \theta_j')] + c_i$$

i = 1, 2,..., n, where $c_i$ is any constant that does not cause an inefficient decision about whether or not to produce.

The ith farmer's expected after-tax profit function with the imposition of such a tax is

$$E[\pi_i(x_i, w, \hat{\theta}_i)] - T_i(x_i, \theta') - c_i. \tag{8}$$

The construction of the tax is such that $x_i'(\theta_i')$ maximizes (8) if the farmer has been truthful. Since a choice other than $x_i'$ will reveal a false report, it follows that the farmer can maximize (8) only if she has been truthful.

Knowing this, and not knowing the tax schedule that she will ultimately face when making her report in the absence of collusion, it follows that the farmer's dominant strategy is to be truthful and to choose $x_i'(\theta')$ to maximize (8). Since this is true for all farmers, the first-best solution will be attained when farmers seek to maximize their expected after-tax profits.

## A Second Best Policy

If the number of farmers is large, then the scheme identified above will require the transmission and processing of a lot of information both in the formulation of the farm specific tax function and subsequent monitoring of farm management. The complexity and cost would likely make the scheme uneconomic. On the other hand, if the number of farmers is small, the scheme may not achieve the first-best solution because of collusion. An alternative incentive structure is presented. This structure is a set of farm specific taxes that maximizes the expected net benefit of production subject to the constraint that the farmers' specialized knowledge remains private, thus reducing the cost and complexity of control. Of course, such a scheme cannot attain the first-best solution. This tax structure is also an extension of an emissions tax scheme presented in Dasgupta et al. [2] for nonstochastic emissions, readily monitorable by source.

Suppose that the $\theta_i$, are continuous and independent random variables from the agency's. Let $\bar{x}_i(\theta_i)$ provide the maximum of

$$E[\pi_i(x_i, w_i, \theta_i) \tag{9}$$

$$-E[D(\bar{x}_1(\theta_1), \ldots, \bar{x}_{i-1}(\theta_{i-1}), x_i, \bar{x}_{i+1}(\theta_{i+1}), \ldots, \bar{x}_n(\theta_n), w, \lambda]$$

$$+\sum_{j\neq i} E[\pi(\bar{x}_j(\theta_j), w, \theta_j]$$

for any realized value of $\theta_i$, i = 1, 2,..., n. Setting $\theta_i = \hat{\theta}_i$, the specific vector $\bar{x}_i(\theta_i)$ that maximizes (9) is $\bar{x}_j(\hat{\theta}_i)$, (i = 1, 2,..., n). Hence the vectors $x_i(\hat{\theta}_i)$, 1 = 1, 2,.., n, provide the maximum expected net benefit from public intervention to control runoff subject to the constraint that the farmers' specialized knowledge remains private. The form of (9) implies that the ith farmer's choice $\hat{x}_i(\theta_i)$ can be obtained by the imposition of a tax on the farmer's input decisions of the form $-[z_i(x_i) + c_i']$ where $z_i(x_i)$ is the bracketed term of (9) and $c_i'$ is any constant that does not result in an efficient decision about whether or not to produce.

## Concluding Comments

Two incentive structures have been presented for the general nonpoint pollution control problem in which emissions are stochastic and unobservable at reasonable cost at the firm and more aggregate levels, and there is differential information about the costs of control. One is incentive compatible and capable of achieving the ex ante efficient outcome while the other economizes on information with a corresponding loss of efficiency.

Both of the incentive structures are firm specific nonlinear taxes on a potentially broad base of inputs influencing the flow of pollutants from the firm. These incentives are sufficiently complex and, even in the case of the second-best incentive, information intensive to raise significant questions about their practicality. However, they do provide insights into economically desirable features of nonpoint incentives. Both of the incentives are designed to maximize expected net benefits, although with different information structures. The difference between the first- and second-best instruments is that the former is designed to obtain and utilize specialized individual information about individual abatement costs while the latter uses existing public knowledge. Further concessions to administrative and compliance costs would involve uniform rather than firm specific input tax structures, linear as opposed to nonlinear tax schedules, truncation of the input base to inputs that are easily monitored while presumably also key polluting or pollution abatement inputs, and specification of policy parameters by means other than cost-benefit assessments. Corresponding to the reduction in administrative and compliance cost would be a loss in the expected net benefits of production.

## Footnotes

1. Nonpoint pollution is largely associated with runoff from open areas such as agricultural land, forest land, open areas such as agricultural land, forest land, mine sites, and paved areas. Agricultural land is the leading nonpoint source in the U.S. (U.S. EPA [11]).

2. In many cases too little may be known about the damage cost function to make use of it in policy design. The analysis presented here will hold for a second-best criterion that involves substituting a penalty function provided by public decision makers for the unknown damage cost function based on the preferences of individuals in formulating expected net benefits.

3. Models for estimating agricultural nonpoint pollution flows from farm fields and watersheds based on observations of land use practices, topography, weather and other relevant factors have been developed and continue to be refined (DeCoursey [4]). Such models reduce but do not eliminate uncertainty about nonpoint pollution flows from individual farms.

4. In general, it is reasonable to assume that firms have better information about the effects of changes in production on their profits when choosing how to reallocate resources in response to a nonpoint policy than the public planner has when choosing a policy. The existence of such a differential information structure is often assumed in the literature on choices among policy instruments (Adar and Griffin [1]; Dasgupta [3]; Dasgupta, et al. [2]; Fishelson [5]; Kerwel [6]; Roberts and Spence [7]; Shortle and Dunn [9]; Weitzman [12]; Yohe [13]).

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