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Abstract

This paper develops an incentive compatible policy to control agricultural pollution, where the government knows the ranges of technology types and risk attitudes but not their distributions across farmers. The policy creates incentives for farmers to participate in the program, but includes constraints to ensure both self-selection of the appropriate policy, and self-compliance with the policy selected. Unknown risk attitudes are accommodated through stochastic efficiency rules. The model is applied empirically to estimate policies to limit nitrate contamination from New York agriculture. The estimated cost of such a program is not large compared to past commodity policies. Payments could be reduced if soils information is used to assign policies. Self-compliance is possible and does not impose a large cost on the government. If the policy were designed under risk neutrality, payments would be substantially below the incentive needed for participation by a risk averse farmer.

An Incentive Compatible Self-Compliant Pollution Policy under Asymmetric Information on Both Risk Attitudes and Technology

Regulating nonpoint source pollution remains one of the most difficult challenges in agricultural environmental policy. At the most basic level, many of the policy difficulties stem from information and actions that are known to polluters but hidden from regulators. Agricultural pollution is unobservable at its source and depends on production practices as well as spatially heterogeneous topographic and climatic factors. Farmers choose different practices and respond to policies differently because of diversity in production technology and risk preferences.

At one extreme, the government could regulate nonpoint source pollution through farm-specific policies, which would require the use of all polluting inputs to be approved and enforced by government officials. Given the advances in geo-spatial technologies, etc., such an approach may be technically feasible, but the costs of information and monitoring are not well understood. Such an approach is certainly not consistent with the voluntary nature of past farm policies (Chambers), and is probably too intrusive to be politically feasible.

Accordingly, there have been recent investigations into decentralized policy schemes that achieve environmental objectives through carefully designed incentives. Wu and Babcock (1995; 1996) designed a policy where the government is aware of various types of farm technologies but does not match them to individual farmers. The program allows farmers to choose one of several combinations of an abatement level and a government payment. The payments are set to induce each farmer to choose the abatement level designed for his type. Peterson and Boisvert (2001a) empirically estimated the payments required for such a policy to reduce nitrate losses from corn production in New York.

Although promising, these proposals only address the problem of hidden information on technology types. This is but one type of hidden information relevant for policy design. Most agricultural production is uncertain, leading to a complex relationship between price changes and input decisions that depend on risk preferences. Leathers and Quiggin, and more recently, Isik caution that without specific knowledge of the distribution of risk attitudes, and the risk increasing or decreasing nature of inputs, the effects of environmental policy on input use and environmental quality may be ambiguous. Since the distribution of risk preferences across farmers is difficult to estimate, a decentralized policy would ideally treat risk preferences as an additional piece of hidden information.

Another major obstacle is that polluting input use usually constitutes a hidden action. Even if farmers agree to limit an input such as chemicals, the actual application rates are difficult to observe and could at best be monitored imperfectly at high cost. For decentralized policies to be practical in these situations, they would have to give farmers an incentive to self-comply.

This paper develops an incentive compatible policy that regards both technology type and risk attitudes as hidden information. The government knows the ranges of these attributes but does not know their distribution across farmers. Both production and pollution are stochastic and differ by technology type. As in previous models, incentive compatibility is achieved through constraints to ensure that farmers will participate in the program and that each type farmer will self-select the appropriate policy. In addition, we extend these models by adding a constraint to ensure that all participants will self-comply with the policy selected.

If risk preferences are hidden information, the analytical difficulty is that the policy constraints cannot be evaluated. Another unique feature of our policy model is that unknown risk attitudes are accommodated through stochastic efficiency rules on the distribution of net returns. The model can be numerically simulated under a broad range of conditions, and we also derive an empirically testable necessary condition for self-selection to be possible. Further, we demonstrate that in certain cases the computational burden of the simulations can be dramatically lowered, and that in these cases the necessary condition for self-selection to be possible is also sufficient. In all cases, the stochastic efficiency approach leads to a policy problem that can ultimately be solved with linear programming methods.

Although the model is applicable to any voluntary environmental program, we demonstrate it empirically for the case of nitrate leaching and runoff in New York. In the simulated program, corn producers would receive a government payment in exchange for reducing nitrogen fertilizer, and different soil types represent distinct technologies. Besides illustrating the proposed methods, we also estimate the portion of program payments that constitute information rents on soil types. Since these rents could be eliminated if soils information were used to assign policies, they represent the value of information to the government. Finally, self-compliance does not impose a large cost on the government, but if the policy were designed under risk neutrality, the payments would be substantially below the incentive needed for participation by a risk averse farmer.

Theoretical Framework

Following Leathers and Quiggin, and Isik, we consider a farmer who must choose an input that affects both output and environmental quality in a random setting. As described more fully below, public environmental objectives can be achieved by creating a policy that pays the farmer $s - ty$ per acre, where s is a fixed acreage payment, $-t$ represents a marginal output payment, and y is output per acre. The policy is conditioned on output, which is both observable and measurable in practice, and it smoothes farm income through payments that are negatively related to output. Profit per acre from production for the ith technology type ($i \in \Theta$) is:

$$\pi^i(x, b_i, t) \equiv (p_y - t)y^i(x, b_i) - p_b b_i - k, \tag{1}$$

where p_y is the price of output, $y^i(\cdot)$ is the technology-specific production function, x represents a random input beyond the farmer's control, b_i is the controllable input with price p_b, and k is fixed cost. Net income per acre is $m_i = \pi^i(x, b_i, t) + s$. Emissions of pollution e^i are jointly produced with output, so that $e^i = g^i(x, b_i, y^i)$. For common cases of agricultural pollution such as runoff, soil and topographic conditions define the technologies in the set Θ, x may be uncertain weather or pest outcomes, and b_i could be the use of a polluting input such as fertilizer or a binary variable representing some production practice. Let the support of x be the interval $[\underline{x}, \overline{x}]$, and assume that x and b_i are defined such that $\pi_x^i \geq 0$ and $de/db_i = g_b^i + g_y^i y_b^i \geq 0$ for all i.

Farmers are assumed to maximize the expected utility of profit per acre. A farmer with a von Neumann-Morgenstern utility function u and technology of type i will select b_i by solving the problem: $\max_{b_i \geq 0} Eu(\pi^i(x, b_i, t) + s)$, where E is the expectation with respect to x. Assume the function u belongs to a known set Ω of continuous real-valued functions. Let the solution to the farmer's problem be denoted $b_i(t, s)$, and let the maximized value of the objective function be denoted $Eu(\pi^i(t, s)) \equiv Eu(\pi^i(x, b_i(t, s), t) + s)$. If emissions are a negative externality, the input level without any policy $b_i(0, 0)$ (and consequently e^i) exceeds the socially optimal level; suppose the government wishes to implement $b_i^* \leq b_i(0,0)$ as input target on technology i.[1]

To implement a different input target on each technology through self-selection, the government must in effect devise a policy "menu," where each item on the menu is a regulation on b with a corresponding compensation payment. Such a scheme can be viewed as a two-staged game of imperfect information, where the government chooses a set of policies in the first stage, and farmers select from these policies in the second stage (Smith and Tomasi).[2] The government must solve this game by backward induction; it must determine how a farmer with each technology would respond to various combinations of payments and regulations, and then incorporate these responses in devising policies of the form (t_i, s_i). The goal is farmers of type i to choose the policy (t_i, s_i) but those of type j to select (t_j, s_j).

If the type of all producers is unknown and all producers are expected to self-comply, then the government's problem is to set policies subject to following three sets of constraints:

$$b_i(t_i, s_i) \leq b_i^* \qquad \text{for all } i \in \Theta, u \in \Omega \tag{2}$$

$$Eu(\pi^i(t_i, s_i)) \geq Eu(\pi^i(0, 0)) \qquad \text{for all } i \in \Theta, u \in \Omega \tag{3}$$

$$Eu(\pi^i(t_i, s_i)) \geq Eu(\pi^i(t_j , s_j)) \qquad \text{for all } i, j \in \Theta, u \in \Omega \tag{4}$$

Constraints in (2) guarantee *self-compliance*. Policies must be set so that privately optimal input use is no larger than the socially desirable level. The *participation constraints* in (3) require that post-policy expected utility is at least as large as pre-policy expected utility. The *self-selection constraints* in (4) guarantee that expected utility for type i's own policy exceeds the expected utility for all other policies. Maximization with respect to b_i is embedded in (3) and (4); the left-hand-sides of both inequalities correspond to an input level of $b_i(t_i, s_i)$, while the right hand-sides correspond to input levels of $b_i(0, 0)$ and $b_i(t_j, s_j)$, respectively.

This combination of constraints assumes both hidden information (adverse selection) and hidden action (moral hazard), and relaxing either assumption leads to a special case of the problem where one set of constraints can be ignored. If the government can assign individual farmers to a technology type, then the self-selection conditions can be ignored, and problem is one of ensuring that farmers of each type will participate as well as self-comply. On the other hand, if farmers' actions can be easily monitored (e.g., if b represents the use of a discrete technology such as a certain irrigation system), then the self-compliance constraints can be ignored. We show below that the policy need not include an output tax in this case, and the problem is to find fixed payments that ensure participation and self-selection.

Stochastic Efficiency Representation

In the formulation above, each set of conditions must be met for every utility function in Ω. If all farmers have identical risk preferences, Ω has a single element and the problem is one of finding separate policies based on technology alone. If Ω contains many elements then a feasible policy could only be found by evaluating the constraint for each utility function, an infinite number of computations in the plausible case where each element of Ω is a point on the continuum of absolute risk aversion coefficients. The only way to avoid such an enumeration is through general criteria that can identify the situations where (t_i, s_i) is the preferred policy for all relevant utility functions.

Stochastic efficiency criteria provide exactly the simplification required. For several specifications of Ω, the statement that $Eu(m) \geq Eu(m')$ for all $u \in \Omega$ can be equivalently expressed by a single stochastic efficiency condition on the distributions of m and m'. A particularly useful such rule is that of second-degree stochastic dominance (SSD). A cumulative distribution $G(m)$ dominates $H(m')$ by SSD if and only if the area under G is nowhere more than that of H and somewhere less than the area under H:

$$\int_{-\infty}^{\tilde{m}} G(m)\,dm \leq \int_{-\infty}^{\tilde{m}} H(m')\,dm' \qquad (5)$$

for all $\tilde{m}$, with strict inequality somewhere. Geometrically, this condition means two things: first, G must start at or to the right of H (i.e., the first non-zero point on G must be at least as large as the first nonzero point on H), and second, the whole distribution G must lie further to the right, in the sense that the accumulated area underneath it must be smaller. Hadar and Russel discovered that dominance by SSD is equivalent to greater expected utility for all utility functions that are increasing and concave; the SSD rule separates attractive alternatives from unattractive ones for all risk-averse decision-makers who prefer more to less.[3]

Here, the cumulative distribution function (cdf) of income for type i farmers is:

$$F_i(m;\, b,\, t,\, s) \equiv \Pr\{\, \pi^i(x,\, b,\, t) + s \leq m \,\} \tag{6}$$

This definition says there is a distribution F_i conditional on each combination of b, t, and s. One consequence of unknown risk preferences is that the optimal input level is not unique. In an SSD setting, the candidates for an optimal input level are those than generate second-degree stochastic efficient (SSE) income distributions. All distributions not in this set are dominated by at least one of the distributions in it, but none of the members of the set is dominated by another member. Given a policy (t, s), the acreage payment s creates an identical parallel shift of the cdf for all input levels, and does not influence the set of SSE input levels. Group i's SSE set can therefore be written as a correspondence that depends on the output payment: $B_i(t) \subset \Re_+$.

To illustrate the use of SSD in the policy scheme, consider two groups (i.e., $\Theta = \{1, 2\}$). The government must choose policies (t_1, s_1) and (t_2, s_2) to implement the input targets b_1^* and b_2^*. The constraints (2) - (4), written in terms of SSD, require the policies to satisfy:

$$b_i \leq b_i^* \qquad \forall b_i \in B_i(t_i),\, i = 1,2 \tag{7}$$

$$F_i(m; b_i, t_i, s_i) \succ F_i(m; b_i^0, 0, 0) \quad \forall b_i \in B_i(t_i), \forall b_i^0 \in B_i(0),\, i = 1,2 \tag{8}$$

$$F_1(m; b_1, t_1, s_1) \succ F_1(m; b_1^2, t_2, s_2) \quad \forall b_1 \in B_1(t_1), \forall b_1^2 \in B_1(t_2) \tag{9}$$

$$F_2(m; b_2, t_2, s_2) \succ F_2(m; b_2^1, t_1, s_1) \quad \forall b_2 \in B_2(t_2), \forall b_2^1 \in B_2(t_1) \tag{10}$$

where "$\succ$" denotes dominance by SSD. Equation (7) represents self-compliance constraints. The government must set an output payment t_i so that the SSE set of input levels lies entirely below b_i^*. The constraints in (8) are the participation conditions— the post-policy distributions (those for input levels in $B_i(t_i)$) must dominate all pre-policy distributions (for input levels in $B_i(0)$). The constraints in (9) and (10) are the self-selection conditions. For farmers in group 1, s_1 and s_2 must be set so that all distributions under their "own" policy (the input levels in $B_1(t_1)$) dominate the distributions under the other policy (input levels in $B_1(t_2)$); a parallel interpretation applies to the constraint for group 2. If all the constraints are met, any risk-averse farmer in group i will choose the policy (t_i, s_i) over (t_j, s_j) or not participating, and will choose an input level no larger than b_i^*.

When written in stochastic efficiency terms, the constraints highlight the two ways that unknown levels of risk aversion affects the policy. First, the whole distribution of returns must be compared to ensure the desired behavior, and second, each constraint must be evaluated over a range of input levels. In essence, each policy payment must include a risk premium that has two 'layers,' which will likely exceed a risk premium calculated in the usual way. In general, ignoring risk and/or risk aversion will lead to a policy that is not incentive compatible.[4]

The SSD conditions also suggest a computational algorithm for finding policies given target input levels b_1^* and b_2^*, estimates of $\pi^1(x, b, t)$ and $\pi^2(x, b, t)$, and knowledge of the distribution of x. The SSD criterion can be implemented numerically by generating discrete distributions of $F_1(\cdot)$ and $F_2(\cdot)$ based on random draws from the distribution of x (Anderson et al.). The steps in the algorithm follow.

1. Find the pre-policy SSE input sets $B_1(0)$ and $B_2(0)$, by iteratively making numerical SSD comparisons of pairs of input levels.
2. Find t_i sufficiently large so that (7) holds, by repeating the procedure in step 1 for successively larger output payments until $B_i(t_i)$ lies entirely below b_i^*.
3. Find the restrictions imposed on s_i by the participation constraints (8). This restriction is

depicted in figure 1. $F_i(\cdot,0,0)$ represents a pre-policy distribution of income that is associated with an input level in $B_i(0)$, and $F_i(\cdot, t_i, 0)$ is an income distribution for an input level in $B_i(t_i)$ but with no acreage payment (i.e., under the policy $(t_i, 0)$). An acreage payment of $s_i > 0$ will shift the distribution to the right in a parallel fashion, as shown by the curve $F_i(\cdot, t_i, s_i)$. The participation constraint says that s_i must be large enough so that $F_i(\cdot, t_i, s_i)$ dominates $F_i(\cdot, 0, 0)$ by SSD, which implies that area A in the figure must exceed area B. By iterating over the input levels in the sets $B_i(0)$ and $B_i(t_i)$, the smallest value of s_i that satisfies (8) can be found numerically. Denoting this minimum value P_i, the participation constraints reduce to $s_i \geq P_i$.

4. Find the restrictions on s_i imposed by the self-selection constraints (9) and (10). This step requires knowledge of the cross-policy input sets $B_1(t_2)$ and $B_2(t_1)$, which can be computed similar to the procedure in step 2. The restrictions imposed by group 1's self-selection constraint are shown in figure 2. It is useful to begin with the assumption that $s_1 = s_2 = 0$. The distributions $F_1(\cdot, t_1, 0)$ and $F_1(\cdot, t_2, 0)$ represent incomes for input levels in $B_1(t_1)$ and $B_1(t_2)$, respectively, with no acreage payments. Assuming that the policy $(t_2, 0)$ is preferred to $(t_1, 0)$, as shown in the figure, s_1 must be enlarged to $\tilde{s}_1$, so that $F_1(\cdot, t_1, \tilde{s}_1)$ dominates $F_1(\cdot, t_2, 0)$ by SSD. Let I_1 represent the smallest value of $\tilde{s}_1$ that satisfies the SSD condition over all combinations of input levels in $B_1(t_1)$ and $B_1(t_2)$. Thus, if $s_2 = 0$, the self-selection constraint is equivalent to $s_1 \geq I_1$. If $s_2 > 0$, the income distribution under group 2's policy shifts to the right by s_2 units, as shown by the dashed curve $F_1(\cdot, t_2, s_2)$. In this case the SSD condition requires s_1 to be enlarged by an extra s_2 units, implying the constraint $s_1 \geq I_1 + s_2$.
5. Find the acreage payments s_i that meet the restrictions found in steps 3-4. Step 4 applied to group 2 yields the constraint $s_2 \geq I_2 + s_1$, where I_2 is the minimum payment needed for group

2 to prefer (t_2, 0) over (t_1, 0). Rearranging the self selection constraints, the government's minimum cost acreage payments can be found by solving the following linear program:

$$\text{Minimize} \quad a_1 s_1 + a_2 s_2 \tag{11}$$

$$\text{Subject to:} \quad s_i \geq P_i, \qquad i = 1, 2 \tag{12}$$

$$s_1 - s_2 \geq I_1 \tag{13}$$

$$s_1 - s_2 \leq I_2 \tag{14}$$

where a_i is the number of acres of land in group i.

This problem is depicted graphically in figure 3. The participation constraints in (12) require that s_1 is on or to the right of the line at P_1 and that s_2 is on or above the line at P_2. The self-selection constraint for group 1 (equation (13)) requires s_1 to lie on or to the right of the 45-degree line starting at I_1; self-selection for group 2 (equation (14)) requires s_1 to lie to the left of the 45 degree line starting at I_2. For the situation depicted in the figure, the feasible region is the shaded area and the objective function is minimized at point d.

Existence of a solution requires the feasible region to be nonempty, which will be true in general if: (i) P_1 and P_2 are finite, and (ii) $I_1 \leq I_2$. The first of these conditions holds by assumption, while the second depends on the technologies of the two groups. A necessary condition for existence can be derived as follows. There are two necessary conditions for one distribution to dominate another by SSD: neither the mean of the dominant distribution nor its lowest observation may be smaller (Anderson et al.).[5] For the self-selection constraints in (9) and (10), these requirements can be written: $E\pi^i(x, b_i, t_i) + s_i \geq E\pi^i(x, b_i^j, t_j) + s_j$, and $\pi^i(\underline{x}, b_i, t_i) + s_i \geq \pi^i(\underline{x}, b_i^j, t_j) + s_j$, where $b_i \in B_i(t_i)$ and $b_i^j \in B_i(t_j)$. Equivalently, $s_i - s_j$ must equal or exceed the larger of $\Delta E\pi^i = E\pi^i(x, b_i^j, t_j) - E\pi^i(x, b_i, t_i)$ and $\Delta\underline{\pi}^i = \pi^i(\underline{x}, b_i^j, t_j) - \pi^i(\underline{x}, b_i, t_i)$ for all permissible b_i and b_i^j. Formally, $s_i - s_j$ is at least as large as:

$$\tilde{I}_i = \max_{\substack{b_i^j \in B_i(t_j), \\ b_i \in B_i(t_i)}} \left\{ E\pi^i(x, b_i^j, t_j) - E\pi^i(x, b_i, t_i), \pi^i(\underline{x}, b_i^j, t_j) - \pi^i(\underline{x}, b_i, t_i) \right\} \tag{15}$$

The necessary condition for separate self-selecting policies to exist is that $\tilde{I}_1 \leq \tilde{I}_2$. Note that it requires some measure of group 2's loss in returns (either in terms of the mean or the lower tail of the distribution) to exceed group 1's loss. That is, one technology is required to be more "productive" in a stochastic sense. This requirement is an instance of the more general "single-crossing property" encountered in the literature (Mas-Collel et al.).

The Government's Policy Alternatives

Figure 3 depicts a situation where separate, self-complying, self-selecting policies are possible. This type of program would give farmers the maximum amount of autonomy in choosing and responding to policies. In some cases, the government may have the ability to monitor compliance and enough information to assign policies, but may still choose to decentralize the program to avoid administrative cost and/or for political feasibility.

If b is an input that can be easily monitored, then the government can create policies that associate fixed payments s_i directly with the targets b_i^*, so that an output payment is not necessary. Peterson and Boisvert (2001b) showed that if self-selecting policies exist in this case for targets $b_1^* < b_2^*$, then payments will be minimized at point d in figure 3, which is the intersection of group 2's participation constraint and group 1's self-selection constraint. This implies that the participation constraint binds for group 2 but is nonbonding for group 1; i.e., group 2 will be just as well off with the policy as without it, but group 1 will be strictly better off due to an information rent.

If the existence conditions for self-selecting payments are not met, then a policy such as the one at point d is impossible. Depending on available information, the alternatives are a uniform policy for all farms, or else assigned policies that differ by group. If the policies are assigned to each group but are still voluntary, then the self selection constraints can be ignored, and the minimum cost payments are the policy at point *c*, where $s_1 = P_1$ and $s_2 = P_2$; farmers in both groups would be just as well off after the program as before.

Even if self-selecting policies are possible, the government can reduce payments by assigning them because the information rent can be eliminated (point *c* is cheaper than point *d*). There is a trade-off between government cost, on the one hand, and the amount of autonomy farmers can be given in selecting policies, on the other.

Risk attitudes are a second dimension of the government's information set. Policies based on SSD are conservative in the sense that the government is assumed to know nothing about risk attitudes other than that farmers are risk averse. While discovering every farmer's risk attitude is unrealistic, several empirical studies have estimated coefficients of absolute risk aversion[6] from cross-sectional data, and collectively these studies represent a plausible set of utility functions that is smaller than the set assumed for SSD. Information on risk attitudes comes in the form of a narrower range of risk attitudes, which may lower program costs because the minimum payment bounds (P_i and I_i) may be a reduced in some cases. Policies can be computed in this case by replacing SSD in the algorithm above with stochastic dominance with respect to a function (SDRF), which isolates preferred distributions for all decision makers with risk aversion coefficients in a specified range (Meyer; King).[7] Doing so for various assumed ranges would trace out the relationship between better knowledge of risk attitudes and government cost.

The Case of Simply Related Variables

While the SSD formulation is feasible to implement numerically as outlined above, the computations can be dramatically simplified under certain conditions. This simplification is due to the concept of *simply related random variables* (Hammond). Two random variables are simply related if their cdf's cross at most once. Each of the SSD conditions in (8) - (10) compares some random variable of the form $m = \pi^i(x, b, t) + s$ to another random variable $m' = \pi^i(x, b', t') + s'$ (e.g., for the participation constraint (8), $t = t_i$, $s = s_i$, and $t' = s' = 0$). The following result describes a sufficient condition for the cdf's of these random variables (F_i and F_i', respectively) to intersect only once, for a given combination of (b, t) and (b', t'):

RESULT 1: *If $\delta_\pi = \pi_x^i(x,b,t) - \pi_x^i(x,b',t')$ is positive (negative) for all x, then F_i and F_i' intersect at most once, and F_i intersects F_i' from above (from below) if the distributions do cross.*

Proofs for this and all other results in this section are in the appendix.

Intuitively, the simply related property follows from the one-to-one correspondence between x and income: each realization of income associated with a unique value of x, and larger incomes are associated with larger x's because $\pi_x^i > 0$. If $\delta_\pi > 0$, then a given change in x causes a larger change in m than in m', so that F_i is geometrically 'flatter' and can only intersect F_i' from above. The opposite case is where $\delta_\pi < 0$, so that F_i is 'steeper' than F_i' . If δ_π switches sign somewhere in the domain of x, then F_i and F_i' may intersect more than once.

Although the condition in Result 1 must be checked empirically and is not guaranteed to hold, it is not unlikely. To see this, suppose without loss of generality that $t < t'$, which implies that $b > b'$ by the usual properties of input demand functions. In this case, $\delta_\pi = (p_y - t)\, y_x^i(x,b) - (p_y - t')\, y_x^i(x,b')$. Since $(p - t) > (p - t')$, δ_π will be positive for all x provided that $y_{xb}^i > 0$. If $y_{xb}^i < 0$ then the sign of δ_π is ambiguous and must be evaluated empirically. Kramer and Pope argued that the simply related property holds for many agricultural applications.

In the case where policies can be monitored so that $t = t' = 0$, the simply related condition is guaranteed, since δ_π is positive (negative) for all x if and only if y_{xb}^i is positive (negative).

Peterson and Boisvert (2001b) showed that these two possibilities correspond to b being a risk increasing (risk decreasing) input, in the sense that if $b > b'$ then m is riskier (less risky) than m' based on the definition proposed by Rothschild and Stiglitz.

The advantage of simply related variables is that the SSD conditions can be very easily evaluated, because the two necessary conditions for SSD are also sufficient. Formally:

RESULT 2: *Suppose m and m' are simply related, with cdfs F_i and F_i', respectively. The sufficient conditions for F_i to dominate F_i' by SSD are: (i) $\underline{m} \geq \underline{m}'$ and (ii) $Em \geq Em'$, where $\underline{m}$ and $\underline{m}'$ are the lowest observations with positive probability.*

This result has two useful implications for solving the policy problem in practice:

RESULT 3: *Suppose that the profits at any two input levels (i.e., $\pi^i(x, b, t)$ and $\pi^i(x, b', t')$) are simply related random variables. Then the SSE set of input levels $B_i(t)$ is a closed interval of real numbers bounded by $\underline{b}(t) = \arg\max_b \pi^i(\underline{x},b,t)$ and $\overline{b}(t) = \arg\max_b E\pi^i(x,b,t)$.*

RESULT 4: *Consider an SSD condition of the form:*

$$F_i(m;b,t,s) \succ F_i(m;b',t',s') \;\forall\; b \in B_i(t), b' \in B_i(t').$$

If the two cdfs are simply related, then this condition is equivalent to the requirement:

$$\begin{aligned} s - s' \geq max\left\{E\pi^i(x,b',t') - E\pi^i(x,b,t),\; \pi^i(\underline{x},b',t') - \pi^i(\underline{x},b,t)\right\} \\ where: \; b' \in \{\underline{b}(t'), \overline{b}(t')\} \\ b \in \{\underline{b}(t), \overline{b}(t)\} \end{aligned} \tag{16}$$

Result 3 allows the each of the SSE sets required in steps 1, 2, and 4 in the algorithm above to be identified by solving two nonlinear maximization problems. Result 4 allows the restrictions on the acreage payments P_i and I_i in steps 3 and 4 to be found by computing a relatively small number of expected and lower-tail profits. In particular, let $\Delta E\pi^i(b', b)$ and $\Delta\underline{\pi}^i(b', b)$ represent the two values inside the max operator in equation (16). These values depends on the input levels

b and b', each of which is an upper- or lower-bound of the input sets $B(t)$ and $B(t')$, respectively (Result 3). Since b and b' each have two possible values, there are four combinations of (b', b) to be examined. Result 4 says that the policy (t, s) will be preferred by SSD over (t', s') if $s - s'$ exceeds the larger of $\Delta E\pi^i(b', b)$ and $\Delta\underline{\pi}^i(b', b)$ across all four combinations of (b', b). Once I_i are computed from equation (16), Result 4 also implies that the condition $I_1 \leq I_2$ is sufficient as well as necessary for self-selection to be possible.

Empirical Application to Nitrate Loss from New York Corn Production

The model is applied empirically to the nitrate leaching and runoff problem from corn production in New York. Much of New York is predominated by multi-crop dairy farms, with about 30% of cropland devoted to corn production annually. Due in part to the use of nitrogen fertilizer on corn acreage, nitrate concentrations in some drinking water supplies have risen above their natural background levels.

Two specific soils (indexed by i = 1, 2) are chosen to represent different technologies, from Hydrologic groups A and B, respectively.[8] Because these soils generate different amounts of nitrate residuals *ceteris paribus*, the limits on fertilizer that meet environmental standards also differ. Production and nitrate residuals are both random because they depend on unpredictable weather variables. Before presenting the policy simulations and the procedure for finding payments in all the cases, the estimated yield functions, the pollution functions, and nitrogen standards are described.

Estimation

Corn silage yield functions are estimated from data collected at field trials run by the Department of Soil, Crop, and Atmospheric Sciences at Cornell University. The data include 276 observations of corn silage yield (y), commercial fertilizer, and manure application at several sites in New York over several crop years; 52 of these observations are from group 1 soils and 224 are from group 2. To obtain a variable that represents total nitrogen applied (b), manure was credited with 3 pounds of nitrogen per ton and combined with the nitrogen in commercial fertilizer. The data were augmented with observations of rainfall in the growing season (x), defined as accumulated precipitation from April through September, from weather stations near the experimental sites.

To gain efficiency, the functions were estimated in a pooled regression using a quadratic specification. The model was fit by maximum likelihood, with the parameters bounded so that the derivative in x is positive to be consistent with the theoretical model. The results are:

$$
\begin{aligned}
y = &\underset{(-5.01)}{-15.12} + \underset{(1.56)}{0.699d_m} + \underset{(9.38)}{25.71d_i} + \underset{(6.67)}{0.1001b} - \underset{(-6.09)}{0.00024b^2} + \underset{(2.04)}{0.000057d_ib^2} + \underset{(10.08)}{1.51x} \\
&\underset{(-9.59)}{-1.37d_ix} - \underset{(-1.40)}{0.0007bx}, \qquad R^2 = 0.56,
\end{aligned}
$$

where t-ratios are in parentheses, and d_m and d_i are dummy variables for manure application and soil group, respectively ($d_1 = 0$, $d_2 = 1$). The interaction terms d_ib^2 and d_ix allow the shape of the yield function in nitrogen and rainfall to differ by group. The estimated coefficients all have theoretically expected signs, and the fit also appears adequate. The estimated coefficients on d_ib^2 and d_ix are both statistically different from zero, and their signs imply that group 2 has a higher marginal product of nitrogen but a smaller marginal product of rainfall. If weather is random, the negative coefficient on the interaction term bx suggests that nitrogen is a risk-decreasing input for both groups, though the parameter was not estimated with great precision ($t = -1.40$).

Evaluating the functions at average rainfall and nitrogen (20.9 in., and 131 lb./acre, respectively), a one-pound increase in nitrogen increases yield by 0.023 tons (45 lb.) and 0.038

tons (76 lb.) per acre for groups 1 and 2, respectively, while a one-inch increase in rainfall raises yield by 1.42 tons and 0.05 tons, respectively.

Profits for group i were simulated by equation (1), where the policy variable b_i is nitrogen from commercial fertilizer.[9] The random variable x takes on values from a sample of growing season rainfall observations at the Ithaca weather station over the 30-year period 1963-1992. The prices p_y and p_b were set at the mean of observed corn silage and nitrogen prices (in constant 1992 dollars) over the same 30 years, where corn silage prices were imputed as a corn grain equivalent. Other costs k were based on enterprise budgets from USDA and Schmit.

Nitrate emissions are defined as the sum of leaching and runoff per acre of cropland: $e^i = e^i_R + e^i_L$. Boisvert et al. estimated a recursive system that relates nitrate leaching and runoff on New York soils to nitrogen application, soil characteristics, and weather variables. This system can be used to simulate nitrate losses as follows:

$$e_R^i = e_R(b_i, \mathbf{x}, \mathbf{c}_i), \qquad e_L^i = e_L(b_i, \mathbf{x}, \mathbf{c}_i, e_R^i)$$

The vector $\mathbf{x}$ contains four weather variables (total annual rainfall, and rainfall within 14 days of planting, fertilizer, and harvest); $\mathbf{c}_i$ is a vector of average soil characteristics for group i (field slope, percent organic matter, soil horizon depth, and the erodibility factor K). See Boisvert et al. for details on the translog specification of the model and estimation procedures.

Distributions of nitrate emissions or each soil were simulated from the weather observations at the Ithaca weather station over the 1963-1992 period. Policy targets for fertilizer b_i^* were computed using chance constraints (Lichtenberg and Zilberman). In particular, b_i^* was chosen to satisfy $\Pr\{e^i_R + e^i_L > e^*\} \le \alpha$, where e^* is a target level of total nitrate emissions, and α is some small probability. These parameters were set at values of $e^* = 25$ and $\alpha = 0.1$ in the simulations, leading to estimated fertilizer targets of $b_1^* = 55$ and $b_2^* = 82$ pounds per acre for the two groups, respectively.

Policy Simulations

To study the effects of hidden actions and information, policies were simulated and compared under several scenarios that vary along three dimensions. First, hidden actions on fertilizer application could be regulated either by conditioning payments on corn production (i.e., *self-compliance*) or through *monitoring* and penalties for non-compliance. Under self-compliance, farmers receive a payment of $s - ty$ per acre, where t is chosen to induce a privately optimal fertilizer level below b_i^*.

Under monitoring, farmers are offered an acreage payment s in exchange for fertilizing at a specified rate. The monitoring mechanism is not modeled explicitly, but it is assumed to be adequate to prevent cheating. For the fertilizer case, this would probably require a permit system for fertilizer purchases, along with on-site checks to verify the application rates on specific fields. Such a monitoring scheme would undoubtedly be costly to the government. The purpose of comparing the two models is to investigate whether the cost of monitoring may be justified through savings in nominal payments. Other practices (e.g., technology adoption) might well be monitored at lower cost.

The second dimension of the policy simulations involves soils information. The government may choose to use soils information to *assign* policies by soil type, in which case each farmer would only have the option of the policy designed for his soil or not participating. If soils information is not used, then the possibilities are either soil specific, *self-selected* policies or else a *uniform* policy for all soils. As shown above, self-selection is only possible under certain conditions that must be tested.[10]

The third dimension is the information on risk attitudes. At one extreme, we assume that the government knows only that farmers are *risk averse* to varying degrees, so that policies must be computed based on SSD. The other extreme is the assumption that all farmers have identical preferences and are *risk neutral*. These two situations illustrate the change in program costs if information on risk attitudes becomes more precise. They also reveal how payments may be set inappropriately if the government assumes farmers are risk neutral while in reality at least some of them are risk averse.

The payments in all models are computed based on the five-step algorithm, using the estimated relationships discussed above. Since the estimated yield function $y^i(x, b)$ is linear in x, the quantity $\delta_\pi = \pi_x^i(x,b,t) - \pi_x^i(x,b',t')$ is a constant (either positive or negative) for any combination of (b, t) and (b', t'). Therefore, by Result 2, the profits are simply related random variables; by Results 3 and 4, the SSD computations can be simplified to involve only mean and lower-tail profits. The computations for the risk neutral model are similar except they involve only mean profits.

Table 1 reports the fertilizer levels, profits, and production for each of the policies, and the payments are in table 2. The upper-left block of numbers in each table represents SSD-based policies that are assigned by soil. If these policies are self-complying, farmers in the two groups will reduce fertilizer from about 83-92 to 46-55 pounds and from 127-139 to 70-82 pounds, respectively (table 1). In so doing, they will receive government payments of $231 – $9.86 $\times y^1$ and $251 – $10.68 $\times y^2$, respectively (table 2). As is required for participation, these payments provide mean incomes at least as large as without the policy, while corn silage yields are reduced by about 1-2 tons (table 1). If fertilizer use can be monitored, then the groups receive acreage payments of about $6 and $12 per acre, respectively (table 2). While the self-complying policies may generate larger net payments in individual years, the expected net payments $E[s_i - t_i y^i]$ are less than the payments under monitoring (table 2). This implies that a self-complying policy is preferable in terms of government costs.

Payments under risk neutrality are strictly less than those under SSD (table 2). The difference in these payments represents an implicit risk premium, which accounts for up to about 47% of payments under risk aversion. This result has two implications. First, it suggests that government costs could be reduced if more information could be collected on risk attitudes. Peterson and Boisvert (2001b) calculated payments with monitoring based on stochastic dominance with respect to a function (where risk attitudes were specified as a subset of those allowed under SSD) and found that government costs were intermediate between the SSD and risk neutral cases. Second, since not all farmers are risk neutral in reality, the risk neutral policies will not meet environmental targets. For all risk-averse farmers, non-participation is a dominant strategy if the risk-neutral payments are offered.[11]

If the government chooses not to use soils information, self-selecting policies in the self-compliance model are impossible because the necessary condition for existence is violated. Intuitively, self selection cannot occur because group 1's policy is preferred by both groups because group 1's payment falls less rapidly in output (t_1 = 9.86, t_2 = 10.68). If s_2 is increased enough so that group 2 prefers (t_2, s_2), then group 1 will prefer it as well. The difficulty is that the marginal productivities of fertilizer are too similar across groups; sensitivity results with a wider gap in marginal productivities are presented below for comparison.

The remaining alternative that does not use soils information is a uniform policy, which is presented in the bottom halves of tables 1 and 2. To ensure that environmental targets are met for both groups, the uniform policy must be set at the more stringent of the two policies. In the self-compliance model, this means that both groups share the policy designed for group 2 (a payment of \$251 – \$10.68×y^i, see table 2), and group 1 will exceed its fertilizer target of 55 pounds (b_1 ranges from 39 to 48 pounds, table 1). Since group 1 is receiving a higher payment than under assigned policies, neglecting to use soils information comes at a cost to the government. This “information rent” of \$3.68 - \$4.24 per acre is about half of the expected payments to group 1 (table 2), and represents the public opportunity value of collecting and/or using information.

Under monitoring, a uniform policy would cost substantially more than assigned policies. Since a monitored policy includes the fertilizer level explicitly, both groups would have to fertilize at 55 pounds per acre to meet both environmental targets (table 1). An acreage payment of \$25.24 is then required to compensate either group for this reduction; about \$19 and \$14 of this payment constitutes an information rent to the two groups, respectively (table 2). These information rents are also much larger than those under self-compliance, which implies the cost of ignoring soils information is higher if farmers’ actions are monitored.

As mentioned above, self-selecting policies are not possible because the estimated marginal productivities are too similar across groups. At the data means, the difference in estimated marginal products of nitrogen is 0.015 tons (30 pounds) per pound of nitrogen, which translates to less than 0.1% of mean yield. This estimated differential may have been muted because of the specific cross section of soils used in the field trials; previous agronomic evidence suggests that light and heavy soils in New York respond to nitrogen quite differently (New York State College of Agriculture and Life Sciences).

To explore the effect of a larger productivity differential, a sensitivity analysis is performed on the coefficient for d_ib^2 in the yield equation, which had a point estimate of

0.000057. Table 3 presents the results for a coefficient value of 0.0001, which raises the difference in marginal products at mean nitrogen to 0.026 tons (52 pounds). In this case, self-selected policies are possible and are reported in the bottom half of the table. The most significant difference between these self-selected policies and the uniform policy in table 2 is that self-compliance no longer has a cost advantage over monitoring. The expected net payments under self-compliance are in the range of $30 per acre for group 1 and $21 for group 2, which are three to four times larger than payments under monitoring. About $26 of the payment to group 1 is an information rent, compared to a $5 rent under monitoring. Unlike the base case in table 2, the cost of ignoring soils information is much smaller if actions are monitored. There appears to be a relationship between the implicit values of hidden actions and hidden information, but the nature of this interaction is an empirical question that depends on technological parameters.

Policy Implications

This paper demonstrates both the theoretical and empirical possibility of successfully designing a voluntary environmental program when the government's information is limited. In particular, we identified the structure of policies necessary to ensure incentive compatibility where both risk attitudes and technology are unknown. We outlined a computational procedure for finding policies that accommodates unknown risk attitudes through stochastic efficiency criteria. The final step in this procedure reduces to a simple linear programming problem. We also derived an empirically verifiable necessary condition for self-selection to be possible, and showed that in certain cases the stochastic efficiency criteria can be simplified to a small number of computations involving lower-tail and mean income.

The model was simulated for a program that would offer government payments to New York corn producers in exchange for fertilizer reductions. The results suggest that such a program could achieve self-compliance at a relatively modest cost; payments would actually need to be increased if fertilizer levels were to be monitored. The expected net payments are below $15 per acre, which is less than typical farm program payments in the past. Self-selection would be possible in cases where the marginal productivity of nitrogen differs substantially across soils.

Soils information is valuable to the government, in the sense that payments could be reduced if policies were assigned to specific soils. This type of information already exists in many states; in New York, for example, the use-value assessment program requires local officials to record each farm's acreage in each of ten soil productivity groups (Thomas and Boisvert). Policy makers would need to weigh these cost savings against the political and other consequences of conditioning policy eligibility and benefits on a farmer's resource setting.

Policies were also simulated for both the risk averse and risk neutral cases. Pannell, Malcom, and Kingwell have argued that the insight gained by modeling risk aversion is more pronounced for discrete decisions (such as the adoption of new technology) than for decisions regarding input use, etc., since in the latter case the results are often very similar to a risk neutral model. In the New York application of our policy model, the risk neutral and risk averse results for optimal inputs and profits are indeed similar, with expected incomes that often differ by less than $1 per acre. However, with respect to the program participation decision, the incentive compatibility constraints magnify the effect of risk aversion, leading to an implicit risk premium that represents as much as 47% of optimal payments. If payments were designed assuming risk neutrality, environmental objectives could well be sacrificed because risk averse farmers would be provided insufficient incentive to participate in the program voluntarily.

Footnotes

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1 The method for finding this regulation is not modeled explicitly. In practice, the choice is often made through a second-best standards approach, which sets regulations to meet some predetermined emissions target (Baumol and Oates).

2 Imperfect information results because the government may not be able to individual farmers to the elements of Θ and Ω, and because the actual use of b may not be observed. In general, this game involves the government and all producers, so that any farmer's choice may depend strategically on the choices of all others. If all policy options are available to any farmer regardless of others' choices, and the distributions of technology and risk attitudes are independent, this strategic interdependence can be ignored and the policy becomes a large number of two-player games between the government and each producer (Xepapadeas).

3 Formally, if $G(m)$ dominates $H(m')$ by SSD, then $Eu(m) \geq Eu(m')$ for all continuous and twice differentiable $u(\cdot)$ with $u' > 0$ and $u'' \leq 0$ (Hadar and Russell, p. 31). Other stochastic efficiency criteria exist for other specifications of the utility set Ω. For example, Meyer has discovered a set of criteria, named stochastic dominance with respect to a function, which can order distributions when the coefficient of absolute risk aversion lies in a specified range.

4 To illustrate, consider the participation constraint in equation (8). Given a t_i, s_i must be large enough so that the policy (t_i, s_i) dominates (0, 0). If risk neutrality is assumed, participation could be secured by a payment of $\overline{s}_i = E\pi^i(x, b_0, 0) - E\pi^i(x, b_i, 0)$, where b_0 and b_i are the solutions to max $E\pi^i(x, b, 0)$ and max $E\pi^i(x, b, t_i)$, respectively. But if farmers are risk averse in reality, this payment will generally be insufficient because it does not include a risk premium. Based on the usual definition, the risk premium required is the value r_i such that

$F_i(m;b_i,t_i,\overline{s}_i+r_i) \succ F_i(m;b_i,0,0)$. However, this risk premium is generally not large enough because the SSD condition must hold *for all* $b_i \in B_i(t_i)$ and $b_0 \in B_i(0)$.

[5] The two necessary conditions are derived by letting $\tilde{m}$ in equation (5) grow arbitrarily large and small, respectively. As $\tilde{m} \rightarrow \infty$, SSD implies that $Em \geq Em'$. For "small" values of $\tilde{m}$, SSD requires the lowest observation on F_i to lie at or to the right of the lowest observation on F_i'.

[6] This coefficient is defined as $a(m) = -u''(m)/u'(m)$, and is positive for risk-averse individuals.

[7] In such simulations, care must be taken to ensure that the risk aversion coefficients from the literature are properly calibrated, since they are not invariant to the level of wealth (Grube).

[8] Hydrologic group is a classification of soils based on their capacity to permit infiltration. A soils are generally coarser and more vulnerable to leaching than B soils (Thomas and Boisvert).

[9] Total nitrogen is the sum of nitrogen from commercial fertilizer and manure, assuming that dairy farmers apply 20 tons of manure per acre to dispose of animal waste.

[10] If self-selection is desired, the government has a commitment problem, in that producers may believe policies will be assigned to them once they reveal their type by selecting a policy. This problem could be avoided through the use of a multiple-year, binding contract, although the government would still know the farmer's type for future contract periods. We are indebted to a reviewer for making this observation.

[11] For our model specification, the risk neutral results are equivalent to those from assuming no uncertainty. As a reviewer points out, the quadratic production function implies that the effect of rainfall on the marginal product of fertilizer is constant, so that max $E\pi^i(x, b, t)$ is equivalent to max $\pi^i(Ex, b, t)$. Thus, in this case, ignoring risk as the same consequences as ignoring risk aversion; both lead to violations of incentive compatibility.

References

Anderson, J.R., J.L. Dillon, and B. Hardaker. *Agricultural Decision Analysis*. Ames, IA: The Iowa State University Press, 1977.

Baumol, W.J. and W.E. Oates. *The Theory of Environmental Policy, Second Edition.* New York, NY: Cambridge University Press, 1988.

Boisvert, R., A. Regmi, and T. Schmit. "Policy Implications of Ranking Distributions of Nitrate Runoff and Leaching from Corn Production by Region and Soil Productivity." *Journal of Production Agriculture* 10(1997):477-483.

Chambers, R.G. "On the Design of Agricultural Policy Mechanisms." *American Journal of Agricultural Economics* 74(1992): 646-654.

Grube, A. H. "Participation in Farm Commodity Programs: A Stochastic Dominance Analysis: Comment." *American Journal of Agricultural Economics* 68(February 1986): 185-188.

Hadar, J. and W. Russell. "Rules for Ordering Uncertain Prospects." *American Economic Review* 59(1969):25-34.

Hammond, J.S. "Simplifying the Choice Between Uncertain Prospects Where Preference is Nonlinear." *Management Science* 20(1971): 1047-72.

Isik, M. "Resource Management under Production and Output Price Uncertainty: Implications for Environmental Policy." *American Journal of Agricultural Economics* 84(August 2002): 557-571.

Kramer, R. A. and R. D. Pope. "Participation in Farm Commodity Programs: A Stochastic Dominance Analysis: Reply." *American Journal of Agricultural Economics* 68(1986): 189-190.

Leathers, H.D. and J.D. Quiggin. "Interactions between Agricultural and Resource Policy: Importance of Attitudes toward Risk." *American Journal of Agricultural Economics* 73(1991): 757-64.

Lichtenberg, E. and D. Zilberman. "Efficient Regulation of Environmental Health Risks." *Quarterly Journal of Economics* 103(1988): 167-178.

Mas-Collel, A., M.D. Whinston, and J.R. Green. *Microeconomic Theory.* New York, NY: Oxford University Press, 1995.

Meyer, J. "Choice Among Distributions." *Journal of Economic Theory* 14(1977): 326-36.

New York State College of Agriculture and Life Sciences. *Cornell Field Crops and Soils Handbook.* Cornell University: Ithaca, NY, 1987.

Pannell, D. J., B. Malcolm, and R. S. Kingwell. “Are We Risking Too Much? Perspectives on Risk in Farm Modelling.” *Agricultural Economics* 23(2000):69-78.

Peterson, J. M. and R. N. Boisvert (2001a). “Control of Nonpoint Source Pollution Through Voluntary Incentive-Based Policies: An Application to Nitrate Contamination in New York.” *Agricultural and Resource Economics Review* 30(2001): 127-138.

Peterson, J. M. and R. N. Boisvert (2001b). “Designing Nonpoint Source Pollution Policies with Limited Information about both Risk Attitudes and Production Technology.” Working Paper 2001-13, Department of Applied Economics and Management, Cornell University.

Rothschild, M. and J.E. Stiglitz. “Increasing Risk I: A Definition.” *Journal of Economic Theory* 2(1970): 225-43.

Schmit, T.D. “The Economic Impact of Nutrient Loading Restrictions on Dairy Farm Profitability.” Unpublished M.S. Thesis, Cornell University, Ithaca, NY, 1994.

Smith, R.B.W. and T.D. Tomasi. “Multiple Agents, and Agricultural Nonpoint-Source Water Pollution Control Policies.” *Agricultural and Resource Economics Review* 28(1999):37-43.

Thomas, A.C. and R.N. Boisvert. “The Bioeconomics of Regulating Nitrates in Groundwater from Agricultural Production through Taxes, Quantity Restrictions, and Pollution Permits.” R.B. 96-06, Department of Agricultural, Resource, and Managerial Economics, Cornell University, Ithaca, NY, 1995.

United States Department of Agriculture, Economic Research Service. *Economic Indicators of the Farm Sector: Costs of Production—Major Field Crops & Livestock and Dairy, 1992.* ECIFS 12-3, August 1994.

Wu, J. and B. Babcock (1995). “Optimal Design of a Voluntary Green Payment Program Under Asymmetric Information.” *Journal of Agricultural and Resource Economics* 20:316-327.

_________ (1996). “Contract Design for the Purchase of Environmental Goods from Agriculture.” *American Journal of Agricultural Economics* 78:935-945.

Xepapadeas, A. *Advanced Principles in Environmental Policy.* Northampton, MA: Edward Elgar Publishing, 1997.

Appendix

Proof of Result 1

Suppose that $\delta_m = \frac{\partial F_i(\hat{m})}{\partial m} - \frac{\partial F_i'(\hat{m})}{\partial m'}$ is negative (positive) for all $\hat{m}$; i.e., F_i is everywhere flatter (steeper) than F_i'. This implies that if the distributions cross, F_i intersects F_i' from above (below). We will prove that δ_m < (>) 0 if and only if δ_π > (<) 0. Let F_x be the cdf of x (i.e., $F_x(a) \equiv \Pr\{x \leq a\}$), and define $X(m)$ and $X'(m')$ as the inverse functions of m and m' respectively, such that $X(\pi^i(x, b, t) + s) = x$ and $X(\pi^i(x, b', t') + s') = x$. Applying $X(\cdot)$ to both sides of the inequalities inside F_i and F_i', based on the definition in (6):

$$F_i(m) = \Pr\{x \leq X(m)\} = F_x(X(m)) \qquad \text{and} \qquad F_i'(m') = \Pr\{x \leq X(m')\} = F_x(X'(m'))$$

These relationships imply that at an intersection point $\hat{m}$:

$$F_i(\hat{m}) = F_i'(\hat{m}) \quad \Rightarrow \quad F_x(X(\hat{m})) = F_x(X'(\hat{m})) \quad \Rightarrow \quad X(\hat{m}) = X'(\hat{m})$$

Letting $\hat{X}$ represent the value of $X(\hat{m}) = X'(\hat{m})$, δ_m can be written in terms of F_x as follows:

$$\delta_m = \frac{\partial F_x(\hat{X})}{\partial X}\frac{\partial X}{\partial m} - \frac{\partial F_x(\hat{X})}{\partial X}\frac{\partial X'}{\partial m} = \frac{\partial F_x(\hat{X})}{\partial X}\left[\frac{\partial X}{\partial m} - \frac{\partial X'}{\partial m}\right] \tag{17}$$

By the inverse function theorem, $\partial X/\partial m = 1/\pi^i_x(x, b, t)$ and $\partial X'/\partial m = 1/\pi^i_x(x, b', t')$. Substituting these relationships into (17) and noting that $\partial F_x/\partial X > 0$ by the definition of a cdf, δ_m < (>) 0 is equivalent to: $1/\pi^i_x(x, b, t)$ < (>) = $1/\pi^i_x(x, b', t')$. Rearranging, $\pi^i_x(x, b, t)$ > (<) $\pi^i_x(x, b', t')$, which is the desired result.

Proof of Result 2

SSD requires that $S(\tilde{m}) = \int_{-\infty}^{\tilde{m}} [F_i(m) - F_i'(m)]dm \leq 0$ for all $\tilde{m}$, with strict inequality for some $\tilde{m}$. We prove this condition holds if F_i and F_i' are simply related and hypotheses (i) and

(ii) are met. There are three cases to consider:

Case 1: F_i and F_i' do not intersect. Under hypotheses (i) and (ii) Result 2, F_i must lie strictly to the right of F_i' in this case. Thus, $F_i(m) < F_i'(m)$ for all m, and $S(\tilde{m}) < 0$ for all $\tilde{m}$.

Case 2. F_i and F_i' intersect at their lower tails. Here $\underline{m} = \underline{m}'$; since the distributions cannot cross a second time, F_i must lie either strictly to the right or left of F_i' for $m > \underline{m}$. Hypothesis (ii) precludes the second possibility, which implies that $F_i(m) < F_i'(m)$ for all $m > \underline{m}$. Thus, $S(\tilde{m}) = 0$ for all $\tilde{m} \le \underline{m} = \underline{m}'$ and $S(\tilde{m}) < 0$ for all $\tilde{m} > \underline{m}$.

Case 3. F_i and F_i' intersect above their lower tails. In this case $F_i(\hat{m}) = F_i'(\hat{m})$ for some $\hat{m} > \underline{m}, \underline{m}'$. Since $\hat{m}$ can be the only intersection point, hypothesis (i) implies that $\underline{m} > \underline{m}'$. Thus, F_i must lie strictly to the right of F_i' up to $\hat{m}$ (i.e., $F_i(m) < F_i(m)$ $\forall m < \hat{m}$), so that $S(\tilde{m}) < 0$ for all $\tilde{m} \le \hat{m}$. For $\tilde{m} > \hat{m}$, $S(\tilde{m}) = S(\hat{m}) + \int_{\hat{m}}^{\tilde{m}} [F_i(m) - F_i'(m)]dm$. The second component is positive and monotonically increasing in $\tilde{m}$ since F_i lies to the left of F_i' after the intersection point (i.e., $F_i(m) > F_i'(m)$ for $m > \hat{m}$). However, hypothesis (ii) guarantees that it never becomes large enough to exceed $S(\hat{m})$ in absolute value. To see this, note that $Em \ge Em'$ means that $\int_{-\infty}^{\infty} m[dF_i - dF_i'] \ge 0$, or, integrating by parts, $m[F_i(m) - F_i'(m)]\Big|_{-\infty}^{\infty} - \int_{-\infty}^{\infty} [F_i(m) - F_i'(m)]dm \ge 0$.

Since $F_m(\underline{m}) = F_{m'}(\underline{m}) = 0$ and $F_m(\overline{m}) = F_{m'}(\overline{m}) = 1$, the first term in brackets equals zero. Therefore, $\lim_{\tilde{m} \to \infty} S(\tilde{m}) \le 0$.

Proof of Result 3

We will show that a b below or above both $\underline{b}(t)$ and $\overline{b}(t)$ is dominated by some other input level but a b between $\underline{b}(t)$ and $\overline{b}(t)$ is not. We do not know a priori whether $\underline{b}(t)$ is larger or smaller than $\bar{b}(t)$. Suppose first that $\underline{b}(t) < \bar{b}(t)$. To begin, note that strict concavity of $\pi^i(\underline{x},b,t)$ and $E\pi^i(x,b,t)$ in b implies that: (i) $\pi^i(\underline{x},b,t)$ is strictly increasing (decreasing) for all $b < (>)\, \underline{b}(t)$, and (ii) $E\pi^i(x,b,t)$ is strictly increasing (decreasing) for all $b < (>)\, \bar{b}(t)$. Thus, for any $b < \underline{b}(t)$:

$$\pi^i(\underline{x},b,t) < \pi^i(\underline{x},\underline{b}(t),t) \quad \text{and} \quad E\pi^i(x,b,t) < E\pi^i(x,\underline{b}(t),t)$$

where the inequalities follow from the definition of $\underline{b}(t)$ and fact (ii), respectively. Therefore, by result 1, $\underline{b}(t)$ dominates b by SSD. Similarly, for any $b > \bar{b}(t)$:

$$\pi^i(\underline{x},b,t) < \pi^i(\underline{x},\bar{b}(t),t) \quad \text{and} \quad E\pi^i(x,b,t) < E\pi^i(x,\bar{b}(t),t)$$

by fact (i) and the definition of $\bar{b}(t)$, implying that $\bar{b}(t)$ dominates b by SSD. Finally, consider any two input levels b, b' such that $\underline{b}(t) \le b < b' \le \bar{b}(t)$. Neither of these input levels can dominate the other because:

$$\pi^i(\underline{x},b,t) < \pi^i(\underline{x},b',t) \quad \text{and} \quad E\pi^i(x,b,t) > E\pi^i(x,b',t)$$

That is, one of the necessary conditions for either b or b' to dominate is violated. A parallel set of arguments verifies that if $\underline{b}(t) > \bar{b}(t)$ then: $\bar{b}(t)$ dominates all $b < \bar{b}(t)$; $\underline{b}(t)$ dominates all $b > \underline{b}(t)$; and for any $b < b'$ in the interval $[\bar{b}(t), \underline{b}(t)]$, neither input level dominates the other.

Proof of Result 4

By Result 3, $B(t)$ is the closed interval of real numbers bounded by $\underline{b}(t)$ and $\bar{b}(t)$. To begin, we must establish that $\forall b \in B(t)$, $\pi^i(\underline{x},b,t)$ is bounded between $\pi^i(\underline{x},\underline{b}(t),t)$ and $\pi^i(\underline{x},\bar{b}(t),t)$, and that $E\pi^i(x,b,t)$ is bounded between $E\pi^i(x,\underline{b}(t),t)$ and $E\pi^i(x,\bar{b}(t),t)$. By the definition of a maximum $\pi^i(\underline{x},b,t) \le \pi^i(\underline{x},\underline{b}(t),t)$ for all $b \in B(t)$. Since $B(t)$ is a closed and bounded interval, any $b \in B(t)$ can be written $b = \alpha\underline{b}(t) + (1-\alpha)\bar{b}(t)$ for some $\alpha \in [0, 1]$. By the concavity of

$\pi^i(\underline{x},b,t)$ in b, $\pi^i(\underline{x},b,t) \geq \alpha\pi^i(\underline{x},\underline{b}(t),t)+(1-\alpha)\pi^i(\underline{x},\overline{b}(t),t) \geq \pi^i(\underline{x},\overline{b}(t),t)$. A parallel set of arguments verifies that $E\pi^i(x,\underline{b}(t),t) \leq E\pi^i(x,b,t) \leq E\pi^i(x,\overline{b}(t),t)$ for all $b \in B(t)$.

Now suppose group i faces the policy alternatives (t, s) and (t', s') and that all of the following conditions are met:

$$\pi^i(\underline{x},\underline{b}(t),t)+s \geq \pi^i(\underline{x},\underline{b}(t'),t')+s', \qquad E\pi^i(x,\underline{b}(t),t)+s \geq \pi^i(\underline{x},\underline{b}(t'),t')+s' \tag{18}$$

$$\pi^i(\underline{x},\underline{b}(t),t)+s \geq \pi^i(\underline{x},\overline{b}(t'),t')+s', \qquad E\pi^i(x,\underline{b}(t),t)+s \geq E\pi^i(x,\overline{b}(t'),t')+s' \tag{19}$$

$$\pi^i(\underline{x},\overline{b}(t),t)+s \geq \pi^i(\underline{x},\underline{b}(t'),t')+s', \qquad E\pi^i(x,\overline{b}(t),t)+s \geq E\pi^i(x,\underline{b}(t'),t')+s' \tag{20}$$

$$\pi^i(\underline{x},\overline{b}(t),t)+s \geq \pi^i(\underline{x},\overline{b}(t'),t')+s', \qquad E\pi^i(x,\overline{b}(t),t)+s \geq E\pi^i(x,\overline{b}(t'),t')+s' \tag{21}$$

Conditions (18) - (19) and the bounds on $\pi^i(\underline{x},b',t')$ and $E\pi^i(x,b',t')$ established above imply that:

$$\pi^i(\underline{x},\underline{b}(t),t)+s \geq \pi^i(\underline{x},b',t')+s', \quad E\pi^i(x,\underline{b}(t),t)+s \geq E\pi^i(x,b',t')+s' \qquad \forall b' \in B(t') \tag{22}$$

Similarly, (20) - (21) and the bounds on profits imply:

$$\pi^i(\underline{x},\overline{b}(t),t)+s \geq \pi^i(\underline{x},b',t')+s', \quad E\pi^i(x,\overline{b}(t),t)+s \geq E\pi^i(x,b',t')+s' \qquad \forall b' \in B(t') \tag{23}$$

Finally, (22) - (23) and the bounds on $\pi^i(\underline{x},b,t)$ and $E\pi^i(x,b,t)$ imply that:

$$\pi^i(\underline{x},b,t)+s \geq \pi^i(\underline{x},b',t')+s', \quad E\pi^i(x,b,t)+s \geq E\pi^i(x,b',t')+s' \quad \forall b \in B(t), \forall b' \in B(t') \tag{24}$$

By Result 2, (24) is sufficient to guarantee that:

$$F_i(m;b,t,s) \succ F_i(m;b',t',s') \;\; \forall b \in B(t),\, \forall b' \in B(t') \tag{25}$$

An equivalent way of expressing the conditions in (18) - (21) is that:

$$s-s' \geq \max\begin{bmatrix} \pi^i(\underline{x},\underline{b}(t'),t')-\pi^i(\underline{x},\underline{b}(t),t) & E\pi^i(x,\underline{b}(t'),t')-E\pi^i(x,\underline{b}(t),t) \\ \pi^i(\underline{x},\overline{b}(t'),t')-\pi^i(\underline{x},\underline{b}(t),t) & E\pi^i(x,\overline{b}(t'),t')-E\pi^i(x,\underline{b}(t),t) \\ \pi^i(\underline{x},\underline{b}(t'),t')-\pi^i(\underline{x},\overline{b}(t),t) & E\pi^i(x,\underline{b}(t'),t')-E\pi^i(x,\overline{b}(t),t) \\ \pi^i(\underline{x},\overline{b}(t'),t')-\pi^i(\underline{x},\overline{b}(t),t) & E\pi^i(x,\overline{b}(t'),t')-E\pi^i(x,\overline{b}(t),t) \end{bmatrix} \tag{26}$$

That is, (26) implies (25), which is the desired result.

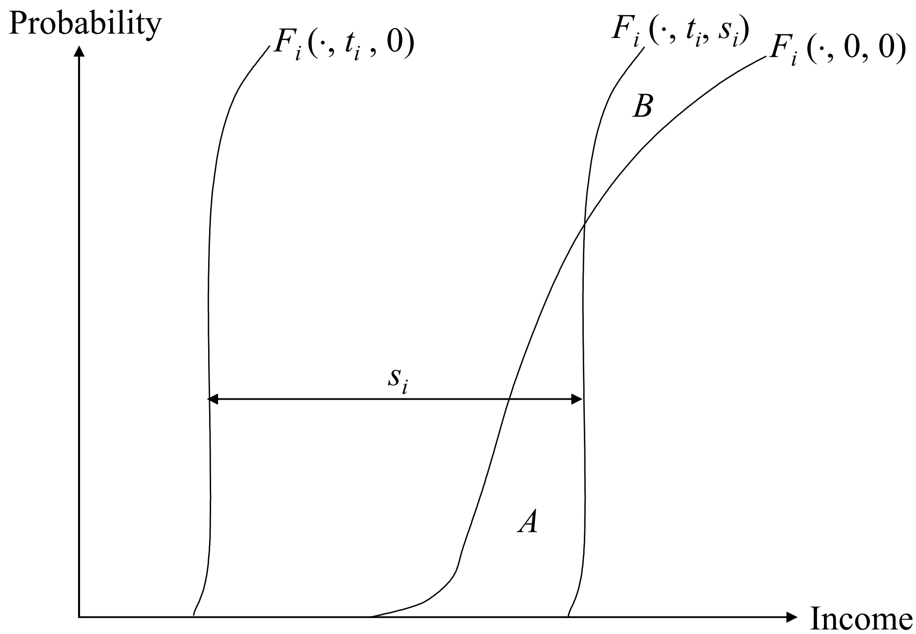

Figure 1. Geometry of the Participation Constraint

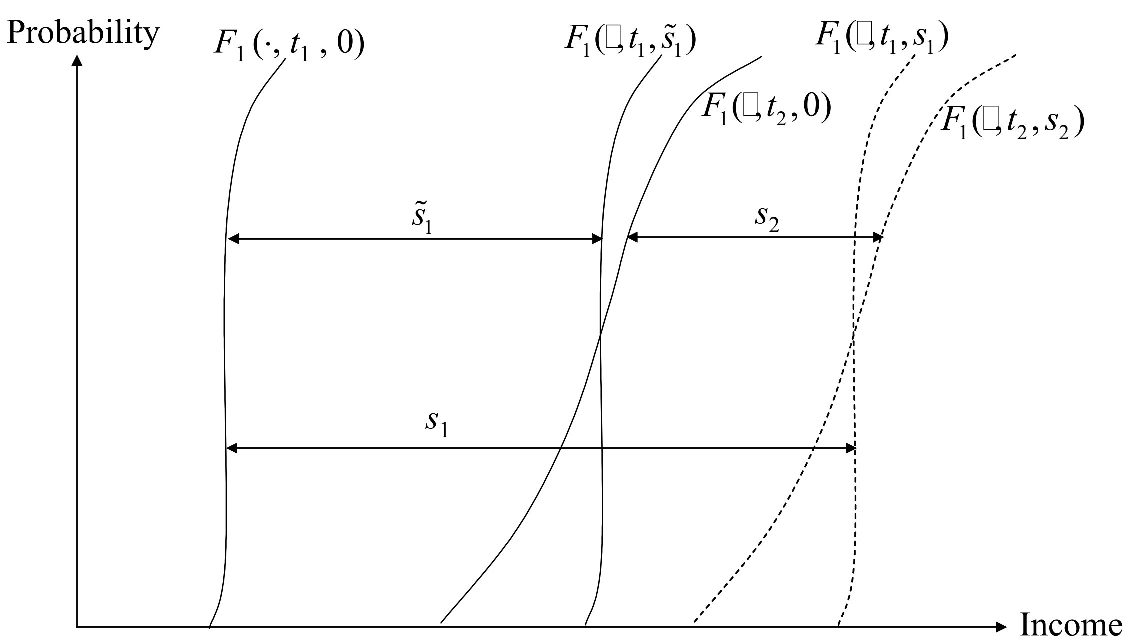

Figure 2. Geometry of the Self-Selection Constraint

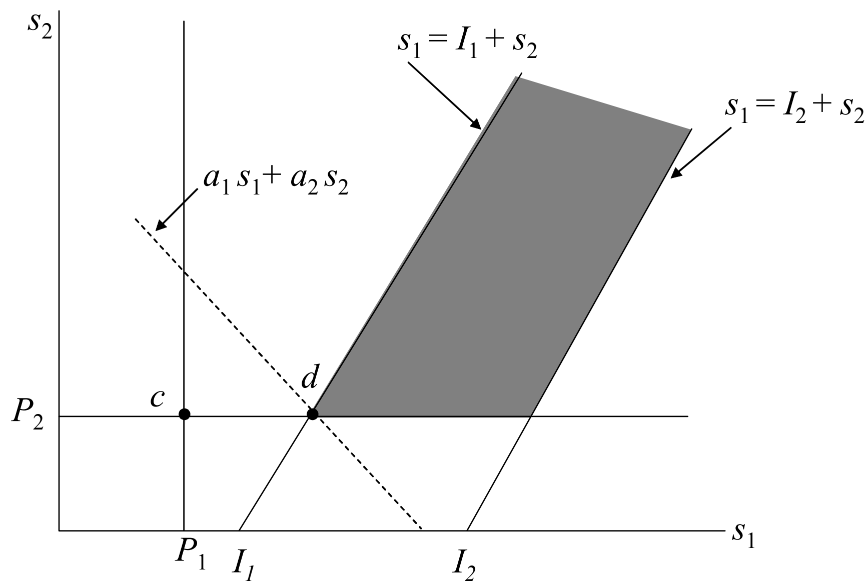

Figure 3. Geometry of the Policy Design Problem

Table 1. Pre- and Post-Policy Fertilizer, Income, and Production, Various Policy Scenarios

	Risk Aversion (SSD)			Risk Neutrality		
Item	Pre-Policy	Self-Compliance	Monitoring	Pre-Policy	Self-Compliance	Monitoring
Assigned Policies by Soil						
Fertlizer, group 1 (lb/acre)	83-92	46-55	55	83	55	55
Mean income, group 1 ($/acre)	225-226	226	229	226	226	226
Mean yield, group 1 (tons/acre)	23.7-23.9	22.8-23.0	23.0	23.7	23.0	23
Fertlizer, group 2 (lb/acre)	127-139	70-82	82	127	82	82
Mean income, group 2 ($/acre)	212-213	215	217	213	213	213
Mean yield, group 2 (tons/acre)	23.8-24.0	22.2-22.7	22.7	23.8	22.7	22.7
Uniform Policy						
Fertlizer, group 1 (lb/acre)	83-92	39-48	55	83	48	55
Mean income, group 1 ($/acre)	225-226	228	248	226	226	241
Mean yield, group 1 (tons/acre)	23.7-23.9	22.5-22.8	23.0	23.7	22.8	23
Fertlizer, group 2 (lb/acre)	127-139	70-82	55	127	82	55
Mean income, group 2 ($/acre)	212-213	215	219	213	213	213
Mean yield, group 2 (tons/acre)	23.8-24.0	22.2-22.7	21.6	23.8	22.7	21.6

Table 2. Mean Optimal Payments and Information Premiums

Item	Risk Aversion (SSD)		Risk Neutrality	
	Self-Compliance	Monitoring	Self-Compliance	Monitoring
Assigned Policies by Soil				
Output payment, group 1 ($/ton)	-9.86	0.00	-8.49	0.00
Acreage payment, group 1 ($/acre)	230.81	6.33	199.24	3.60
Expected net payment, group 1 ($/acre)	3.61-6.53	6.33	3.61	3.60
Output payment, group 2 ($/ton)	-10.68	0.00	-9.54	0.00
Acreage payment, group 2 ($/acre)	251.06	11.62	223.43	7.29
Expected net payment, group 2 ($/acre)	9.13-13.69	11.62	7.30	7.29
Uniform Policy				
Output payment ($/ton)	-10.68	0.00	-9.54	0.00
Acreage payment ($/acre)	251.06	25.24	223.43	18.63
Expected net payment, group 1 ($/acre)	7.29-10.77	25.24	5.66	18.63
Soils information rent, group 1 ($/acre)	3.68-4.24	18.91	2.05	15.03
Expected net payment, group 2 ($/acre)	9.13-13.69	25.24	7.30	18.63
Soils information rent, group 2 ($/acre)	0.00	13.62	0.00	11.34

Table 3. Mean Optimal Payments and Information Premiums, Self-selecting Policies

Item	Risk Aversion (SSD)		Risk Neutrality	
	Self-Compliance	Monitoring	Self-Compliance	Monitoring
Assigned Policies by Soil				
Output payment, group 1 ($/ton)	-9.86	0.00	-8.49	0.00
Acreage payment, group 1($/acre)	230.81	6.33	199.24	3.60
Expected net payment, group 1 ($/acre)	3.61-6.53	6.33	3.61	3.60
Output payment, group 2 ($/ton)	-9.00	0.00	-8.08	0.00
Acreage payment, group 2 ($/acre)	237.01	5.15	213.31	5.15
Expected net payment, group 2($/acre)	20.82-22.01	5.15	19.25	5.15
Self-Selected Policies				
Output payment, group 1 ($/ton)	-9.86	0.00	-8.49	0.00
Acreage payment, group 1($/acre)	256.85	11.48	222.77	8.75
Expected net payment, group 1 ($/acre)	29.65-32.58	11.48	27.14	8.75
Soils information rent, group 1 ($/acre)	26.04	5.15	23.53	0.00
Output payment, group 2 ($/ton)	-9.00	0.00	-8.08	0.00
Acreage payment, group 2 ($/acre)	237.01	5.15	213.31	5.15
Expected net payment, group 2 ($/acre)	20.82-22.01	5.15	19.25	5.15
Soils information rent, group 2 ($/acre)	0.00	0.00	0.00	0.00

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