Multiple Agents, and Agricultural Nonpoint-Source Water Pollution Control Policies

Rodney B.W. Smith and Theodore D. Tomasi

Assuming asymmetric information over farmer profits and zero transaction costs, prior literature has suggested that when regulating nonpoint source water pollution, a tax on management practices (inputs) can implement full-information allocations and is superior to a tax on estimated runoff. Using mechanism design theory under asymmetric information, this paper shows that under the same assumptions, management practice taxes and taxes on estimated runoff are equally efficient.

Griffin and Bromley (G-B) examined the relative efficiency of four pollution control policies: a tax on estimated runoff, a tax on farm management practices (i.e., a tax on inputs), runoff standards, and farm management practice standards. In their **multiple-farmer** model, high measurement costs prohibited the regulatory agency from observing the amount of pollution runoff from a farm; a distinguishing feature of NPS pollution. The regulator could, however, monitor each farmer's input levels and knew each farmer's profit structure. Then, using a model of fate and transport of pollutants (an estimated runoff function), the regulator inferred levels of pollution runoff from the farm.[1] Given perfect information on farmer technologies and no transaction costs, they found that (when suitably specified) the four policies were equally efficient as least-cost pollution control devices.

Shortle and Dunn (S-D) examined the relative efficiency of the four policies under asymmetric information. In their **single farm** model, the farmer had private information concerning his or her own profit structure. In their paper it was shown that despite the lack of information on the part of the regulator, a management practice tax existed that could induce the farmer to choose *ex-ante* efficient levels of polluting inputs. The S-D management practice tax was a nonlinear function of the inputs used, with the tax being equal to the expected environmental damages caused by the runoff (plus a constant). They argued that unless estimated runoff is linear in inputs, the S-D tax on estimated runoff will be unable to provide the farmer with incentives to choose *ex-ante* efficient input levels. It was concluded that management practice taxes typically would be preferred to runoff standards, management practice standards, and taxes on estimated runoff.

To understand the potential consequences of transaction costs, Smith and Tomasi (S-T) examined the effects that a tax-induced deadweight cost (a form of transaction cost) might have on the efficiency of management practice taxes. Using a single farm model similar to S-D, S-T found that, given transaction costs, a management practice tax is not always superior and is (second-best) optimal only in special circumstances: if transaction costs are high enough management practice taxes are less efficient than management practice standards. As in S-D, S-T found that with zero transaction costs management practice taxes implement *ex-ante* efficient input allocations. Also, not surprisingly, S-T show that full-information allocations are not implementable in the presence of tax related deadweight costs.

Although most of the S-D discussion was concerned with the single-farmer case, they discussed briefly the problem of regulating multiple farmers under asymmetric information. They concluded that with two or more farmers, neither the S-D management practice tax (nor the tax on estimated runoff) would be unable to implement full-information allocations. However, Shortle and Abler (S-A) revisited the multiple farmer problem and showed that without transaction costs when "communication" between the regulator and farm-

Rodney B.W. Smith is an Assistant professor, in the Department of Agricultural and Applied Economics, University of Minnesota. Theodore D. Tomasi is a Consultant with ECG Consultants, Wilmington Delaware.

ers is possible, a Groves (1973) version of the S-D management practice tax could, in principle, implement full-information allocations. S-A, however, said nothing about the properties of a tax on estimated runoff, nor did they inform the reader that Groves' result requires at least three agents.

This paper revisits S-D and argues that optimal management practice taxes and estimated runoff taxes are equivalent in that they can both implement *ex-ante* efficient input choices. This result holds for the multiple farmer case where each farmer's profit structure is his or her private information. Furthermore, as in S-D there are no transaction costs.

The next section describes the basic economic environment and characterizes the properties of full-information allocations. The third section discusses direct revelation mechanisms and the related notions of incentive compatibility and voluntary participation. The fourth section shows that a (nonlinear) tax on estimated runoff can implement full information allocations. We also outline the steps involved in establishing similar results for a (nonlinear) tax on management practices, and discuss why our results differ from those of S-D. The last section concludes.

The Basic Problem

There are n farmers indexed by $i = 1, \ldots, N$. In the absence of regulation, a representative profit-maximizing farmer i chooses input vector $\mathbf{x}_i \in R^m$ to maximize

$$\Pi(\mathbf{x}_i,\theta_i) = E_w\tilde{\Pi}(\mathbf{x}_i,w,\theta_i)$$

Here, w is an *ex-post* realization of a random variable that is unknown to the farmer at the time $\mathbf{x}_i$ is chosen; E_w is the expectations operator with respect to w; and θ_i is a scalar index of farmer profitability (called the farmer's "type") known to the farmer, but not to the regulator. If the farmer's profitability index is θ_i, then we say he is a *type*-θ_i farmer. Here $\tilde{\Pi}$ $(\mathbf{x}_i,w,\theta_i)$ is the profit a type-θ_i, farmer generates if he uses input vector $\mathbf{x}_i$, and state w occurs, and $\tilde{\Pi}(\mathbf{x}_i,\theta_i)$ is that farmer's expected profit. To simplify subsequent notation we assume the regulator believes each θ_i follows the uniform distribution, with support given by the interval $\Theta = [0,1]$.

Assumption 1: For $i = 1, \ldots, n$ and $j = 1, \ldots, m$ and for all θ_i:

$$\text{(i)}\ \frac{\partial\Pi}{\partial\theta_i}(\mathbf{x}_i,\theta_i) > 0, \quad \text{(ii)}\ \frac{\partial\Pi}{\partial x_{ij}}(\mathbf{x}_i,\theta_i) \geq 0,$$

$$\text{(iii)}\ \frac{\partial^2\Pi}{\partial x_{ij}^2}(\mathbf{x}_i,\theta_i) < 0, \quad \text{(iv)}\ \frac{\partial^2\Pi}{\partial x_{ij}\partial\theta_i}(\mathbf{x}_i,\theta_i) \geq 0.$$

Here x_{ij} is the jth input of farmer i. In other words, expected profits are (i) increasing in farmer type, (ii) increasing and strictly concave in inputs (over the relevant range), and (iii) expected marginal profits are increasing in farmer type.

The relationship between an input vector, $\mathbf{x}_i$ and the runoff that vector causes is represented by a stochastic runoff function, $g_i;R^{N+2} \rightarrow R$, with runoff levels denoted by $r_i = g_i(\mathbf{x}_i,w,\mu)$. Here, μ is a random variable representing the regulator's uncertainty about actual runoff. The agency's joint density for μ and w is given by $f(w,\mu)$. The expected runoff generated by the vector $\mathbf{x}_i$ is

$$\bar{r}_i(\mathbf{x}_i) = \int\int g_i(\mathbf{x}_i,w,e)f(w,e)dwde.$$

Runoff causes water quality damage, $D(r_1,r_2,\ldots,r_n)$. We assume that D is convex and twice continuously differentiable in each $r_i(\mathbf{x}_i)$. The expected damage caused by input vectors $\mathbf{x} = (\mathbf{x}_1, \ldots, \mathbf{x}_n)$ is

$$\bar{D}(\mathbf{x}_1,\mathbf{x}_2,\ldots,\mathbf{x}_n) = \int\int D(g_1(\mathbf{x}_1,w,e), g_2(\mathbf{x}_2,w,e), \ldots, g_n(\mathbf{x}_n,w,e)) f(w,e)dwde.$$

If the regulator knew each farmer's type and incurred no transaction costs, then the *full-information* (*ex-post* efficient)[2] choice of input vectors, $\mathbf{x}^* = (\mathbf{x}_1^*, \ldots, \mathbf{x}_n^*)$, maximizes

$$\sum_{i=1}^{n}\Pi(\mathbf{x}_i,\theta_i) - \bar{D}(\mathbf{x}_1,\mathbf{x}_2,\ldots,\mathbf{x}_n).$$

And hence, simultaneously solves the set of $(n \times m)$ first-order conditions:

$$\frac{\partial\Pi}{\partial x_{ij}}(\mathbf{x}_i,\theta_i) - \frac{\partial\bar{D}}{\partial x_{ij}}(\mathbf{x}_1,\mathbf{x}_2,\ldots,\mathbf{x}_n) = 0, \quad i = 1,\ldots,n, \quad j = 1,\ldots,m.$$

The full-information problem can be viewed as one where the regulator observes each farmer's private information costlessly and tells each one that if he or she does not choose the socially optimal input bundle he or she will be assessed an extremely large fine.[3]

Direct Revelation Incentive Schemes Regulating Input Use

In what follows we assume that θ_i is known only to farmer i, (θ_i is the private information of farmer i).

In such a case fines such as the one described above are unavailable. Using a truthful direct revelation (TDR) mechanism (see Guesnerie and Laffont, Laffont and Tirole, or Myerson) we develop the properties of an optimal *ex-post* efficient incentive scheme.[5] The *direct revelation mechanism* we consider operates as follows: (i) each farmer is offered an incentive scheme (tax schedule), denoted $\{T_i(\bar{r}_i(\mathbf{x}_i(\theta))),\mathbf{x}_i(\hat{\theta})\}_{\hat{\theta},\Theta^N}$, composed of an estimated runoff tax function and an input function. The tax schedules are a function of the vector of types reported by farmers: $\hat{\theta} = (\hat{\theta}_i,\hat{\theta}_{-i})$; where each scalar $\hat{\theta}_i$ is the profit index reported by farmer i, and $\hat{\theta}_{-i} = (\hat{\theta}_1, \ldots, \hat{\theta}_{i-1},\hat{\theta}_{i+1}, \ldots, \hat{\theta}_n)$ is the vector of profit indices reported by the n-1 other farmers. After observing the tax schedule, each farmer reports a $\hat{\theta}_i$ to the regulator. The regulator observes the vector $\hat{\theta}$ and offers farmer i the contract $(t_i(\hat{\theta}_i, \hat{\theta}_{-i}),\mathbf{x}_i(\hat{\theta}_i,\hat{\theta}_{-i}))$ where $t_i(\hat{\theta}_i,\hat{\theta}_{-i}) = T_i(\bar{r}_i(\mathbf{x}_i(\hat{\theta}_i,\hat{\theta}_{-i})))$. Given truth- telling by all others, if it is optimal for farmer i to report his true type, then we refer to the mechanism as a *(Bayesian) truthful direct revelation* mechanism.[5]

Note that the direct revelation mechanism described above is a dynamic, two-staged game of imperfect information. In the first stage the regulator chooses an instrument (tax scheme). In the second stage the farmers choose a type to report. The subgame-perfect Bayesian-Nash equilibrium of this game is arrived at via backwards-induction: (i) the regulator first determines the farmers' optimal response to the tax scheme, (ii) she then incorporates the best responses functions into her objective function and chooses the optimal tax scheme.

Incentive Compatibility

The farmers' best response to any arbitrary contract schedule is summarized in the incentive compatibility, or truthtelling, constraints. Let $\theta = (\theta_1,\theta_2, \ldots, \theta_n)$ denote a vector of farmer types. Given each other farmer reports his type honestly, a type-θ_i farmer reporting $\hat{\theta}_i$ earns an expected profit equal to

$$\pi(\hat{\theta}_i,\theta_i;\theta_{-i}) = E_{\theta_{-i}}\{\Pi(\mathbf{x}_i(\hat{\theta}_i,\theta_{-i}),\theta_i) - t_i(\hat{\theta}_i,\theta_{-i})\}.$$

Incentive compatibility—reporting θ_i truthfully is optimal for each farmer—satisfies

$$(1)\quad \theta_i \in \operatorname{argmax}_{\hat{\theta}_i} \pi(\hat{\theta}_i,\theta_i;\theta_{-i}), \quad \forall\, \hat{\theta}_i,\theta_i \in \Theta.$$

The incentive compatibility (IC) constraint gives us the optimal relationship between the input vector as a function of θ, and the tax as a function of θ. Guesnerie and Laffont show that the incentive compatibility condition holds if the following two conditions hold at $\hat{\theta}_i = \theta_i$.

(2)

$$\begin{aligned}\pi_{\hat{\theta}_i}(\hat{\theta}_i,\theta_i;\theta_{-i}) &= E_{\theta_{-i}}\left\{\sum_{j=1}^{m}\left[\frac{\partial\Pi}{\partial x_{ij}}(\mathbf{x}_i,\theta_i)\frac{\partial x_{ij}}{\partial\hat{\theta}_i}(\hat{\theta}_i,\theta_{-i}) - \frac{\partial T_i}{\partial\bar{r}_i}(\bar{r}_i(\mathbf{x}_i))\frac{\partial r_i}{\partial x_{ij}}(\mathbf{x}_i)\frac{\partial x_{ij}}{\partial\hat{\theta}_i}(\hat{\theta}_i,\theta_{-i})\right]\right\}\\ &= E_{\theta_{-i}}\left\{\sum_{j=1}^{m}\left[\frac{\partial\Pi}{\partial x_{ij}}(\mathbf{x}_i,\theta_i)\frac{\partial x_{ij}}{\partial\hat{\theta}_i}(\hat{\theta}_i,\theta_{-i}) - \frac{\partial t_{ij}}{\partial\hat{\theta}_i}(\hat{\theta}_i,\theta_{-i})\right]\right\} = 0,\end{aligned}$$

(3)

$$E_{\theta_{-i}}\left\{\sum_{j=1}^{m}\left[\frac{\partial\Pi}{\partial x_{ij}}(\mathbf{x}_i(\hat{\theta}_i,\theta_{-i}),\theta_i)\frac{\partial x_{ij}}{\partial\hat{\theta}_i}(\hat{\theta}_i,\theta_{-i})\right]\right\} \geq 0$$

(For a proof see Guesnerie and Laffont, or Laffont and Tirole.) Here, $\pi_{\hat{\theta}_i}(\cdot\cdot)\,|_{\hat{\theta}_i=\theta_i}$, the partial derivative of π with respect to farmer i's reported type (evaluated at $\hat{\theta}_i = \theta_i$), is the first-order condition for truthtelling. By equation (2) the input and (estimated runoff) tax functions must be chosen so the expected marginal benefit from misrepresenting his type a little—e.g., reporting $\hat{\theta}_i = \theta_i + \Delta$—is just offset by the expected marginal cost of doing so (where Δ is some small constant). The expected marginal benefit is $E_{\theta_{-i}}\{\sum_{j=1}^{m}(\partial\Pi)/(\partial x_{ij})\,(\partial x_{ij})/(\partial\theta_i)\}$ and the expected marginal cost is $E_{\theta_{-i}}\{\partial t_i/\partial\theta_i\}$. Equation (3) is the second order condition for truthtelling. Combined with Assumption 1, a sufficient condition for equation (3) is the following *monotonicity condition:*

$$(4)\quad \frac{\partial x_{ij}}{\partial\hat{\theta}_i}(\hat{\theta}_i,\theta_{-i}) \geq 0,\ \forall\, \hat{\theta} \in \Theta,\ i = 1, \ldots, n,\quad j = 1, \ldots, m.$$

Given farmer i's profits increase in θ_i, equation (4) says that if marginal net profits are increasing (decreasing) in farmer type, the farmer should be allocated more (less) of the input.

Voluntary Participation

In addition to satisfying incentive compatibility, we assume the tax schedule must also satisfy a *voluntary participation* constraint, and not force a farmer out of business: i.e., $\forall\, \hat{\theta}_i,\theta_i \in \Theta$,

$$(5)\quad \pi(\hat{\theta}_i,\theta_i;\theta_{-i}) \geq \bar{\pi}.$$

Without loss of generality we set $\bar{\pi}$ equal to 0.[6] Since the voluntary participation constraint must hold for all possible farmer types, equation (5) must hold for all possible θ. This set of rationality constraints can be replaced by a single constraint as follows. For a given θ, farmer i's profit is given by

$$\tilde{\pi}_i(\theta) = \Pi(x_i(\theta_i,\theta_{-i}),\theta_i) - t_i(\theta_i,\theta_{-i}).$$

Given θ_i, represent farmer i's expected profit by

$$(6)\quad \pi_i(\theta_i) = E_{\theta_{-i}}\{\tilde{\pi}_i(\theta_i,\theta_{-i})\} = E_{\theta_{-i}}\{\Pi(x_i(\theta_i,\theta_{-i}),\theta_i) - t_i(\theta_i,\theta_{-i})\}.$$

By (1) and the envelope theorem, truthtelling implies:

$$(7)\quad \pi_i'(\theta_i) = E_{\theta_{-i}}\left\{\frac{\partial \Pi_i}{\partial \theta_i}(x_i(\theta_i,\theta_{-i}),\theta_i)\right\}.$$

Integrating (7) between zero and θ_i yields

$$(8)\quad \pi_i(\theta_i) = \pi_i(0) + E_{\theta_{-i}}\left\{\int_0^{\theta_i}\frac{\partial \Pi_i}{\partial \theta_i}(x_i(s,\theta_{-i}),s)ds\right\},$$

and given assumption 1, it follows that $\pi_i(\theta_i)$ is increasing in $\theta_i \forall \theta_i \in \Theta$. It follows that equation (5) is satisfied as long as

$$(9)\quad \pi_i(0) = 0.$$[7]

The Optimal Tax Schedule under Asymmetric Information

This section develops the regulator's optimal incentive scheme given asymmetric information over the farmer's type. We proceed by first setting up the regulator's optimization problem. We then develop the optimal input function and end with a characterization of the optimal tax function.

For a given θ, the expected net social benefits associated with an arbitrary tax schedule is

$$B(\mathbf{x},\theta) = \sum_{i=1}^{n}\{\Pi(\mathbf{x}_i(\theta),\theta_i) - t_i(\theta) + t_i(\theta)\} - \overline{D}(\mathbf{x}(\theta)) = \sum_{i=1}^{n}\Pi(\mathbf{x}_i(\theta),\theta_i) - \overline{D}(\mathbf{x}(\theta)).$$

Note that B is the objective function associated with the full-information problem. Since Π is strictly concave in x and D is convex in $\mathbf{x}$, it follows that $B(\mathbf{x},\theta)$ is strictly concave in $\mathbf{x}$. Then the regulator's problem is to choose $\{\mathbf{x}(\theta), \mathbf{t}(\theta)\}_{\theta \in \Theta^N}$ to solve:

$$(10)\quad \max_{\{\mathbf{x}(\theta)\}}\{E_\theta\{B(\mathbf{x}(\theta),\theta)\}; \text{ subject to (4), (7), and (9)}\}.$$

To further simplify the problem we impose the following restriction on B.

Assumption 2:

$$\sum\sum_{jk \neq ij}\frac{\partial^2 B}{\partial x_{ij}^2}(\mathbf{x}(\theta),\theta)\frac{\partial x_{ij}}{\partial \theta_i} \geq -\frac{\partial \Pi}{\partial x_{ij}\partial \theta_i}(\mathbf{x}_i(\theta),\theta).$$

Assumption 2 requires that the change in marginal net social benefits associated with a change in farmer type is not too small. Later we show that invoking assumption 2 ensures that the monotonicity condition, equation (4), is satisfied. Given assumption 2, program (10) is a pointwise optimization problem. Specifically, in the appendix we show that (10) is equivalent to the following optimization problem:

$$(11)\quad \max_{\{x(\theta)\}} E_\theta\left\{\sum_{i=1}^{n}\Pi(\mathbf{x}_i(\theta),\theta_i) - \overline{D}(\mathbf{x}(\theta))\right\},$$

subject to

$$(12)\quad E_{\theta_{-i}}\{t_i(\theta_i,\theta_{-i})\} = E_{\theta_{-i}}\left\{\Pi(\mathbf{x}_i(\theta_i,\theta_{-i}),\theta_i) - (1-\theta_i)\frac{\partial \Pi}{\partial \theta_i}(\mathbf{x}_i(\theta_i,\theta_{-i}),\theta_i)\right\},\quad i = 1,\ldots,n.$$

In principle, the regulator could solve the optimization problem given by (11) and (12) by first choosing, for each $\theta \in \times_{i=1}^{n}\Theta$, the optimal input vector $\mathbf{x}^*(\theta)$ maximizing (11) and then construct the corresponding tax (12) according to expression (15) found in the appendix.

The necessary conditions for an optimum include: For each $\theta \in \times_{i=1}^{n}\Theta$, $\mathbf{x}_{i=1}^{N}$ or Θ^N

$$(13)\quad \frac{\partial \Pi}{\partial x_{ij}(\theta)}(\mathbf{x}_i^*(\theta),\theta_i) = \frac{\partial \overline{D}}{\partial x_{ij}(\theta)}(\mathbf{x}^*(\theta)),\quad i = 1,\ldots,n,\quad j = 1,\ldots,m$$

$$(14)\quad T_i(r_i(\mathbf{x}_i^*(\theta))) = t_i(\theta) = \Pi(\mathbf{x}_i^*,\theta_i) - (1-\theta_i)\frac{\partial \Pi}{\partial \theta_i}(\mathbf{x}_i^*,\theta_i),\quad i = 1,\ldots,n,$$

Hence, as revealed in (13), the optimal contract scheme chooses the full-information input vectors. The corresponding tax satisfies expression (14).[8] Without regulation the profit-maximizing farmer chooses input levels so marginal net profits are equal to zero. Hence, when $\partial\overline{D}/\partial x_{ij} = 0$ farmers' input choices will be efficient. However, when $\partial\overline{D}/\partial x_{ij} > 0$ the level of input j chosen by farmer i will be too high. The reader can take the total derivative of (13) with respect to θ_i to verify that if assumption 2 holds, then the monotonicity condition (4) holds.

For any input vector satisfying (13), equation (14) gives the estimated runoff tax that *implements* that input vector. In other words, consider an input vector $\mathbf{x}_i(\theta)$ satisfying expression (13). Equation (14) defines the corresponding tax $t_i(\theta)$ that induces the farmer to choose $\mathbf{x}_i(\theta)$, i.e., report $\hat{\theta}_i = \theta_i$. The optimal tax is equal to the difference between the farmer's net profit level and the increment in profit associated with a small change in farmer type (weighted by the likelihood of the farmer having a higher type[9]). Of course the difference may be positive or negative.

Note that to model the characteristics of a management practice tax under asymmetric information one needs only to reinterpret the tax T_i. For example, define a tax as the function of the input vector $\mathbf{x}_i$, say $t_i(0) = \overline{T}_i(\mathbf{x}_i(\theta))$ and substitute $\overline{T}$ into all expressioins containing $t_i(\theta)$. The reader can verify that after making all appropriate substitutions, the objection function (SB) and the necessary condition (13) remain the same. For all intents and purposes, expression (14) is unchanged also, and equivalent results follow. Hence consistent with Shortle and Abler's discussion, a management practice tax also implements the full-information allocations.

In short, we conclude management practice and estimated runoff taxes are equivalent and can (in principle) implement full information allocations under asymmetric information, even when there exist multiple polluters. Why do our results differ from those of S-D? In the mechanism design approach the regulator first ascertains the farmers' best responses to any possible policy-expression (2). Armed with this information, the regulator uses equation (13) to define the full-information vector profile that links the farmer's profit structure directly to the damage function. The regulator then uses equations (2) or (14) to link the optimal tax function with the optimal input vector. The result being that it can implement full-information allocations under asymmetric information. On the other hand, in S-D the regulator makes no use of the farmers' likely reaction to proposed policies and instead links the tax directly to the damage function (with the tax equal to the damage function plus a constant). Such behavior by the regulator would be analogous to a Stackelberg leader contemplating an output level and not trying to infer the likely output decisions of its followers. Hence, the mechanism design approach incorporates more information in the decision process than that utilized in S-D.

The S-D analysis is restricted to a more narrow class of potential tax schemes than the analysis presented here. Although *for the type of tax analyzed in the S-D model* management practice taxes generally outperform estimated runoff taxes, this result does not hold for the larger class of potential tax schemes that mechanism design theory admits. Viewed another way, in S-D the tax schemes are chosen exogeneously and then checked to see if they can implement full-information allocations; given farmer and regulator preferences. However, here the properties of a tax scheme are chosen endogenously as a function of farmer and regulator preferences.

One implication of the above result is that instead of attempting to monitor the input (or output) decisions of one or more polluters, in principle the regulator could achieve the same results by measuring ambient pollution levels. As an example, say a firm was composed of several production plants and was the sole source of water pollution in a watershed. Then instead of monitoring and regulating the input levels of each plant, the regulator might achieve similar results by applying appropriate penalties to measured ambient pollution levels.

Conclusion

This paper revisits the papers of Shortle and Dunn, and Smith and Tomasi, and examines the problem of controlling nonpoint water pollution from multiple sources in the presence of adverse selection. We argue that both estimated runoff taxes and management practice taxes can implement full information allocations, hence, management practice schemes and taxes on estimated runoff are equivalent mechanisms.

The problem of controlling NPS pollution continues to challenge policy-makers because of the diversity of informational deficiencies involved. Yet, given that NPS pollution remains a major source of environmental degradation, the problem is deserving of investigation. An important next step in addressing the NPS pollution problem is that of designing actual policies that embody properties of first- and second-best instruments like those considered here.

References

Buck, R.C. 1978. *Advanced Calculus,* 3rd edition. McGraw-Hill. New York, New York.

Chambers, R.G. 1989. "On the Design of Agricultural Policy Mechanisms." *Amer. J. Agri. Econ.* 74:646–54.

Dasgupta, P., P. Hammond, and E. Maskin. 1979. "The Implementation of Social Choice Rules: Some Results on Incentive Compatability." *Rev. Econ. Studies* 46:185–216.

Griffin R., and D. Bromley. 1982. "Agricultural Runoff as a Nonpoint Externality." *Amer. J. Agri. Econ.* 64:547–52.

Groves, T. 1973. "Incentives in Teams." *Econometrica* 41:617–31.

Guesnerie, R., and J.-J. Laffont. 1984. "A Complete Solution to a Class of Principal–Agent Problems with an Application to the Control of a Self-Managed Firm." *J. Pub. Econ.* 25(Dec):329–69.

Laffont, J.J., and J. Tirole. 1986. "Using Cost Observation to Regulate Firms." *J. Pol. Econ.* 94(June):614–41.

______1993. *A Theory of Incentives in Procurement and Regulation.* MIT Press. Cambridge Massachusetts.

Myerson, R.B. 1979. "Incentive Compatibility and the Bargaining Problem." *Econometrica* 47:61–73.

Shortle, J., and D. Abler. 1994. "Incentives for Nonpoint Pollution Control." In C. Dosi and T.G. Tomasi (eds), *Non-point-Source Pollution Regulation: Issues and Analysis.* Kluwer Academic Publishers.

Shortle, J., and J. Dunn. 1986. The Relative Efficiency of Agricultural Source Water Pollution Control Policies." *American Journal of Agricultural Economics* 67:668–77.

Smith, R.B.W., and J.F. Shogren 1999. "Voluntary Incentive Design for Endangered Species Protection." Manuscript, University of Minnesota.

Smith, R.B.W., and T.G. Tomasi. 1995. "Transaction Costs and the Relative Efficiency of Agricultural Source Pollution Control Policies." *Journal of Agricultural and Resource Economics* 20:277–290 (December).

Notes

1. In an earlier paper, Griffin and Bromley also examined the implications of using an estimated runoff function in design of policy to control agricultural pollution. S-D extend the Griffin and Bromley model to include a stochastic element in the runoff function, as well as asymmetric information between regulator and firm.

2. In Shortle and Abler, as in this paper, there are two different classes of uncertainty. One type is based on the uncertainty of future weather conditions and the uncertainty imbedded in the expected runoff function. The other uncertainty is based on the farmers' private information. In the (scant) multiple-agent adverse selection literature (see Laffont and Tirole, 1991) there are two types of revelation mechanisms. A mechanism is *ex-post* efficient if it implements full information allocations after types are revealed. In such a case, from the agents' standpoint if two or more agents are being regulated, the mechanism is stochastic. In other words, in such a case the regulator will not know how much each agent should produce, retire, etc, until after the agents' types are revealed. Hence, the agents will not know, for example, how many units of an input to use and the corresponding tax rate until after everyone has reported their type (see Smith and Shogren). A mechanism is *ex-ante* efficient if for each agent the mechanism implements a full-information allocation given expectations of all other agents' types. From the agent's standpoint, an *ex-ante* efficient mechanism is deterministic. Hence, what S-A defines as first-best (or *ex-ante* efficiency) is typically referred to as *ex-post* efficiency, while the S-A definition of second-best would be viewed as *ex-ante* efficiency.

3. This type of instrument is often referred to as a *knife-edged* instrument.

4. The information requirements for implementing a direct-revelation scheme are potentially demanding. For instance, to implement the direct revelation tax scheme considered here, the government must know the structure of the profit function and the distribution of θ_i.

5. Several authors have shown that nothing is lost when modeling a mechanism as a TDR mechanism (see Dasgupta, Hammond, and Maskin; Myerson, 1981). This observation—called the *revelation principle*—says that for any equilibrium of any good mechanism there exists an equivalent direct-revelation mechanism that involves truthtelling.

6. It is, of course, possible that the optimum involves driving the farmer out of business, but we do not consider this degenerate case further.

7. The farmer can always say he is a type-θ_i farmer and earn an expected profit equal to:

$$\begin{aligned}\pi(0,\theta_i,\theta_{-i}) &= E_{\theta_{-i}}\{\Pi(x_i(0,\theta_{-i}),\theta_i) - t_i(0,\theta_{-i})\}\\ &\geq E_{\theta_{-i}}\{\Pi(x_i(0,\theta_{-i}),0) - t_i(0,\theta_{-i})\}\\ &= \pi(0,0;\theta_{-i}).\end{aligned}$$

8. Strictly speaking, after the set of all possible input vectors are chosen the expected tax is chosen to satisfy expression (12).

9. The term $(1 - \theta_i)$ is actually the inverse of the hazard rate where θ_i is the probability distribution function associated with a random variable that is uniformly distributed between zero and one. In a more general case, given a distribution function $F(\theta_i)$, the term $(1 - \theta_i)$, would be equal to $1 - F(\theta_i)/f(\theta_i)$, where $f(\theta_i)$ is the probability distribution function.

Appendix

Here we show that contraints given by expressions (7), and (9) can be collapsed into expression (12).

First, combining equations (6) and (8) gives

$$E_{\theta_{-i}}\{t_i(\theta_i,\theta_{-i})\} = E_{\theta_{-i}}\left\{ \sum_{i=1}^{n} \Pi(\mathbf{x}_i(\theta),\theta_i) - \int_0^{\theta_i} \frac{\partial\Pi}{\partial\theta_i}(\mathbf{x}_i(s,\theta_{-i}),s)ds \right\},$$
$$i = 1, \ldots, n.$$

Taking the expectation of the above expression with respect to θ_i gives

$$\begin{aligned} E_{\theta_i}\{E_{\theta_{-i}}\{t_i(\theta_i,\theta_{-i})\}\} &= E_{\theta_i}E_{\theta_{-i}}\left\{ \sum_{i=1}^{n} \Pi(\mathbf{x}_i(\theta),\theta_i) \right\} \\ &\quad - E_{\theta_i}E_{\theta_{-i}}\left\{ \int_0^{\theta_i} \frac{\partial\Pi}{\partial\theta_i}(\mathbf{x}_i(s,\theta_{-i}),s)ds \right\} \\ &= E_{\theta}\left\{ \sum_{i=1}^{n} \Pi(\mathbf{x}_i(\theta),\theta_i) \right\} \\ &\quad - E_{\theta_{-i}}\left\{ \int_{\underline{\theta}}^{\overline{\theta}} \int_0^{\theta_i} \frac{\partial\Pi}{\partial\theta_i}(\mathbf{x}_i(s,\theta_{-i}),s)ds \right\} \end{aligned}$$

Applying Fubini's theorem (see Buck, pages 186–188) to the double integral term above gives

$$\begin{aligned} E_{\theta}\{t_i(\theta)\} &= E_{\theta}\left\{ \sum_{i=1}^{n} \Pi(\mathbf{x}_i(\theta),\theta_i) \right\} \\ &\quad - E_{\theta_{-i}}\left\{ \int_{\underline{\theta}}^{\overline{\theta}} \frac{\partial\Pi}{\partial\theta_i}(\mathbf{x}_i(s,\theta_{-i}),s) \int_{\theta_i}^{\overline{\theta}} ds \, d\theta_i \right\} \\ &= E_{\theta}\left\{ \sum_{i=1}^{n} \Pi(\mathbf{x}_i(\theta),\theta_i) \right\} \\ &\quad - E_{\theta_{-i}}\left\{ \int_{\underline{\theta}}^{\overline{\theta}} (1-\theta_i) \frac{\partial\Pi}{\partial\theta_i}(\mathbf{x}_i(\theta_i,\theta_{-i}),\theta_i)d\theta_i \right\} \\ &= E_{\theta}\left\{ \sum_{i=1}^{n} \Pi(\mathbf{x}_i(\theta),\theta_i) - (1-\theta_i)\frac{\partial\Pi}{\partial\theta_i}(\mathbf{x}_i(\theta_i,\theta_{-i}),\theta_i) \right\}. \end{aligned}$$

Or, for each θ:

$$t_i(\theta) = \Pi(\mathbf{x}_i(\theta),\theta_i) - (1-\theta_i)\frac{\partial\Pi}{\partial\theta_i}(\mathbf{x}_i(\theta),\theta_i), \quad i = 1, \ldots, n. \tag{15}$$

Finally, taking the expectation of (15) with respect to θ_{-i} gives expression (12).