ABSTRACT

Title of Dissertation: A LEAST-COST MECHANISM TO ACHIEVE AGRICULTURAL INCOME AND CONSERVATION TARGETS UNDER ASYMMETRIC INFORMATION

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Two policy goals dominate United States' agricultural programs: voluntary land retirement for environmental purposes and countercyclical income support. Traditionally, these goals have been pursued with separate policies. This policy separation is efficient with perfect information regarding farm productivity. A more realistic assumption, however, is that farmers have better information regarding their own productivity than the government. The focus of the dissertation is to analyze least cost agricultural policy with this type of asymmetric information.

I first use a mechanism design framework to show that it is optimal to have a combined income support-land retirement program rather than separate programs. For land retirement, farmers have an incentive to overstate productivity

in order to receive a higher rental payment. For income support, farmers have an incentive to understate productivity to receive a higher income support payment. With high output prices, the first effect dominates. With low prices, the second dominates. Farmers' ability to use private information to their advantage increases the cost to the government of reaching its targets. If contract commitment takes place when output prices are uncertain, the two incentives can countervail each other, reducing the cost of the policy to the government.

In the second part of the dissertation, I extend the literature by showing how one can implement the policy using actual data. I conduct a numerical simulation to determine the exact payment and land set aside for each farmer. To calibrate the simulation, I apply stochastic frontier analysis to a data set of US farmers. I thus obtain consistent estimates of the key determinants of the contracts: the farm profit function and the probability distribution of profitability levels across the sector.

Simulation results show that unlike current programs, the least cost contract is likely to involve pooling. Farmers with different profitability levels receive identical expected payments for idling identical acreage. The countervailing incentives created by the least-cost policy almost eliminate the information advantage of farmers, significantly reducing cost relative to current programs.

A LEAST-COST MECHANISM TO ACHIEVE AGRICULTURAL INCOME AND CONSERVATION TARGETS UNDER ASYMMETRIC INFORMATION

by

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DEDICATION

To My Family

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Introduction

The United States government spent over $92 billion on the agricultural sector in the years of the Federal Agriculture Improvement and Reform (FAIR) Act (1996-2002). The two largest objectives of these expenditures were income support (over 75 percent) and environmental conservation (over 10 percent) (National Agricultural Statistical Service 2003). Under the FAIR Act, there was little linkage between these two objectives. Income support consisted primarily of lump-sum payments per acre of production. Conservation payments were mostly subsidies to remove land from production. Little has changed in these respects with passage of the 2002 Farm Security and Rural Investment Act.

In this dissertation, I model "green-payments" programs that simultaneously achieve environmental and income support goals. I show that properly linking income support payments to land set aside for environmental purposes is the least costly means of achieving both objectives. This result stands in contrast to current practice and conventional intuition based on Tinbergen (1963) that the number of policy instruments should equal the number of policy targets.

The combined program's advantage comes from efficient use of information. A producer's willingness to participate in an environmental program reveals private information regarding production costs. A well-designed green payments program takes advantage of this information to channel income support payments to less-profitable producers. The cost-effectiveness of a green payments program depends on timing with respect to output price uncertainty.

Contracts signed when prices are uncertain reduce the cost to the government of inducing producers to reveal their information. The intuition behind this result comes from the conflicting incentives created by a voluntary land set aside program and an income support program. For a voluntary land set-aside program, the higher the opportunity cost of the land, the more the government needs to offer to induce a farmer to refrain from cultivating it. Since the opportunity cost is essentially the foregone profit, farmers have an incentive to overstate their profitability. For income support, farmers have the opposite incentive. If the government's objective is to administer payments such that all farmers attain a minimum income level, farmers have an incentive to understate their true profitability in order to receive a higher subsidy.

Output price is decisive in determining which of these incentives dominates. When price is high, income support subsidies are low, so the dominant incentive is to overstate profitability. When output price is low, the opposite occurs. If contracting takes place after price is known, farmers know in which direction they should misrepresent their true type. However, if contracting takes place when prices are uncertain, the two incentives countervail each other. Since a farmer cannot simultaneously over and under-state their type, his declaration of profitability is closer to the truth. In fact, for some farmers the two incentives may cancel out completely.

Although these results are robust to alternative specifications of producer technology, the precise allocation of payments and land set-asides for each producer is not. An additional contribution of this dissertation is to develop a methodology for empirically calibrating a mechanism design model using readily available data. Two necessary ingredients for implementing the optimal green payments program are profit functions for different types of producers and a probability density function of producer types. Given that type is unobservable, a key problem is how to infer this information from observed data.

To solve this problem, I borrow econometric approaches used to evaluate differences in technical efficiency across firms. Specifically, I adapt the composed error structure developed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). This structure is commonly used in stochastic frontier analysis to estimate parameters of a cost function that explicitly incorporates producer heterogeneity. The random error in the cost function is assumed to have two components: symmetrically distributed, zero-mean statistical noise, and a skewed, non-zero mean component representing producer type. The parameters of a probability distribution for type are calculated from the residuals of the cost function. I use the results of the cost function estimation to calculate the corresponding profit function for each producer type. This profit function is used with the estimated probability distribution of types to simulate the optimal allocation of payments and land set-asides.

In the remaining sections of this introduction, I describe the stylized facts of historical agricultural policy on which the model is based and present an outline of the rest of the dissertation.

1.1 Stylized Characteristics of United States' Agricultural Policy

The analysis of the dissertation is based on agricultural income support and environmental policies in the United States from 1985-2002.

1.1.1 Income Support

In the United States, agricultural income support policies from 1985-2002 share the characteristic that payments are countercyclical, varying inversely with output prices. The income support element of the model in this paper is based upon this stylized fact. Government provides greater assistance to producers when output prices are low than when prices are high. In addition, payments are based upon acres under production, not output *per se*. Roughly speaking, acres eligible for payments are those previously dedicated to production of a program crop, less acres diverted to a land set aside program. Income support policies in this period are deficiency payments, production flexibility contracts, and marketing loss assistance payments.

Between 1985 and 1996 deficiency payments were the primary means of providing income support. Before each growing season, the government announced a target price for a program crop. In exchange for participation in an acreage reduction program (ARP), producers received payments equal to the difference between the target price and the prevailing market price for the commodity, multiplied by program yield (estimated yield per acre in 1985). Government payments decreased as market price increased, with no payments being made if the market price was higher than the target price.

The 1996 FAIR Act replaced deficiency payments with production flexibility contracts. Under the new policy, producers received fixed payments per acre of land previously eligible for deficiency payments. Unlike deficiency payments, production flexibility contracts did not vary with output prices.

When prices reached low levels in 1998-2001, however, Congress responded by approving supplemental marketing loss assistance payments (Gardner 2002). This legislation effectively increased the amounts farmers received from production flexibility contracts for each of those years. Thus, marketing loss assistance effectively made income support countercyclical from 1996-2001 as had previously been the case with deficiency payments, and as explicitly became the case with the 2002 legislation.

1.1.2 Conservation

Paid land diversion programs can be classified in two groups, short-term and long-term land retirement. For short-term programs such as the ARP, land was idled for one year, and the decision for idling land was made at the beginning of each planting season. For long-term programs such as the Conservation Reserve Program (CRP), land is idled for periods of at least ten years.

To be eligible for commodity program payments such as deficiency payments, producers could not grow program crops on a given percentage of their acres. Each year the Secretary of Agriculture determined the proportion of land to be idled. This figure was based upon anticipated supply and demand conditions. Supply restriction, not conservation, was the primary motivation for the ARP. The ARP was eliminated in the 1996 FAIR Act.

Since 1985 the largest land retirement program in the United States has been the CRP. The CRP's emphasis was originally to reduce soil erosion on highly erodible land. The CRP has since been extended in the Food, Agriculture, Conservation, and Trade Act of 1990, the 1996 FAIR Act, and the 2002 farm legislation. Over time, congress shifted emphasis from erosion control to achieving more broadly defined environmental benefits.

Participating producers agree to retire land from production for a period of 10-15 years in exchange for annual rental payments. CRP enrollment is structured as an auction. Producers propose an area of land to set aside and submit a bid for annual rent. As of 2000, annual CRP payments amounted to about \$1.8 billion with an average rental payment of almost \$50 per acre (Farm Services Agency 2002).

1.2 Organization of Dissertation

The dissertation is organized as follows. In Chapter 2, I develop the theory used to describe the characteristics of a least cost agro-environmental program. The analysis takes as given environmental and income support objectives drawn from the preceding section. The interaction between the government and farmers is modeled as a principal-agent problem under conditions of asymmetric information. Asymmetric information exists inasmuch as producers are assumed to have better information regarding the productivity of their land than the government.

The government's objective is to assign a quantity of land to be idled and a transfer payment for each agricultural producer that minimizes total government expenditures subject to the policy constraints. The environmental policy is modeled as a minimum amount of land that must be idled for the entire sector. The income support policy is modeled as a minimum income level that must be received by each producer regardless of the level of randomly determined output prices. In addition, producers must willingly participate in the program.

One conclusion of Chapter 2 is that the characteristics of the optimal land and transfer allocation depends upon the government's beliefs regarding the distribution of types and the nature of the profit function. In Chapters 3 and 4, I develop and implement a methodology for empirically inferring this information from a data set that does not contain producer types. In Chapter 3, I develop the agricultural production technology used in later chapters to model policy design. I explicitly specify how type affects the set of feasible input-output decisions available to each producer, and draw out the implications for producer cost and profit functions. In Chapter 4, I describe the data set and the steps taken to convert the raw data into input and output prices and quantities. I then conduct the estimation and report the results.

In Chapter 5, I use the parameter estimates obtained in Chapter 4 to perform a simulation of the optimal green-payments scheme derived in Chapter 2. The purpose of this exercise is to illustrate how the techniques developed in the previous chapters can be put together to design an optimal contract under a given set of assumptions.

Finally, Chapter 6 concludes by discussing policy implications of the dissertation. In addition, I recognize the limitations of the analysis, and explore possibilities for relaxing restrictive assumptions imposed in the preceding chapters.

Chapter 2

An Optimal Green Payments Program

In this chapter, I consider the problem of minimizing the cost of achieving agricultural income support and environmental objectives. The income support goal is modeled as a minimum income threshold that all producers must attain, regardless of output price. The environmental goal is a quantity of land that must be retired from agricultural production. Producers are heterogeneous in terms of profit earned from cultivating a given quantity of land, but otherwise identical. Output price is uncertain at the time the policy is designed, but known when production is undertaken.

As a baseline, I first characterize the optimal program under the assumption that producer heterogeneity is common information. I then examine the policy implications of relaxing this assumption. I first analyze the impact of timing on the cost of the programs. Timing does not affect the cost of the program if information is symmetric. However timing does affect the program cost under asymmetric information. I show that an *ex post* mechanism in which contract commitment takes place after output price is known is more costly than an *ex ante* mechanism. Price uncertainty effectively reduces the value of private information to producers. Next, I compare the optimal green payments program with a stylized version of the separated income support and environmental policies under the FAIR Act.

The analytical techniques are based upon the monopoly-regulation model developed by Baron and Myerson (1982) and generalized by Guesnerie and Laffont (1994). Baron and Myerson (1982) deal with the problem of optimal regulation of a monopolist when cost of production is private information to the firm. One of the challenges of the regulator is to properly account for the underlying incentive of a firm to overstate its true costs. Lewis and Sappington (1989a) and Lewis and Sappington (1989b) expanded this analysis to include circumstances under which the agent may have simultaneous "countervailing" incentives to overstate and understate their private information. Maggi and Rodríguez-Clare (1995) and Jullien (2000) show that the general characteristics of the optimal contract vary greatly depending on the particular functional specification of the objective function.

Another article influential in this analysis is Bontems and Bourgeon (2000). These authors show how the contract designer can gain by using a random lottery to introduce countervailing incentives where they would otherwise be absent. Although the mechanics of the models presented here differ from Bontems and Bourgeon (2000), random price fluctuations act as a natural randomization device to introduce countervailing incentives.

In the next section, I model the government's constrained objective. I also illustrate the least cost program under symmetric information. In Section 2, I relax the assumption of symmetric information and characterize optimal *ex post* and *ex ante* programs. I then compare the optimal green payments program to actual policy. In Section 3, I discuss implications of the results.

2.1 The Model

Risk-neutral producers are characterized by identical observable fixed land endowments $\overline{a}$, and a productivity parameter $\theta \in \Theta \equiv \left[\underline{\theta}, \overline{\theta}\right]$. The value of θ is referred to as a producer's *type*. A producer's type is private information, but the probability distribution of types for the entire sector is common knowledge. The probability density function and cumulative distribution functions of type are denoted by $f(\theta)$ and $F(\theta)$, respectively.

Producers use a variable input vector $\mathbf{x} \in \Re^n_+$ to create aggregate output $q \in \Re_+$. The variable input price vector is $\mathbf{w} \in \Re^n_{++}$, and output price is p. Output price has a Bernoulli distribution with outcomes "low" (p_ℓ) with probability $\rho \in (0,1)$, and "high" (p_h) with probability $1-\rho$. Production takes place after price uncertainty is resolved.

Maximum profit earned by a producer type θ from cultivating $a \in [\underline{a}, \overline{a}]$ acres at prices p and $\mathbf{w}$ is a thrice continuously differentiable function $\pi(p, a, \theta)$:

$$\pi(p, a, \theta) \equiv \sup_{\mathbf{x}, q} \{pq - \mathbf{w}'\mathbf{x} : \mathbf{x} \text{ can produce } q \text{ given } a, \theta\}. \tag{2.1}$$

I assume the following regularity conditions:

(R1) $\dfrac{\partial \pi(p,a,\theta)}{\partial a} > 0;$

(R2) $\dfrac{\partial^2 \pi(p,a,\theta)}{\partial a^2} < 0;$

(R3) $\dfrac{\partial \pi(p,a,\theta)}{\partial \theta} > 0;$

(R4) $\dfrac{\partial^2 \pi(p,a,\theta)}{\partial a \partial \theta} > 0;$

(R5) $f(\theta) > 0$, and $\dfrac{d}{d\theta}\left[\dfrac{F(\theta)-\mu}{f(\theta)}\right] > 0$ for $\mu \in [0,1];$

(R6) $\dfrac{\partial^3 \pi(p,a,\theta)}{\partial a^2 \partial \theta}$ and $-\dfrac{\partial^3 \pi(p,a,\theta)}{\partial a \partial \theta^2} \leq 0.$

(R7) $\pi(p,a,\theta) = g(\theta)\,\tilde{\pi}(p,a)$, where $\tilde{\pi}(p,a) \equiv \pi\left(p,a,\overline{\theta}\right).$

Conditions (R1) and (R2) state that marginal returns to land are positive but diminishing as land use increases. These restrictions can be interpreted in various ways. For example, a fixed factor such as “management” causes diminishing marginal returns to land. Alternatively, soil quality can be thought of as heterogeneous within a farm. In this case, a producer would set aside least productive acres first. Condition (R3) indicates that a higher value of θ is desirable: profit is always increasing in type. (R4) is the “Spence-Mirrlees” condition. This condition indicates that higher types always need to be compensated more for a marginal reduction in a than lower types.

Condition (R5) is a variant of the monotone hazard rate assumption. Condition (R6) restricts the signs of the third derivatives of the profit function. Although the intuition for (R5) and (R6) is not strong, variants on these assumptions are commonly used in the literature to prevent pooling equilibria arising from technical characteristics of the probability distribution or third derivatives of the value function. See, for example, Fudenberg and Tirole (1991), p. 263. The rationale for imposing them here is to isolate the effect that incentives have on policy design. For treatment of problems where these restrictions are relaxed, consult Guesnerie and Laffont (1994).

Assumption (R7) implies θ is similar to the notion of non-biased technical change in the sense that it does not affect relative input or output shares. That is to say, employing Hotelling’s Lemma the profit-maximizing ratios of revenue to total profit or the ratio of input expenditure to total profit are independent of type:

$$\frac{\partial \pi(p,a,\theta)}{\partial p} \cdot \frac{p}{\pi(p,a,\theta)} = \frac{g(\theta)\, pq^*}{g(\theta)\, \tilde{\pi}(p,a)} = \frac{pq^*}{\tilde{\pi}(p,a)} \tag{2.2}$$

$$\frac{\partial \pi(p,a,\theta)}{\partial w_i} \cdot \frac{w_i}{\pi(p,a,\theta)} = \frac{g(\theta)\, w_i x_i^*}{g(\theta)\, \tilde{\pi}(p,a)} = \frac{w_i x_i^*}{\tilde{\pi}(p,a)}, \quad i = 1, ..., n \tag{2.3}$$

where $q^*, \mathbf{x}^*$ are the optimal output and input vector for $\theta = 1$.

Note that (R4) and (R6) imply $g'(\theta) > 0$ and $g''(\theta) > 0$, respectively. I impose (R7) to focus the analysis on one specification of the way type affects the technology. It is not essential, however. Analogous results can be obtained for other specifications of $\pi(p, a, \theta)$. For a detailed treatment of other cases, see Maggi and Rodríguez-Clare (1995) orJullien (2000).

The stylized agro-environmental policy has three features. First, the government must ensure that each producer attains a minimum income level. Second, the government must ensure that the sector idles enough land to achieve a minimum level of environmental benefits. Third, the program must be voluntary. The task of the government is to design a policy that satisfies these constraints at least cost to taxpayers.

Let the variables $a(\theta), t(p_\ell, \theta), t(p_h, \theta)$ indicate the terms of a contract for type θ, where $a(\theta)$ is the amount of land cultivated and $t(p, \theta)$ is a price-contingent transfer. Following Hueth (2000) and Bourgeon and Chambers (2000), the income constraint is modeled as a requirement that all producers earn at least minimum income m:

$$\pi(p, a(\theta), \theta) + t(p, \theta) \geq m, \quad \text{for all } \theta, p. \tag{2.4}$$

Following Smith (1995), the environmental constraint is a requirement that the average quantity of land idled across all producers be at least A acres:

$$\int_\Theta [\overline{a} - a(\theta)]\, dF(\theta) \geq A \tag{2.5}$$

Environmental benefits accrue to land taken out of production for extended periods of time. Therefore the amount of land cultivated by a given type does not change with output price.

To ensure the program is voluntary, producers must be compensated for the *ex post* opportunity cost of idled land. A contract cannot leave a producer worse off *ex post* than he would have been in its absence. This participation constraint is expressed:

$$\pi\left(p, a\left(\theta\right), \theta\right) + t\left(p, \theta\right) \geq \pi\left(p, \overline{a}, \theta\right), \quad \text{for all } \theta, p. \tag{2.6}$$

One can partition Θ into three consecutive intervals based on the relative importance of the income and participation constraints. Define Θ_L as the interval of types for which the income constraint binds if $p = p_h$:

$$\Theta_L \equiv \left\{\theta : \pi\left(p_h, \overline{a}, \theta\right) < m\right\}. \tag{2.7}$$

Define Θ_M as the interval of types for which the income constraint binds if and only if $p = p_\ell$:

$$\Theta_M \equiv \left\{\theta : m \leq \pi\left(p_h, \overline{a}, \theta\right) \ \right\} \cap \left\{\theta : \pi\left(p_\ell, \overline{a}, \theta\right) \leq m \ \right\}. \tag{2.8}$$

Define Θ_H as the interval of types for the income constraint does not bind if $p = p_\ell$:

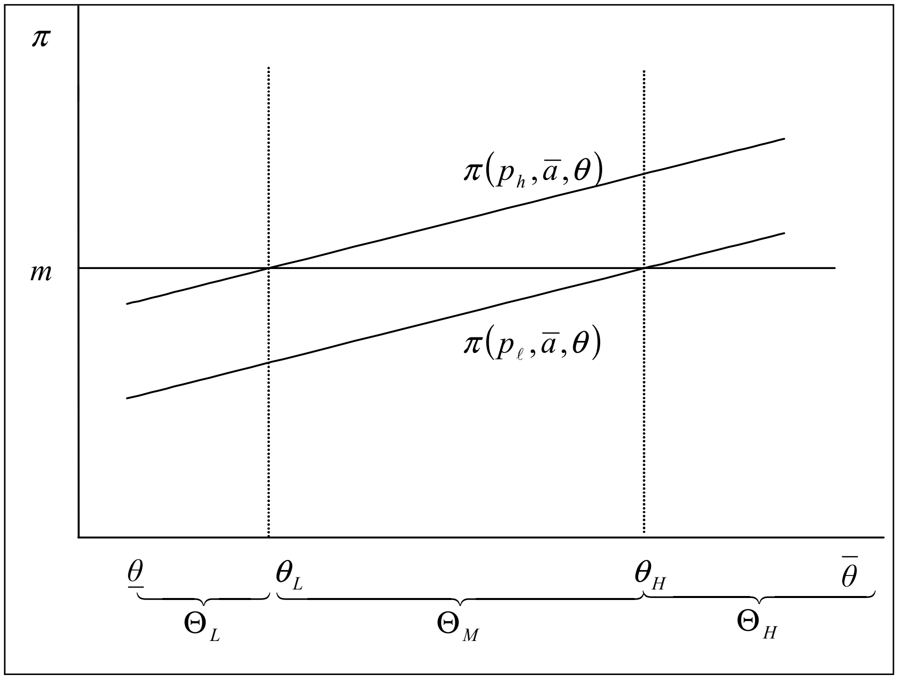
$$\Theta_H \equiv \left\{\theta : m < \pi\left(p_\ell, \overline{a}, \theta\right) \ \right\}. \tag{2.9}$$

Let θ_L and θ_H denote the lower and upper bounds of Θ_M. These three intervals are illustrated in Figure 2.1.

This partition of Θ simplifies treatment of the income and participation constraints. For Θ_L, if the income constraint is satisfied then the participation constraint is necessarily satisfied as well since:

$$\pi\left(p_h, a\left(\theta\right), \theta\right) + t\left(p_h, \theta\right) \geq m > \pi\left(p_h, \overline{a}, \theta\right). \tag{2.10}$$

Figure 2.1: Minimum Income Threshold



For Θ_H, satisfaction of the participation constraint implies that the income constraint is also satisfied since:

$$\pi\left(p_\ell, a\left(\theta\right), \theta\right) + t\left(p_\ell, \theta\right) \geq \pi\left(p_\ell, \bar{a}, \theta\right) > m. \tag{2.11}$$

Finally, for Θ_M satisfaction of the income constraint implies the participation constraint is satisfied for $p = p_\ell$, and satisfaction of the participation constraint implies that the income constraint is satisfied for $p = p_h$:

$$\pi\left(p_\ell, a\left(\theta\right), \theta\right) + t\left(p_\ell, \theta\right) \geq m > \pi\left(p_\ell, \bar{a}, \theta\right), \tag{2.12}$$

$$\pi\left(p_h, a\left(\theta\right), \theta\right) + t\left(p_h, \theta\right) \geq \pi\left(p_h, \bar{a}, \theta\right) > m. \tag{2.13}$$

2.2 Symmetric Information

Let $T(\theta) \equiv \rho t(p_\ell, \theta) + [1-\rho] t(p_h, \theta)$ denote expected transfers. If θ is common knowledge, the government's problem is to assign transfers $t(p, \theta)$ and land cultivated $a(\theta)$ to each type so as to minimize the expected cost of satisfying the income, participation, and environmental constraints:

$$\min_{t(p,\theta), a(\theta)} \int_\Theta T(\theta)\, dF(\theta) \tag{2.14}$$

subject to: (2.4), (2.5), (2.6).

Denote surplus payments in excess of the minimum necessary to satisfy (2.4) and (2.6) by:

$$s(p,\theta) \equiv \pi(p, a(\theta), \theta) + t(p,\theta) - \max\{m, \pi(p, \overline{a}, \theta)\}, \tag{2.15}$$

and expected surplus by

$$S(\theta) \equiv \rho s(p_\ell, \theta) + (1-\rho) s(p_h, \theta). \tag{2.16}$$

I can then replace (2.4) and (2.6) with:

$$s(p,\theta) \geq 0 \text{ for all } \theta, p. \tag{2.17}$$

Let

$$\Pi(a,\theta) \equiv \rho\pi(p_\ell, a, \theta) + (1-\rho)\pi(p_h, a, \theta) \tag{2.18}$$

denote expected profit. Replace $T(\theta)$ in (2.14) by

$$T(\theta) = \begin{cases} S(\theta) - \Pi(a(\theta), \theta) + m & \theta \in \Theta_L \\ S(\theta) - \Pi(a(\theta), \theta) + \rho m + [1-\rho]\pi(p_h, \overline{a}, \theta) & \theta \in \Theta_M \\ S(\theta) - \Pi(\overline{a}, \theta) & \theta \in \Theta_H \end{cases}, \tag{2.19}$$

to obtain the Lagrangian:

$$\min_{a(\theta),s(p,\theta),\lambda,\tau(p,\theta),\alpha(\theta)} \int_{\Theta_L} \left[S(\theta) - \Pi(a(\theta),\theta) + m\right] dF(\theta) \tag{2.20}$$
$$+ \int_{\Theta_M} \left[S(\theta) - \Pi(a(\theta),\theta) + \rho m + [1-\rho]\,\pi(p_h,\overline{a},\theta)\right] dF(\theta)$$
$$+ \int_{\Theta_H} \left[S(\theta) - \Pi(a(\theta),\theta) + \Pi(\overline{a},\theta)\right] dF(\theta)$$
$$-\lambda \int_{\Theta} \left[\overline{a} - a(\theta) - A\right] dF(\theta)$$
$$- \int_{\Theta} \left[\tau(p_\ell,\theta)\, s(p_\ell,\theta) + \tau(p_h,\theta)\, s(p_h,\theta) + \alpha(\theta)\left[\overline{a} - a(\theta)\right]\right] d\theta.$$

Here λ is the Lagrange multiplier for (2.5), $\tau(p,\theta)$ are the Lagrange multipliers for (2.17), and $\alpha(\theta)$ is the Lagrange multiplier for the constraint $a(\theta) \leq \bar{a}$. From pointwise optimization, the necessary conditions for an optimal land allocation are:

$$\Pi_a(a(\theta),\theta) - \frac{\alpha(\theta)}{f(\theta)} - \lambda \geq 0 \tag{2.21}$$
$$a(\theta) \geq 0 \tag{2.22}$$
$$a(\theta)\left[\Pi_a(a(\theta),\theta) - \alpha(\theta) - \lambda\right] = 0 \tag{2.23}$$
$$\bar{a} - a(\theta) \geq 0 \tag{2.24}$$
$$\alpha(\theta) \geq 0 \tag{2.25}$$
$$\alpha(\theta)\left[\bar{a} - a(\theta)\right] = 0 \tag{2.26}$$
$$\int_{\Theta} \left[\overline{a} - a(\theta) - A\right] dF(\theta) \geq 0 \tag{2.27}$$
$$\lambda \geq 0 \tag{2.28}$$
$$\lambda \int_{\Theta} \left[\overline{a} - a(\theta) - A\right] dF(\theta) = 0 \tag{2.29}$$

Equations (2.21) - (2.29) describe the optimal land allocation. For an interior solution, the marginal profit of land is λ for each type. Condition (R2) ensures that this solution is a minimum. Together with (R2) and (R4), (2.21) implies that for an interior solution land use is strictly increasing across types. Also, note that condition (R1) and (2.21) require that λ be *strictly* positive for any land to be idled by any type. Consequently, the environmental constraint must be binding for any $A > 0$.

The necessary conditions for surplus payments are:

$$
\begin{aligned}
f(\theta) - \tau(p, \theta) &= 0 && (2.30) \\
\tau(p, \theta) &\geq 0 && (2.31) \\
s(p, \theta) &\geq 0 && (2.32) \\
\tau(p, \theta)\, s(p, \theta) &= 0. && (2.33)
\end{aligned}
$$

Equations (2.30) and (2.33) describe the optimal surplus allocation. By (R5), equation (2.30) implies that $\tau(p, \theta)$ is strictly positive. Therefore, by (2.33) no type receives surplus payments in either price state.

Intuitively, since the government can observe type, it can make contracts contingent on θ. The government can offer each producer a take-it-or-leave-it contract such that environment, income and participation constraints are satisfied with no surplus payments. The economically efficient amount of land idled by each type satisfies the equimarginal principle: the amount of profit lost by idling an additional acre is equal across all producers. With perfect information, this outcome can be attained by separate environmental and income support policies similar to those in the FAIR Act. A CRP based on a simple offer price for acres idled ensures that the equimarginal principle is satisfied. Any difference between the income and participation constraints and income earned from selling crops and participating in the CRP could then be eliminated by lump sum transfers.

2.3 Asymmetric Information

The first-best program allows the government to make payments contingent on each producer's actual type. This assumption can be relaxed by allowing payments to be contingent upon observable producer actions, i.e., the amount of land each producer commits to idle. In this section I consider two classes of policies. *Ex post* policies require producers to commit to a contract after p is known. *Ex ante* policies require producers to commit to a contract before p is known. I then compare the optimal policy to a stylized version of the FAIR Act.

Modeling is simplified by making use of the Revelation Principle (Myerson 1979). The Revelation Principle allows one to restrict attention to mechanisms that are direct and truthful. In the context of this problem, a direct mechanism is one in which producers report θ. For a truthful mechanism, producers do not find it optimal to report θ falsely.

2.3.1 *Ex Post* Mechanism

The requirement that a mechanism be truthful restricts the set of feasible contracts available to the government. Let $a\left(\tilde{\theta}\right)$ and $t\left(p,\tilde{\theta}\right)$ be the terms of a contract a producer receives by reporting type $\tilde{\theta}$. For an *ex post* policy, a truthful mechanism requires that for all types, producer income (profit plus transfer) be maximized by reporting the true type θ:

$$\theta \in \arg\max_{\tilde{\theta}} \left\{\pi\left(p, a\left(\tilde{\theta}\right), \theta\right) + t\left(p, \tilde{\theta}\right)\right\},\ \forall\ \left(\theta, \tilde{\theta}\right) \in \Theta^2, p. \tag{2.34}$$

For an interior solution, a necessary condition for satisfaction of (2.34) is:

$$\pi_a\left(p, a\left(\theta\right), \theta\right) a'\left(\theta\right) + t_\theta\left(p, \theta\right) = 0, \forall\ \theta, p. \tag{2.35}$$

At the optimum, the second order condition is:

$$\pi_{aa}(p, a(\theta), \theta) a'(\theta)^2 + \pi_a(p, a(\theta), \theta) a''(\theta) + t_{\theta\theta}(p, \theta) \leq 0, \forall\ \theta, p. \tag{2.36}$$

Differentiating (2.35) implies:

$$\pi_{aa}(p, a(\theta), \theta) a'(\theta)^2 + \pi_a(p, a(\theta), \theta) a''(\theta) + t_{\theta\theta}(p, \theta) + \pi_{a\theta}(p, a(\theta), \theta) a'(\theta) = 0 \tag{2.37}$$

Using (2.37), the second order condition simplifies to:

$$-\pi_{a\theta}(p, a(\theta), \theta) a'(\theta) \leq 0, \forall\ \theta, p. \tag{2.38}$$

Therefore, using (R4) a truthful *ex post* mechanism requires the land allocation to be monotonically non-decreasing in type:

$$a'(\theta) \geq 0. \tag{2.39}$$

Using (2.35), differentiation of (2.15) for each price state and each interval Θ_L, Θ_M, Θ_H yields:

$$s_\theta(p, \theta) = \pi_\theta(p, a(\theta), \theta), \forall\ \theta \in \Theta_L,\ p; \tag{2.40}$$

$$s_\theta(p_\ell, \theta) = \pi_\theta(p_\ell, a(\theta), \theta), \forall\ \theta \in \Theta_M; \tag{2.41}$$

$$s_\theta(p_h, \theta) = \pi_\theta(p_h, a(\theta), \theta) - \pi_\theta(p_h, \overline{a}, \theta), \forall\ \theta \in \Theta_M; \tag{2.42}$$

$$s_\theta(p, \theta) = \pi_\theta(p, a(\theta), \theta) - \pi_\theta(p, \overline{a}, \theta), \forall\ \theta \in \Theta_H,\ p. \tag{2.43}$$

A truthful mechanism imposes restrictions on the rate of change of surplus across types. Surplus may increase or decrease in type depending on θ and p. For Θ_L, $s_\theta(p, \theta) > 0$, whereas for Θ_H , $s_\theta(p, \theta) < 0$. For Θ_M, $s_\theta(p_\ell, \theta) > 0$, and $s_\theta(p_h, \theta) < 0$.

To illustrate the intuition behind this result, consider the situation faced by types belonging to Θ_M. Suppose producers are offered the first-best contract schedule. If price is low producers can only increase utility by mimicking a lower type. To see this, recall that the first-best contract assigns a payment to each type just sufficient to attain the minimum income level. A producer earns more profit from cultivating a given quantity of land than any lower type. A producer could take a contract intended for a lower type, cultivate the amount of land required by the contract, and receive the transfer for the lower type. The size of the transfer would be enough to bring the lower type to the minimum income level. It would therefore bring a higher type above the minimum income level. Thus, a higher type could profitably mimic a lower type if the government offered the higher type a contract yielding zero surplus. A lower type could not improve his utility by mimicking a higher type, however. By accepting a contract that gives a higher type zero surplus, the lower type's surplus would be negative. Surplus payments are therefore required to make it incentive compatible for higher types to pick the contract intended for them. The rate of change in surplus is given by equation (2.41). Types in Θ_L face this incentive structure even if price is high, thus equation (2.40).

If price is high, the reverse occurs. The opportunity cost of land is increasing in type. Suppose the government tried to pay all producers exactly the opportunity cost of their land. A low type could profitably choose a contract for a higher type. He would obtain a transfer larger than the opportunity cost of his idled land. Surplus payments required to induce truth-telling are therefore decreasing in type at the rate indicated in equation (2.42). Producers in Θ_H face this incentive even if price is low, thus equation (2.43).

Combine equations (2.40)-(2.43) to obtain equations of motion for $s(p,\theta)$:

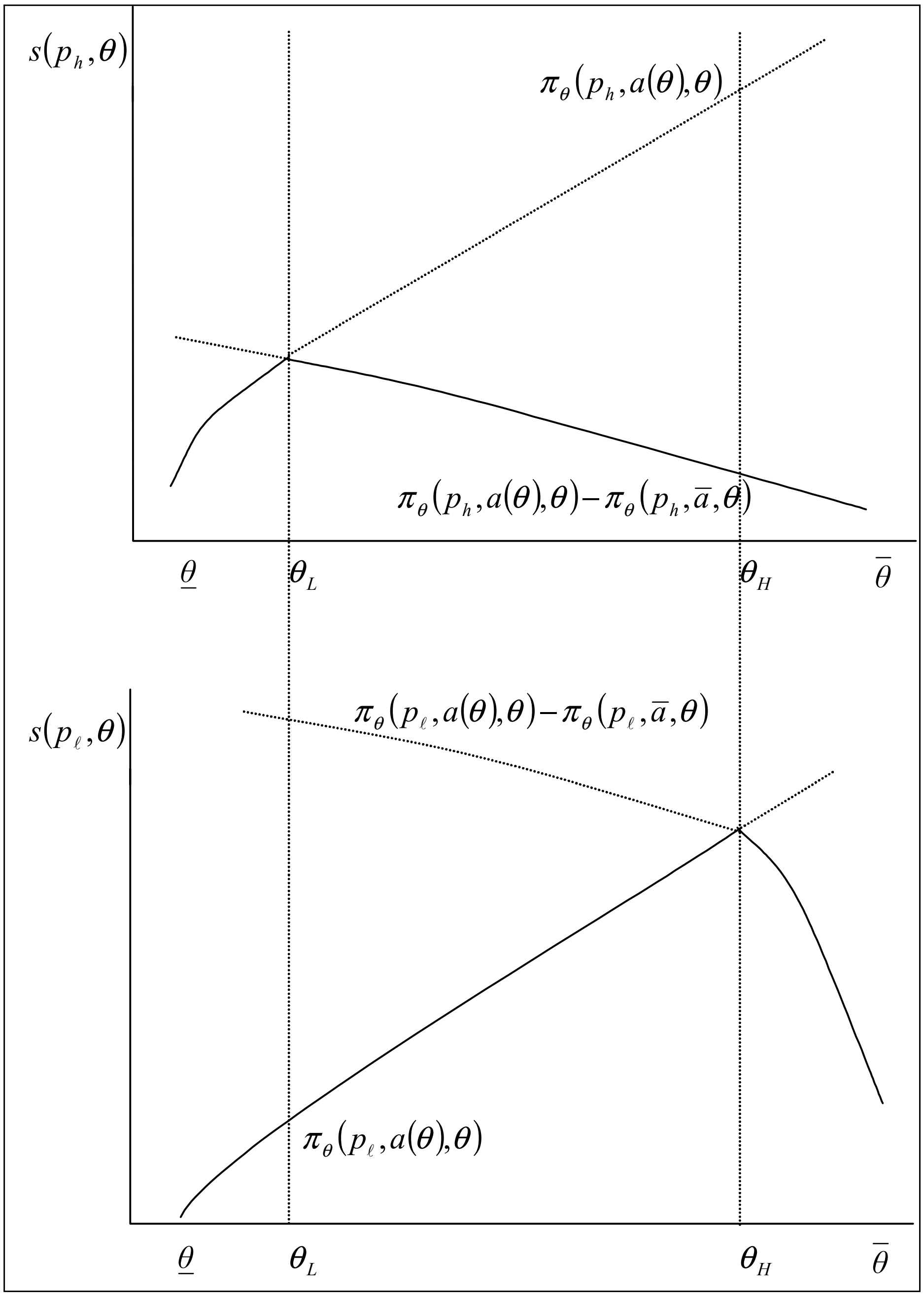
$$s_\theta(p_\ell,\theta) = \begin{cases} \pi_\theta(p_\ell, a(\theta), \theta) & \theta \in \Theta_L \cup \Theta_M \\ \pi_\theta(p_\ell, a(\theta), \theta) - \pi_\theta(p_\ell, \overline{a}, \theta) & \theta \in \Theta_H \end{cases}; \tag{2.44}$$

$$s_\theta(p_h,\theta) = \begin{cases} \pi_\theta(p_h, a(\theta), \theta) & \theta \in \Theta_L \\ \pi_\theta(p_h, a(\theta), \theta) - \pi_\theta(p_h, \overline{a}, \theta) & \theta \in \Theta_M \cup \Theta_H \end{cases}. \tag{2.45}$$

Surplus in both states initially increases in θ, reaches a peak, then decreases. If price is low, the peak occurs at θ_H. If price is high, the peak occurs at θ_L. These two functions are depicted in Figure 2.2. The two local minima for $s(p,\theta)$ are located at the extreme types $\underline{\theta}$ and $\bar{\theta}$.

Rewrite the first-best Lagrangian (2.20), to account for these constraints:

Figure 2.2: *Ex Post* Surplus



$$
\begin{aligned}
&\min_{a(\theta),s(p,\theta),\lambda,\tau(p,\theta),\gamma(p,\theta),\alpha(\theta)} \int_{\Theta_L} \Big\{ S(\theta) - \Pi(a,\theta) + m \\
&+ \frac{\rho\left\{\gamma(p_\ell,\theta)\left[s_\theta(p_\ell,\theta) - \pi_\theta(p_\ell, a(\theta),\theta)\right] - \tau(p_\ell,\theta)\, s(p_\ell,\theta)\right\}}{f(\theta)} \\
&+ \frac{(1-\rho)\,\gamma(p_h,\theta)\left[s_\theta(p_h,\theta) - \pi_\theta(p_h, a(\theta),\theta)\right]}{f(\theta)} \\
&- \frac{(1-\rho)\,\tau(p_h,\theta)\, s(p_h,\theta)}{f(\theta)} \Big\}\, dF(\theta) \\
&+ \int_{\Theta_M} \Big\{ S(\theta) - \Pi(a,\theta) + \rho m + [1-\rho]\,\pi(p_h,\overline{a},\theta) \\
&+ \frac{\rho\left\{\gamma(p_\ell,\theta)\left[s_\theta(p_\ell,\theta) - \pi_\theta(p_\ell, a(\theta),\theta)\right] - \tau(p_\ell,\theta)\, s(p_\ell,\theta)\right\}}{f(\theta)} \\
&+ \frac{(1-\rho)\,\gamma(p_h,\theta)\left[s_\theta(p_h,\theta) - \pi_\theta(p_h, a(\theta),\theta) + \pi_\theta(p_h,\overline{a},\theta)\right]}{f(\theta)} \\
&- \frac{(1-\rho)\,\tau(p_h,\theta)\, s(p_h,\theta)}{f(\theta)} \Big\}\, dF(\theta) \\
&+ \int_{\Theta_H} \Big\{ S(\theta) - \Pi(a,\theta) + \Pi(\overline{a},\theta) \\
&+ \frac{\rho\left\{\gamma(p_\ell,\theta)\left[s_\theta(p_\ell,\theta) - \pi_\theta(p_\ell, a(\theta),\theta) + \pi_\theta(p_\ell,\overline{a},\theta)\right] - \tau(p_\ell,\theta)\, s(p_\ell,\theta)\right\}}{f(\theta)} \\
&+ \frac{(1-\rho)\,\gamma(p_h,\theta)\left[s_\theta(p_h,\theta) - \pi_\theta(p_h, a(\theta),\theta) + \pi_\theta(p_h,\overline{a},\theta)\right]}{f(\theta)} \\
&- \frac{(1-\rho)\,\tau(p_h,\theta)\, s(p_h,\theta)}{f(\theta)} \Big\}\, dF(\theta) \\
&- \lambda \int_{\Theta} \left[\overline{a} - a(\theta) - A\right] dF(\theta) - \int_{\Theta} \alpha(\theta)\left[\overline{a} - a(\theta)\right] d\theta.
\end{aligned}
\tag{2.46}
$$

subject to: (2.39).

Here $\gamma(p,\theta)$ is the Lagrange multiplier for (2.44) and (2.45), $\tau(p,\theta)$ is the Lagrange multiplier for (2.17), and $\alpha(\theta)$ is the Lagrange multiplier for the constraint $a(\theta) \leq \bar{a}$. Following standard practice (e.g., Fudenberg and Tirole (1991)), I do not explicitly include the monotonicity condition (2.39) in the Lagrangian. Instead, I solve for the optimal solution ignoring this constraint. Afterwards I check to ensure that the solution satisfies (2.39).

Integrating objective function (2.46) by parts yields:

$$
\begin{aligned}
&\min_{a(\theta),s(p,\theta),\lambda,\tau(p,\theta),\gamma(p,\theta),\alpha(\theta)} \int_{\Theta} \{S(\theta) - \Pi(a,\theta) - \lambda[\overline{a} - a(\theta) - A] \\
&-\frac{\alpha(\theta)}{f(\theta)}[\overline{a} - a(\theta)] - \frac{\rho\gamma(p_\ell,\theta)}{f(\theta)}\pi_\theta(p_\ell, a(\theta), \theta) - \frac{(1-\rho)\gamma(p_h,\theta)}{f(\theta)}\pi_\theta(p_h, a(\theta), \theta) \\
&-\frac{\rho\gamma_\theta(p_\ell,\theta) + \tau(p_\ell,\theta)}{f(\theta)} s(p_\ell,\theta) \\
&-\frac{(1-\rho)\gamma_\theta(p_h,\theta) + \tau(p_h,\theta)}{f(\theta)} s(p_h,\theta)\Bigg\} dF(\theta) \\
&+\int_{\Theta_L} m dF(\theta) + \int_{\Theta_M} \rho m + [1-\rho]\pi(p_h, \overline{a}, \theta) dF(\theta) + \int_{\Theta_H} \Pi(\overline{a},\theta) dF(\theta) \\
&+\rho\left[\gamma\left(p_\ell,\bar{\theta}\right) s\left(p_\ell,\bar{\theta}\right) - \gamma(p_\ell,\underline{\theta}) s(p_\ell,\underline{\theta})\right] \\
&+(1-\rho)\left[\gamma\left(p_h,\bar{\theta}\right) s\left(p_h,\bar{\theta}\right) - \gamma(p_h,\underline{\theta}) s(p_h,\underline{\theta})\right].
\end{aligned} \tag{2.47}
$$

The necessary conditions for optimal land cultivation are:

$$
\begin{aligned}
&\Pi_a(a(\theta),\theta) + \frac{\rho\gamma(p_\ell,\theta)}{f(\theta)}\pi_{a\theta}(p_\ell, a(\theta), \theta) \\
&+\frac{(1-\rho)\gamma(p_h,\theta)}{f(\theta)}\pi_{a\theta}(p_h, a(\theta), \theta) - \lambda - \frac{\alpha(\theta)}{f(\theta)} \geq 0.
\end{aligned} \tag{2.48}
$$

$$
a(\theta) \geq 0 \tag{2.49}
$$

$$
\begin{aligned}
&a(\theta)\Bigg[\Pi_a(a(\theta),\theta) + \frac{\rho\gamma(p_\ell,\theta)}{f(\theta)}\pi_{a\theta}(p_\ell, a(\theta), \theta) \\
&+\frac{(1-\rho)\gamma(p_h,\theta)}{f(\theta)}\pi_{a\theta}(p_h, a(\theta), \theta) - \lambda - \frac{\alpha(\theta)}{f(\theta)}\Bigg] = 0.
\end{aligned} \tag{2.50}
$$

$$
\bar{a} - a(\theta) \geq 0 \tag{2.51}
$$

$$
\alpha(\theta) \geq 0 \tag{2.52}
$$

$$
\alpha(\theta)[\bar{a} - a(\theta)] = 0 \tag{2.53}
$$

$$
\int_{\Theta}[\overline{a} - a(\theta) - A] dF(\theta) \geq 0 \tag{2.54}
$$

$$
\lambda \geq 0 \tag{2.55}
$$

$$
\lambda\int_{\Theta}[\overline{a} - a(\theta) - A] dF(\theta) = 0 \tag{2.56}
$$

Note from (2.48) that unlike the full information case, the equimarginal principle is not satisfied. For interior solutions, the marginal profit of land is equal to λ minus the distortion $\frac{\rho\gamma(p_\ell,\theta)}{f(\theta)}\pi_{a\theta}\left(p_\ell, a\left(\theta\right), \theta\right) + \frac{(1-\rho)\gamma(p_h,\theta)}{f(\theta)}\pi_{a\theta}\left(p_h, a\left(\theta\right), \theta\right)$. Consequently, this marginal profit is not equal across all types.

The necessary conditions for $s\left(p, \theta\right)$ are:

$$
\begin{aligned}
\gamma_\theta\left(p,\theta\right) + \tau\left(p,\theta\right) - f\left(\theta\right) &= 0 && (2.57)\\
\tau\left(p,\theta\right) &\geq 0 && (2.58)\\
s\left(p,\theta\right) &\geq 0 && (2.59)\\
\tau\left(p,\theta\right) s\left(p,\theta\right) &= 0 && (2.60)
\end{aligned}
$$

Unlike the full information case, (2.57) indicates that $\tau\left(p,\theta\right)$ is not necessarily strictly positive for all types. The necessary conditions for optimal endpoints $s\left(p,\underline{\theta}\right)$ and $s\left(p,\overline{\theta}\right)$ are:

$$
\begin{aligned}
-\gamma\left(p,\underline{\theta}\right) &\geq 0 && (2.61)\\
s\left(p,\underline{\theta}\right) &\geq 0 && (2.62)\\
\gamma\left(p,\underline{\theta}\right) s\left(p,\underline{\theta}\right) &= 0 && (2.63)\\
\gamma\left(p,\overline{\theta}\right) &\geq 0 && (2.64)\\
s\left(p,\overline{\theta}\right) &\geq 0 && (2.65)\\
\gamma\left(p,\overline{\theta}\right) s\left(p,\overline{\theta}\right) &= 0 && (2.66)
\end{aligned}
$$

Integration of (2.57) implies:

$$\int_{\underline{\theta}}^{\overline{\theta}} \gamma_{\theta}(p,z)\,dz = \int_{\theta}^{\overline{\theta}} f(z)\,dz - \int_{\underline{\theta}}^{\overline{\theta}} \tau(p,z)\,dz \tag{2.67}$$

$$\gamma\left(p,\overline{\theta}\right) + \int_{\theta}^{\overline{\theta}} \tau(p,z)\,dz - 1 = \gamma\left(p,\underline{\theta}\right) - \int_{\underline{\theta}}^{\theta} \tau(p,z)\,dz. \tag{2.68}$$

Define:

$$\mu(p,\theta) \equiv \int_{\underline{\theta}}^{\theta} \tau(p,z)\,dz - \gamma\left(p,\underline{\theta}\right). \tag{2.69}$$

By construction, $\tau(p,\theta) \geq 0$. Therefore, (2.105), (2.64), and (2.68) imply $\mu(p) \in [0,1]$. Integration of (2.57) for an interior type implies:

$$\int_{\underline{\theta}}^{\theta} \gamma_{\theta}(p,z)\,dz = \int_{\underline{\theta}}^{\theta} f(z)\,dz - \int_{\underline{\theta}}^{\theta} \tau(p,z)\,dz \tag{2.70}$$

$$\gamma(p,\theta) - \gamma\left(p,\underline{\theta}\right) = F(\theta) - \int_{\underline{\theta}}^{\theta} \tau(p,z)\,dz \tag{2.71}$$

$$\gamma(p,\theta) = F(\theta) - \mu(p,\theta). \tag{2.72}$$

Note from Figure 2.2, that if it is optimal for any type in a given price state to receive zero surplus it will be one of the endpoints $\underline{\theta}$ or $\bar{\theta}$. For all other types $\tau(p,\theta) = 0$. Next, observe that if one endpoint optimally receives strictly positive surplus, the other must optimally receive zero surplus. To see this, consider the contrary. If both extremes receive strictly positive surplus, then $\tau(p,\theta) = 0$ for all types. In addition, (2.63) and (2.66) imply $\gamma\left(p,\underline{\theta}\right) = \gamma\left(p,\overline{\theta}\right) = 0$. Consequently, (2.68) implies $0 = 1$, which is clearly a contradiction.

If $s\left(p,\overline{\theta}\right) > 0$, the left hand side of (2.68) is -1 for all types, therefore $\mu(p,\theta) = 1$ and $\gamma(p,\theta) = F(\theta) - 1$. If $s\left(p,\underline{\theta}\right) > 0$, the right hand side of (2.68) is zero for all types, therefore $\gamma(p,\theta) = F(\theta)$.

Let $D_{\ell}(\gamma(p_{\ell},\theta), \gamma(p_h,\theta))$ and $D_h(\gamma(p_{\ell},\theta), \gamma(p_h,\theta))$ denote the differences in surplus between the extreme types in each state:

$$\begin{aligned} D_\ell\left(\gamma\left(p_\ell,\theta\right),\gamma\left(p_h,\theta\right)\right) &\equiv s\left(p_\ell,\bar{\theta}\right)-s\left(p_\ell,\underline{\theta}\right) \\ &= \int_\Theta \pi_\theta\left(p_\ell,a^*,\theta\right)d\theta-\int_{\theta_H}^{\bar{\theta}}\pi_\theta\left(p_\ell,\overline{a},\theta\right)d\theta \quad (2.73) \\ D_h\left(\gamma\left(p_\ell,\theta\right),\gamma\left(p_h,\theta\right)\right) &\equiv s\left(p_h,\bar{\theta}\right)-s\left(p_h,\underline{\theta}\right) \\ &= \int_\Theta \pi_\theta\left(p_h,a^*,\theta\right)d\theta-\int_{\theta_L}^{\bar{\theta}}\pi_\theta\left(p_h,\overline{a},\theta\right)d\theta, \quad (2.74) \end{aligned}$$

where $a^*\equiv a^*\left(\gamma\left(p_\ell,\theta\right),\gamma\left(p_h,\theta\right)\right)$ is the quantity of land that satisfies (2.48).

Note from (2.48) that for an interior solution:

$$\begin{aligned} \frac{\partial a^*}{\partial\gamma\left(p_\ell\right)} &= \frac{-\dfrac{\rho\pi_{a\theta}\left(p_\ell,a^*,\theta\right)}{f\left(\theta\right)}}{\Pi_{aa}+\dfrac{\rho\gamma\left(p_\ell,\theta\right)\pi_{aa\theta}\left(p_\ell,a^*,\theta\right)+\left(1-\rho\right)\gamma\left(p_h,\theta\right)\pi_{aa\theta}\left(p_h,a^*,\theta\right)}{f\left(\theta\right)}} \\ &> 0;\ \text{and} \quad (2.75) \\ \frac{\partial a^*}{\partial\gamma\left(p_h\right)} &= \frac{\dfrac{-\left(1-\rho\right)\pi_{a\theta}\left(p_h,a^*,\theta\right)}{f\left(\theta\right)}}{\Pi_{aa}+\dfrac{\rho\gamma\left(p_\ell,\theta\right)\pi_{aa\theta}\left(p_\ell,a^*,\theta\right)+\left(1-\rho\right)\gamma\left(p_h,\theta\right)\pi_{aa\theta}\left(p_h,a^*,\theta\right)}{f\left(\theta\right)}} \\ &> 0, \quad (2.76) \end{aligned}$$

due to (R2), (R4), and (R6). Therefore, both D_ℓ and D_h are decreasing in $\mu\left(p,\theta\right)$. Finally, denote the values of $\mu\left(p,\theta\right)$ that give both extremes zero surplus as:

$$\hat{\mu}\left(p_\ell,\theta\right) = \left\{\hat{\mu}:D_\ell\left(F\left(\theta\right)-\hat{\mu},\gamma\left(p_h,\theta\right)\right)=0\right\} \quad (2.77)$$

$$\hat{\mu}\left(p_h,\theta\right) = \left\{\hat{\mu}:D_h\left(\gamma\left(p_\ell,\theta\right),F\left(\theta\right)-\hat{\mu}\right)=0\right\}. \quad (2.78)$$

Note that since all interior types receive positive surplus, $\int_{\underline{\theta}}^{\theta}\tau\left(p,z\right)dz=0$ for all $\theta<\bar{\theta}$. Consequently, referring to (2.69) $\hat{\mu}\left(p,\theta\right)$ must be constant across all types.

The values of $\mu\left(p,\theta\right)$ that satisfy the necessary conditions for an optimum can therefore be characterized as follows:

$$\mu\left(p_{\ell},\theta\right)=\begin{cases}0 & \text{if } D_{\ell}\left(F\left(\theta\right),\gamma\left(p_{h},\theta\right)\right)\leq 0\\ \hat{\mu}\left(p_{\ell},\theta\right) & \begin{array}{l}\text{if } D_{\ell}\left(F\left(\theta\right)-1,\gamma\left(p_{h},\theta\right)\right)<0,\\ \text{and } 0<D_{\ell}\left(F\left(\theta\right),\gamma\left(p_{h},\theta\right)\right)\end{array}\\ 1 & \text{if } 0\leq D_{\ell}\left(F\left(\theta\right)-1,\gamma\left(p_{h},\theta\right)\right)\end{cases} \tag{2.79}$$

$$\mu\left(p_{h}\right)=\begin{cases}0 & \text{if } D_{h}\left(\gamma\left(p_{\ell},\theta\right),F\left(\theta\right)\right)\leq 0\\ \hat{\mu}\left(p_{h}\right) & \begin{array}{l}\text{if } D_{h}\left(\gamma\left(p_{\ell},\theta\right),F\left(\theta\right)-1\right)<0,\\ \text{and } 0<D_{h}\left(\gamma\left(p_{\ell},\theta\right),F\left(\theta\right)\right)\end{array}\\ 1 & \text{if } 0\leq D_{h}\left(\gamma\left(p_{\ell},\theta\right),F\left(\theta\right)-1\right)\ .\end{cases} \tag{2.80}$$

It remains to verify that the solutions satisfy the monotonicity condition (2.39). For an interior solution, differentiation of (2.48) yields:

$$\frac{da^{*}}{d\theta}=-\frac{\Pi_{a\theta}+\rho\left[\frac{d}{d\theta}\left(\frac{\gamma^{\ell}}{f}\right)\pi_{a\theta}^{\ell}+\frac{\gamma^{\ell}}{f}\pi_{a\theta\theta}^{\ell}\right]+\left[1-\rho\right]\left[\frac{d}{d\theta}\left(\frac{\gamma^{h}}{f}\right)\pi_{a\theta}^{h}+\frac{\gamma^{h}}{f}\pi_{a\theta\theta}^{h}\right]}{\Pi_{aa}+\rho\frac{\gamma^{\ell}}{f}\pi_{aa\theta}^{\ell}+\left[1-\rho\right]\frac{\gamma^{h}}{f}\pi_{aa\theta}^{h}}. \tag{2.81}$$

Here, a superscript ℓ or h indicates that the function is evaluated at $p=p^{\ell}$ or p^{h}. Regularity conditions (R2), (R4), (R5), and (R6) ensure that the right hand side of this equation is strictly positive, hence the monotonicity condition is satisfied for all of the above cases.

To further characterize the solution requires knowing the specific structure of $\pi\left(p,a,\theta\right)$ and $f\left(\theta\right)$. Regardless of the optimal value of $\gamma\left(p,\theta\right)$, however, the optimal *ex post* mechanism does not achieve the first best. No land allocation indicated by a possible value of $\gamma\left(p,\theta\right)$ satisfies necessary condition (2.21) for an optimal first best contract. Moreover, although at least one type receives zero surplus *ex post*, it may be the case that all types receive positive expected surplus. At most, only the two extreme types receives zero expected surplus.

On the contrary, for the first-best mechanism *all* types receive zero expected surplus. In the next section, I examine the effect of changing the time of contract commitment on the green payments program.

2.3.2 *Ex Ante* Mechanism

Ex ante and *ex post* mechanisms differ in the implications of income, participation, and truth-telling constraints. Risk-neutrality of both the government and producers implies that both parties are indifferent between contracts that yield the same expected surplus with different combinations of *ex post* surplus. Thus, any contract with weakly positive expected surplus can be implemented with payouts such that *ex post* surplus is weakly positive in each state. Without loss of generality, I replace the income and participation constraints (2.17) with the expected surplus constraint:

$$S(\theta) \geq 0. \tag{2.82}$$

Since this constraint is less restrictive than the two constraints (2.17), the optimal *ex ante* mechanism cannot be more costly than the optimal *ex post* mechanism. To see how the relaxed constraint affects the cost of the mechanism, it is necessary to more fully characterize the optimal *ex ante* contract schedule.

For an *ex ante* policy to be truthful, expected producer income must be maximized by reporting the true type θ:

$$\theta \in \arg\max_{\tilde{\theta}} \left\{ \Pi\left(a\left(\tilde{\theta}\right), \theta\right) + T\left(\tilde{\theta}\right) \right\}, \ \forall \ \left(\theta, \tilde{\theta}\right) \in \Theta^2. \tag{2.83}$$

This requirement has two implications for the set of feasible contract allocations. A necessary condition for satisfaction of (2.83) is:

$$\Pi_a\left(a\left(\theta\right),\theta\right)a'\left(\theta\right)+T_\theta\left(\theta\right)=0,\forall\ \theta. \tag{2.84}$$

At the optimum, the second-order condition is:

$$\Pi_{aa}\left(a\left(\theta\right),\theta\right)a'\left(\theta\right)^2+\Pi_a\left(a\left(\theta\right),\theta\right)a''\left(\theta\right)+T_{\theta\theta}\left(\theta\right)\leq 0,\forall\ \theta. \tag{2.85}$$

Differentiating (2.84) yields:

$$\Pi_{aa}\left(a\left(\theta\right),\theta\right)a'\left(\theta\right)^2+\Pi_a\left(p,a\left(\theta\right),\theta\right)a''\left(\theta\right)+T_{\theta\theta}\left(\theta\right)+\Pi_{a\theta}\left(a\left(\theta\right),\theta\right)a'\left(\theta\right)=0 \tag{2.86}$$

Consequently, the second order condition simplifies to:

$$-\Pi_{a\theta}\left(a\left(\theta\right),\theta\right)a'\left(\theta\right)\leq 0. \tag{2.87}$$

Using (R4), expression (2.87) implies that a truthful *ex ante* mechanism requires the land allocation to be monotonically non-decreasing in type:

$$a'\left(\theta\right)\geq 0. \tag{2.88}$$

Using (2.84), differentiation of (2.16) for each price state and each interval Θ_L, Θ_M, Θ_H implies:

$$S'\left(\theta\right)=\begin{cases}\Pi_\theta\left(a\left(\theta\right),\theta\right) & \theta\in\Theta_L\\ \Pi_\theta\left(a\left(\theta\right),\theta\right)-\left[1-\rho\right]\pi_\theta\left(p_h,\overline{a},\theta\right) & \theta\in\Theta_M\\ \Pi_\theta\left(a\left(\theta\right),\theta\right)-\Pi_\theta\left(\overline{a},\theta\right) & \theta\in\Theta_H\end{cases} \tag{2.89}$$

Rewriting the first-best Lagrangian (2.20) to account for these constraints yields:

$$
\begin{aligned}
\min_{a(\theta),S(\theta),\lambda,\tau(\theta),\gamma(\theta),\alpha(\theta)} & \int_{\Theta_L} \{S(\theta) - \Pi(a,\theta) + m \\
& + \frac{\gamma(\theta)[S'(\theta) - \Pi_\theta(a(\theta),\theta)] - \tau(\theta) S(\theta)}{f(\theta)} \Big\} dF(\theta) \\
& + \int_{\Theta_M} \Big\{ S(\theta) - \Pi(a,\theta) + \rho m + (1-\rho)\pi(p_h, \overline{a}, \theta) \\
& + \frac{\gamma(\theta)[S'(\theta) - \Pi_\theta(a(\theta),\theta) + (1-\rho)\pi_\theta(p_h, a(\theta), \theta)]}{f(\theta)} \\
& - \frac{\tau(\theta) S(\theta)}{f(\theta)} \Big\} dF(\theta) \\
& + \int_{\Theta_H} \{S(\theta) - \Pi(a,\theta) + \Pi(\overline{a},\theta) \\
& + \frac{\gamma(\theta)[S'(\theta) - \Pi_\theta(a(\theta),\theta) + \Pi_\theta(\overline{a},\theta)] - \tau(\theta) S(\theta)}{f(\theta)} \Big\} dF(\theta) \\
& - \lambda \int_\Theta [\overline{a} - a(\theta) - A] \, dF(\theta) - \int_\Theta \alpha(\theta)[\overline{a} - a(\theta)] \, d\theta.
\end{aligned} \tag{2.90}
$$

subject to: (2.88).

Here $\gamma(\theta)$ and $\tau_L(\theta)$ are the Lagrange multipliers for constraints (2.89) and (2.82), and $\alpha(\theta)$ is the Lagrange multiplier for the constraint $a(\theta) \leq \bar{a}$. The monotonicity condition (2.88) is not explicitly included in the Lagrangian. Instead, I solve for the optimal solution ignoring this constraint, then check to ensure it is satisfied.

Integrate (2.90) by parts to obtain:

$$
\begin{aligned}
\min_{a(\theta),S(\theta),\lambda,\tau(\theta),\gamma(\theta),\alpha(\theta)} & \int_{\Theta} \{S(\theta) - \Pi(a,\theta) - \lambda[\overline{a} - a(\theta) - A] \\
& - \frac{\gamma(\theta)}{f(\theta)} \Pi_\theta(a(\theta),\theta) - \frac{\gamma'(\theta) + \tau(\theta)}{f(\theta)} S(\theta) - \frac{\alpha(\theta)}{f(\theta)}[\overline{a} - a(\theta)] \Big\} dF(\theta) \\
& + \int_{\Theta_L} m dF(\theta) + \int_{\Theta_M} \rho m + (1-\rho)\pi(p_h, \overline{a}, \theta) \, dF(\theta) \\
& + \int_{\Theta_H} \Pi(\overline{a},\theta) \, dF(\theta) - \gamma(\underline{\theta}) S(\underline{\theta}) + \gamma(\bar{\theta}) S(\bar{\theta}).
\end{aligned} \tag{2.91}
$$

By pointwise optimization, the necessary conditions for optimal land cultivation are:

$$
\begin{aligned}
\Pi_a\left(a\left(\theta\right),\theta\right)+\frac{\gamma\left(\theta\right)}{f\left(\theta\right)}\Pi_{a\theta}\left(a\left(\theta\right),\theta\right)-\lambda-\frac{\alpha\left(\theta\right)}{f\left(\theta\right)} &\geq 0 && (2.92)\\
a\left(\theta\right) &\geq 0 && (2.93)\\
a\left(\theta\right)\left[\Pi_a\left(a\left(\theta\right),\theta\right)+\frac{\gamma\left(\theta\right)}{f\left(\theta\right)}\Pi_{a\theta}\left(a\left(\theta\right),\theta\right)-\lambda-\frac{\alpha\left(\theta\right)}{f\left(\theta\right)}\right] &= 0 && (2.94)\\
\bar{a}-a\left(\theta\right) &\geq 0 && (2.95)\\
\alpha\left(\theta\right) &\geq 0 && (2.96)\\
\alpha\left(\theta\right)\left[\bar{a}-a\left(\theta\right)\right] &= 0 && (2.97)\\
\int_\Theta\left[\bar{a}-a\left(\theta\right)-A\right]dF\left(\theta\right) &\geq 0 && (2.98)\\
\lambda &\geq 0 && (2.99)\\
\lambda\int_\Theta\left[\bar{a}-a\left(\theta\right)-A\right]dF\left(\theta\right) &= 0 && (2.100)
\end{aligned}
$$

As with the *ex post* mechanism, notice from (2.92) that asymmetric information introduces a distortion in the optimal land allocation. The marginal profit of land is not equated across types. It equals λ minus the distortion $\frac{\gamma(\theta)}{f(\theta)}\Pi_{a\theta}\left(a\left(\theta\right),\theta\right)$.

The necessary conditions for expected surplus are:

$$
\begin{aligned}
\gamma'\left(\theta\right)+\tau\left(\theta\right)-f\left(\theta\right) &= 0 && (2.101)\\
\tau\left(\theta\right) &\geq 0 && (2.102)\\
S\left(\theta\right) &\geq 0 && (2.103)\\
\tau\left(\theta\right)S\left(\theta\right) &= 0 && (2.104)
\end{aligned}
$$

Similar to the the *ex post* case, (2.101) indicates that $\tau\left(\theta\right)$ may not be strictly positive for all types. Consequently some types may receive positive expected surplus. Necessary conditions for the optimal endpoints of $S\left(\theta\right)$ are:

$$-\gamma(\underline{\theta}) \geq 0 \tag{2.105}$$

$$S(\underline{\theta}) \geq 0 \tag{2.106}$$

$$S(\underline{\theta})\gamma(\underline{\theta}) = 0 \tag{2.107}$$

$$\gamma(\overline{\theta}) \geq 0 \tag{2.108}$$

$$S(\overline{\theta}) \geq 0 \tag{2.109}$$

$$S(\overline{\theta})\gamma(\overline{\theta}) = 0 \tag{2.110}$$

To characterize the solution, note the shape of $S(\theta)$ as described in (2.89). For Θ_L, expected surplus is always increasing in type, whereas for Θ_H expected surplus is always decreasing. For Θ_M, expected surplus may be increasing or decreasing, depending upon $a(\theta)$. For example, see the lower panels of Figures 2.3 - 2.9.

Define the allocation $\hat{a}(\theta)$ as:

$$\hat{a}(\theta) \equiv \{a : \Pi_\theta(a,\theta) = [1-\rho]\,\pi_\theta(p_h,\overline{a},\theta)\}. \tag{2.111}$$

If $a(\theta) = \hat{a}(\theta)$ for some $\theta \in \Theta_M$, then $S'(\theta) = 0$. Note that (2.88) and (R4) imply that if $a(\theta) < \hat{a}(\theta)$, then $S'(\theta) < 0$, and if $a(\theta) > \hat{a}(\theta)$, then $S'(\theta) > 0$. At this level of generality, there are many possible solutions to the government's problem.

Assumption (R7) simplifies the analysis by making $\hat{a}(\theta)$ a constant $\hat{a}$ for all θ. Under (R7)

$$\Pi_\theta(a,\theta) = g'(\theta)\,\tilde{\Pi}(a), \tag{2.112}$$

where

$$\tilde{\Pi}(a) \equiv \rho\tilde{\pi}(p_\ell,a) + [1-\rho]\,\tilde{\pi}(p_h,a). \tag{2.113}$$

Consequently, (2.111) simplifies to:

$$\hat{a}(\theta) = \hat{a} = \left\{ a : \tilde{\Pi}(a) = [1-\rho]\,\tilde{\pi}(p_h, \overline{a}) \right\}. \tag{2.114}$$

Since the monotonicity condition (2.88) requires that the land allocation be non-decreasing in type, (R7) implies that in the interval Θ_M, $S(\theta)$ is roughly U-shaped, achieving its minimum for any type(s) that cultivate $\hat{a}$ acres (see Figure 2.6). If no types in Θ_M cultivate $\hat{a}$, then $S(\theta)$ is monotonically increasing or decreasing as follows:

$$\begin{aligned} S'(\theta) &> 0 \quad \text{if } a(\theta_L) > \hat{a} \\ S'(\theta) &< 0 \quad \text{if } a(\theta_H) < \hat{a}. \end{aligned} \tag{2.115}$$

Denote the (possibly empty) subinterval of types within Θ_M that cultivate $\hat{a}$ as $\hat{\Theta}_M$, with lower and upper bounds θ_1 and θ_2. Since $\underline{\theta}$, $\bar{\theta}$, and $\hat{\Theta}_M$ are all local minima of $S(\theta)$, if it is optimal for any type(s) to receive zero expected surplus it will be one of these.

First, note that it is optimal for at least one of these minima to receive zero expected surplus. To see this, consider the contrary. Integration of (2.101) implies:

$$\int_{\underline{\theta}}^{\overline{\theta}} \gamma'(\theta)\, d\theta = \int_{\underline{\theta}}^{\overline{\theta}} f(\theta)\, d\theta - \int_{\underline{\theta}}^{\overline{\theta}} \tau(\theta)\, d\theta \tag{2.116}$$

$$\gamma\left(\overline{\theta}\right) - \gamma\left(\underline{\theta}\right) = 1 - \int_{\underline{\theta}}^{\overline{\theta}} \tau(\theta)\, d\theta \tag{2.117}$$

If all types strictly positive expected surplus, then $\tau(\theta) = 0$. In addition, (2.107) and (2.110) imply $\gamma(\underline{\theta}) = \gamma\left(\overline{\theta}\right) = 0$. Consequently, (2.117) implies $0 = 1$, clearly a contradiction.

Consider the case in which no interior type receives zero expected surplus. Rearranging expression (2.117) yields:

$$\gamma\left(\overline{\theta}\right) - 1 + \int_{\theta}^{\overline{\theta}} \tau\left(\theta\right) d\theta = \gamma\left(\underline{\theta}\right) - \int_{\underline{\theta}}^{\theta} \tau\left(z\right) dz \tag{2.118}$$

Define:

$$\mu\left(\theta\right) \equiv \int_{\underline{\theta}}^{\theta} \tau\left(z\right) dz - \gamma\left(\underline{\theta}\right). \tag{2.119}$$

Integration of (2.101) for an interior type implies:

$$\int_{\underline{\theta}}^{\theta} \gamma'\left(\theta\right) d\theta = \int_{\underline{\theta}}^{\theta} f\left(\theta\right) d\theta - \int_{\underline{\theta}}^{\theta} \tau\left(\theta\right) d\theta \tag{2.120}$$

$$\gamma\left(\theta\right) = F\left(\theta\right) + \gamma\left(\underline{\theta}\right) - \int_{\underline{\theta}}^{\overline{\theta}} \tau\left(\theta\right) d\theta \tag{2.121}$$

$$\gamma\left(\theta\right) = F\left(\theta\right) - \mu\left(\theta\right). \tag{2.122}$$

The solution of the problem can take one of several qualitatively different forms depending upon which of the local minima of $S\left(\theta\right)$ are global minima. Which case applies cannot be determined *a priori* since it depends in turn upon the particular specifications of $\pi\left(p, a, \theta\right)$ and $f\left(\theta\right)$.

If only the highest type receives zero surplus then $S\left(\underline{\theta}\right) > 0$ and $\gamma\left(\underline{\theta}\right) = 0$ by (2.107) and $\mu\left(\theta\right) = 0$ for all types. If only the lowest type receives zero surplus then $S\left(\bar{\theta}\right) > 0$, $\gamma\left(\overline{\theta}\right) = 0$, and $\mu\left(\theta\right) = 1$ for all types.

A third alternative is that only both extreme types receive zero surplus. Define

$$\begin{aligned} D\left(\gamma\left(\theta\right)\right) &\equiv S\left(\bar{\theta}\right) - S\left(\underline{\theta}\right) \\ &= \int_{\Theta} \Pi_{\theta}\left(a^{*}\left(\theta, \gamma\left(\theta\right), \lambda\right), \theta\right) d\theta \\ &\quad - \int_{\Theta_M} \left[1 - \rho\right] \pi_{\theta}\left(p_h, \overline{a}, \theta\right) d\theta - \int_{\Theta_H} \Pi_{\theta}\left(\overline{a}, \theta\right) d\theta, \end{aligned} \tag{2.123}$$

where $a^{*}\left(\theta, \gamma\left(\theta\right), \lambda\right)$ is the quantity of land that satisfies (2.92).

From (2.92):

$$\begin{aligned} \frac{\partial a^*}{\partial \gamma} &= \frac{-\Pi_{a\theta}\left(a^*,\theta\right)}{f\left(\theta\right)\Pi_{aa}\left(a^*,\theta\right)+\gamma\left(\theta\right)\Pi_{aa\theta}\left(a^*,\theta\right)} \\ &> 0, \end{aligned} \tag{2.124}$$

due to (R2), (R4), and (R6). Therefore, D is decreasing in $\mu(\theta)$. For both extremes to receive zero expected surplus it must be the case that

$$\mu(\theta) = \hat{\mu}(\theta) \equiv \{\hat{\mu} : D(F(\theta) - \hat{\mu}) = 0\}. \tag{2.125}$$

Note that since expected surplus is positive for all interior types, $\int_{\underline{\theta}}^{\overline{\theta}} \tau(\theta)\, d\theta = 0$ for all $\theta < \overline{\theta}$. Consequently, $\hat{\mu}(\theta)$ is constant across type.

If a central interval of types $\theta \in \hat{\Theta}_M$ receive zero expected surplus, then integration of (2.101) from $\underline{\theta}$ to θ_1 implies:

$$\int_{\underline{\theta}}^{\theta_1} \gamma'(\theta)\, d\theta = \int_{\underline{\theta}}^{\theta_1} f(\theta)\, d\theta - \int_{\underline{\theta}}^{\theta_1} \tau(\theta)\, d\theta \tag{2.126}$$

$$\gamma\left(\overline{\theta}\right) - \gamma\left(\underline{\theta}\right) = F(\theta_1) - \int_{\underline{\theta}}^{\theta_1} \tau(\theta)\, d\theta \tag{2.127}$$

Rearranging (2.127):

$$\gamma(\theta_1) - F(\theta_1) + \int_{\theta}^{\theta_1} \tau(\theta)\, d\theta = \gamma\left(\underline{\theta}\right) - \int_{\underline{\theta}}^{\theta} \tau(z)\, dz. \tag{2.128}$$

Let

$$\mu_1(\theta) \equiv \int_{\underline{\theta}}^{\theta} \tau(z)\, dz - \gamma\left(\underline{\theta}\right). \tag{2.129}$$

If $S\left(\underline{\theta}\right) > 0$, then $\gamma\left(\underline{\theta}\right)$ and $\mu_1(\theta) = 0$ for $\theta \in \left[\underline{\theta}, \theta_1\right]$.

Alternatively, it may be the case that both $\underline{\theta}$ and all $\theta \in \hat{\Theta}_M$ receive zero surplus. Define:

$$\begin{aligned} D_1(\gamma(\theta)) &\equiv S(\theta_1) - S\left(\underline{\theta}\right) \\ &= \int_{\underline{\theta}}^{\theta_1} \Pi_\theta\left(a^*\left(\theta, \gamma(\theta), \lambda\right), \theta\right) d\theta - \int_{\theta_L}^{\theta_1} [1-\rho]\, \pi_\theta\left(p_h, \overline{a}, \theta\right) d\theta. \end{aligned} \tag{2.130}$$

In this case, $D_1(\gamma(\theta)) = 0$ and

$$\mu_1(\theta) = \hat{\mu}_1(\theta) \equiv \{\hat{\mu} : D_1(F(\theta) - \hat{\mu}) = 0\}, \text{ for } \theta \in [\underline{\theta}, \theta_1].$$

Similarly, let

$$\mu_2(\theta) \equiv 1 - \gamma(\bar{\theta}) - \int_\theta^{\bar{\theta}} \tau(z)\,dz.$$

If $S(\bar{\theta}) > 0$, then $\gamma(\underline{\theta}) = 0$ and $\mu_2(\theta) = 1$ for $\theta \in [\theta_2, \bar{\theta}]$. It also may be the case that $\bar{\theta}$ and all $\theta \in \hat{\Theta}_M$ receive zero surplus.

Define:

$$\begin{aligned} D_2(\gamma(\theta)) &\equiv S(\bar{\theta}) - S(\theta_2) \qquad (2.131) \\ &= \int_{\theta_2}^{\bar{\theta}} \Pi_\theta(a^*(\theta, \gamma(\theta), \lambda), \theta)\,d\theta - \int_{\theta_2}^{\theta_H} [1-\rho]\,\pi_\theta(p_h, \overline{a}, \theta)\,d\theta \\ &\quad - \int_{\Theta_H} \Pi_\theta(\overline{a}, \theta)\,d\theta. \end{aligned}$$

In this case $D_1(\gamma(\theta)) = 0$ and

$$\mu_2(\theta) = \hat{\mu}_2(\theta) \equiv \{\hat{\mu} : D_2(F(\theta) - \hat{\mu}) = 0\}, \text{ for } \theta \in [\theta_2, \bar{\theta}].$$

Table 2.1 summarizes the possible optimal paths of $a(\theta)$. These land allocations and corresponding expected surplus paths are illustrated in Figures 2.3 - 2.9.

It remains to verify that these possible solutions satisfy the monotonicity condition (2.39). Differentiation of (2.92) for an interior solution yields:

$$\frac{da^*}{d\theta} = -\frac{\Pi_{a\theta} + \Pi_{a\theta}\frac{d}{d\theta}\left(\frac{\gamma(\theta)}{f(\theta)}\right) + \frac{\gamma(\theta)}{f(\theta)}\Pi_{a\theta\theta}}{\Pi_{aa} + \frac{\gamma(\theta)}{f(\theta)}\Pi_{aa\theta}}. \qquad (2.132)$$

Regularity conditions (R2), (R4), (R5), and (R6) ensure that the right hand side of this equation is strictly positive, hence the monotonicity condition is satisfied for all of the above cases.

Table 2.1: Optimal Land Allocation

Land Allocation	Interval	Condition
1. $a^*(\theta, F(\theta) - 1, \lambda)$	$\theta \in \Theta$	$D(F(\theta) - 1)$, and $D_1(F(\theta) - 1) > 0$
2. $a^*(\theta, F(\theta), \lambda)$	$\theta \in \Theta$	$D(F(\theta))$, $D_2(F(\theta)) < 0$
3. $a^*(\theta, F(\theta) - \hat{\mu}(\theta), \lambda)$	$\theta \in \Theta$	$D_1(F(\theta) - \hat{\mu}(\theta)) > 0$, $D_2(F(\theta) - \hat{\mu}(\theta)) < 0$, and $D(F(\theta) - \hat{\mu}(\theta)) = 0$
4. $a^*(\theta, F(\theta), \lambda)$ $\hat{a}$ $a^*(\theta, F(\theta) - 1, \lambda)$	$\theta < \theta_1$ $\theta \in \hat{\Theta}_M$ $\theta > \theta_2$	$D_1(F(\theta)) < 0$, and $D_2(F(\theta) - 1) > 0$
5. $a^*(\theta, F(\theta) - \hat{\mu}_1(\theta), \lambda)$ $\hat{a}$ $a^*(\theta, F(\theta) - \hat{\mu}_2(\theta), \lambda)$	$\theta < \theta_1$ $\theta \in \hat{\Theta}_M$ $\theta > \theta_2$	$D_1(F(\theta) - \hat{\mu}_1(\theta))$ and $D_2(F(\theta) - \hat{\mu}_2(\theta)) = 0$
6. $a^*(\theta, F(\theta) - \hat{\mu}_1(\theta), \lambda)$ $\hat{a}$ $a^*(\theta, F(\theta) - 1, \lambda)$	$\theta < \theta_1$ $\theta \in \hat{\Theta}_M$ $\theta > \theta_2$	$D_1(F(\theta) - \hat{\mu}_1(\theta)) = 0$, and $D_2(F(\theta) - 1) > 0$
7. $a^*(\theta, F(\theta), \lambda)$ $\hat{a}$ $a^*(\theta, F(\theta) - \hat{\mu}_2(\theta), \lambda)$	$\theta < \theta_1$ $\theta \in \hat{\Theta}_M$ $\theta > \theta_2$	$D_1(F(\theta)) < 0$, and $D_2(F(\theta) - \hat{\mu}_2(\theta)) = 0$

Figure 2.3: *Ex Ante* Land Allocation 1

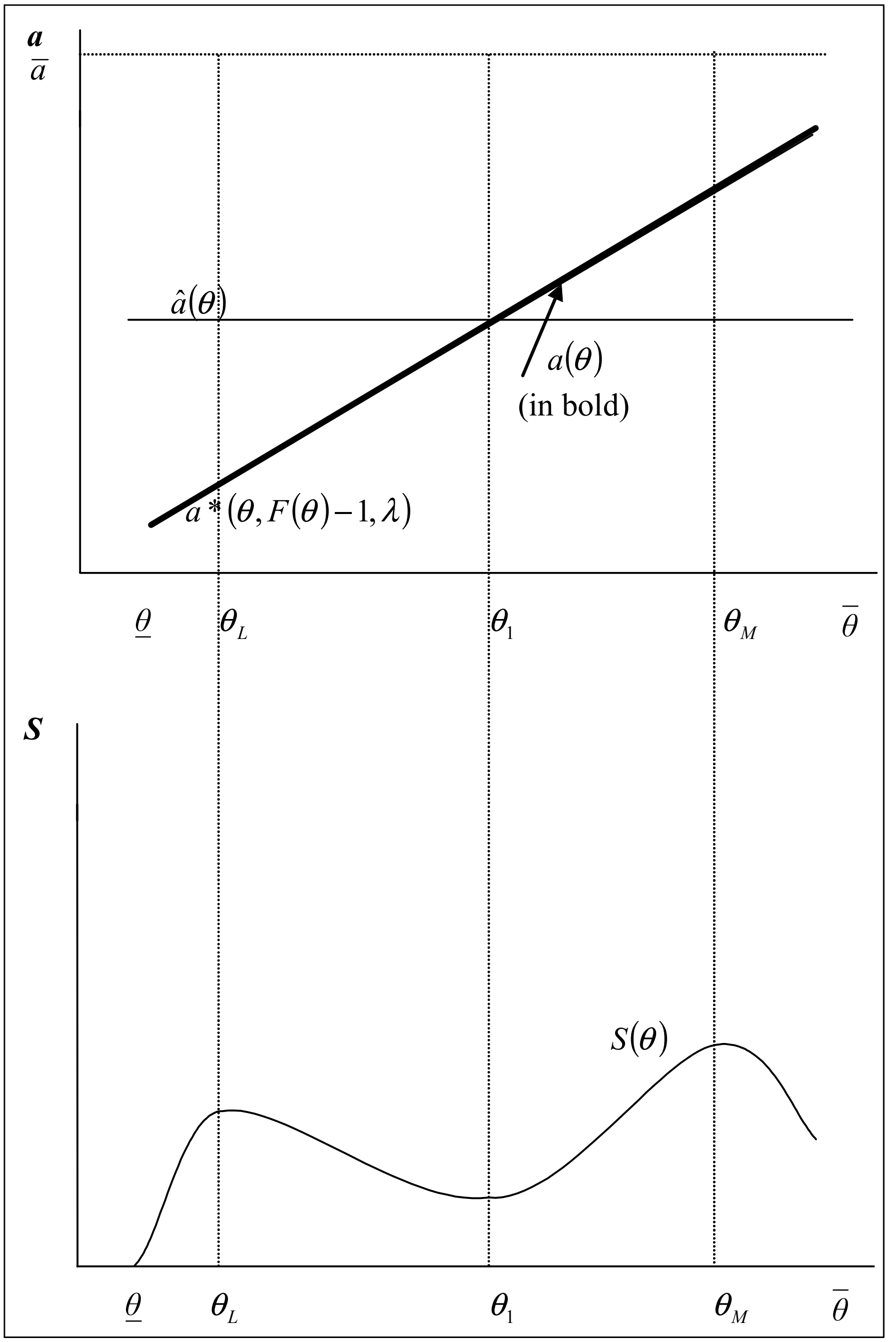


Figure 2.4: *Ex Ante* Land Allocation 2

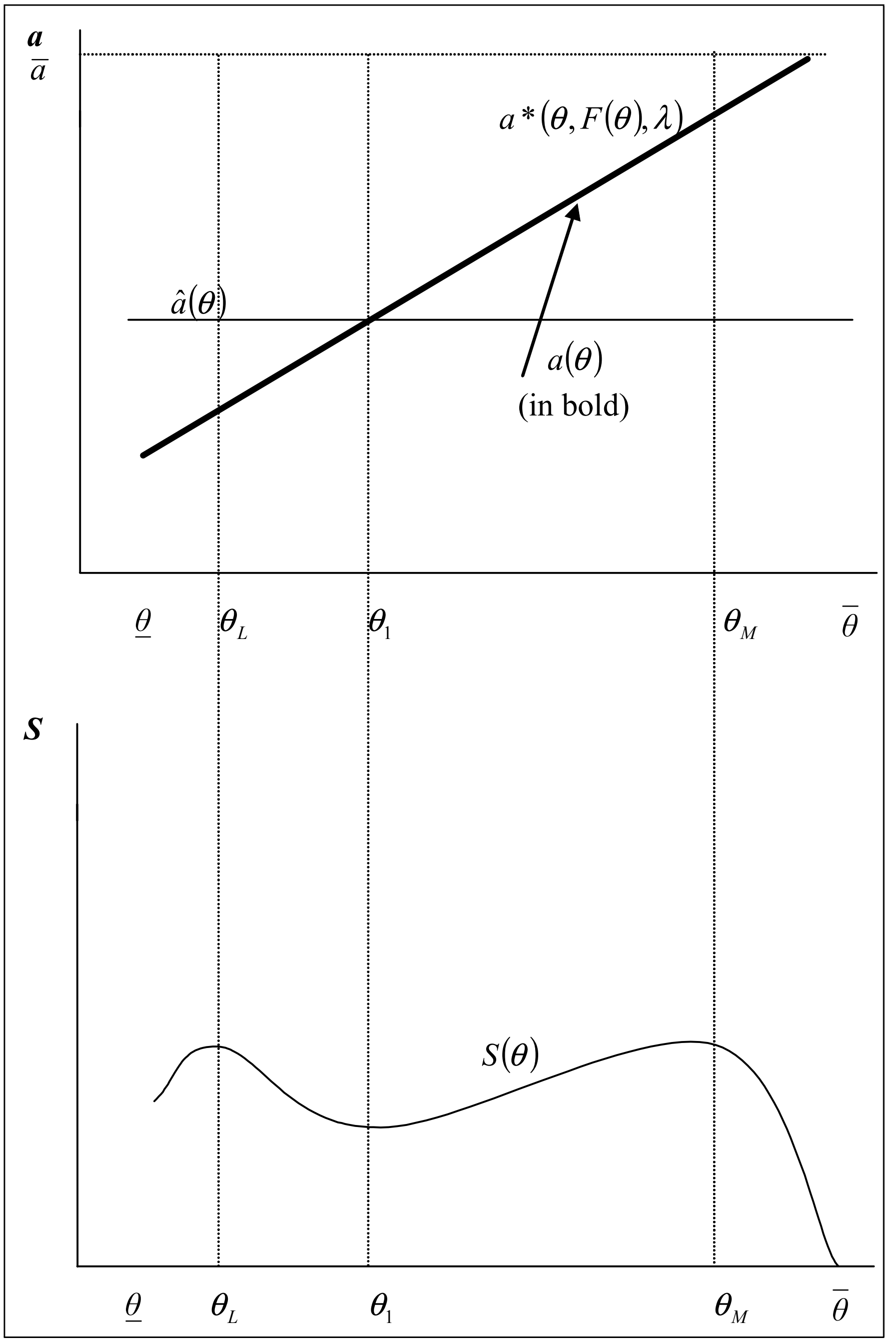


Figure 2.5: *Ex Ante* Land Allocation 3

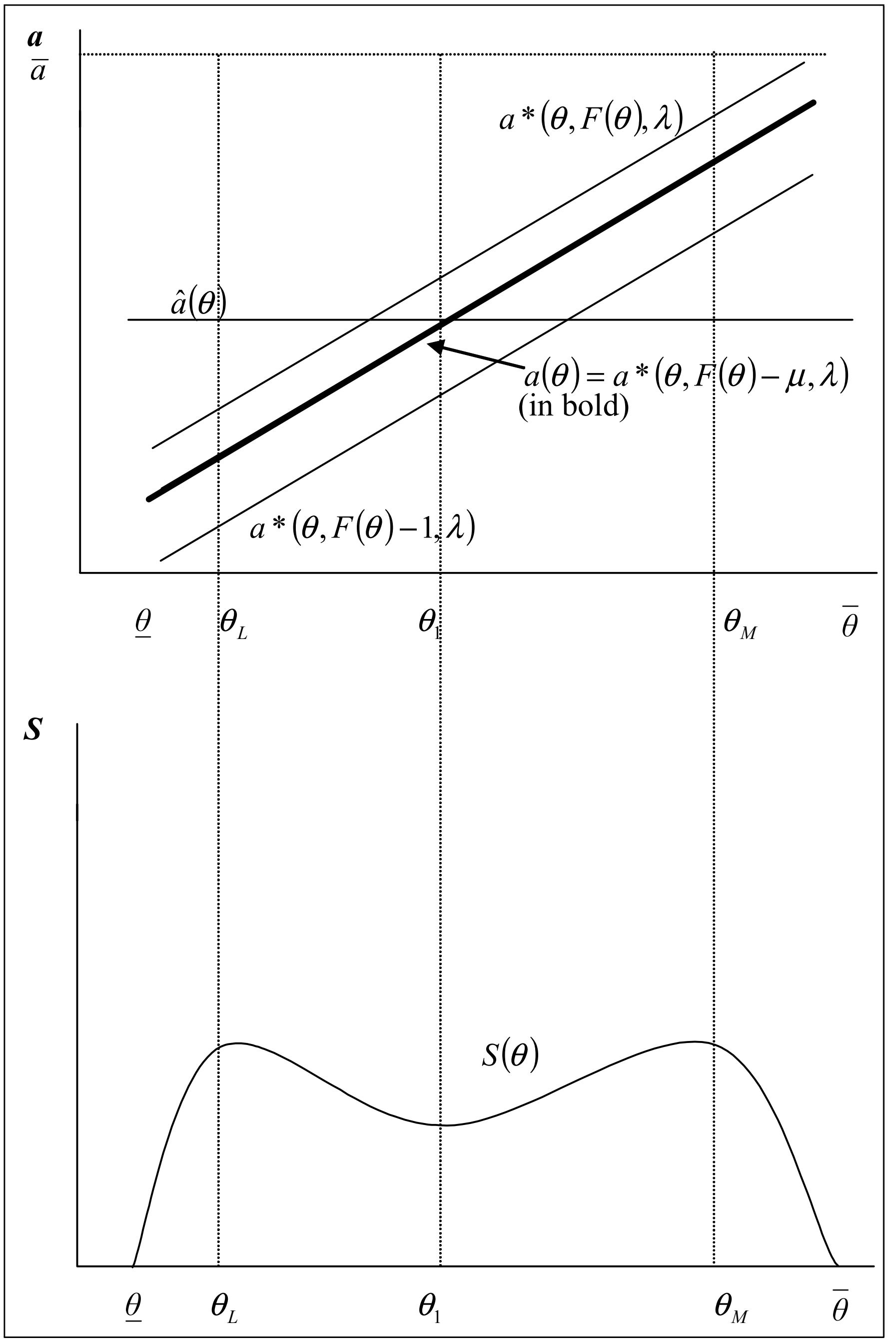


Figure 2.6: *Ex Ante* Land Allocation 4

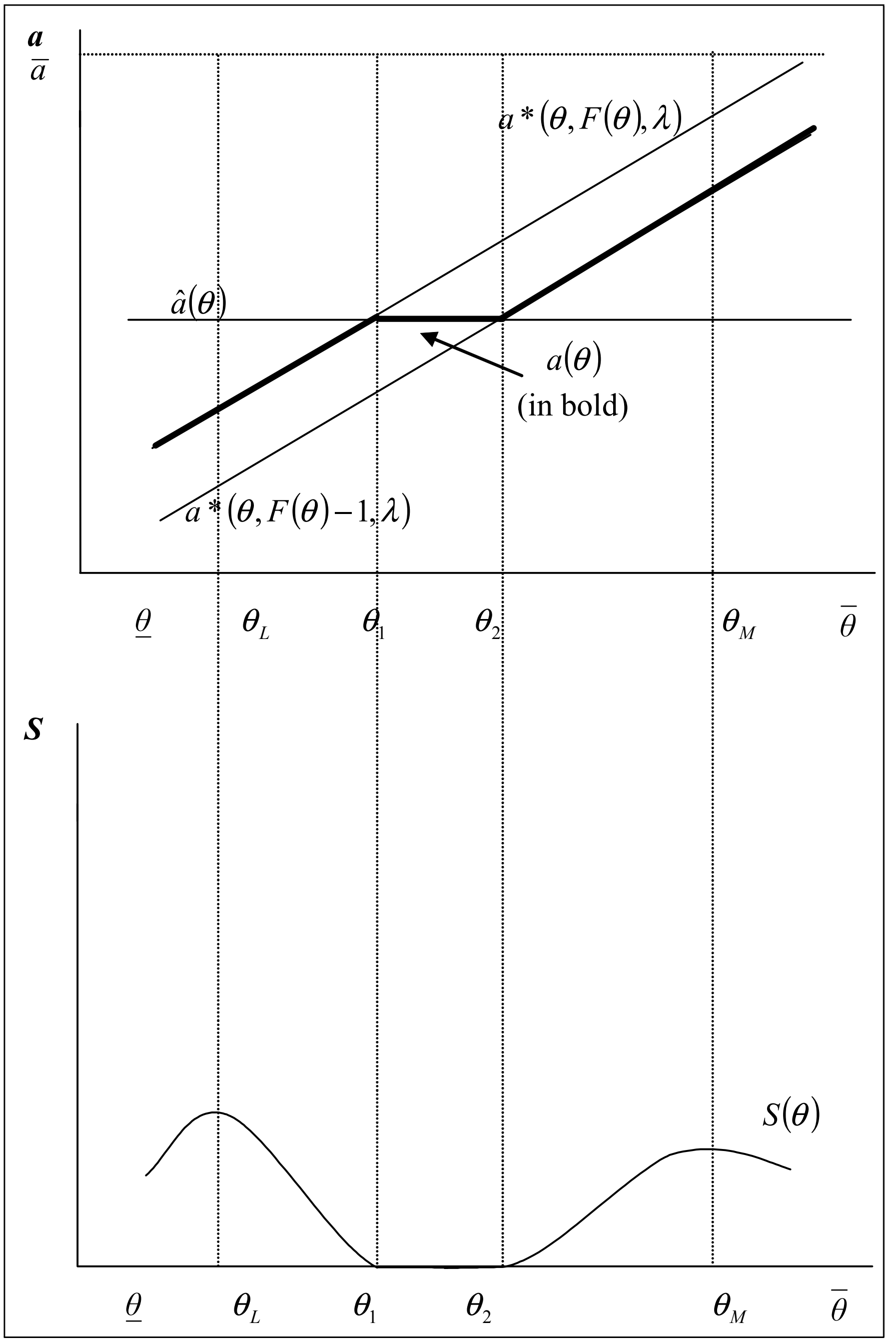


Figure 2.7: *Ex Ante* Land Allocation 5

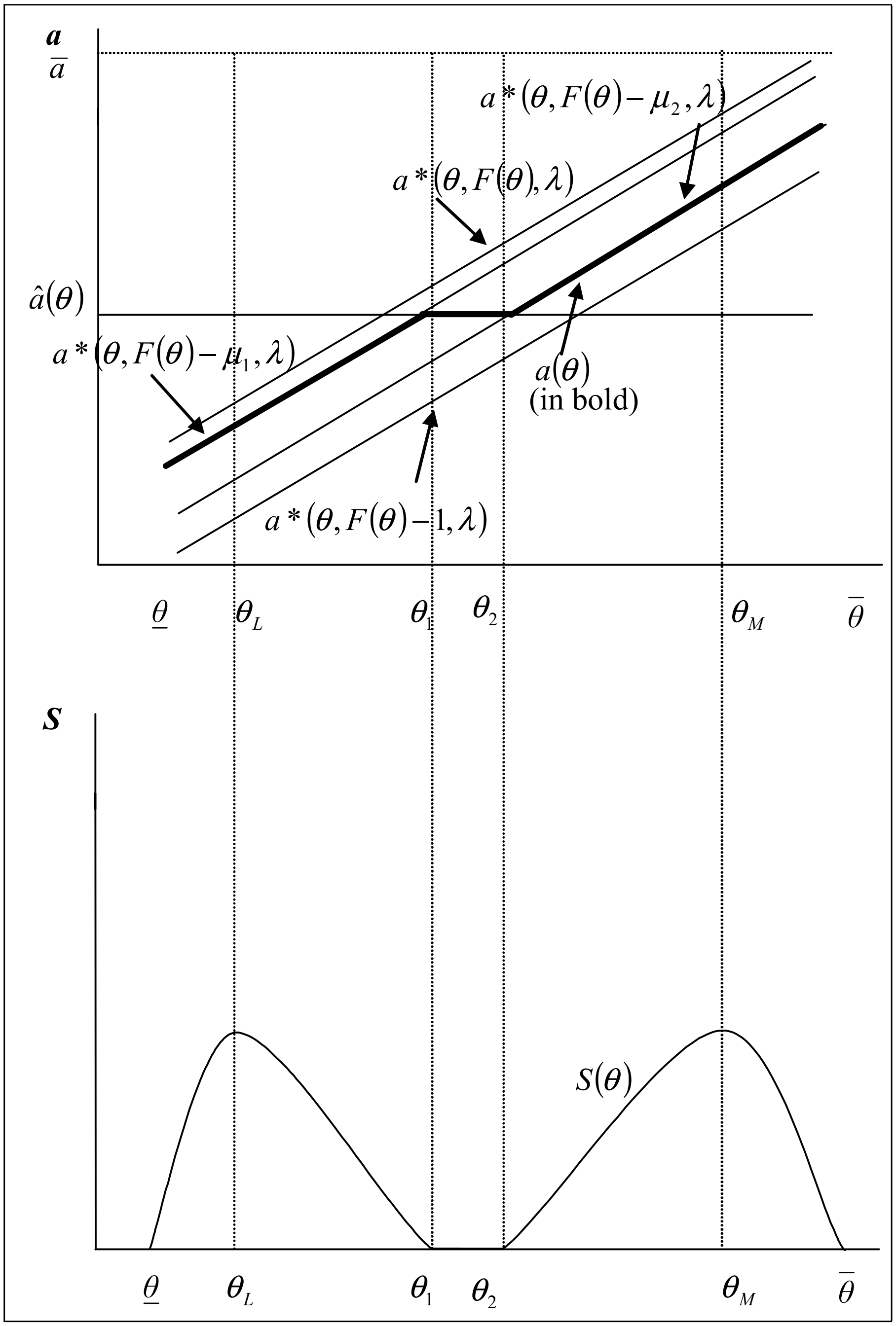


Figure 2.8: *Ex Ante* Land Allocation 6

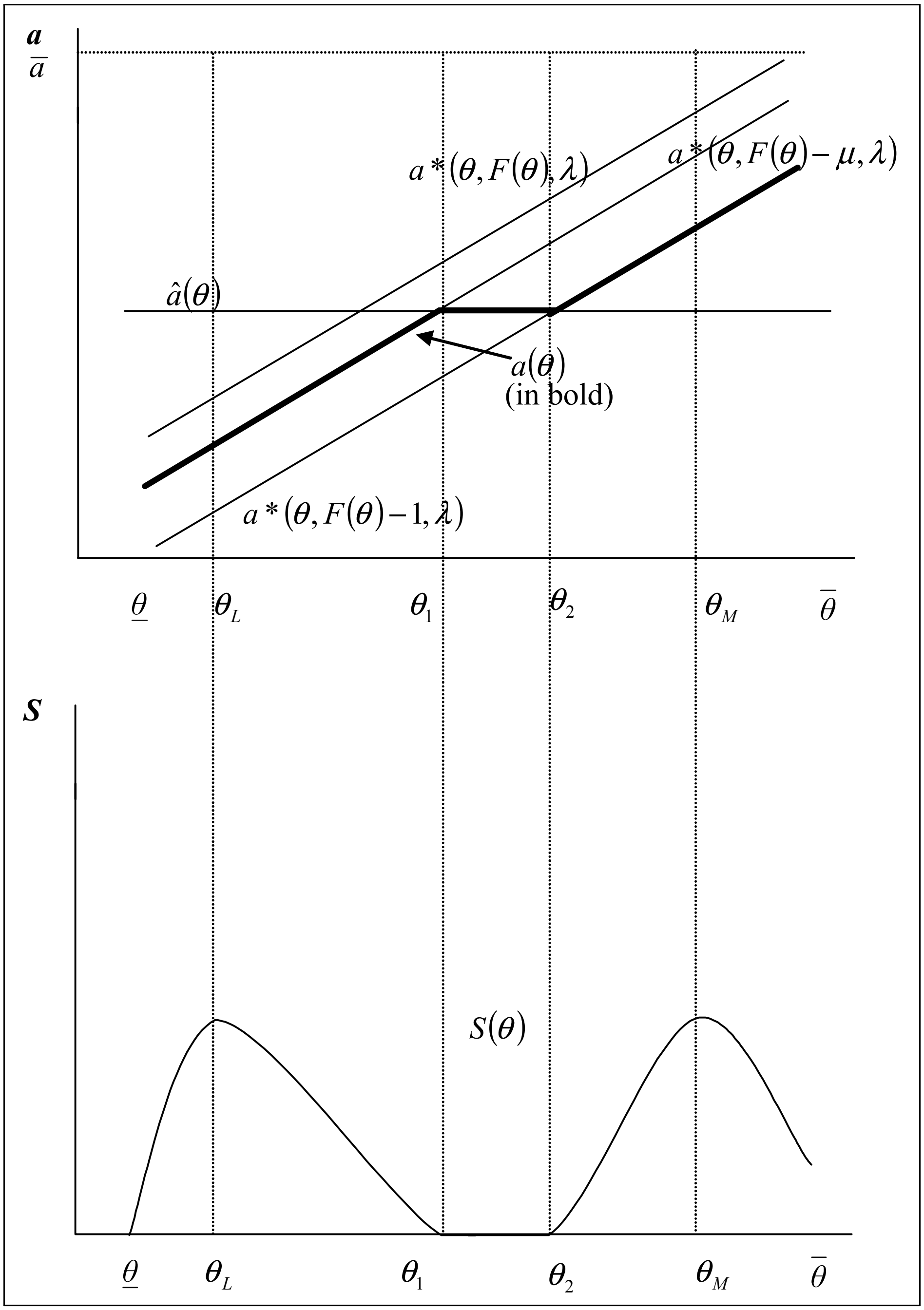
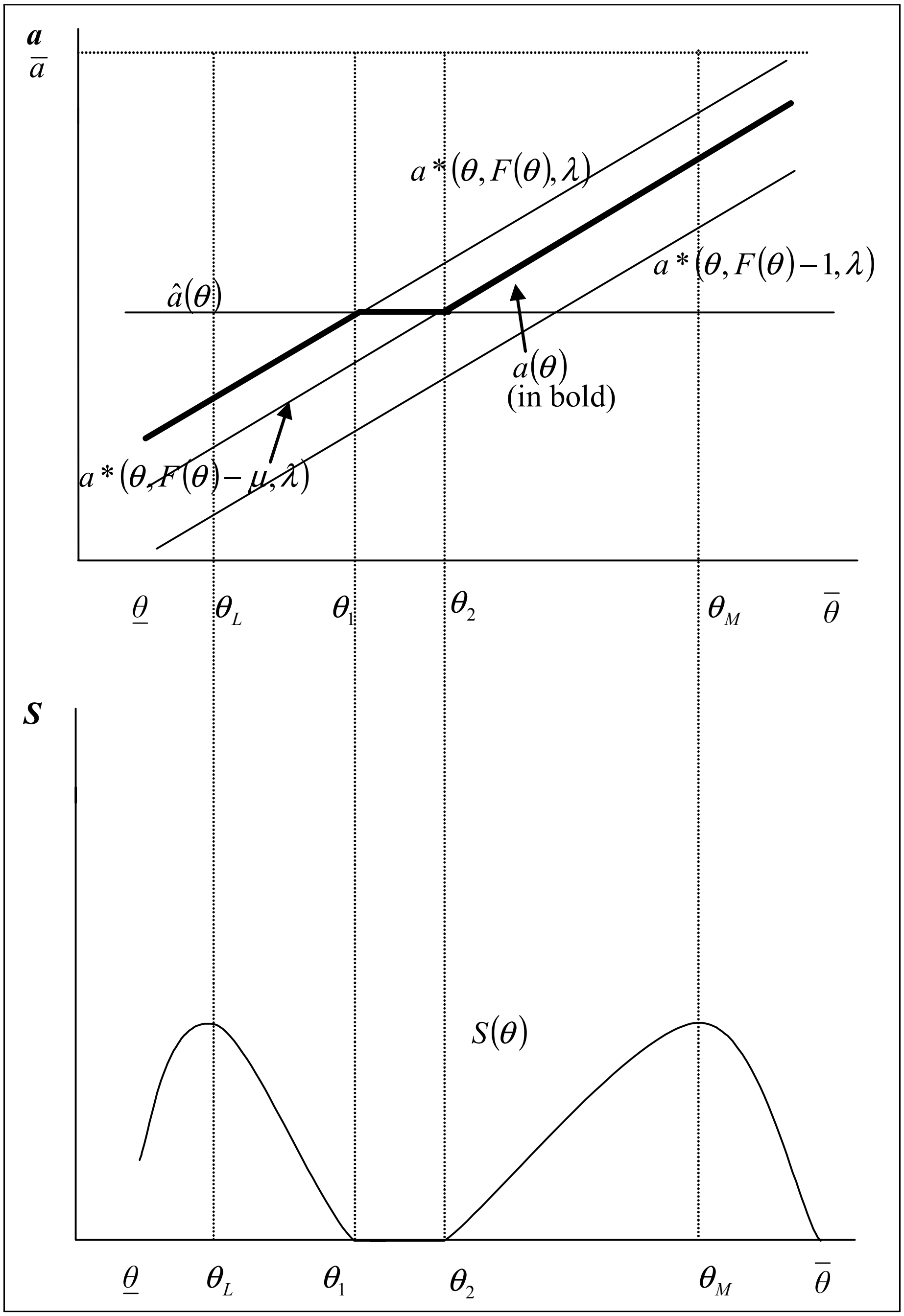


Figure 2.9: *Ex Ante* Land Allocation 7



None of the solutions listed in Table 2.1 can be ruled out *a priori*. Examining Figures 2.3 - 2.9 we can observe several possible outcomes regarding expected surplus. In each outcome at least one type receives zero expected surplus. However, it is also possible that both extreme types receive zero expected surplus, an interval of interior types receives zero expected surplus, or some combination thereof.

In Figure 2.3, the dominant incentive for all types is to mimic the lowest type. As a result, only the lowest type receives zero surplus. The type (θ_1) for which the slope of expected surplus is zero is a local minimum and receives strictly positive expected surplus. In Figure 2.4, this situation is reversed with only the highest type receiving zero expected surplus. In Figure 2.5, all interior types are indifferent between mimicking either extreme type. Note that this does not mean that the incentive to overstate type exactly countervails the incentive to understate type, leaving the producer without any incentive to misrepresent the true type. Instead the producer might profitably imitate either a higher or lower type, it turns out that the expected surplus received either way is exactly the same. Consequently, only the two extreme types receive zero expected surplus. In Figures 2.3 - 2.5, countervailing incentives are not strong enough to make pooling optimal, either in land cultivated or surplus received.

In Figure 2.6, for $\hat{\Theta}_M$ the expected gain from overstating type if $p = p_h$ is exactly countervailed by the expected loss should the realized price be p_ℓ. These types require no expected surplus payments to state their true type. For types to the left of $\hat{\Theta}_M$ the dominant incentive is to overstate type. The opposite is true for those to the right. Figures 2.7 - 2.9 differ only in the respect that some types not in $\hat{\Theta}_M$ are indifferent between overstating and understating type. Note again that these producers might profitably overstate or understate type, the expected gain being the same. In each case depicted in Figures 2.6 - 2.9, countervailing incentives result in an optimal pooling both in land use and land cultivated for types belonging to $\hat{\Theta}_M$.

Which solution applies depends on the specific functional form of $\Pi(a, \theta)$ and $f(\theta)$ and the values of prices and other parameters in the model. The characteristics of the various solutions differ greatly: some exhibit pooling in land allocated to an interval of types, while others do not; some allow expected surplus to be eliminated for several types, while others give positive expected surplus to all types except one or two. Thus, even a general qualitative description of what an optimal green payments mechanism looks like is impossible without specifying $\Pi(a, \theta)$ and $f(\theta)$.

Since the optimal *ex post* mechanism is more constrained than the optimal *ex ante* mechanism it cannot be less costly. However, this analysis goes farther, showing that in some circumstances, the *ex post* contract must be more costly. To see this, compare (2.79) and (2.80) with Table 2.1 and note that a land allocation that satisfies the necessary conditions for the *ex post* contract does not satisfy the necessary conditions for an optimal *ex ante* contract. For example, requiring an interval of types to idle the same quantity of land is never optimal for an *ex post* mechanism. As a result, an *ex post* mechanism cannot reduce costs to the level of an *ex ante* contract when such pooling is optimal. Moreover, for the *ex ante* mechanism at least one type always receives zero expected surplus. It may also be the case that expected surplus payments can be completely eliminated for an entire interval of types. For the *ex post* mechanism, however, at most two types receive zero expected surplus, and in some cases no type receives zero expected surplus.

2.3.3 FAIR Act

For comparison, I examine a stylized version of the income support and land set aside programs in the 1996 FAIR Act. As discussed in Chapter 1, income support in the FAIR Act can be modeled as lump-sum payments conditional on prevailing output price. Land set asides in the Conservation Reserve Program (CRP) were conducted using a competitive auction. The land set asides were for at least a 10-year period. Since farmers were not certain whether average output prices would be high or low during that period this program is treated as an *ex ante* mechanism.

The key difference between this policy and the optimal *ex ante* policy is that the FAIR Act uses two policy instruments to attain two policy targets. This structure contrasts with the optimal mechanism which essentially kills two birds with one stone, using a single payment to achieve both income and environmental goals.

It is impossible to capture all the detail of an actual policy in a simplified model. I therefore focus attention on an "optimal" FAIR Act in the policy setting described in Section 2.1. This policy seeks to minimize the cost of attaining income and environmental objectives subject to the additional constraints that equal lump-sum income support payments are made to all farmers.

First consider the government's problem with respect to the environmental program. The CRP is unconcerned with income support, however it still must satisfy the participation constraint (2.6). Hence, it is as if all types belong to Θ_H. Smith (1995) has derived a least-cost CRP in a similar setting. Using the notation of previous sections, the government's objective function for the CRP is:

$$\min_{T(\theta),a(\theta)} \int_{\Theta} T(\theta)\, dF(\theta) \tag{2.133}$$

subject to (2.5), (2.134), (2.135), and (2.136).

Expected CRP surplus payments, $S_c(\theta)$, are those received in excess of the participation constraint:

$$S_c(\theta) \equiv T(\theta) - [\Pi(\bar{a},\theta) - \Pi(a(\theta),\theta)] \geq 0. \tag{2.134}$$

In this case, incentive compatibility requires that expected surplus be decreasing for all types:

$$S_c'(\theta) = \Pi_\theta(a(\theta),\theta) - \Pi_\theta(\bar{a},\theta) \leq 0; \tag{2.135}$$

and that land cultivated must be non-decreasing in type,

$$a'(\theta) \geq 0. \tag{2.136}$$

This problem is simplified by changing $S_c(\theta)$ for $T(\theta)$ in the objective function and writing the Lagrangian temporarily ignoring constraint (2.136):

$$\begin{aligned} &\min_{a(\theta),S(\theta),\lambda,\tau(\theta),\gamma(\theta)} \int_{\Theta} \{S_c(\theta) - \Pi(a,\theta) + \Pi(\bar{a},\theta) - \lambda[\overline{a} - a(\theta) - A] \\ &-\frac{\alpha(\theta)}{f(\theta)}[\overline{a} - a(\theta)] \\ &+\frac{\gamma(\theta)[S_c'(\theta) - \Pi_\theta(a(\theta),\theta) + \Pi_\theta(\overline{a},\theta)] - \tau(\theta)S_c(\theta)}{f(\theta)}\Bigg\}\, dF(\theta), \end{aligned} \tag{2.137}$$

where λ is the Lagrange multiplier for (2.5), $\gamma(\theta)$ is the Lagrange multiplier for (2.135), $\tau(\theta)$ is the Lagrange multiplier for (2.134), and $\alpha(\theta)$ is the Lagrange multiplier for the constraint $a(\theta) \leq \bar{a}$. After integration by parts this expression becomes:

$$\begin{aligned}
&\min_{a(\theta),S(\theta),\lambda,\tau(\theta),\gamma(\theta)} \int_{\Theta} \{S_c(\theta) - \Pi(a(\theta),\theta) + \Pi(\overline{a},\theta) - \lambda[\overline{a} - a(\theta) - A] \\
&-\frac{\alpha(\theta)}{f(\theta)}[\overline{a} - a(\theta)] - \frac{\gamma(\theta)}{f(\theta)}\Pi_\theta(a(\theta),\theta) - \frac{\gamma'(\theta) + \tau(\theta)}{f(\theta)}S_c(\theta)\Big\} dF(\theta) \\
&-\gamma(\underline{\theta}) S_c(\underline{\theta}) + \gamma(\bar{\theta}) S_c(\bar{\theta}). \qquad (2.138)
\end{aligned}$$

The necessary conditions for optimal land cultivation are:

$$\begin{aligned}
\Pi_a(a(\theta),\theta) + \frac{\gamma(\theta)}{f(\theta)}\Pi_{a\theta}(a(\theta),\theta) - \lambda - \frac{\alpha(\theta)}{f(\theta)} &\geq 0. \qquad (2.139)\\
a(\theta) &\geq 0 \qquad (2.140)\\
a(\theta)\left[\Pi_a(a(\theta),\theta) + \frac{\gamma(\theta)}{f(\theta)}\Pi_{a\theta}(a(\theta),\theta) - \lambda - \frac{\alpha(\theta)}{f(\theta)}\right] &= 0 \qquad (2.141)\\
\bar{a} - a(\theta) &\geq 0 \qquad (2.142)\\
\alpha(\theta) &\geq 0 \qquad (2.143)\\
\alpha(\theta)[\bar{a} - a(\theta)] &= 0 \qquad (2.144)\\
\int_{\Theta}[\overline{a} - a(\theta) - A]\, dF(\theta) &\geq 0 \qquad (2.145)\\
\lambda &\geq 0 \qquad (2.146)\\
\lambda \int_{\Theta}[\overline{a} - a(\theta) - A]\, dF(\theta) &= 0 \qquad (2.147)
\end{aligned}$$

The necessary conditions for $S_c(\theta)$ are:

$$\begin{aligned}
\gamma'(\theta) + \tau(\theta) - f(\theta) &= 0 \qquad (2.148)\\
\tau(\theta) &\geq 0 \qquad (2.149)\\
S_c(\theta) &\geq 0 \qquad (2.150)\\
\tau(\theta) S_c(\theta) &= 0 \qquad (2.151)
\end{aligned}$$

Necessary conditions for optimal endpoints of $S_c(\theta)$ are:

$$
\begin{aligned}
-\gamma\left(\underline{\theta}\right) &\geq 0 && (2.152)\\
S_c\left(\underline{\theta}\right) &\geq 0 && (2.153)\\
S_c\left(\underline{\theta}\right)\gamma\left(\underline{\theta}\right) &= 0 && (2.154)\\
\gamma\left(\overline{\theta}\right) &\geq 0 && (2.155)\\
S_c\left(\overline{\theta}\right) &\geq 0 && (2.156)\\
S_c\left(\overline{\theta}\right)\gamma\left(\overline{\theta}\right) &= 0. && (2.157)
\end{aligned}
$$

Since $S_c'(\theta) \leq 0$ if any type receives zero surplus it will be $\overline{\theta}$. Suppose $S_c\left(\overline{\theta}\right) > 0$. In that case $\tau(\theta) = 0$ for all types, and $\gamma\left(\underline{\theta}\right) = \gamma\left(\overline{\theta}\right) = 0$. Condition (2.148) can be integrated to obtain:

$$
\begin{aligned}
\gamma(\theta) &= F(\theta) - 1, \text{ and} && (2.158)\\
\gamma(\theta) &= F(\theta). && (2.159)
\end{aligned}
$$

Consequently, the conjecture is false that optimally $S_c\left(\overline{\theta}\right) > 0$. If $S_c\left(\overline{\theta}\right) = 0$, then integration of (2.148) implies:

$$
\gamma(\theta) = F(\theta). \tag{2.160}
$$

Inserting (2.160) into first order condition (2.139) reveals that land cultivation is increasing in type, with no pooling. Surplus is decreasing in type, with all types receiving strictly positive surplus except for $\overline{\theta}$, which receives zero surplus. Intuitively, since the CRP must compensate producers for the opportunity cost of their land, all producers have an incentive to overstate type. Since lower types have relatively greater scope to overstate their type, they must receive higher surplus payments to induce truth-telling.

In addition, notice that although surplus is decreasing in type, total income is increasing in type. Total income is profit earned from production plus CRP transfers. Using (2.134) we can rewrite total income in terms of surplus payments rather than transfers:

$$\begin{aligned} T(\theta) + \Pi(a(\theta), \theta) &= S_c(\theta) + [\Pi(\bar{a}, \theta) - \Pi(a(\theta), \theta)] && (2.161) \\ &\quad + \Pi(a(\theta), \theta) \\ &= S_c(\theta) + \Pi(\bar{a}, \theta). && (2.162) \end{aligned}$$

The rate of change of total income across types is therefore:

$$\begin{aligned} S_c'(\theta) + \Pi_\theta(\bar{a}, \theta) &= \Pi_\theta(a(\theta), \theta) - \Pi_\theta(\bar{a}, \theta) + \Pi_\theta(\bar{a}, \theta) && (2.163) \\ &= \Pi_\theta(a(\theta), \theta), && (2.164) \end{aligned}$$

which is positive by (R3).

Now consider the income support program. Since it provides equal lump-sum transfers to all farmers, it does not make payment contingent upon land set aside. Suppose the expected lump-sum income support payments P are designed to ensure that the lowest-type producer attains minimum income m. Further, suppose that the agency administering the program knows that the CRP results in a distribution of farm income that is increasing in type, with the lowest type earning $S_c(\underline{\theta}) + \Pi(\bar{a}, \underline{\theta})$. The lowest lump-sum payment P is therefore:

$$P = m - S_c(\underline{\theta}) - \Pi(\bar{a}, \underline{\theta}). \qquad (2.165)$$

Total expected surplus from CRP and income support is total payments received in excess of the amount necessary to satisfy the income constraint:

$$\begin{aligned} P+T(\theta)-[m-\Pi(a(\theta),\theta)] &= P+S_c(\theta)+\Pi(\bar{a},\theta) \\ &\quad -\Pi(a(\theta),\theta)-[m-\Pi(a(\theta),\theta)] \\ &= P+S_c(\theta)+\Pi(\bar{a},\theta)-m. \end{aligned}$$

The rate of change of total expected surplus is therefore the same as the rate of change of total income (2.164). Total expected surplus is increasing, with $\underline{\theta}$ receiving zero surplus.

The land allocation corresponding to (2.160) is that corresponding to the second example in Table 2.1. Therefore, the FAIR land allocation may be equivalent to that of an optimal *ex ante* mechanism, but not necessarily. Suppose that the structure of $\Pi(a,\theta)$ and $f(\theta)$ are such that this land allocation is in fact optimal. Even in this case the payment scheme of the FAIR contract is not identical to the contract schedule of the optimal *ex ante* mechanism for the entire range of types. From equation (2.89) we see that total expected surplus for the two mechanisms are the same for Θ_L. However, expected surplus is growing at a faster rate for the FAIR mechanism than the optimal mechanism for Θ_M and Θ_H. Hence, even in the best of circumstances the FAIR Act provides excessive payments to relatively high types, relative to an optimal *ex ante* mechanism. These excess payments represent the cost of not properly using information obtained from the environmental program to shape the income support program.

2.4 Discussion

In this chapter I have examined four mechanisms for achieving income support and environmental objectives of agricultural policy. As a baseline I first considered the first-best mechanism. This mechanism is only feasible if the government directly observes the productivity of each producer's land. With this policy there is no pooling in terms of land set asides. The amount of land cultivated is strictly increasing in land productivity such that the marginal profit from land is equal for all types. Payments received by producers are exactly enough to ensure that farmers voluntarily participate and that they attain the minimum income level. Hence, no type receives surplus payments.

Next I considered two types of mechanisms that are feasible when productivity is privately known to producers. The two types of mechanisms differ by when contracting takes place. For an *ex post* mechanism contracting takes place after output price is known. For an *ex ante* mechanism contracting takes place before output price is known.

Even if beliefs regarding prices are commonly held, price uncertainty unambiguously helps the government. As in Bontems and Bourgeon (2000), the random variable does this by creating countervailing incentives for producers. Intuitively, price uncertainty weakens the incentive some producers have to misrepresent their true type. Some producers have an incentive to over-state their type in one price state and under-state their type in the other. Price uncertainty effectively adds a cost to misrepresenting type if they guess output price incorrectly. Consequently, they require less surplus to reveal their true type than if price were known. For some types, countervailing incentives may be strong enough that all incentive to misrepresent type is eliminated. In this case, surplus payments are eliminated for all these types.

The intuition regarding the superiority of *ex ante* mechanism can be supported mathematically. The objective function of the two mechanisms are identical.

The only difference is that the *ex post* contract has an additional constraint. Thus, the *ex post* contract can be no better than the *ex ante* contract. The analysis in this chapter allows the stronger statement that the *ex post* mechanism is unambiguously costlier than the *ex ante* mechanism. This conclusion can be seen by noting that the optimal land allocation for the *ex post* mechanism does not satisfy the necessary conditions for an optimal *ex ante* mechanism.

Finally, we compared an optimal *ex ante* green payments mechanism with a stylized version of actual *ex ante* policies that treat income support and environmental goals separately. Separate policies similar to those enacted in the 1996 FAIR legislation are not least cost. The land allocation resulting from separated policies does not generally satisfy the necessary conditions for the optimal *ex ante* mechanism. There is one special case in which the land allocation of the FAIR Act does satisfy the necessary condition for an optimum. However, even in this case expected surplus payments are higher than for the optimal *ex ante* mechanism.

In a context of imperfect information it is not optimal to use separate policies to achieve environmental and income support goals. The costs of achieving both objectives are linked to hidden information regarding land productivity. A least cost program uses information from participation in one program to determine payments in the other. In addition, making contract commitment when output price is uncertain reduces cost.

Finally, this chapter highlights the crucial role of empirical analysis in designing an optimal green payments program. The characteristics of the optimal contract schedule are highly sensitive to the government's beliefs regarding producer technology and the distribution of producer types. For example, for some sets of beliefs it is optimal for an interval of types to idle the same amount of land, whereas for others it is not. The rest of the dissertation deals with the problems of i) estimating a producer profit function and a probability density function for types using readily available data, and ii) using these estimates to calibrate an optimal green payments contract schedule.

Chapter 3

Empirical Model: Theory

This chapter develops an empirically tractable model of agricultural production that can be used to calibrate the optimal green payments program derived in the previous chapter. The fundamental problem deals with how to estimate a model of agricultural production that not only allows for unobservable heterogeneity in productivity across observations, but provides an estimate of the distribution of productivity levels (producer types) across the population.

The chapter begins by specifying a technology that defines type in terms of a parameter that affects the set of inputs required to produce a given set of outputs. I then draw out the implications of these technological assumptions for cost-minimizing behavior. In the second section, I describe an econometric strategy for estimating a cost function that includes the type parameter. Estimation results provide structural estimates that can be used to generate a profit function for each type as well as a function for the distribution of types across the population.

3.1 Technology

3.1.1 Input Requirement Set

The data do not include any directly observable measure of productivity differences across farms. To infer this information, I first specify how type affects production. Specifically, I assume type indicates the effectiveness with which inputs are used to produce output. All else equal, higher types require fewer inputs to produce the same output as lower types.

Producers are characterized by two fixed factors, one observable and one not. The observed factor is land, denoted $a \in \Re_{++}$. The unobserved factor is the producer's type, θ. To make the model empirically tractable, I specify type as a productivity index normalized over the support $\Theta \equiv (0, 1]$. Let $\mathbf{x} \in \Re^n_+$ denote the variable-input vector and $q \in \Re_+$ denote aggregate output. The variable-input requirement set $V(q, a, \theta)$ is defined:

$$V(q, a, \theta) \equiv \{\mathbf{x} : \mathbf{x} \text{ can produce } q \text{ given } a, \theta\}. \tag{3.1}$$

Assume $V(q, a, \theta)$ has the following properties:

(V1) $V(q, a, \theta)$ is closed;

(V2) $V(q, a, \theta)$ is a convex set;

(V3) $\mathbf{x} \in V(q, a, \theta) \Rightarrow \lambda\mathbf{x} \in V(q, a, \theta), \lambda \geq 1$.

(V4) $V(q, a, \lambda\theta) = \frac{1}{\lambda} V(q, a, \theta), \lambda > 0$.

Properties (V1) and (V2) are regularity conditions that allow exploitation of duality theory to represent $V(q, a, \theta)$ with a variable cost function. Property (V3) allows variable inputs to be weakly disposable. Inputs can expand along a ray from the origin without reducing feasible output. Property (V4) specifies the effect of θ on production. An increase in type implies a proportional radial expansion of the input requirement set. For example, referring to Figure 3.1, if θ_2 is twice θ_1, it can produce the same output with half of each variable input, given a. Together with (V3), (V2) implies that a producer can do no worse than a lower type since for any given output level its set of feasible input bundles completely includes the set of feasible input bundles for all lower types.

3.1.2 Cost and Profit Functions

For a vector of variable input prices $\mathbf{w} \in \Re^n_{++}$ the minimum variable cost function $C(\mathbf{w}, q, a, \theta)$ is defined:

$$C(\mathbf{w}, q, a, \theta) \equiv \inf_{\mathbf{x}} \{\mathbf{w}'\mathbf{x} : \mathbf{x} \in V(q, a, \theta)\}. \tag{3.2}$$

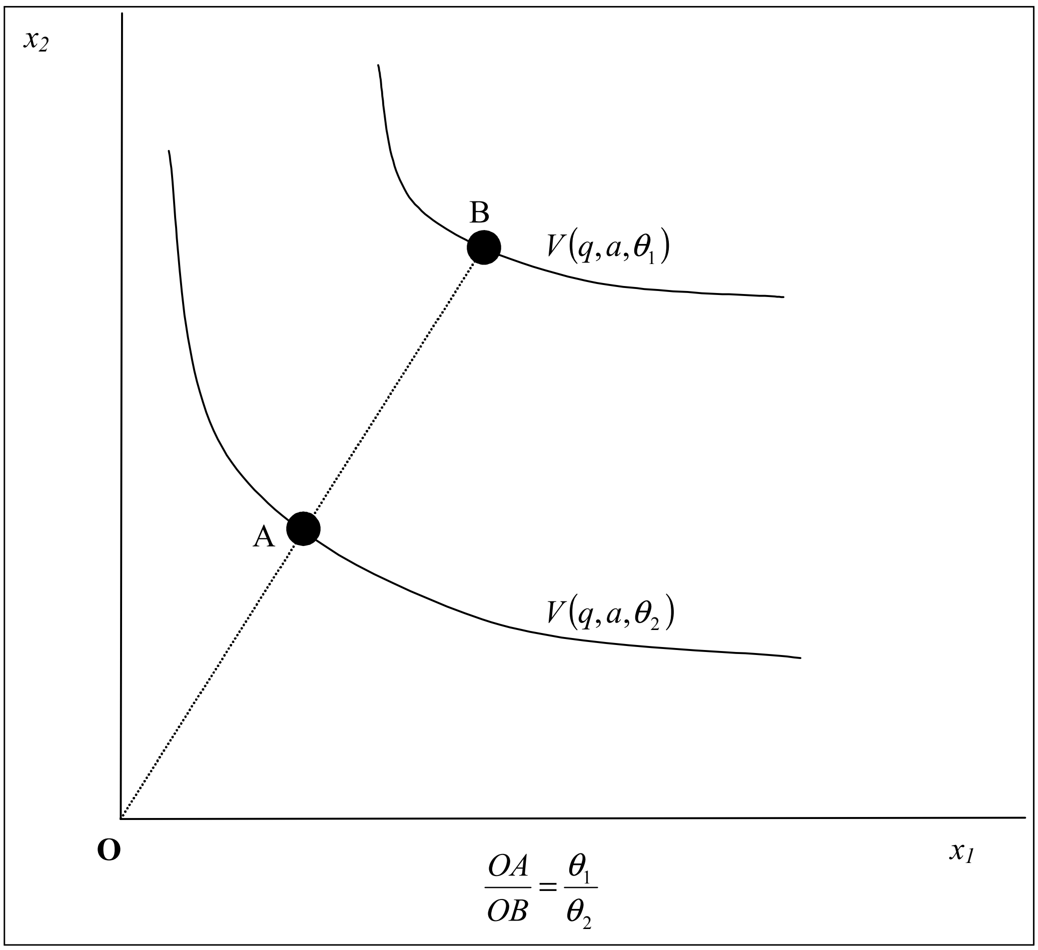
It follows from (V4) that an increase in type by a factor $\lambda > 0$ implies a proportional decrease in the minimum cost of producing q with a:

$$\begin{aligned} C(\mathbf{w}, q, a, \lambda\theta) &= \inf_{\mathbf{x}} \{\mathbf{w}'\mathbf{x} : \mathbf{x} \in V(q, a, \lambda\theta)\} \\ &= \inf_{\mathbf{x}} \left\{\mathbf{w}'\mathbf{x} : \mathbf{x} \in \frac{1}{\lambda} V(q, a, \theta)\right\} \\ &= \inf_{\mathbf{x}} \{\mathbf{w}'\mathbf{x} : \mathbf{x}\lambda \in V(q, a, \theta)\} \\ &= \frac{1}{\lambda} \inf_{\mathbf{x}\lambda} \{\mathbf{w}'\mathbf{x}\lambda \colon \mathbf{x}\lambda \in V(q, a, \theta)\} \\ &= \frac{1}{\lambda} C(\mathbf{w}, q, a, \theta). \end{aligned} \tag{3.3}$$

Define the cost frontier $\tilde{C}(\mathbf{w}, q, a)$ as the minimal cost function across all types:

$$\begin{aligned} \tilde{C}(\mathbf{w}, q, a) &\equiv \inf_{\theta} \{C(\mathbf{w}, q, a, \theta)\} \\ &= C(\mathbf{w}, q, a, 1). \end{aligned} \tag{3.4}$$

Figure 3.1: Type and Productivity



It follows directly from (3.3) that:

$$\ln C(\mathbf{w}, q, a, \theta) = \ln \tilde{C}(\mathbf{w}, q, a) - \ln \theta. \tag{3.5}$$

When an interior solution exists, Shephard's Lemma yields the following expenditure share equations for a cost-minimizing producer,:

$$\frac{w_i x_i{}^*}{C(\mathbf{w}, q, a, \theta)} = \frac{\partial \ln C(\mathbf{w}, q, a, \theta)}{\partial \ln w_i} = \frac{\partial \ln \tilde{C}(\mathbf{w}, q, a)}{\partial \ln w_i}, \ \ i = \{1, ..., n\}, \tag{3.6}$$

where $x_i{}^*$ is the cost-minimizing quantity of input i.

For a given output price $p \in \Re_{++}$, the maximum variable profit function $\pi(p, \mathbf{w}, a, \theta)$ is defined,

$$\pi(p, \mathbf{w}, a, \theta) \equiv \sup_q \{pq - C(\mathbf{w}, q, a, \theta)\}. \tag{3.7}$$

Let q^* be the profit maximizing output quantity.. For an interior solution, profit maximization implies:

$$p = \frac{\partial C(\mathbf{w}, q^*, a, \theta)}{\partial q}. \tag{3.8}$$

Algebraic manipulation of (3.8) yields the ratio of revenue to cost:

$$\begin{aligned} \frac{pq^*}{C(\mathbf{w}, q, a, \theta)} &= \frac{\partial C(\mathbf{w}, q^*, a, \theta)}{\partial q} \cdot \frac{q^*}{C(\mathbf{w}, q^*, a, \theta)} \\ &= \frac{\partial \ln \tilde{C}(\mathbf{w}, q^*, a)}{\partial \ln q}. \end{aligned} \tag{3.9}$$

3.2 Estimation Strategy

I use equations (3.5), (3.6) and (3.9) to estimate the technological parameters for profit-maximizing producers (Diewert 1982). For the translog case, the system of equations for a typical observation is:

$$
\begin{aligned}
\ln \frac{C(\mathbf{w}, q^*, a, \theta)}{w_n} &= \beta_0 + \sum_{i=1}^{n-1} \beta_i \ln \frac{w_i}{w_n} + \beta_q \ln q^* + \beta_a \ln a \\
&+ \sum_{i=1}^{n-1} \sum_{j=1}^{n-1} \frac{\beta_{ij}}{2} \ln \frac{w_i}{w_n} \ln \frac{w_i}{w_n} + \sum_{i=1}^{n-1} \beta_{qi} \ln q^* \ln \frac{w_i}{w_n} \\
&+ \sum_{i=1}^{n-1} \beta_{ai} \ln a \ln \frac{w_i}{w_n} + \frac{\beta_{qq}}{2} (\ln q^*)^2 + \beta_{qa} \ln q^* \ln a \\
&+ \frac{\beta_{aa}}{2} (\ln a)^2 - \ln \theta + \ln v_0 \qquad (3.10) \\
\frac{w_i x_i{}^*}{C(\mathbf{w}, q^*, a, \theta)} &= \beta_i + \sum_{j=1}^{n-1} \beta_{ij} \ln \frac{w_i}{w_n} + \beta_{qi} \ln q^* + \beta_{ai} \ln a + v_i \ , \qquad (3.11) \\
i &= 1, ..., n-1 \\
\frac{pq^*}{C(\mathbf{w}, q^*, a, \theta)} &= \beta_q + \sum_{i=1}^{n-1} \beta_{qi} \ln \frac{w_i}{w_n} + \beta_{qq} \ln q^* + \beta_{qa} \ln a + v_n \ , \qquad (3.12)
\end{aligned}
$$

where $\mathbf{v} \equiv (v_0, v_1, ..., v_n)'$ is a vector of statistical noise. I eliminate the n^{th} expenditure share equation due to its linear dependence upon the other expenditure share equations. I impose the symmetry condition $\beta_{ij} = \beta_{ji} \forall i, j$. I also impose positive linear homogeneity of the cost frontier in input prices through the following restrictions:

$$
\beta_n = 1 - \sum_{i=1}^{n-1} \beta_i ; \beta_{in} = - \sum_{i=1}^{n-1} \beta_{ij} \forall i ; \beta_{qn} = - \sum_{i=1}^{n-1} \beta_{qi} ; \beta_{an} = - \sum_{i=1}^{n-1} \beta_{an} . \qquad (3.13)
$$

Since θ cannot be observed, it is treated as a random variable. I impose the following assumptions upon the distributions of $\mathbf{v}$ and θ :

(A1) $E[\mathbf{v} | a, p, \mathbf{w}, \theta] = \mathbf{0}$;

(A2) $E[(v_0^3) | a, p, \mathbf{w}, \theta] = 0$;

(A3) $\ln \theta$ has a normal distribution independent of all other variables with a mean of zero truncated at zero from above (a *half-normal* distribution). The probability density function of θ is:

$$
f(\theta) = \begin{cases} \frac{1}{\theta \sigma_\theta} \sqrt{\frac{2}{\pi}} \exp \left(-\frac{1}{2} \left(\frac{\ln \theta}{\sigma_\theta} \right)^2 \right) & , \theta \in (0, 1] \\ 0 & , \text{otherwise} \end{cases} \qquad (3.14)
$$

(A4) θ is identically and independently distributed across observations.

By (A1), the vector $\mathbf{v}$ is assumed to be a mean-zero disturbance vector. I do not make any assumption regarding a particular parametric family of distributions for $\mathbf{v}$. However, (A2) requires that the skewness of the statistical noise for the cost equation (3.10) be zero, i.e., this disturbance is symmetrically distributed. This assumption allows us to attribute any observed skewness in the residuals to the unobserved type parameter.

Combined with (A2), assumption (A3) provides the structure necessary to infer the distribution of types from the residuals of (3.10). Following the stochastic frontier analysis literature, see for example Kumbhakar and Lovell (2000), I assume $\ln \theta$ follows a half-normal distribution.[1] The scale parameter of this distribution, σ_θ, is the standard deviation of the corresponding non-truncated normal distribution. The mean and skewness of $\ln \theta$ are respectively:

$$E[\ln \theta] = -\sigma_\theta \sqrt{\frac{2}{\pi}}, \tag{3.15}$$

and

$$E\left[(\ln \theta - E[\ln \theta])^3\right] = \sigma_\theta^3 \left(1 - \frac{4}{\pi}\right) \sqrt{\frac{2}{\pi}}. \tag{3.16}$$

Since θ is distributed independently of v_0, $E[v_0 \ln \theta] = E[v_0]\, E[\ln \theta] = 0$.

The expected value of the composite disturbance $v_0 - \ln \theta$ conditioned on the exogenous variables is:

$$E[v_0 - \ln \theta | a, p, \mathbf{w}] = E[v_0] - E[\ln \theta] = \sigma_\theta \sqrt{\frac{2}{\pi}}. \tag{3.17}$$

To understand the effect of type on estimation, add $\sigma_\theta \sqrt{\frac{2}{\pi}}$ to β_0 and subtract $\sigma_\theta \sqrt{\frac{2}{\pi}}$ from the composite disturbance in equation (3.10) (Olson, Schmidt and

[1] Although the half-normal is the most commonly used specification, other alternatives include exponential, gamma, and binomial.

Waldman 1980). The new composite disturbance has zero mean:

$$E\left[v_0 - \ln\theta - \sigma_\theta\sqrt{\frac{2}{\pi}}|a, p, \mathbf{w}\right] = E\left[v_0\right] - E\left[\ln\theta\right] - \sigma_\theta\sqrt{\frac{2}{\pi}} = 0. \tag{3.18}$$

Thus, an otherwise consistent regression technique that assumes a zero-mean disturbance vector yields a biased estimate of the intercept. Rather than estimating β_0, it estimates $\beta_0 + \sigma_\theta\sqrt{\frac{2}{\pi}}$. All other parameter estimates are consistent, however.

Estimation of the system proceeds in two steps. First, I estimate the entire system assuming a mean zero disturbance vector. In the second step, I use residuals from the first step to correct the bias in the intercept.

Due to the presence of the endogenous variable q^* on the right-hand side of (3.10), an ordinary least squares procedure yields inconsistent parameter estimates. One way to correct the endogeneity problem is to use a generalized method of moments (GMM) approach. This approach effectively uses output price as an instrument for q^*. Output price is well suited as an instrument since it is theoretically be correlated with q^* via equation (3.12), yet θ, $\mathbf{v}$ and p are uncorrelated (assumptions (A1) and (A3)).

For producer s, represent equations (3.10)-(3.12) in stacked form as

$$\mathbf{Y}_s = \mathbf{X}_s\boldsymbol{\beta} + \boldsymbol{\epsilon}_s, \tag{3.19}$$

where $\mathbf{Y}_s$ is the $(n+1 \times 1)$ vector of left-hand side variables

$$\mathbf{Y}_s \equiv \left(\ln\frac{C_s}{w_{ns}}, \frac{w_{1s}x_{1s}}{C_s}, ..., \frac{w_{n-1s}x_{n-1s}}{C_s}, \frac{p_s q_s}{C_s}\right)', \tag{3.20}$$

$\mathbf{X}_s$ is the $(n+1 \times k)$ vector of right-hand side variables arranged so that cross-equation parameter restrictions are imposed

$$\mathbf{X}_s \equiv \begin{bmatrix} 1 & \ln\frac{w_{1s}}{w_{ns}} & \cdots & \ln\frac{w_{n-1s}}{w_{ns}} & \ln q_s & \ln a_i & \frac{1}{2}\left(\ln\frac{w_{1s}}{w_{ns}}\right)^2 & \ldots \\ 0 & 1 & & 0 & 0 & 0 & \ln\frac{w_{1s}}{w_{ns}} & \ldots \\ 0 & 0 & & 0 & 0 & 0 & 0 & \ldots \\ \vdots & \vdots & & & & & & \\ 0 & 0 & & 1 & 0 & 0 & 0 & \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & \ldots \end{bmatrix}, \tag{3.21}$$

$\boldsymbol{\beta}$ is the $(k \times 1)$ parameter vector

$$\boldsymbol{\beta} \equiv \begin{bmatrix} \beta_0 + \sigma_\theta\sqrt{\frac{2}{\pi}} \\ \beta_1 \\ \vdots \\ \beta_{n-1} \\ \beta_q \\ \vdots \end{bmatrix}, \tag{3.22}$$

and $\boldsymbol{\epsilon}_s$ is the $(n+1 \times 1)$ disturbance vector

$$\boldsymbol{\epsilon}_s \equiv \begin{bmatrix} v_0 + \ln\theta - \sigma_\theta\sqrt{\frac{2}{\pi}} \\ v_1 \\ v_2 \\ v_3 \\ v_4 \end{bmatrix}.$$

Let $\mathbf{z}_s$ be a vector of exogenous variables for observation s (substitute p_s for q_s in the first row of $\mathbf{X}_s$):

$$\mathbf{z}_s = \left(1, \ln\frac{w_{1s}}{w_{ns}}, ..., \ln\frac{w_{n-1s}}{w_{ns}}, \ln p_s, \ln a, ...\right). \tag{3.23}$$

Finally, $\mathbf{Z}_s$ is a $(n+1 \times k\,(n+1))$ block diagonal matrix of the $\mathbf{z}_s$ vector:

$$\mathbf{Z}_s = \begin{bmatrix} \mathbf{z}_s & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{z}_s & & \mathbf{0} & \mathbf{0} \\ \vdots & & \ddots & & \vdots \\ \mathbf{0} & \mathbf{0} & & \mathbf{z}_s & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{0} & \mathbf{z}_s \end{bmatrix}. \tag{3.24}$$

For the ensuing analysis, assume that the rank condition is satisfied: rank $\mathbf{Z}_s'\mathbf{X}_s$ $=$ columns of $\mathbf{X}_s$.

By assumptions (A5) and (A6) $E\left[\boldsymbol{\epsilon}|\mathbf{z}\right] = \mathbf{0}$. Hence,

$$E\left[\mathbf{Z}_s'\boldsymbol{\epsilon}_s\right] = \mathbf{0}. \tag{3.25}$$

Let $\mathbf{e}_s\left(\hat{\boldsymbol{\beta}}\right)$ denote the sample residuals obtained by an estimator $\hat{\boldsymbol{\beta}}$:

$$\mathbf{e}_s\left(\hat{\boldsymbol{\beta}}\right) \equiv \mathbf{Y}_s - \mathbf{X}_s\hat{\boldsymbol{\beta}}.$$

The sample analog to (3.25) for a given estimator is thus:

$$S^{-1}\sum_{s=1}^{S}\mathbf{Z}_s'\mathbf{e}_s\left(\hat{\boldsymbol{\beta}}\right). \tag{3.26}$$

Following Hansen (1982), a consistent estimator of $\boldsymbol{\beta}$ minimizes the weighted sum of squares of these sample analogs to the theoretical moment (3.25):

$$\hat{\boldsymbol{\beta}} = \arg\min_{\tilde{\boldsymbol{\beta}}}\left\{\left[S^{-1}\sum_{s=1}^{S}\mathbf{Z}_s'\mathbf{e}_s\left(\tilde{\boldsymbol{\beta}}\right)\right]'\hat{\mathbf{W}}\left[S^{-1}\sum_{s=1}^{S}\mathbf{Z}_s'\mathbf{e}_s\left(\tilde{\boldsymbol{\beta}}\right)\right]\right\}. \tag{3.27}$$

Here $\hat{\mathbf{W}}$ is a symmetric positive semidefinite matrix that converges in probability to a nonrandom positive semidefinite matrix $\mathbf{W}$ as $S \to \infty$.

Let the matrix $\mathbf{X}$ of dimensions $(S \cdot (n+1) \times k)$ denote the full sample equation by equation stacked form of $\mathbf{X}_s$:

$$\mathbf{X} = \begin{bmatrix} 1 & \ln \frac{w_{11}}{w_{n1}} & \ln \frac{w_{21}}{w_{n1}} & \ldots \\ \vdots & \vdots & \vdots & \\ 1 & \ln \frac{w_{1S}}{w_{nS}} & \ln \frac{w_{2S}}{w_{nS}} & \ldots \\ 0 & 1 & 0 & \ldots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix}. \tag{3.28}$$

Similarly, let matrix $\mathbf{Z}$ of dimensions $(S \cdot (n+1) \times k \cdot (n+1))$ denote the full-sample equation-by-equation stacked form of $\mathbf{Z}_s$:

$$\mathbf{Z} = \begin{bmatrix} \mathbf{z}_1 & \mathbf{0} & \mathbf{0} & \ldots \\ \vdots & \vdots & \vdots & \\ \mathbf{z}_S & \mathbf{0} & \mathbf{0} & \ldots \\ \mathbf{0} & \mathbf{z}_1 & \mathbf{0} & \ldots \\ \vdots & \vdots & \vdots & \\ \mathbf{0} & \mathbf{z}_S & \mathbf{0} & \ldots \\ \mathbf{0} & \mathbf{0} & \mathbf{z}_1 & \ldots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix}. \tag{3.29}$$

Since $\mathbf{e}_s(\boldsymbol{\beta})$ is linear in $\boldsymbol{\beta}$, the solution to (3.27) is:

$$\hat{\boldsymbol{\beta}} = \left(\mathbf{X}'\mathbf{Z}\hat{\mathbf{W}}\mathbf{Z}'\mathbf{X}\right)^{-1}\left(\mathbf{X}'\mathbf{Z}\hat{\mathbf{W}}\mathbf{Z}'\mathbf{Y}\right). \tag{3.30}$$

The choice of weighting matrix depends upon the severity of the assumptions one wishes to impose on heteroskedasticity and correlation between equations and across observations. Any symmetric positive semidefinite matrix that converges in probability to a nonrandom positive semidefinite matrix can be used to calculate consistent parameter estimates (Hansen 1982). The efficiency of the model and the consistency of standard error estimates depends on the choice of weighting matrix. This is essentially a generalized instrumental variables procedure. It would be exactly two-stage least squares with a weighting matrix of $(\mathbf{Z}'\mathbf{Z})'$.

If each observation $s \in S$ is independent of the others, the optimal (least variance) choice of $\mathbf{W}$ is (Wooldridge 2002):

$$\mathbf{W}^{-1} = \boldsymbol{\Lambda} = E\left[\mathbf{Z}_s' \boldsymbol{\epsilon}_s \boldsymbol{\epsilon}_s' \mathbf{Z}_s\right]. \tag{3.31}$$

Using this weighting matrix the asymptotic covariance matrix for $\hat{\boldsymbol{\beta}}$ is consistently estimated by:

$$S\left[\mathbf{X}'\mathbf{Z}\left[\hat{\boldsymbol{\Lambda}}\right]^{-1}\mathbf{Z}'\mathbf{X}\right]^{-1}, \tag{3.32}$$

where $\hat{\boldsymbol{\Lambda}}$ is a consistent estimator of $\boldsymbol{\Lambda}$ (Wooldridge 2002).

A useful starting point for obtaining $\hat{\boldsymbol{\Lambda}}$ is the system two-stage least squares (2SLS) weighting matrix:

$$\left[\hat{\mathbf{W}}_{2SLS}\right]^{-1} = S^{-1}\sum_{s=1}^{S}\mathbf{Z}_s'\mathbf{Z}_s. \tag{3.33}$$

Since $\hat{\mathbf{W}}_{2SLS}$ is a symmetric positive semidefinite matrix that converges in probability, the estimator $\hat{\boldsymbol{\beta}}_{\mathrm{2SLS}}$ is consistent.

This estimator is not efficient if there is any correlation in the errors across equations. The residuals $\mathbf{e}_s\left(\hat{\boldsymbol{\beta}}_{\mathrm{2SLS}}\right)$ are useful, however, in calculating $\hat{\boldsymbol{\Lambda}}$ under less restrictive assumptions.[2] For example, the three-stage least squares (3SLS) estimator is robust to homoskedastic correlation across equations. Suppose that the conditional variance matrix of $\boldsymbol{\epsilon}_s$ is constant given $\mathbf{Z}_s$:

$$\boldsymbol{\Omega} \equiv E\left[\boldsymbol{\epsilon}_s\boldsymbol{\epsilon}_s'\right] = E\left[\boldsymbol{\epsilon}_s\boldsymbol{\epsilon}_s'|\mathbf{Z}_s\right]. \tag{3.34}$$

[2] The discussion regarding choice of weighting matrix is a brief summary of techniques described by (Wooldridge 2002)

By the Law of Iterated Expectations:

$$E\left[\mathbf{Z}_s'\boldsymbol{\epsilon}_s\boldsymbol{\epsilon}_s'\mathbf{Z}_s\right] = E\left[\mathbf{Z}_s'E\left[\boldsymbol{\epsilon}_s\boldsymbol{\epsilon}_s'|\mathbf{Z}_s\right]\mathbf{Z}_s\right] \tag{3.35}$$

$$= E\left[\mathbf{Z}_s'\boldsymbol{\Omega}\mathbf{Z}_s\right], \tag{3.36}$$

Then,

$$\hat{\boldsymbol{\Omega}} = S^{-1}\sum_{s=1}^{S}\mathbf{e}_s\left(\hat{\boldsymbol{\beta}}_{\mathrm{2SLS}}\right)\mathbf{e}_s\left(\hat{\boldsymbol{\beta}}_{\mathrm{2SLS}}\right)'. \tag{3.37}$$

is a consistent estimator of $\boldsymbol{\Omega}$, and

$$\hat{\boldsymbol{\Lambda}}_{3SLS}=S^{-1}\sum_{s=1}^{S}\mathbf{Z}_s'\hat{\boldsymbol{\Omega}}\mathbf{Z}_s. \tag{3.38}$$

is a consistent estimator of $\boldsymbol{\Lambda}$.

The estimator $\hat{\boldsymbol{\beta}}_{3SLS}$ calculated using $\hat{\mathbf{W}}_{3SLS} = \left[\hat{\boldsymbol{\Lambda}}_{3SLS}\right]^{-1}$ is not asymptotically efficient for more general forms of $\boldsymbol{\Lambda}$. An estimator robust to arbitrary heteroskedasticity can be calculated by letting $\boldsymbol{\Omega}$ vary by observation. In this case, the consistent estimator for the heteroskedasticity robust weighting matrix $\hat{\boldsymbol{\Lambda}}_{HR}$ is (Wooldridge 2002):

$$\hat{\boldsymbol{\Lambda}}_{HR}=S^{-1}\sum_{s=1}^{S}\mathbf{Z}_s'\mathbf{e}_s\left(\hat{\boldsymbol{\beta}}_{\mathrm{2SLS}}\right)\mathbf{e}_s\left(\hat{\boldsymbol{\beta}}_{\mathrm{2SLS}}\right)'\mathbf{Z}_s. \tag{3.39}$$

Finally, in addition to arbitrary heteroskedasticity the researcher may wish to allow for correlation in the errors for different observations in a given group or cluster. For example, there may be unobserved factors commonly affecting all producers in the same county in the same year. Similarly, one may believe that the effects of an unobserved shock to a county persists through time. The heteroskedasticity robust weighting matrix can be modified to provide asymptotically efficient parameter estimates in the presence of arbitrary correlation between the errors of observations belonging to the same cluster (Wooldridge 2003).

Suppose there are G independent clusters indexed $g = 1, ..., G$. Let members of a cluster be indexed $m = 1, ..., M_g$, where M_g is the total membership of cluster g. Let $\mathbf{Z}_g$ denote the stacked matrices of exogenous variables for all members of a cluster:

$$\mathbf{Z}_g = \begin{bmatrix} \mathbf{Z}_1 \\ \vdots \\ \mathbf{Z}_{M_g} \end{bmatrix}. \tag{3.40}$$

Let $\mathbf{e}_g\left(\hat{\boldsymbol{\beta}}_{2\text{SLS}}\right)$ denote the stacked 2SLS residuals for the members of cluster g:

$$\mathbf{e}_g\left(\hat{\boldsymbol{\beta}}_{2\text{SLS}}\right) = \begin{bmatrix} \mathbf{e}_1\left(\hat{\boldsymbol{\beta}}_{2\text{SLS}}\right) \\ \vdots \\ \mathbf{e}_{M_g}\left(\hat{\boldsymbol{\beta}}_{2\text{SLS}}\right) \end{bmatrix}. \tag{3.41}$$

In this case, Pepper (2002) shows the optimal weighting matrix (3.31) is replaced by:

$$\mathbf{W}^{-1} = \boldsymbol{\Lambda} = E\left[\mathbf{Z}_g'\boldsymbol{\epsilon}_g\boldsymbol{\epsilon}_g'\mathbf{Z}_g\right]. \tag{3.42}$$

This matrix is consistently estimated by the heteroskedasticity and correlation robust weighting matrix:

$$\hat{\boldsymbol{\Lambda}}_{HCR} = S^{-1}\sum_{s=1}^{S}\mathbf{Z}_g'\mathbf{e}_g\left(\hat{\boldsymbol{\beta}}_{2\text{SLS}}\right)\mathbf{e}_g\left(\hat{\boldsymbol{\beta}}_{2\text{SLS}}\right)'\mathbf{Z}_g. \tag{3.43}$$

If heteroskedasticity and clustering are not present in the data, the parameters estimated by the weighting matrices $\hat{\boldsymbol{\Lambda}}_{3SLS}$, $\hat{\boldsymbol{\Lambda}}_{HR}$, and $\hat{\boldsymbol{\Lambda}}_{HCR}$ are asymptotically equivalent. If heteroskedasticity is present, but there is no clustering, estimators calculated with $\hat{\boldsymbol{\Lambda}}_{HR}$ and $\hat{\boldsymbol{\Lambda}}_{HCR}$ are asymptotically equivalent and more efficient than those calculated with $\hat{\boldsymbol{\Lambda}}_{3SLS}$. Finally, if heteroskedasticity and clustering are present estimators calculated with $\hat{\boldsymbol{\Lambda}}_{HCR}$ are asymptotically more efficient than the other two weighting matrices. The finite sample implications of using a more robust estimator than necessary are unclear, however (Wooldridge 2002).

Whichever estimator of $\boldsymbol{\beta}$ is ultimately chosen, it estimates

$$\beta_0 + \sigma_\theta \sqrt{\frac{2}{\pi}} \tag{3.44}$$

rather than β_0. To estimate the intercept parameter consistently requires a consistent estimate for σ_θ. Adapting Olson, Schmidt and Waldman (1980), one can recover a consistent estimator for σ_θ from the residuals of a GMM regression.

Due to (A2) the skewness of v_0 is zero. By (A3) the skewness of the composite disturbance $v_0 + E[\ln\theta] - \ln\theta$ depends exclusively on θ:

$$\begin{aligned} E\left[(v_0 - (\ln\theta - E[\ln\theta]))^3\right] &= E\left[v_0^3 - 3v_0^2(\ln\theta - E[\ln\theta]) + \right. \\ &\quad \left. 3v_0^2(\ln\theta - E[\ln\theta])^2 - (\ln\theta - E[\ln\theta])^3\right] \\ &= -E\left[(\ln\theta - E[\ln\theta])^3\right] \\ &= -\sigma_\theta^3 \left(1 - \frac{4}{\pi}\right)\sqrt{\frac{2}{\pi}}. \end{aligned} \tag{3.45}$$

Let e_{0s} denote the residual from equation (3.10) for producer s using one of the GMM estimators described above. Since moments of the residuals are consistent estimators of the central moments of the population disturbances,

$$\operatorname{plim} \sum_{s=1}^{S} \frac{e_{0s}^3}{S} = E\left[v_0 - (\ln\theta - E[\ln\theta])^3\right] = -\sigma_\theta^3\left(1 - \frac{4}{\pi}\right)\sqrt{\frac{2}{\pi}}. \tag{3.46}$$

Rearranging terms yields $\hat{\sigma}_\theta$, a consistent estimator for σ_θ:

$$\hat{\sigma}_\theta = -\frac{\sum_{s=1}^{S} \frac{e_{0s}^3}{S}}{\left(1 - \frac{4}{\pi}\right)\sqrt{\frac{2}{\pi}}}. \tag{3.47}$$

Consequently, a consistent estimate of β_0 is obtained by subtracting $\hat{\sigma}_\theta\sqrt{\frac{2}{\pi}}$ from the GMM estimate of the intercept.

Recall from Chapter 2 that characterization of the optimal green payments program requires two components: a profit function for each type of producer and a probability distribution for type. The procedures described in this chapter provide this information. The estimated technological parameters of the cost function can be used to generate a parametric profit function for each type. In addition, the estimator $\hat{\sigma}_\theta$ can replace σ_θ in (3.14) to obtain a consistent estimate of the probability density function of producer types.

3.3 Discussion

In this chapter, I have developed an internally consistent methodology for estimating a translog cost frontier for profit-maximizing producers with unobservable heterogeneity. I began by explicitly specifying a heterogeneous technology. Specifically, I assumed that different types of producers differ in the quantity of observable inputs necessary to produce a given output. This specification is convenient since the corresponding cost function is log-linear in the unobserved technological productivity parameter representing producer type. As a result, by assuming a parametric probability density function for types, I can treat type as an additional stochastic disturbance in the regression. The problem then becomes one of inferring the parameters of both the cost function and the type probability density function from the data. It is for this reason that I use a cost function approach rather than estimating a profit function directly. Once the parameters of the cost function are estimated it is straightforward to calculate the corresponding profit function.

The estimation strategy proceeds in two steps. In the first step, the cost function is estimated ignoring producer heterogeneity. Since output is endogenous for profit-maximizing producers, a GMM technique is employed, effectively using output price as an instrument for output. The GMM estimator yields consistent and asymptotically efficient estimates of all parameters in the cost function with the exception of the intercept in the cost equation. This intercept is biased by the expected value of the log of types.

In the second step, I eliminate this bias. To do so, I recognize that while the white noise component of the disturbance is symmetric, the type component is positively skewed. Producers can only have higher cost than the most productive type. Any skewness in the residuals of the first step is attributed to type. I use the empirical skewness of the residuals to estimate the scale parameter of the probability distribution of producer types. This estimate allows consistent estimation of the expected value of the natural log of the type parameter and correction of the bias in the intercept of the cost function.

In the next chapter I use United States' agricultural data to estimate the parameters for a cost function with hidden information. These parameters are then used to calibrate a simulation of the green payments mechanism of Chapter 2.

Chapter 4

Empirical Model: Estimation

In this chapter, I implement the estimation strategy described in Chapter 3. I use data from the United States Department of Agriculture (USDA) to estimate a cost frontier and a probability distribution for producer types. The estimated parameters are then used to formulate a producer profit function that incorporates type.

In the first section, I describe the data set and the manipulations taken to transform the raw data into economically meaningful variables. In section two I describe the estimation results.

4.1 Data

Producer cost and returns data come from 1997-2000 *Agricultural Resource Management Study* (ARMS) surveys conducted by the National Agricultural Statistics Service (NASS) of the USDA. Each year's survey is a stratified random sample of agricultural producers. Among other items, surveys collect producer-level data on input expenditures and output quantities.

With the exception of production acres, ARMS surveys only record input dollar amounts (expenditures or asset value), not prices and quantities. For outputs, quantities are reported. Since price data are necessary to estimate a cost system, I use other sources. Where possible, state-level price indexes are used. However, for most inputs only national-level indexes are available. The sources of disaggregated input and output prices are summarized in Tables 4.1 and 4.2.

The data contain information on producers across the continental United States. The USDA Economic Research Service developed farm resource regions to group farms with similar physiographic, soil, and climatic characteristics. To model producers with similar characteristics, I limit the analysis to producers located in the "Heartland" Farm Resource Region. The Heartland, illustrated in Figure 4.1 consists of the entire states of Illinois, Indiana, and Iowa, as well as portions of Kentucky, Minnesota, Missouri, Nebraska, Ohio, and South Dakota. It is the region with most farms, most cropland, and greatest value of production (Economic Research Service 2000). The breakdown of observations by state and year is displayed in Table 4.3.

To account for the year in which an observation is surveyed I employ four binary dummy variables, $d_{97}, ..., d_{00}$. The dummy variable assumes a value of unity if an observation is surveyed in that year, a value of zero otherwise. For example, if an observation occurs in 1997, then $d_{97} = 1, d_{98} = d_{99} = d_{00} = 0$. Year dummies should capture systemic production shocks for the whole region such as weather and technology.

The surveys record capital assets (producer-owned machinery and vehicles) as estimated market value at year end. I calculate the price of capital as the implicit user cost of capital services. Assuming perfect second-hand markets, this price

Table 4.1: Sources for Input Prices

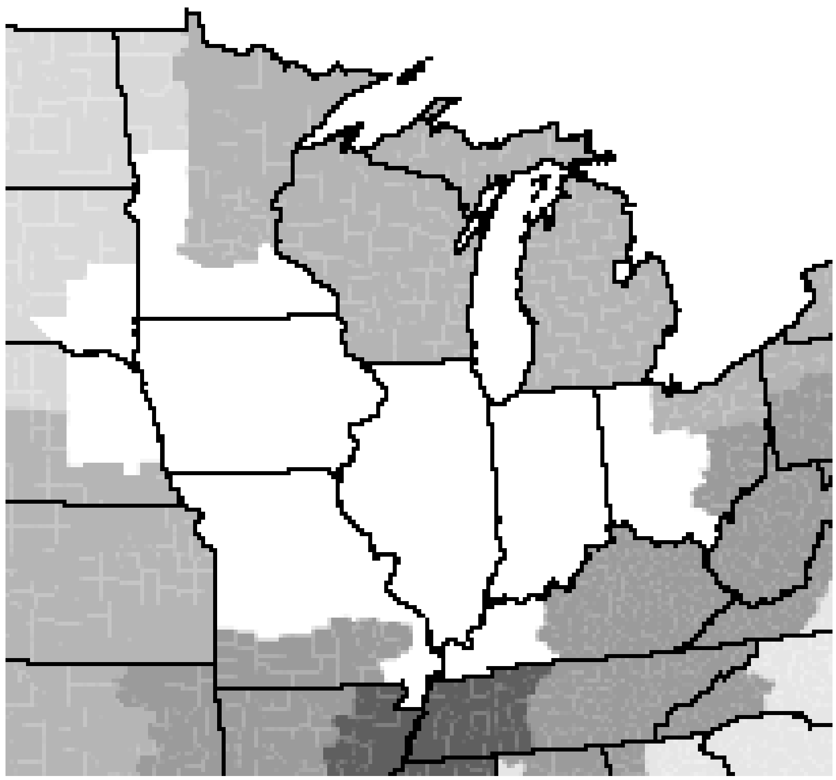
Input	Coverage	Source
Labor	State	BLS (2002)
Energy		
Diesel	State	NASS (2004)
Gasoline	State	NASS (2004)
LP Gas	State	NASS (2004)
Electricity	State	NASS (2004)
Materials		
Seed	US	NASS (2002)
Fertilizer	US	NASS (2002)
Chemicals	US	NASS (2002)
Supplies	US	NASS (2002)
Feed	US	NASS (2002)
Livestock	US	NASS (2002)
Poultry	US	NASS (2002)
Custom Work	US	NASS (2002)
Vehicle/Machinery Repairs	US	NASS (2002)
Capital		
Vehicles owned	US	BLS (2002)
Machinery owned	US	BLS (2002)
Vehicle/Machinery lease	US	BLS (2002)
Investment expenditure	US*	Federal Reserve (2002)

*Interest rate on Moody's Baa corporate bond

Table 4.2: Sources for Output Prices

Output	Coverage	Source
Crops		
Barley	State marketing year average	NASS (2002)
Canola	State marketing year average	NASS (2002)
Cotton	State marketing year average	NASS (2002)
Fruit	State marketing year average	NASS (2002)
Hay	State marketing year average	NASS (2002)
Oats	State marketing year average	NASS (2002)
Peanuts	State marketing year average	NASS (2002)
Potatoes	State marketing year average	NASS (2002)
Rice	State marketing year average	NASS (2002)
Sorghum	State marketing year average	NASS (2002)
Soybeans	State marketing year average	NASS (2002)
Sugar Beets	State marketing year average	NASS (2002)
Sugar Cane	State marketing year average	NASS (2002)
Tobacco	State marketing year average	NASS (2002)
Vegetables	State marketing year average	NASS (2002)
Wheat	State marketing year average	NASS (2002)
Livestock		
Cattle	State annual average	NASS (2002)
Dairy	State annual average	NASS (2002)
Eggs	State annual average	NASS (2002)
Hogs	State annual average	NASS (2002)
Poultry	US annual average	NASS (2002)

Figure 4.1: USDA "Heartland" Farm Resource Region



Source: ERS (2000).

Table 4.3: Number of Observations by State and Year

	Year				
State	1997	1998	1999	2000	**Total**
IL	399	210	314	265	**1,188**
IN	222	130	176	184	**712**
IA	399	272	297	225	**1,193**
KY	86	37	36	27	**186**
MN	280	153	213	215	**861**
MO	193	86	136	139	**554**
NE	121	61	100	60	**342**
OH	162	85	131	91	**469**
SD	105	22	62	53	**242**
Total	**1,967**	**1,056**	**1,465**	**1,259**	**5,747**

is what a producer could earn by renting capital equipment to others. Following Hall and Jorgenson (1967), user cost reflects: i) opportunity cost of financial resources locked into physical capital; ii) physical depreciation of capital; and iii) change in price of new capital assets.[1] The opportunity cost of capital in year t, r_t, is assumed to be the interest rate on Moody's Baa rated corporate bonds for the current year. Producers are assumed to have perfect foresight regarding interest rates.

To calculate physical depreciation of capital, I employ the declining balance method in a similar fashion to Chambers and Vasavada (1983). Bureau of Labor Statistics (2001) estimates are used to approximate service lives of motor vehicles (17 years), agricultural machinery except tractors (17 years), and farm tractors (14 years). The depreciation rate is calculated by solving the following equation for δ:

$$P_S = P_A (1 - \delta)^L , \tag{4.1}$$

where P_S and P_A are real salvage and acquisition prices and L is service life. I do not have information for the salvage value. I assume that the value of equipment at end of service life is one percent of acquisition price, so

$$\delta = 1 - (0.01)^{\frac{1}{L}} . \tag{4.2}$$

The change in the price of capital assets is the annual percent change in the price indexes. I use Bureau of Labor Statistics producer price indexes for new construction, motor vehicles, farm machinery, and tractors for the corresponding categories. I assume that producers have perfect foresight regarding capital gains.

Let p_{kt} denote the asset price of capital for year t. I base the user cost

[1] I do not have data on capital taxes, thus my user cost calculations may be biased downwards.

of capital services for that year (w_{kt}) on the Berndt (1991) adaptation of the formula presented in Hall and Jorgenson (1967):

$$w_{kt} = p_{kt}\left(r_t + \delta - \frac{p_{kt} - p_{kt-1}}{p_{kt}}\right). \tag{4.3}$$

BLS provides asset price and depreciation information for the categories of tractors and other farm machinery. However, ARMS survey responses group these two assets together. I calculate user cost of this component of capital using a weighted average of the "tractors and machinery" response. The weights (60 and 40 percent, respectively) correspond to the average weights employed in the USDA's monthly Agricultural Prices to calculate their Prices Paid index.

I calculate capital stock in each category by dividing value of assets by the corresponding cost of capital services. I assume flow of capital services is proportional to capital stock.

I aggregate outputs into a single category comprising all crop and livestock production. Aggregate inputs are capital, labor, energy, materials, and land. A sufficient condition for input aggregation is homothetic separability of the production function of the aggregate input in its constituent components (Chambers 1988). Williams and Shumway (1998) found that this condition was satisfied for similar agricultural input aggregations in the United States. Similar aggregate inputs are commonly used in agricultural research, see for example O'Donnell, Shumway and Ball (1999) and Ball, Gollop, Kelly-Hawke and Swinnand (1999).

Although sufficient, homothetic separability is not a necessary condition for aggregation. The generalized composite commodity theorem (GCCT) is an alternative sufficient condition (Lewbel 1996). Use of the GCCT can justify aggregation when homothetic separability does not hold. Specifically, the GCCT states that commodities may be consistently aggregated if "the relative difference between the individual commodity price and the aggregate commodity price [is] independent of the aggregate commodity price" (Davis, Lin and Shumway 2000). Davis, Lin and Shumway (2000) provide evidence that the GCCT allows aggregation of US agricultural output commodities into a single composite category.

I calculate a multilateral Tornqvist price index based on Caves, Christensen and Diewert (1982) for each aggregate commodity for each state and year. Calculation of the multilateral Tornqvist index proceeds in two steps. I first create a hypothetical entity. For this entity, the price and quantity for each component of the aggregate commodity is the geometric mean of that component's price and quantity for all states and years. For example, for the "energy" input the components are gasoline, diesel, natural gas, liquid propane gas, and electricity. The price of gasoline for the hypothetical entity is the geometric mean gasoline price for the entire sample.

In the second step, I calculate a bilateral Tornqvist index between each actual state-year combination and the hypothetical entity. The bilateral Tornqvist price index between state-year i and the hypothetical entity h is denoted I_{ih}. It is defined as:

$$I_{ih} = \prod_{j} \left(\frac{w_{ji}}{w_{jh}} \right)^{S_j}. \tag{4.4}$$

It is a weighted geometric mean of the ratio of the price of component j in state-year i (w_{ji}) to price of the same component in h (w_{jh}) for all components of the aggregate input. For inputs, the weights S_j correspond to the arithmetic mean (across the state-year and hypothetical entity) of expenditure on component j as a proportion of expenditure on all components of the aggregate input. For outputs the weight is a function of revenues rather than expenditures. For each component:

$$S_j = \frac{1}{2}\left[\frac{w_{ji}x_{ji}}{\sum_j w_{ji}x_{ji}} + \frac{w_{jh}x_{jh}}{\sum_j w_{jh}x_{jh}}\right]. \tag{4.5}$$

Here x_{ji} is the quantity of component j in state-year i and w_{jh} is the price of the same component in the hypothetical entity.

Table 4.4 presents descriptive statistics for the final variables used in the regressions.

4.2 Estimation Results

I first estimate a translog cost frontier. The goal of this exercise is to provide the parameters necessary to simulate the optimal green payments program. Therefore, some trade-offs are necessary, sacrificing flexibility of the cost function for the sake of computational tractability and theoretical consistency. Specifically, I impose restrictions on some of the parameters in order to obtain a closed-form for a well-behaved profit function. It is the results from this second round of estimations of the less-flexible cost function that I use to calibrate the simulation in Chapter 5.

I first estimate equations (3.10)-(3.12) using $\hat{\mathbf{\Lambda}}_{3SLS}$, $\hat{\mathbf{\Lambda}}_{HR}$, and $\hat{\mathbf{\Lambda}}_{HCR}$. In each case, I run four separate regressions, eliminating a different expenditure share equation each time. Ideally, the estimated cost function would satisfy a number of theoretical and practical requirements. Theoretically, a well-behaved cost function is monotonically increasing and concave in input prices for all observations. In order to obtain an analytical solution for profit-maximizing output from equation (3.12) β_{qq} must equal zero. *A priori*, there is no theoretical reason for β_{qq} to have a particular value. Imposing this restriction forces size elasticity to

Table 4.4: Descriptive Statistics

Variable	Minimum	Maximum	Mean	Std. Dev.
Cost	2,272	206,149,050	433,150	2,813,276
Revenue	253	207,941,362	528,745	2,974,676
Output	258	190,164,314	525,530	2,743,266
Land	2	18,000	988	984
Prices				
Capital	0.97	1.06	1.00	1.03
Labor	0.78	1.13	1.00	1.09
Energy	0.80	1.30	1.00	1.13
Materials	0.96	1.03	1.00	1.03
Output	0.89	1.18	1.01	0.10
Expenditure Shares				
Capital	0.00	0.82	0.17	0.11
Labor	0.00	0.46	0.04	0.03
Energy	0.00	0.98	0.41	0.16
Materials	0.00	0.91	0.38	0.15

be independent of output quantity.

Appendix A.1 reports the results for these 12 regressions. The results do not satisfy either the theoretical or practical requirements stated above. Monotonicity and concavity are not satisfied for a majority of the observations for any regression (Table A.4). I therefore use a less flexible formulation. I impose homotheticity ($\beta_{qi} = \beta_{qa} = 0$; $i = 1, ..., n$), and constant factor expenditure shares ($\beta_{ij} = \beta_{ia} = 0$; $i, j = 1, ..., n$) and $\beta_{qq} = 0$.

The resulting cost function is a slight modification of the Cobb-Douglas form that allows the elasticity of cost to land to vary with land use:

$$C\left(w, q, a, \theta\right) = \theta^{-1} \exp\left(\textstyle\sum_i \delta_i d_i\right) q^{\beta_q} \textstyle\prod_j w_j^{\beta_j} a^{\beta_a + \beta_{aa} \ln a}. \tag{4.6}$$

This specification does not guarantee monotonicity and concavity will be satisfied. However, if monotonicity is satisfied, this cost function is concave in input prices.

Appendix A.2 reports the results for the 12 regressions run with specification (4.6). All the parameter estimates from all 12 regressions result in Cobb-Douglas cost functions that satisfy monotonicity and concavity in input prices. I tested how well the data support these restrictions. To do so, I designed a (14×24) matrix of ones and zeros, $\mathbf{R}$, such that $\mathbf{R}\boldsymbol{\beta} = \mathbf{0}$ for the 14 parameters that appear in the translog specification but do not appear in (4.6). Let $\hat{\boldsymbol{\beta}}$ be the vector of translog parameter estimates and $\hat{\mathbf{W}}$ be the asymptotic covariance matrix (3.32). Under the null hypothesis that the cost function has the form (4.6), the statistic $\mathbf{R}\hat{\boldsymbol{\beta}}' \left(\mathbf{R}\hat{\mathbf{W}}\mathbf{R}'\right) \mathbf{R}\hat{\boldsymbol{\beta}}$ is asymptotically distributed as a χ^2 random variable with 14 degrees of freedom (Wooldridge 2002). Unfortunately, the data do not support the null hypothesis. This test rejects the null at a 99 percent level for each regression (see Table A.4). Although this specification is restrictive, more flexible forms do not ensure monotonicity and concavity are satisfied for a majority of the data points.

With the exception of the parameters associated with the dummy variables, the parameter estimates for specification (4.6) are of the same sign and similar magnitude across all 12 regressions. The four 3SLS sets of parameter estimates are practically identical. Except the dummy parameters, almost all the heteroskedasticity-robust sets of parameter estimates are within .01 units of each other and the respective 3SLS estimates. The clustering-robust estimates differ more greatly depending upon which input share equation was eliminated. Each set of parameter estimates for this error specification is typically with .02 units, again with the exception of the dummy variables. For eleven of the regressions, the residuals to equation (3.10) have a positive skewness as desired, the exception being the clustering-robust specification with the capital share equation eliminated. A negative skewness of these residuals is not consistent with assumption (A3). If the residuals show were to show a negative skewness, alternative specifications of $f(\theta)$, such as a binomial distribution, would be appropriate (Carree 2002). For the purpose of calibrating the simulation, I chose the estimates obtained using the clustering-robust weighting matrix eliminating the labor expenditure share equation. The parameter values used in the simulation are displayed in Table 4.5.

The bias in the dummy parameters is corrected by subtracting $E[\ln \theta]$ from each term. The corrected dummy parameters are listed in Table 4.6.

The estimates provide a reasonably good fit for the cost equation (4.6) with an R^2 of 0.80. The predicted expenditure shares $\beta_k, \beta_\ell, \beta_e, \beta_m$ are also close to the average input expenditure shares for the data set of 38, 17, 4, and 41 percent respectively.

It is difficult to compare these results with those of previous research due to differences in data and model specification. The closest published example in terms of methodology is the translog cost system estimated by Ray (1982). Ray estimated a system of equations similar to (3.10)-(3.12), without correcting for output endogeneity. His data set consisted of national aggregates from 1939-1977. Inputs and outputs were defined slightly differently. Most notably, his capital input included land, he had three input categories (fertilizer; feed, seed and livestock; and miscellaneous) rather than the energy and materials categories employed here, and he had two outputs (crops and livestock) rather than one. His own-price elasticities, η_{ii}, were calculated using the following formula for input i:

$$\eta_{ii} = \frac{\beta_{ii} + S_i^2 - S_i}{S_i},$$

where S_i is the expenditure share equation for input i. My elasticities are calculated by the same formula (where $\beta_{ii} = 0$).

Table 4.7 compares input own-price elasticities calculated from $\beta_k, \beta_\ell, \beta_e, \beta_m$,

Table 4.5: Parameter Estimates

Parameter	Value	std. error
$\delta_{97} + \sigma_\theta \sqrt{\frac{2}{\pi}}$	0.9918	1.4290
$\delta_{98} + \sigma_\theta \sqrt{\frac{2}{\pi}}$	1.0431	1.4306
$\delta_{99} + \sigma_\theta \sqrt{\frac{2}{\pi}}$	0.9795	1.4319
$\delta_{00} + \sigma_\theta \sqrt{\frac{2}{\pi}}$	0.6430	1.4259
β_k	0.3906	0.0079
β_ℓ	0.1652	0.0141
β_e	0.0442	0.0095
β_m	0.3999	0.0084
β_a	-0.8756	0.4438
β_q	1.2021	0.0079
β_{aa}	0.1000	0.0680
$\sigma_\theta \sqrt{\frac{2}{\pi}}$	0.3359	...

Table 4.6: Corrected Dummy Parameter Values

Parameter	Value
δ_{97}	0.6559
δ_{98}	0.7072
δ_{99}	0.6436
δ_{00}	0.3071

with these Ray (1982).

Using equation (3.8) and the parameter estimates above, profit maximizing output $q^*(p, \mathbf{w}, a, \theta)$ is:

$$q^*(p, \mathbf{w}, a, \theta) = \left[\frac{\beta_q \exp\left(\sum_{i=97}^{00} \delta_i d_i\right) \prod_{j=1}^{n} w_j^{\beta_j} a^{\beta_a + \beta_{aa} \ln a}}{\theta p} \right]^{\frac{1}{1-\beta_q}}. \tag{4.7}$$

Substituting this expression for q^* in the right hand side of (3.7) yields the profit function:

$$\pi(p, \mathbf{w}, a, \theta) = \left[\beta_q - 1\right] \cdot \left[\frac{\beta_q^{\beta_q} \exp\left(\sum_{i=97}^{00} \delta_i d_j\right) \prod_{j=1}^{n} w_j^{\beta_j} a^{\beta_a + \beta_{aa} \ln a}}{\theta p^{\beta_q}} \right]^{\frac{1}{1-\beta_q}}. \tag{4.8}$$

This profit function is used to simulate the optimal green payments program in the next chapter.

4.3 Discussion

Ideally, one would like an estimated cost function to be flexible. This property allows the data to determine technological characteristics such as elasticities of

Table 4.7: Input Own-Price Elasticities

Input	Sheriff (2004)	Ray (1982)
k	-0.61	-0.53
ℓ	-0.83	-0.84
e	-0.96	-0.16[a]
m	-0.60	-0.34[b]

[a]miscellaneous inputs. [b]feed, seed, and livestock.

substitution among inputs. Unfortunately, the data can generate technological characteristics that are inconsistent with economic theory. In the present case, the translog cost functions were not well-behaved in two respects for many observations in the sample. Cost was decreasing in input prices for many observations. In addition, input own-price elasticities were positive for many observations, indicating that input demands were increasing in price.

Rather than use a theoretically inappropriate cost function, I chose to use a more restrictive functional form. The modified Cobb-Douglas specification resulted in the monotonicity property being satisfied for all inputs and observations. As a result, all input own-price elasticities are negative, as desired. The price of obtaining such a well-behaved cost function is that all input substitution elasticities are forced to unity. Nonetheless, this specification can be considered a first-order approximation to the "true" underlying cost function.

Applying the estimation techniques described in the previous chapter to the Cobb-Douglas cost function was straightforward. The parameter estimates are robust to arbitrary heteroskedasticity and correlation of errors within counties. In the next chapter I use these estimates to calibrate a simulation of the optimal green payments mechanism.

Chapter 5

Simulation

In this chapter I conduct a simulation combining the mechanism design model of Chapter 2 with the empirical results of Chapter 4. The objective is to demonstrate how a cost-minimizing green payments program can be implemented. Using the structural parameters estimated in Chapter 4, I show how one can characterize the optimal contract schedule in terms of amount of land idled by each type of producer and payments received. One can see if pooling occurs, and if so, over what range of types. Further, we can compare the costs of alternative mechanisms. *A priori*, we know that the *ex ante* green payment mechanism dominates an *ex post* mechanism and a stylized version of actual farm programs, but by how much? This simulation provides estimates of the magnitude of the benefits that could be obtained were policy to switch from existing programs to the *ex ante* green payments mechanism. In addition, the difference in cost between the *ex ante* and first best programs provides an estimate of the value of attempting to collect detailed information regarding producer productivity levels.

Before proceeding, there are some caveats. The simulation relies on actual farm production data to estimate the parameters. However, as in any modeling endeavor there are still several simplifying assumptions. Many of these assumptions have been noted in previous chapters. I will not catalog every such assumption, but would like to draw attention to a few that figure prominently in this simulation.

First is the assumption that all farms are of equal size. The data set used to estimate the parameters of the simulation contains farms ranging from 2 to 18,000 acres. This analysis makes no attempt to explain why some farms are larger than others. I assume that farm size is exogenous during the time-frame of interest. To keep calculations tractable, I restrict attention to a hypothetical group of farms of 2,000 acres each.[1] This assumption is largely made for convenience. In principle, if farm size is observable, separate contract menus could be offered to different farm sizes.

I also assume outputs can be combined into one aggregate, and that it is the price index of this aggregate with which policy-makers are concerned. This may not be such a strong assumption since prices of agricultural commodities tend to be positively correlated (Gardner 2002). Since three out of four years in the sample had below average output price, I assign a probability of 0.75 to the low-price state. The two output price levels are calculated as the mean of the three low price years and the mean of the high price year. In reality output price does not follow such a binomial distribution. An extension of this model could account for a smoother distribution of a continuous range of output prices. I also assume input prices are fixed. In actuality of course input prices vary.

Income support and environmental goals are chosen somewhat arbitrarily. However, the simulation programming easily allows experimentation with differ-

[1] The expected farm-size for any randomly chosen acre of land in the sample was approximately 1,970 acres.

ent values for these parameters.

Finally, the simulation differs from the theoretical analysis in one key aspect. The theoretical analysis takes the land set-aside target, A, as given. One of the outputs is the optimal shadow price, λ, associated with this constraint. To solve the system numerically in this manner is quite expensive in terms of computer time. Therefore I adopt an alternative approach. I begin with an assumed shadow value for idled land, and from that obtain the optimal amount of land to idle. The interpretation of the results differs from the theoretical section as follows. Rather than comparing the costs of achieving the policy targets, I compare the net benefits, assuming that the marginal value of idled land is constant over the relevant range. I conduct the simulation using two values for this shadow value. In the first simulation, this value is set at zero. The results tell us if some land idling should occur even if there is no environmental benefit to doing so. Such idling may be optimal if it reduces income support payments by inducing different type farmers to select different contracts. In the second simulation, the constant shadow value of idled land is set equal to the average CRP rental rate for the region.

The next section details how the simulation is designed. In Section 2, I provide results for the four policy alternatives when there is are no environmental benefits. In Section 3, I provide results for the four alternatives when idled land produces a constant marginal benefit. I compare the results of the simulations and provide policy implications in Section 4.

5.1 Simulation Design

I programmed the simulation using Gauss for Windows, 5.0 (Aptech, 2002). The program solves nonlinear equations by numerical iteration and approximates integrals with Riemann sums.

The simulation shows how four policy alternatives would perform on a sample of 2,000-acre farms. These farms are located in the geographic region of the United States denoted as the "Heartland" resource region by the USDA Economic Research Service. I assume that farm type enters each producer's profit function as described in equation (4.8).

Table 5.1 displays the values of the input price indexes. Table 5.2 displays values of the output price index, with the corresponding probability of each price state occurring.

The lower bound of $\ln\theta$ with a half-normal distribution function is $-\infty$. To make the model tractable, I truncate the distribution from below at -1, assuming that the government is not concerned with land cultivated or profit earned by these types. This truncation excludes roughly 1 percent of farms. The remaining farm types are assumed to be distributed with a mean-zero log-normal

Table 5.1: Input Prices

Price	Value
w_k	0.999
w_ℓ	0.998
w_e	1.005
w_m	1.001

Table 5.2: Output Prices

Price	Value	Probability
p_ℓ	0.887	0.75
p_h	1.183	0.25

distribution truncated from above by zero:

$$f(\theta) = \begin{cases} \dfrac{\frac{1}{\theta\sigma_\theta\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{\ln\theta}{\sigma_\theta}\right)^2\right)}{\Phi(0) - \Phi\left(\frac{-1}{\sigma_\theta}\right)} & , \theta \in [e^{-1}, 1] \\ 0 & , \text{otherwise} \end{cases} . \tag{5.1}$$

Here, $\Phi(\cdot)$ is the standard normal cumulative distribution function. Type is measured with a precision of 0.001. The distribution of types is depicted in Figure 5.1.

Table 4.5 displays the parameters of the profit frontier. Figure 5.2 depicts the corresponding expected profit frontier $\Pi\left(a, \bar{\theta}\right)$. Decreasing returns to land begin at about 400 acres, after which profit is strictly concave in land.

In the simulations I analyze two policy scenarios. In the first, there is no environmental constraint. In the second, there are both environmental and income constraints.[2] As pointed out by Bourgeon and Chambers (2000) in the case of two producer types, information asymmetry may make it optimal for the government to require producers to idle land even if there are no environmental benefits. I analyze this scenario to see if any such idling is optimal, and if so for what range of types. The second scenario examines the case discussed in Chapter 2 wherein both environmental and income constraints bind. For each scenario, I

[2] The case of an environmental constraint without an income constraint has already been examined by Smith (1995).

Figure 5.1: Distribution of Types

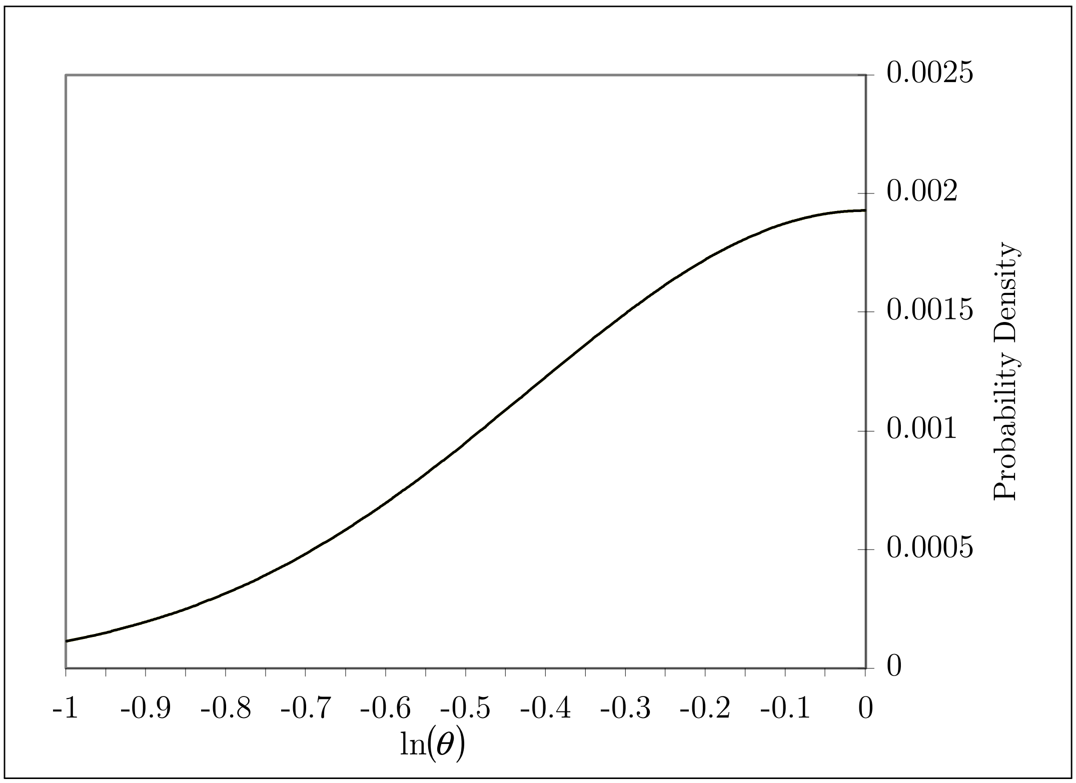
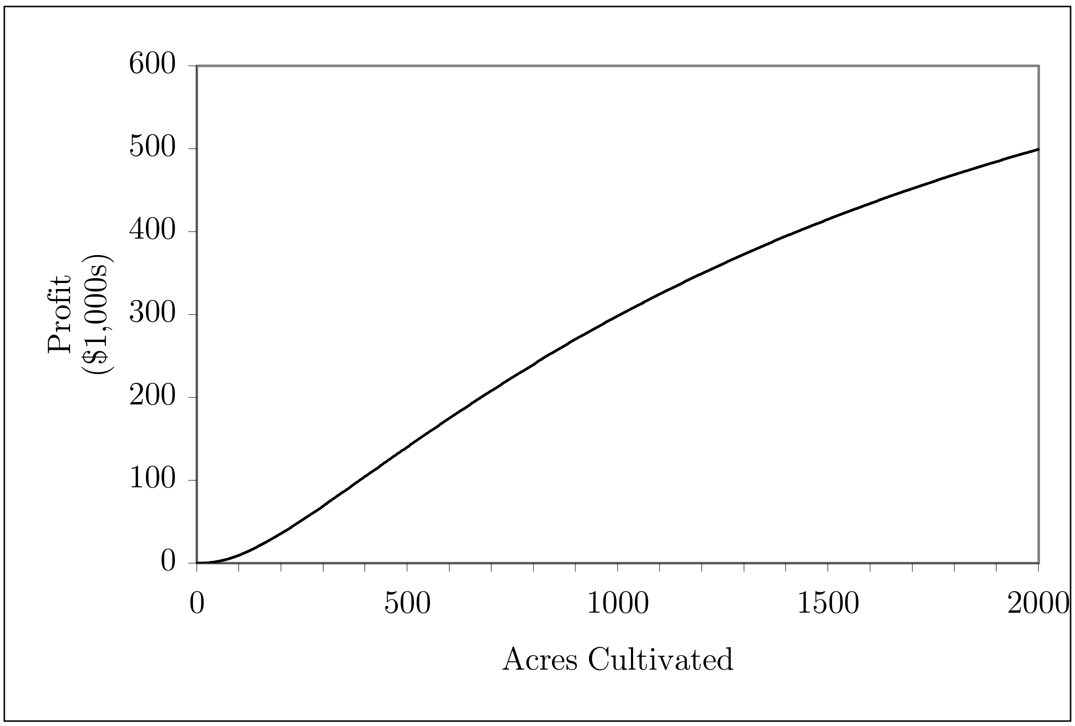


Figure 5.2: Expected Profit Frontier, $\Pi\left(a, \bar{\theta}\right)$



compare four alternatives: the first-best, *ex ante*, *ex post*, and stylized FAIR Act programs.

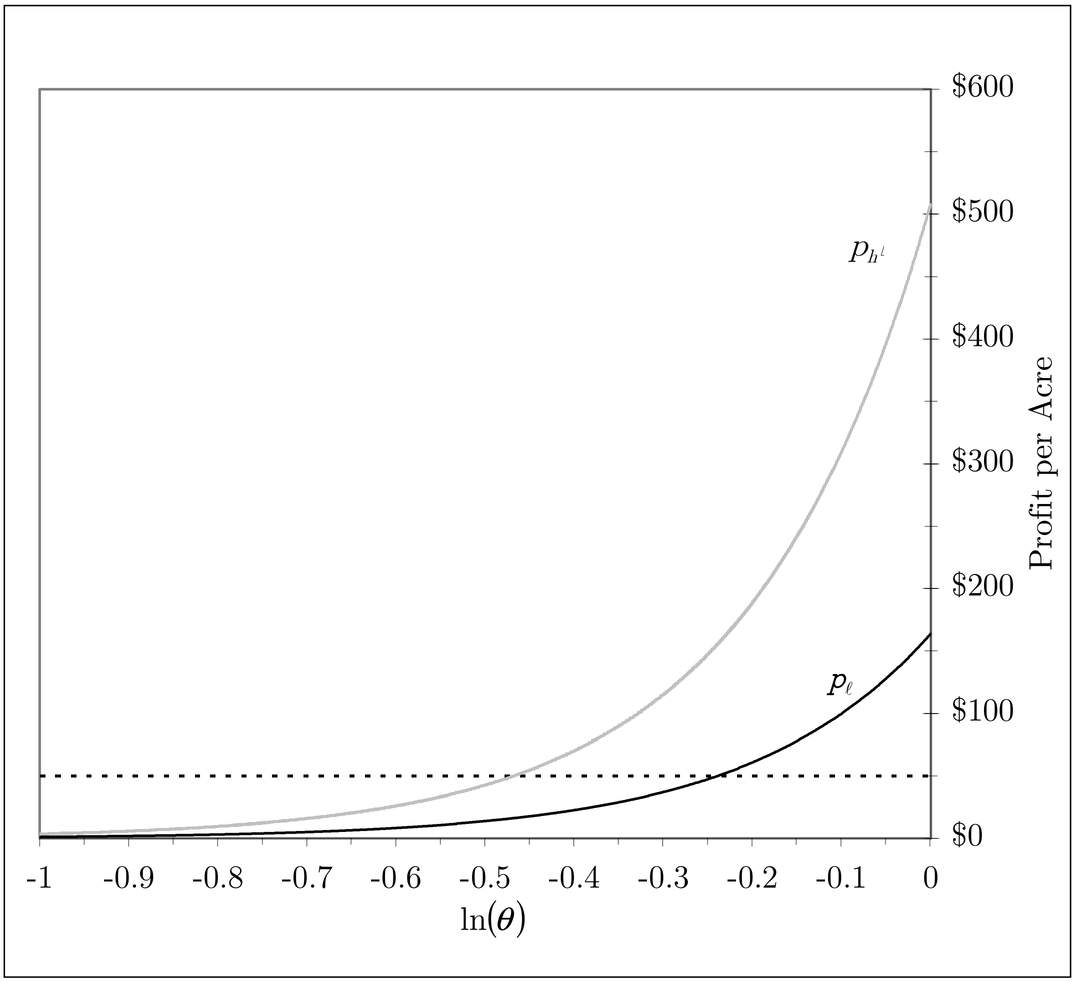
In both scenarios, the income support objective is defined as ensuring that all types above e^{-1} earn at least \$50 per acre.[3] Profit earned by type when cultivating all 2,000 acres is illustrated in Figure 5.3. The types corresponding to θ_L and θ_H are $e^{-0.468}$ and $e^{-0.240}$, respectively. For the first scenario the marginal environmental benefit from idling a unit of land is assumed to be zero. For the second scenario, the marginal environmental benefit is based upon average CRP rental payments. In 2002, the average CRP rental payment per acre for the nine states considered here was about \$71 per acre (Farm Service Agency 2002). For lack of better information, I assume that the marginal benefit for an acre of idled land is constant at \$71. The environmental objective is defined such that the shadow price of land idled is \$71. In other words, for the first scenario the value of the Lagrange multiplier λ for each program is set to 0, while for the second scenario it is set to 71.

5.2 Scenario 1: No environmental constraint

In this section, I model the case where idling land does not bring any benefits of its own. Bourgeon and Chambers (2000) showed that even in this case some idling may be optimal. Intuitively, requiring lower types to idle land has two effects. It increases the cost of the policy by requiring larger transfers to ensure that these types achieve the income constraint. Since it is more costly for higher types to idle land than lower types, land idling reduces the incentive of higher

[3] This value is approximately the expected profit per acre of the mean type.

Figure 5.3: Profit per acre by type and output price, no land idled



types to mimic lower types. This second effect reduces the cost of the policy by reducing surplus payments to higher types. This scenario is interesting since the environmental constraint does not bind if the average number of acres idled, A, is less than the average idled with no environmental constraint.

To perform the simulation, I set the value of the Lagrange multipliers λ for the first best, *ex ante*, *ex post*, and FAIR Act programs equal to zero.

5.2.1 First Best Program

From equation (2.21), the first order condition for optimal land allocation is:

$$\Pi_a \left(a\left(\theta\right), \theta\right) = \lambda, \tag{5.2}$$

for an interior solution. By (R1) the left-hand-side of (5.2) is always positive. Consequently, for $\lambda = 0$ there is a corner solution for all types such that $a\left(\theta\right) = \overline{a}$.

The first-best land allocation is depicted in Figure 5.4. If information is symmetric, idling land increases transfers necessary to ensure that the income support is met without any corresponding benefit in terms of reducing surplus payments to higher types. As a result, it is never optimal to idle land without an environmental constraint. The expected cost of the first best mechanism is simply the cost of ensuring that all types meet the income constraint while cultivating all land in each price state. Expected payments necessary to satisfy this constraint are depicted in Figure 5.5. Expected surplus payments are zero for all types. Expected transfers are gradually decreasing until θ_H. There is a kink in the allocation of expected transfers at θ_L since types between θ_L and θ_H require transfers only if output price is p_ℓ, whereas types below θ_L require transfers in both price states. No transfers are necessary for types above θ_H. The average cost per producer of this program is approximately \$27,800.

Figure 5.4: First-Best Program, No Environmental Constraint, Acres Cultivated by Type

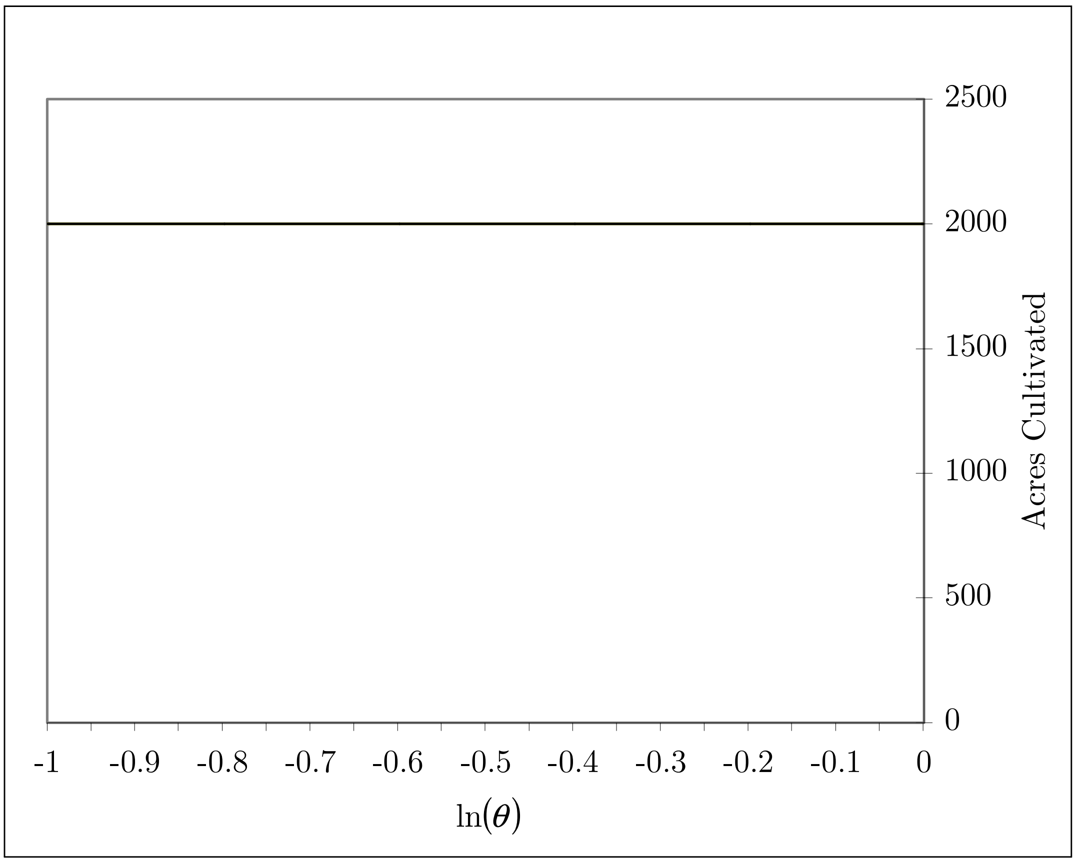
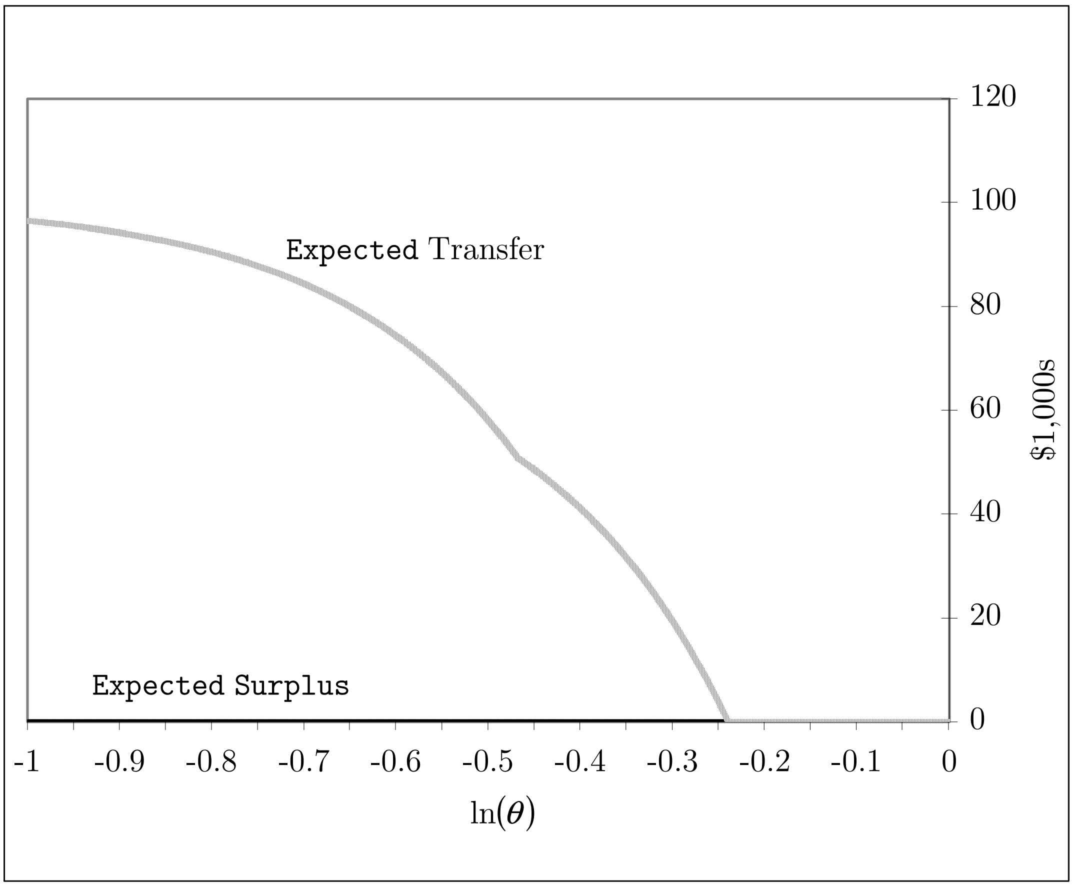


Figure 5.5: First-Best Program, No Environmental Constraint, Expected Payments by Type



5.2.2 *Ex Ante* Program

From equation (2.92), the first-order condition for an interior solution for the optimal *ex ante* land allocation is:

$$\Pi_a\left(a\left(\theta\right),\theta\right)+\frac{\gamma\left(\theta\right)}{f\left(\theta\right)}\Pi_{a\theta}\left(a\left(\theta\right),\theta\right)=\lambda. \tag{5.3}$$

Since the sign of the left-hand side of (5.3) does not depend upon a due to conditions (R1) and (R4) a bang-bang solution results if $\lambda=0$. If the left-hand-side of (5.3) is negative, land cultivated will be at the minimum, whereas if it is positive, land cultivated will be at the maximum. It may be the case that the land allocation is constant at $\hat{a}$ for an interior interval of types if the left-hand-side of (5.3) evaluated at $a\left(\theta\right)=\hat{a}$ for this interval is equal to zero.

To calculate $\gamma\left(\theta\right)$, I first compute the value of $\hat{a}$ using equation (2.111). For the profit frontier specified in (4.8), $\hat{a}$ solves:

$$\hat{a}^{\beta_a+\frac{\beta_{aa}}{2}\ln\hat{a}}=\left[\frac{\bar{a}^{\beta_a+\frac{\beta_{aa}}{2}\ln\bar{a}}}{p_h^{\beta_q}}\right]\left[\frac{\left(1-\rho\right)}{\rho p_\ell^{\frac{-\beta_q}{1-\beta_q}}+\left(1-\rho\right)p_h^{\frac{-\beta_q}{1-\beta_q}}}\right]^{1-\beta_q}. \tag{5.4}$$

For the parameter estimates in Table 4.5, $\hat{a}$ is approximately 845 acres.

The next step is to solve first-order condition (5.3). *A priori*, the value of the Lagrange multiplier $\gamma\left(\theta\right)$ is unknown. Consulting Table 2.1, I check to see if there is a value for $\mu_1\in(0,1)$ such that for $a^*\left(\theta,F\left(\theta\right)-\mu_1,\lambda\right)$, both the lowest type and an interior type idling $\hat{a}$ acres receive zero expected surplus. For $\lambda=0$, there is: $\mu_1=0.50503$, for interior type $\ln\left(\theta_1\right)=-0.353$. Next, I check to see if there is a value for $\mu_2\in\left(\mu_1,1\right)$ such that for $a^*\left(\theta,F\left(\theta\right)-\mu_2,\lambda\right)$ the both the highest type and an interior type idling $\hat{a}$ acres receive zero expected surplus. In this case, $\mu_2=0.70047$, for $\ln\left(\theta_2\right)=-0.240$.

The land allocation for the program is depicted in Figure 5.6. A central pooling interval does exist, with bounds θ_1 and θ_2. All types below θ_1 cultivate 425 acres, all types in the pooling interval cultivate 845 acres, and all types above θ_2 cultivate 2,000 acres. Intuitively, by requiring a producer to idle an additional acre of land, the government increases the cost of meeting the income constraint of that type, while reducing the cost of surplus payments to all higher types. For all types below θ_1, this calculation always favors idling an additional acre. For all types above θ_2, this calculation never favors idling. For types in the pooling interval, the cost of the program does not depend upon the number of acres idled. However, the only way it is incentive compatible for a pooling interval to exist is if all types idle $\hat{a}$.

Expected payments are depicted in Figure 5.7. To be incentive compatible, two producers cannot be offered different transfers for idling the same quantity of land. There are three tiers of payments: all producers idling 1,325 acres receive about \$99,000, all types idling 1,115 acres receive about \$75,000, and all types idling zero acres receive zero payments. Expected surplus increases until θ_L. From θ_L to θ_1, expected surplus decreases since the opportunity cost of the idled land is higher than the minimum income constraint if output price is p_h for these types. For all types above θ_1, there are no expected surplus payments. The average amount of land idled is 812 acres, and the average cost of the program per producer is approximately \$51,500.

Figure 5.6: *Ex Ante* Program, No Environmental Constraint, Acres Cultivated by Type

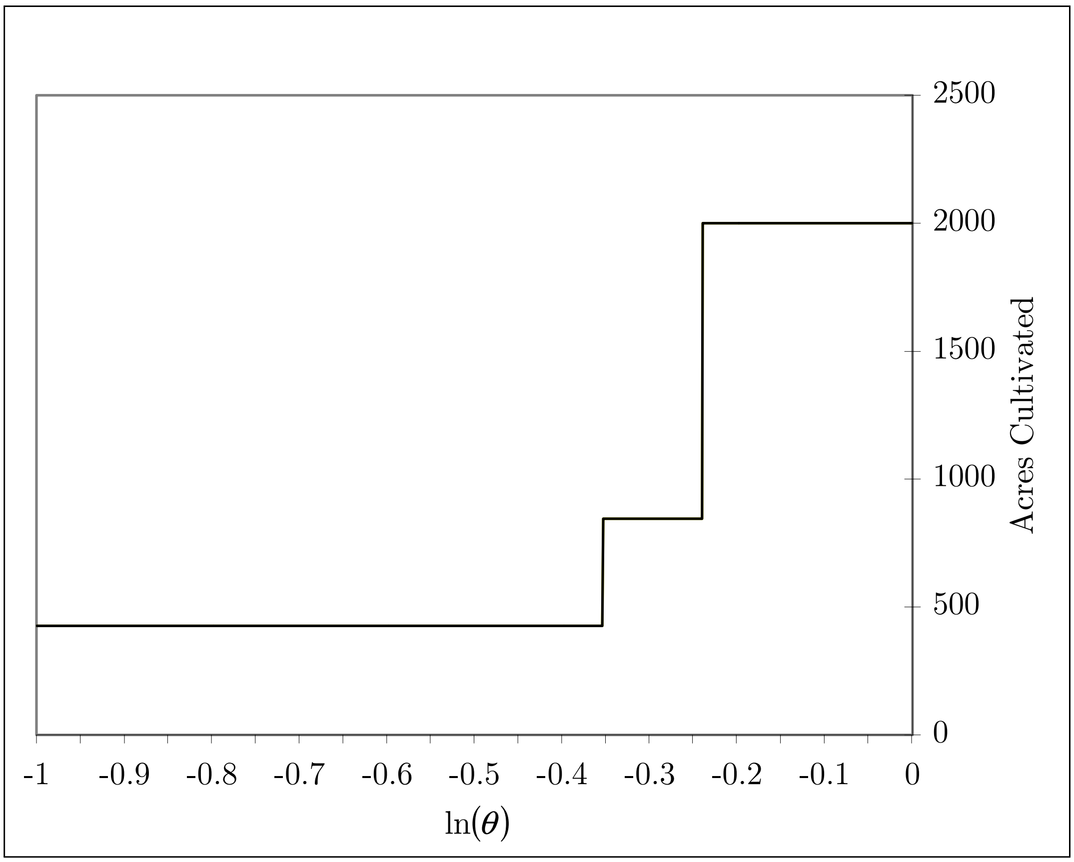
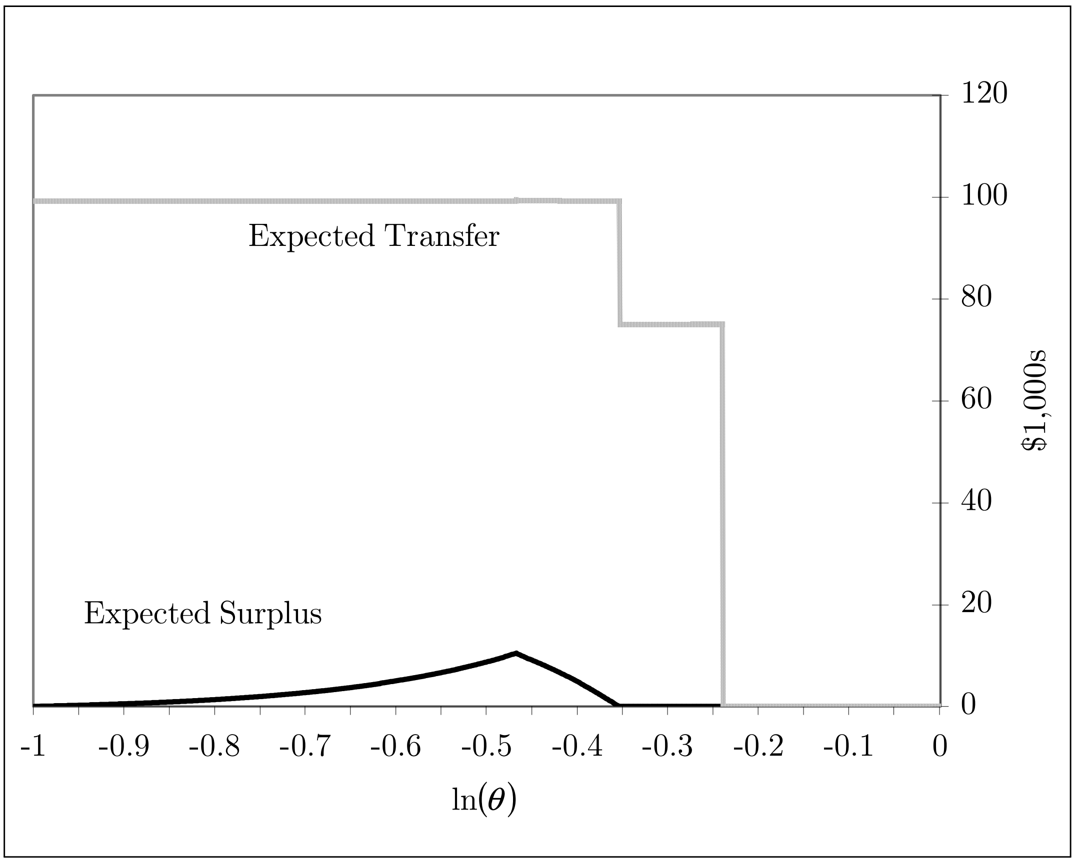


Figure 5.7: *Ex Ante* Program, No Environmental Constraint, Expected Payments by Type



5.2.3 *Ex Post* Program

From equation (2.48), the first-order condition for an interior solution for the optimal *ex post* land allocation is:

$$\Pi_a\left(a\left(\theta\right),\theta\right)+\frac{\rho\gamma\left(p_\ell,\theta\right)}{f\left(\theta\right)}\pi_{a\theta}\left(p_\ell,a\left(\theta\right),\theta\right)+\frac{\left(1-\rho\right)\gamma\left(p_h,\theta\right)}{f\left(\theta\right)}\pi_{a\theta}\left(p_h,a\left(\theta\right),\theta\right)=\lambda \tag{5.5}$$

For $\lambda = 0$, this is another bang-bang solution since the sign of the left-hand side of (5.5) does not depend upon a. If the left-hand-side of (5.5) is negative, land cultivated will be at the minimum, whereas if it is positive, land cultivated will be at the maximum. Unlike the *ex ante* case, however there can be no central pooling interval for the *ex post* mechanism.

To calculate $\gamma\left(p_\ell,\theta\right)$ and $\gamma\left(p_h,\theta\right)$, I conjecture that optimally $s\left(p_\ell,\underline{\theta}\right) = s\left(p_h,\bar{\theta}\right) = 0$. These Lagrange multipliers then take the following values:

$$\gamma\left(p_\ell,\theta\right) = F\left(\theta\right)-1 \tag{5.6}$$

$$\gamma\left(p_h,\theta\right) = F\left(\theta\right). \tag{5.7}$$

Figure 5.9 depicts surplus in each price state as well as expected surplus arising from these values for the costate variables. No type receives less than zero surplus in either state, so income and participation constraints are satisfied. Hence, the conjectured solution is optimal.

The land allocation for this program is depicted in Figure 5.8. There are pooling equilibria around two corner solutions. All types less than $e^{-0.362}$, idle the maximum acres, while all higher types idle no acres. Expected payments are depicted in Figure 5.10. There are two payment tiers. Producers idling 1,375 acres receive approximately \$107 thousand, while producers idling no acres receive about \$43 thousand. All types receive positive expected surplus. Expected surplus increases until θ_L, then decreases after the participation constraint becomes binding for p_h. Expected surplus reaches its minimum for $\ln(\theta) = -0.363$ where idled acreage switches from 1,375 to zero. After this point expected surplus increases again until θ_L, where the income constraint ceases to be binding for p_ℓ. The average number of acres idled per producer is 595. The average cost per producer of the *ex post* mechanism is \$67,200.

5.2.4 FAIR Act

Since the purpose of the CRP is to idle land for environmental benefits, I model the actual program in this scenario as consisting only of lump-sum production flexibility contracts paid equally to all farms. The land allocation is illustrated in Figure 5.11. As in the first-best case, no acres are idled.

The amount of the expected payment is simply:

$$m - \left[\rho\pi\left(p_\ell, \bar{a}, \underline{\theta}\right) + (1-\rho)\,\pi\left(p_h, \bar{a}, \underline{\theta}\right)\right]. \tag{5.8}$$

Figure 5.12 depicts expected payments. All types receive an identical lump sum payment of about \$96,500. The lowest type receives zero expected surplus. Expected surplus is weakly increasing for all types. There are two kinks in the expected surplus path. The first occurs at θ_L when the income constraint ceases to be binding for p_h and the second occurs at θ_H when the income constraint ceases to bind for p_ℓ. The average cost of this program is approximately \$96,500.

Figure 5.8: *Ex Post* Program, No Environmental Constraint, Acres Cultivated by Type

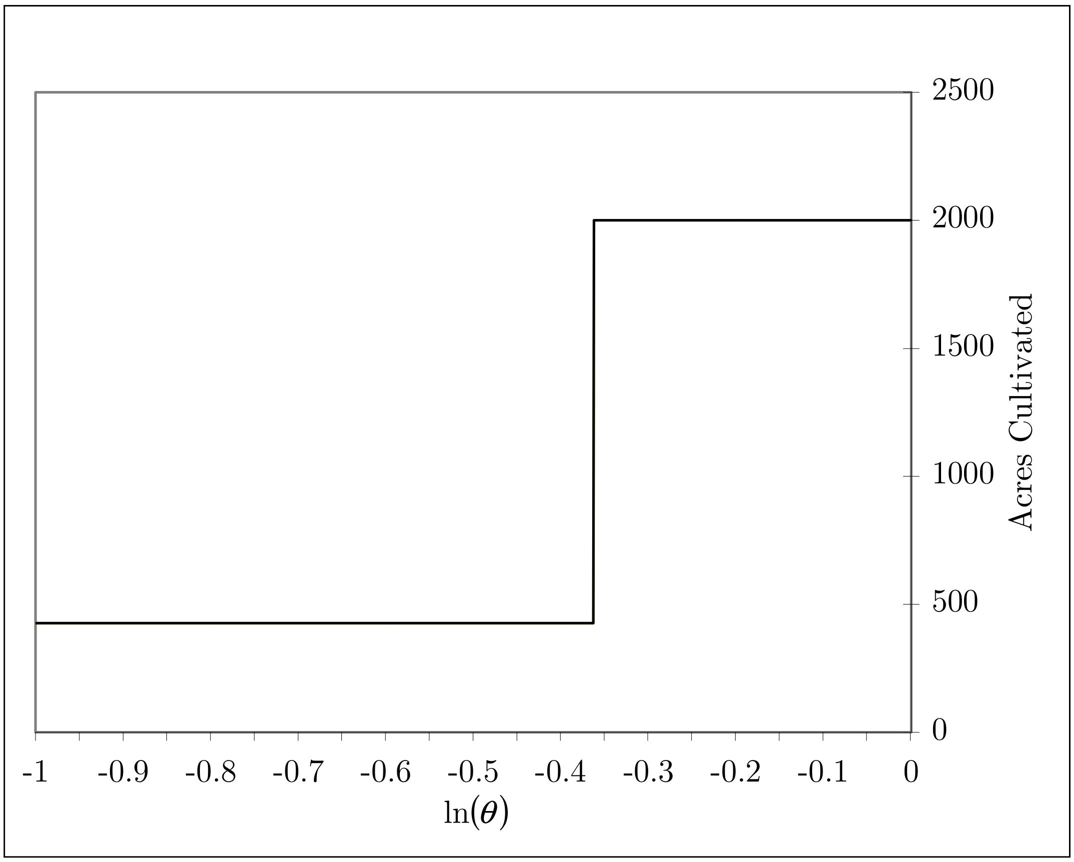


Figure 5.9: *Ex Post* Program, No Environmental Constraint, Surplus by Type

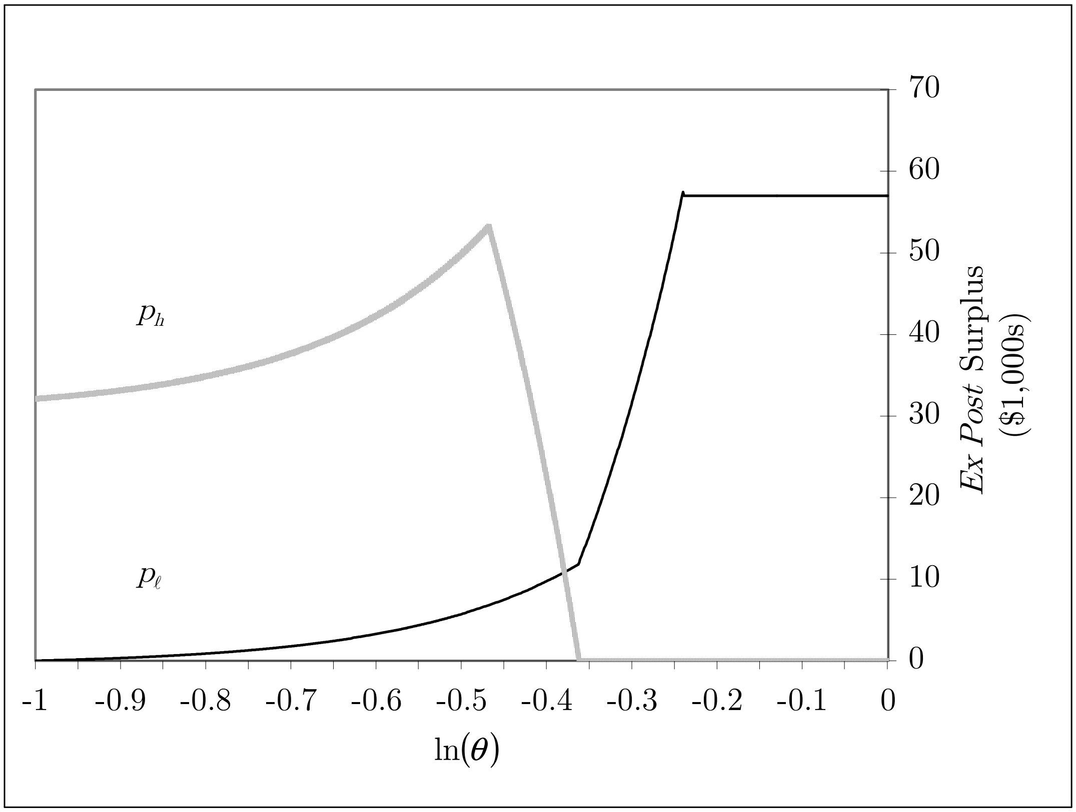


Figure 5.10: *Ex Post* Program, No Environmental Constraint, Expected Payments by Type

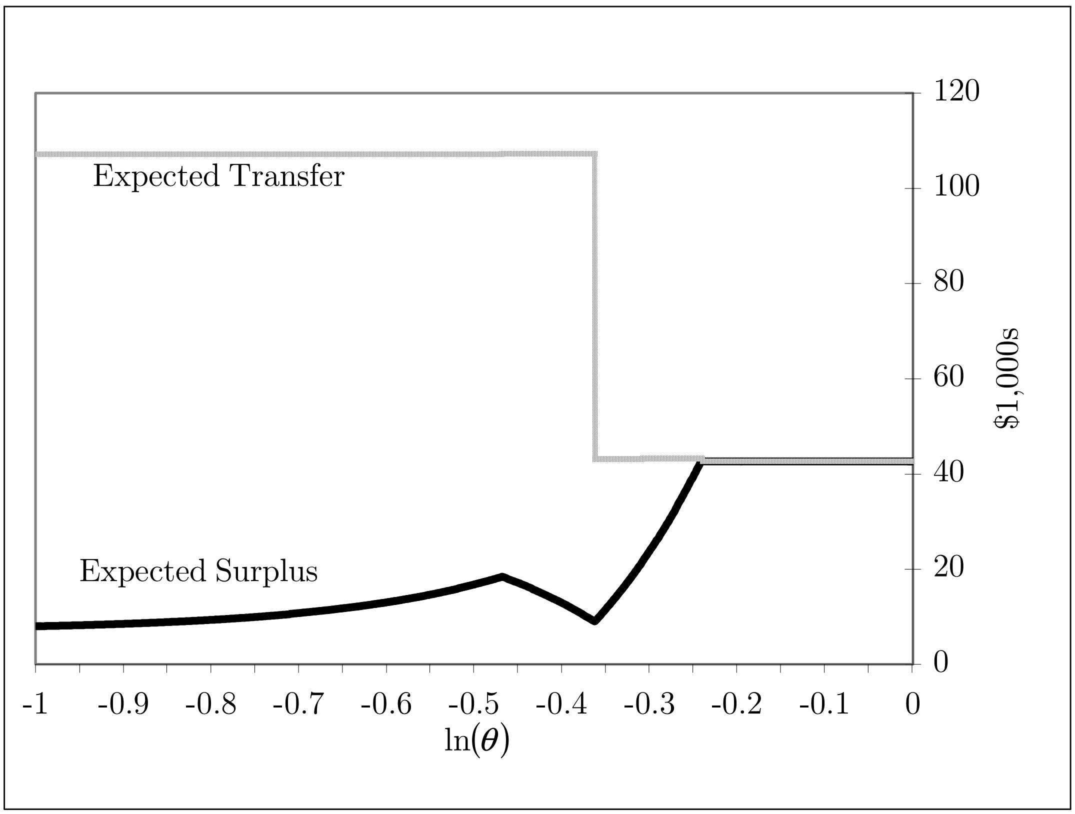


Figure 5.11: FAIR Act, No Environmental Constraint, Acres Cultivated by Type

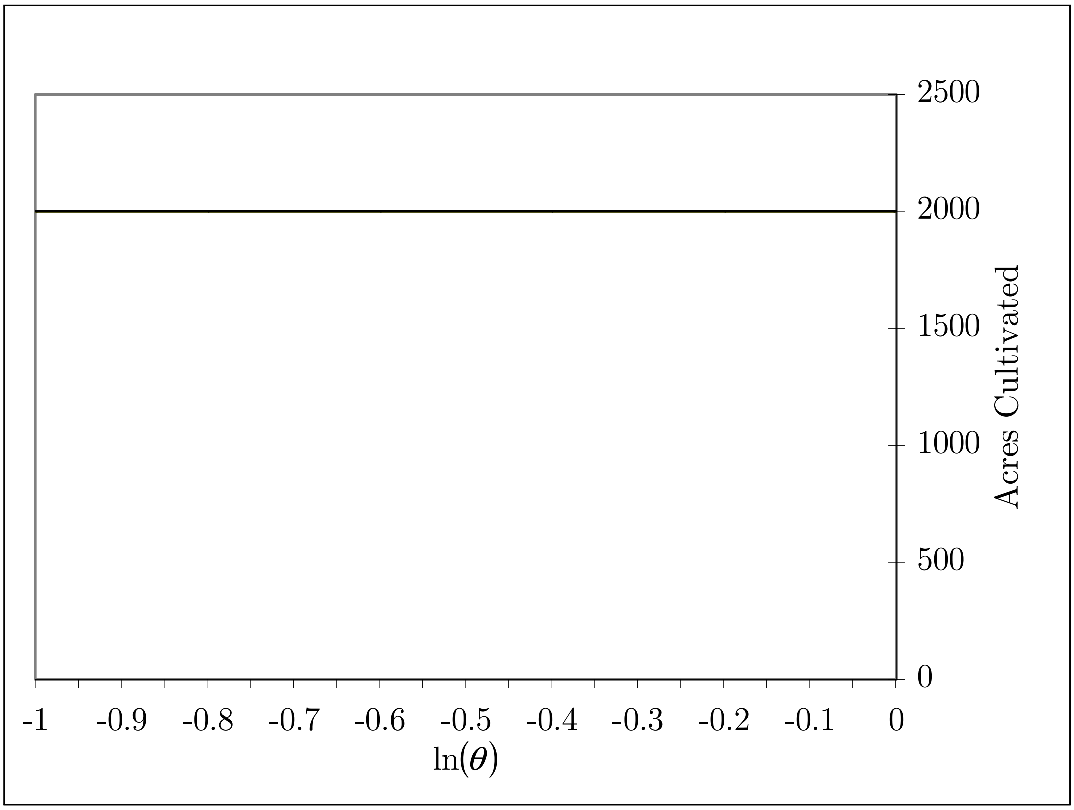
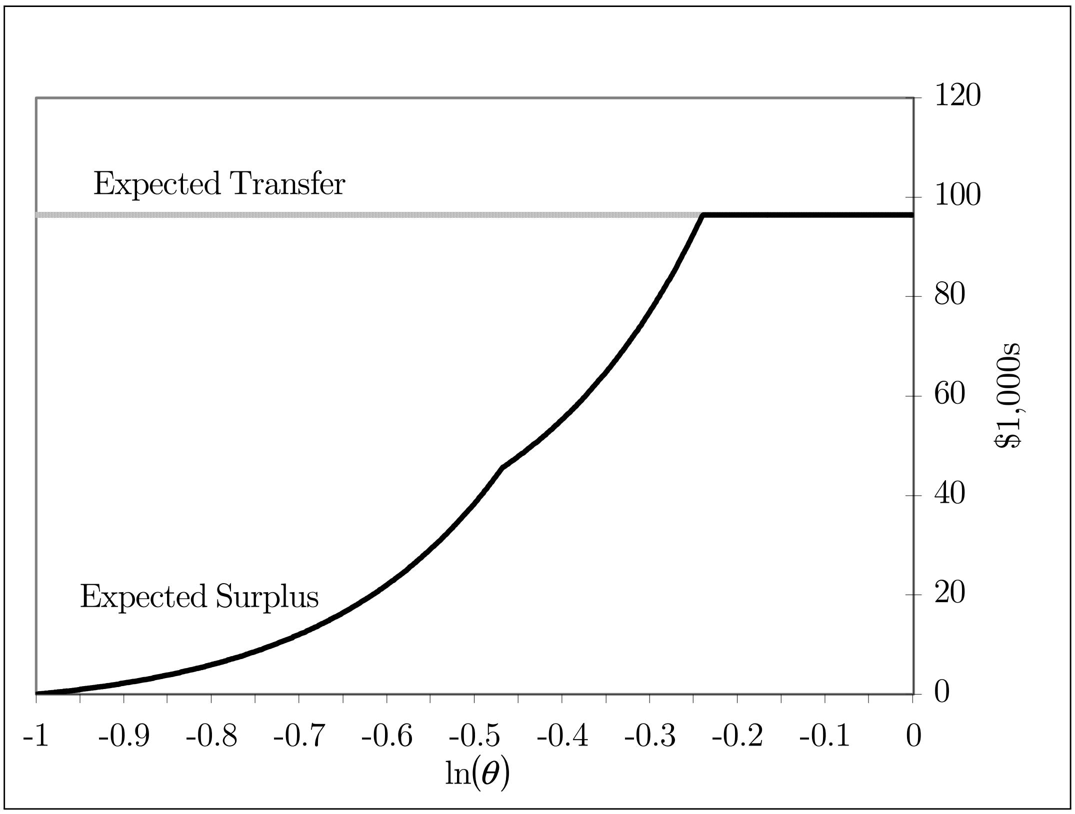


Figure 5.12: FAIR Act, No Environmental Constraint, Expected Payments by Type



5.3 Scenario 2: Environmental Constraint

In this section, I model the case where idling land creates a marginal social benefit of \$71 per acre. *A priori*, it is impossible to know if the optimal program exhibits any pooling, and if so, over which interval of types. I first characterize the first-best program, determining the land allocation and payments per producer. I then calculate average cost per producer and average environmental benefits. I compare these results to those for the *ex ante*, *ex post*, and stylized actual programs.

To perform the simulation, I set the value of the Lagrange multipliers λ for the first-best program in equation (2.21), the *ex ante* program in equation (2.90), the *ex post* program in equation (2.46), and the FAIR Act in equation (2.137) equal to 71. As before, the income constraint is defined as ensuring that all types above e^{-1} earn at least \$50 per acre.

5.3.1 First-Best Program

The land allocation of the first best contract is calculated by solving first-order condition (2.21) to obtain the optimal amount of land cultivated by each type for $\lambda = 71$. Since there are no information asymmetries, there are no surplus payments. Expected transfers are simply the payments necessary to ensure that income and participation constraints are met for each type, given the amount of land idled.

Figure 5.13 illustrates the land cultivated and expected transfer received by each type with the first-best contract allocation. There are two sets of corner solutions for land allocations. All types below -0.326 idle the maximum amount of land, and all types above -0.142 idle no land. Intuitively, efficiency requires that the equimarginal principle be satisfied. That is to say, the marginal opportunity cost of idling an additional acre should be equal for all producers. For the two corner solutions this condition would require that very low types idle more than the maximum acreage permissible, and very high types idle less than zero acres.

Figure 5.14 depicts expected payments. No type receives expected surplus. Expected transfers decrease gradually for Θ_L. Expected transfers begin to rise after θ_L since the participation constraint becomes binding for p_h. However, since land cultivation is increasing in type above $e^{-0.326}$, expected transfers decline again after that point. The rate of decline of expected transfers slows after θ_H since the income constraint no longer binds. Once type $e^{-0.142}$ is reached all transfers cease since none of these producers idles any land. The average amount of land idled per farm is 882 acres for an average environmental benefit of \$62,600. The average cost per producer is about \$53,600.

5.3.2 *Ex Ante* Program

The first step to characterize this program is to solve first-order condition (2.92). As for the scenario with no environmental benefits, the value of the Lagrange multiplier $\gamma(\theta)$ is initially unknown. Consulting Table 2.1, I check to see if there is a value for $\mu_1 \in (0,1)$ such that for $a^*(\theta, F(\theta) - \mu_1, \lambda)$, the lowest type and an interior type θ_1 idling $\hat{a}$ acres both receive zero expected surplus. For $\lambda = 71$, there is: $\mu_1 = 0.36336$, for an interior type $\ln(\theta_1) = -0.346$. Next, I check to see if there is a value for $\mu_2 \in (\mu_1, 1)$ such that for $a^*(\theta, F(\theta) - \mu_1, \lambda)$, both the highest type and an interior type θ_2 idling $\hat{a}$ acres both receive zero expected surplus. In this case, $\mu_2 = 0.54940$, for $\ln(\theta_2) = -0.260$.

The land allocation corresponding to this solution is depicted in Figure 5.15.

Figure 5.13: First-Best Program, With Environmental Constraint, Acres Cultivated by Type

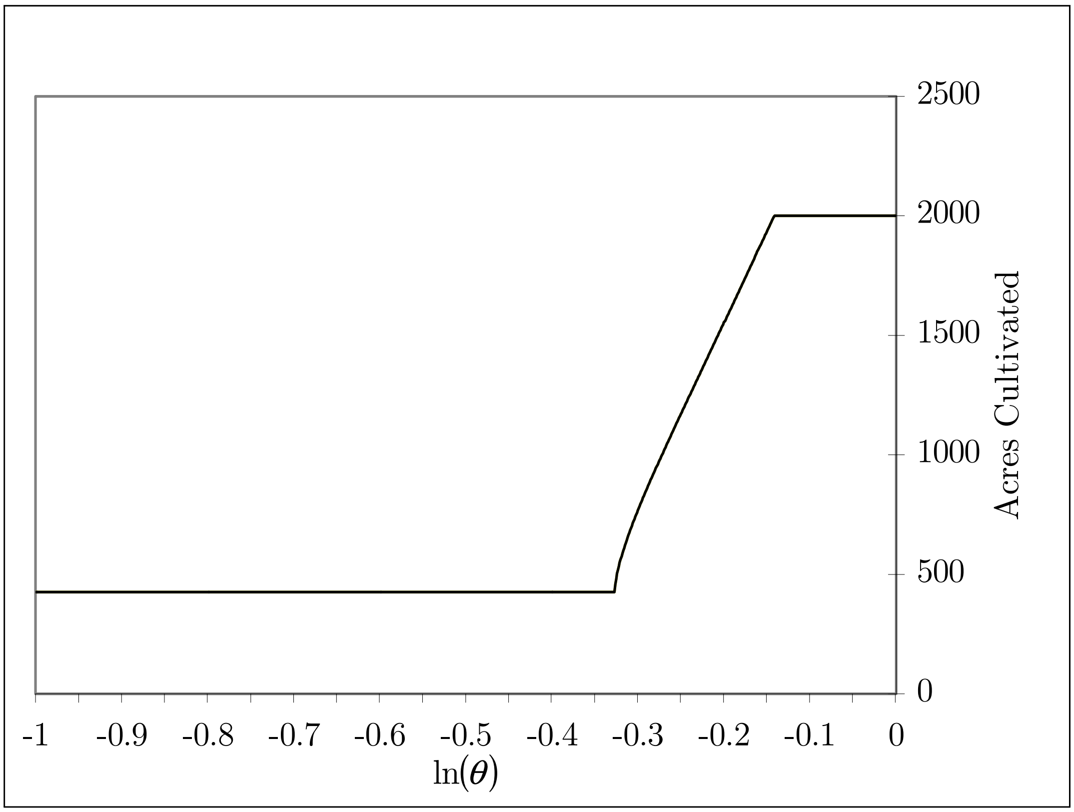
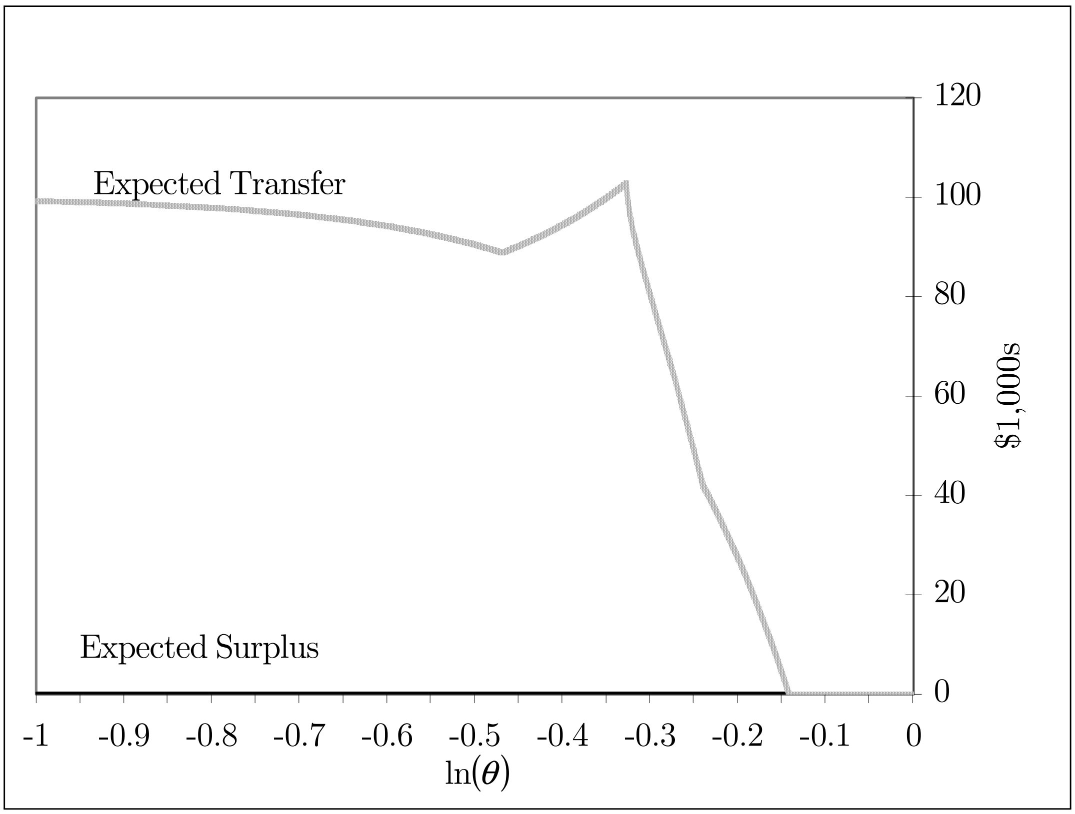


Figure 5.14: First-Best Program, With Environmental Constraint, Expected Payments by Type



There are three pooling intervals. All types below $e^{-0.359}$ idle the maximum amount of land. Land cultivated increases until a central interval of types from θ_1 to θ_2. These types cultivate 845 acres. Land use then increases until type $e^{-0.211}$.

Expected payments are depicted in Figure 5.16. Expected transfers are a decreasing function of acres cultivated, and can be divided into four intervals. All types lower than $e^{-0.359}$ idle 1,675 acres and receive about $99,200. Land idled and transfer received is decreasing in type from $e^{-0.359}$ until θ_1. From θ_1 to θ_2 all types idle 1,155 acres and receive an expected transfer of about $75,000. Land idled and transfer received again is decreasing in type from θ_2 until $e^{-0.211}$, after which no land is idled and no transfer received. Expected surplus begins at zero for $\underline{\theta}$, increases until θ_L, then decreases to zero for θ_1. From θ_1 to θ_2 all types receive zero expected surplus. Expected surplus increases from θ_2 to θ_H, then decreases to zero at $e^{-0.211}$, after which no type receives expected surplus. The average amount of land idled per farm is 816 acres for an environmental benefit of $58 thousand per producer. The average cost per producer is about $51,570.

5.3.3 *Ex Post* Program

A necessary condition for an interior solution of the optimal *ex post* contract is that the land allocation for each type satisfy equation (2.48). As in the first scenario, one cannot determine the values of $\gamma(p_\ell, \theta)$ and $\gamma(p_h, \theta)$ *a priori*. Instead, I conjecture that optimally $s(p_\ell, \underline{\theta}) = s(p_h, \bar{\theta}) = 0$. The Lagrange multipliers take the corresponding values:

Figure 5.15: *Ex Ante* Program, With Environmental Constraint, Acres Cultivated by Type

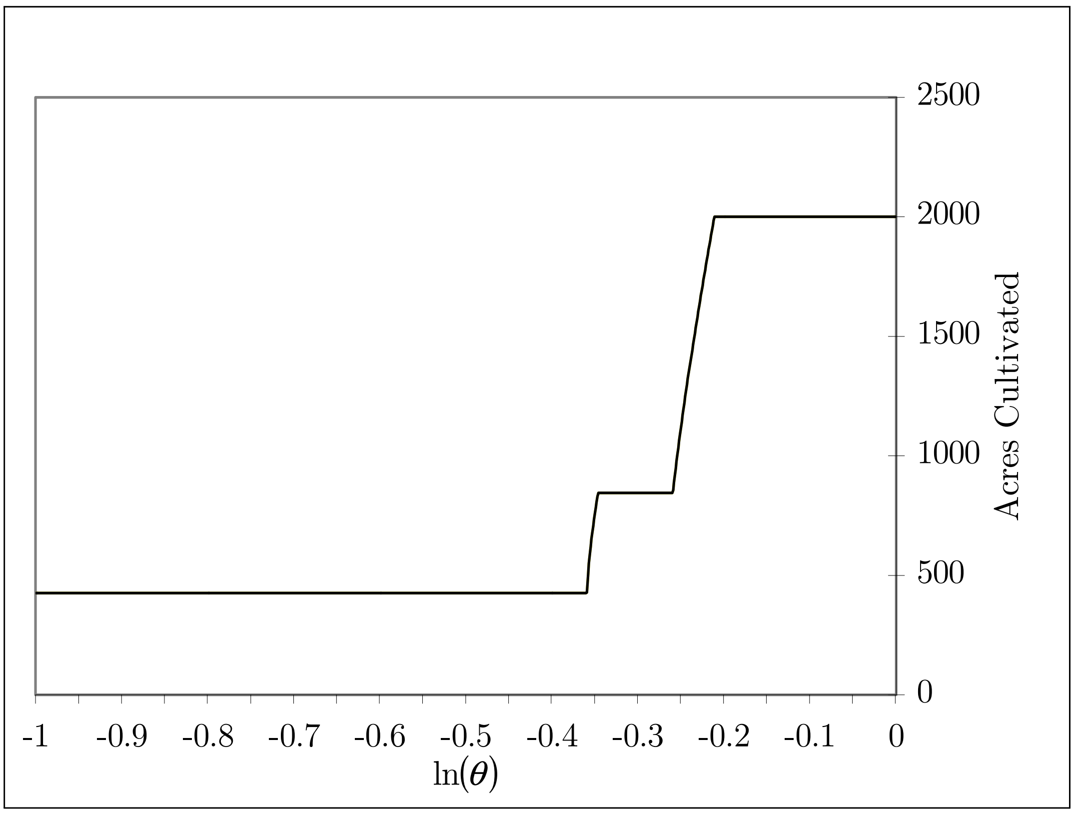
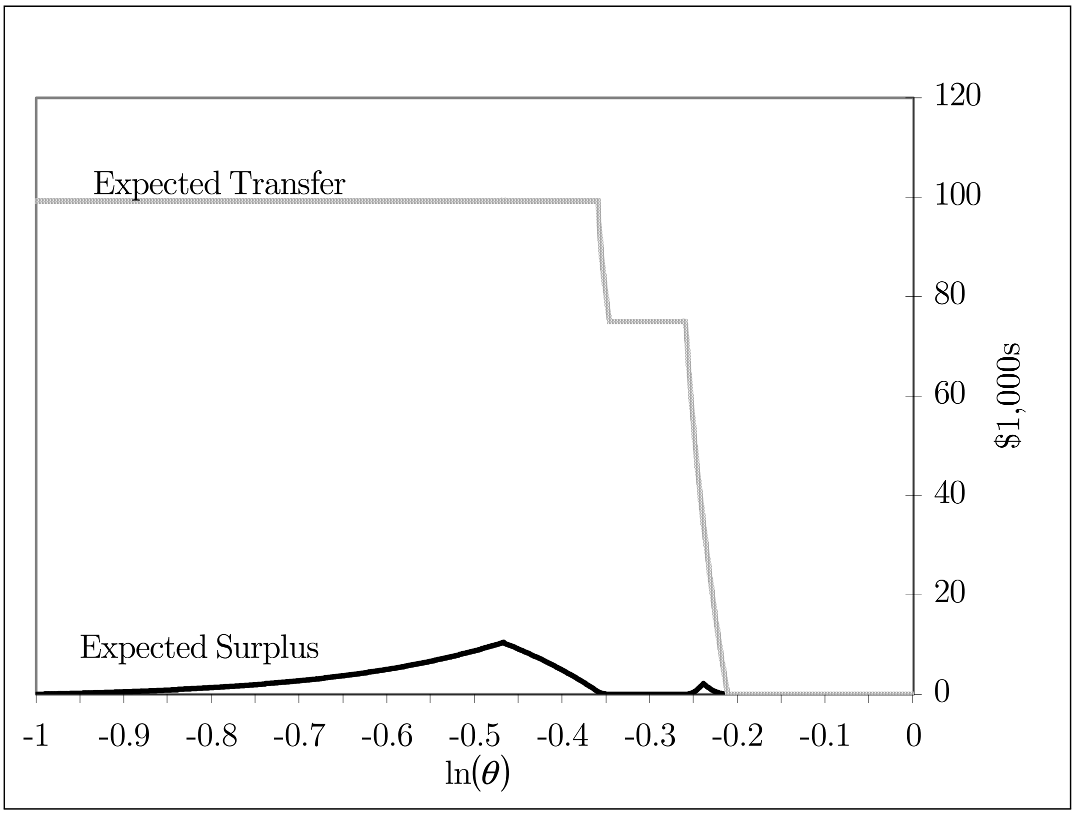


Figure 5.16: *Ex Ante* Program, With Environmental Constraint, Expected Payments by Type



$$\begin{aligned}\gamma(p_\ell,\theta) &= F(\theta)-1 \quad (5.9)\\ \gamma(p_h,\theta) &= F(\theta)\,. \quad (5.10)\end{aligned}$$

I then calculate the amount of land idled per farm by solving (2.48) using these values and setting $\lambda = 71$. Figure 5.18 depicts surplus in each price state as well as expected surplus arising from these values for the Lagrange multipliers. No type receives less than zero surplus in either state, so income and participation constraints are satisfied. Hence, this solution is optimal.

The land allocation for this program is depicted in Figure 5.17. There are pooling equilibria around two corner solutions. All types less than $e^{-0.294}$ idle the maximum acres, while all types above $e^{-0.234}$ idle no acres. Acres cultivated are strictly increasing in type for all other types. Unlike the *ex ante* mechanism, there is no pooling across an interior interval of types.

Figure 5.19 depicts expected payments. As in the case with no environmental constraint, all types receive strictly positive expected surplus. The average amount of land idled is 809 acres, for an environmental benefit of about \$54,400 per producer. The average cost per producer is \$76,100.

5.3.4 FAIR Act

For the program based on the FAIR Act, I calculate acres idled per farm in the CRP by solving (2.139) with $\lambda = 71$. Figure 5.20 depicts the land allocation for the CRP. Maximum acreage is idled for all types below $e^{-0.576}$. Acres cultivated are then strictly increasing in type until $e^{-0.424}$ after which no idling takes place.

Expected lump-sum production flexibility contract payments are based upon the additional transfers necessary to ensure that $\underline{\theta}$ meets the minimum income

Figure 5.17: *Ex Post* Program, With Environmental Constraint, Acres Cultivated by Type

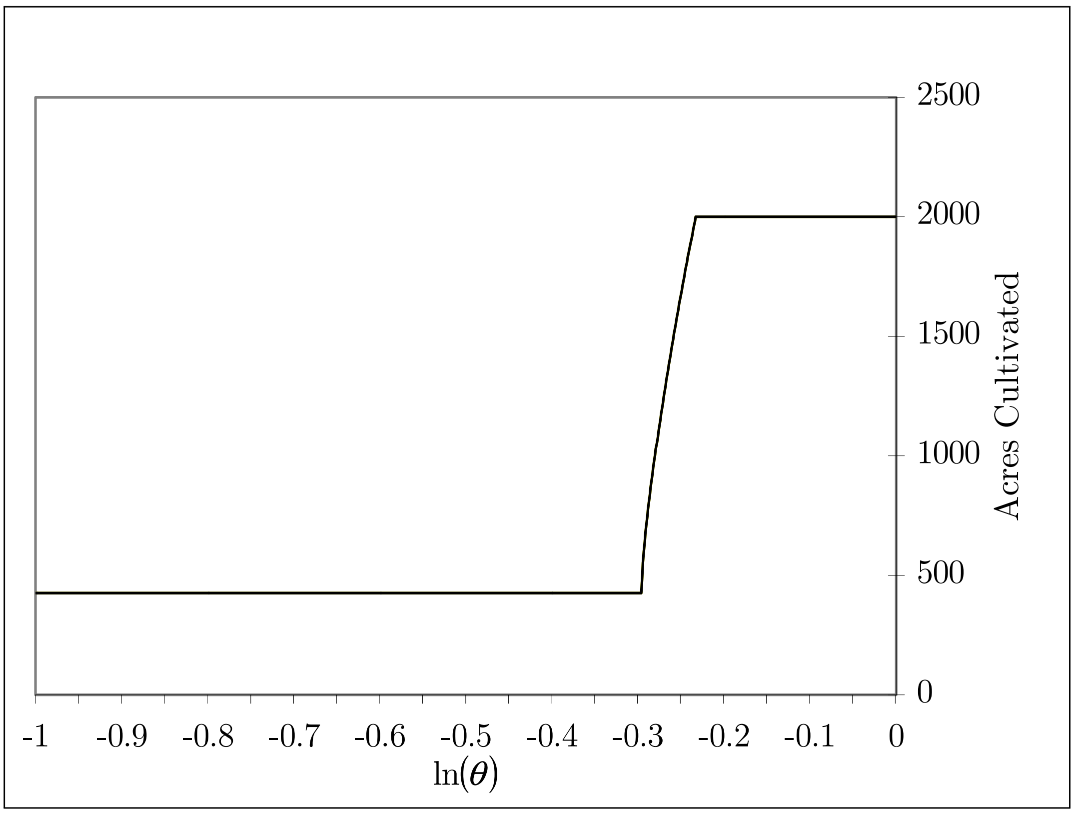


Figure 5.18: *Ex Post* Program, With Environmental Constraint, Surplus by Type

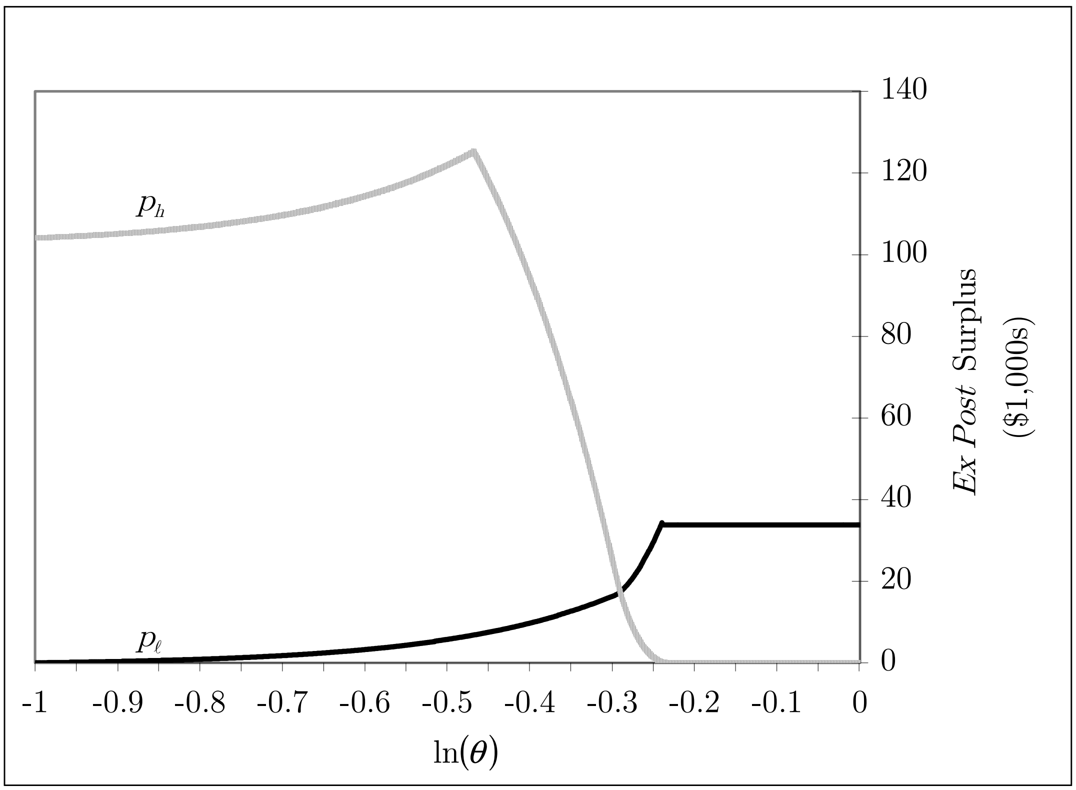
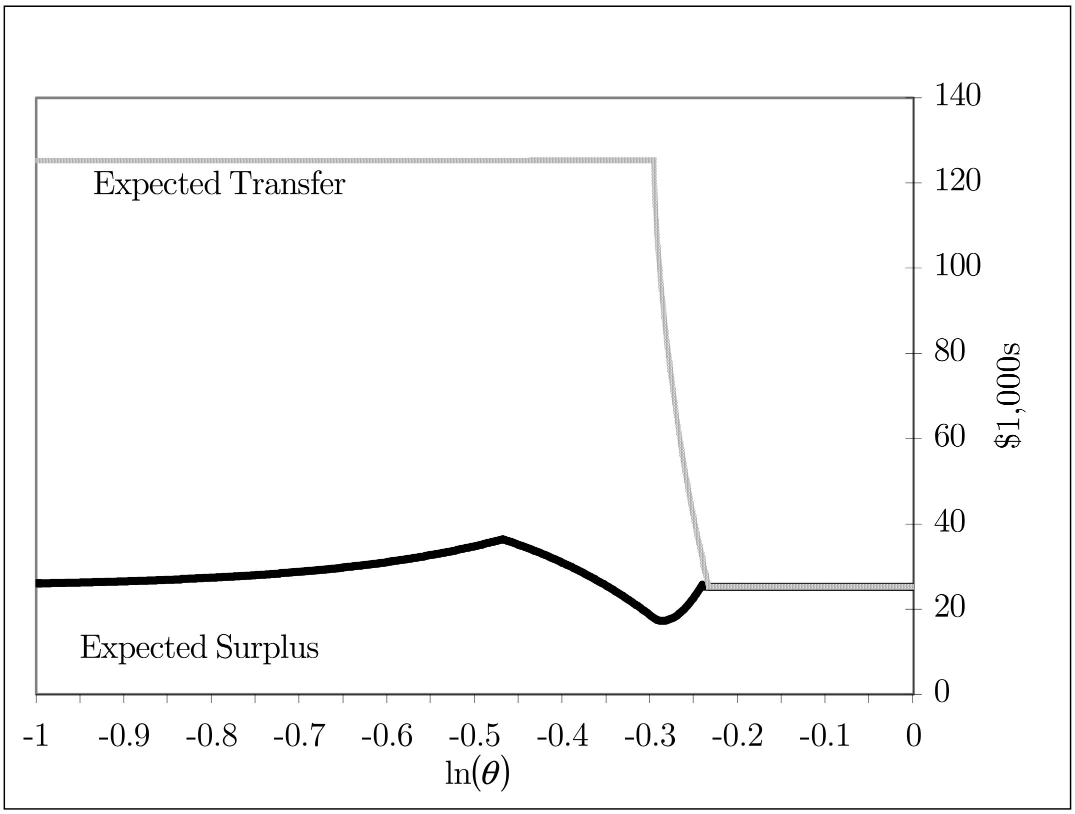


Figure 5.19: *Ex Post* Program, With Environmental Constraint, Expected Payments by Type



constraint once surplus payments from the CRP are factored in:

$$m - [\rho\pi(p_\ell, \bar{a}, \underline{\theta}) + (1-\rho)\pi(p_h, \bar{a}, \underline{\theta})] - S_c(\underline{\theta}).$$

Figure 5.12 depicts expected payments. All types below -0.576 receive an expected transfer of about \$99,200. All types above $e^{-0.424}$ receive an expected transfer of about \$69 thousand. Expected transfers are strictly decreasing in type for all other types. As in the first scenario, the lowest type receives zero expected surplus. Expected surplus is weakly increasing for all types. There are two kinks in the expected surplus path. The first occurs at θ_L when the income constraint ceases to be binding for p_h and the second occurs at θ_H when the income constraint ceases to bind for p_ℓ. The average idled is 342 acres, for an average environmental benefit of \$24,300 per producer. The average cost of this program is approximately \$75,500 per producer.

5.4 Discussion

The simulations undertaken in this chapter compared four policy alternatives for achieving environmental and income targets in the agricultural sector under two scenarios regarding environmental benefits. Under the first, land idled yields no environmental benefits, while under the second, each acre of idled land yields \$71 of benefits.

The simulations run under the first scenario generalize the results of Bourgeon and Chambers (2000) from two types of producers to a continuum of types and more than one output price. Since the problem considered by Bourgeon and Chambers (2000) considers a single output price, their solution corresponds most closely to the *ex post* mechanism considered here. For this case, extending the

Figure 5.20: FAIR Act, With Environmental Constraint, Acres Cultivated by Type

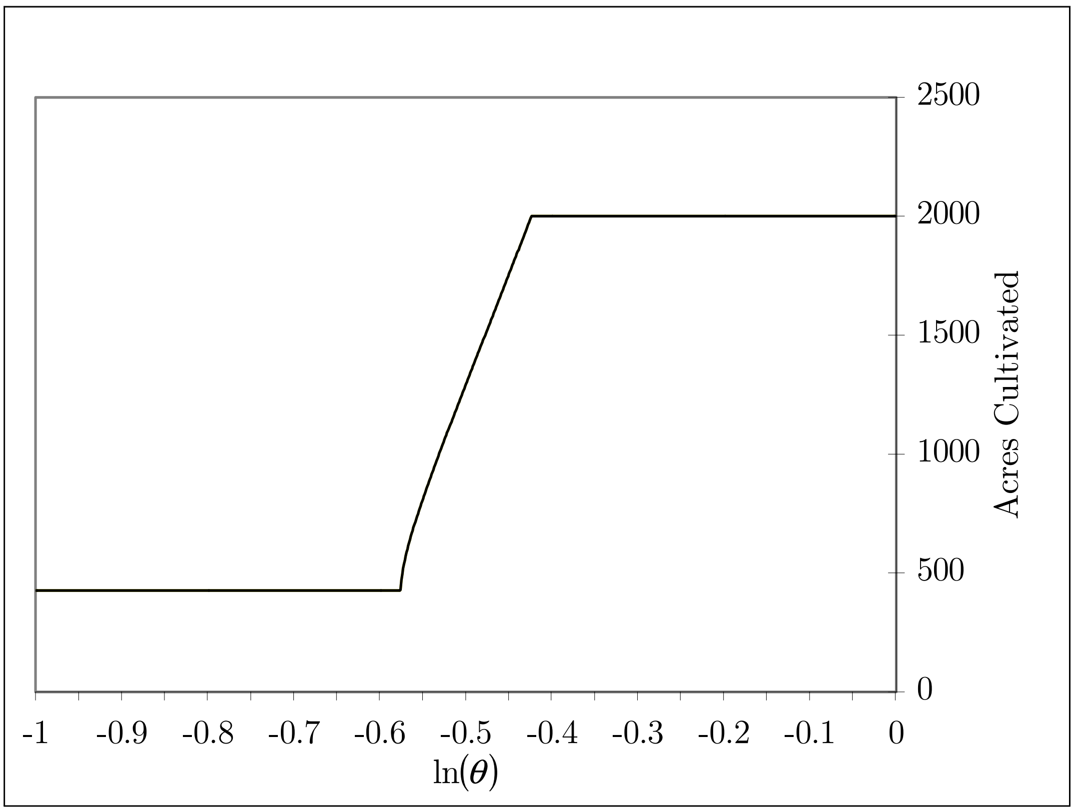
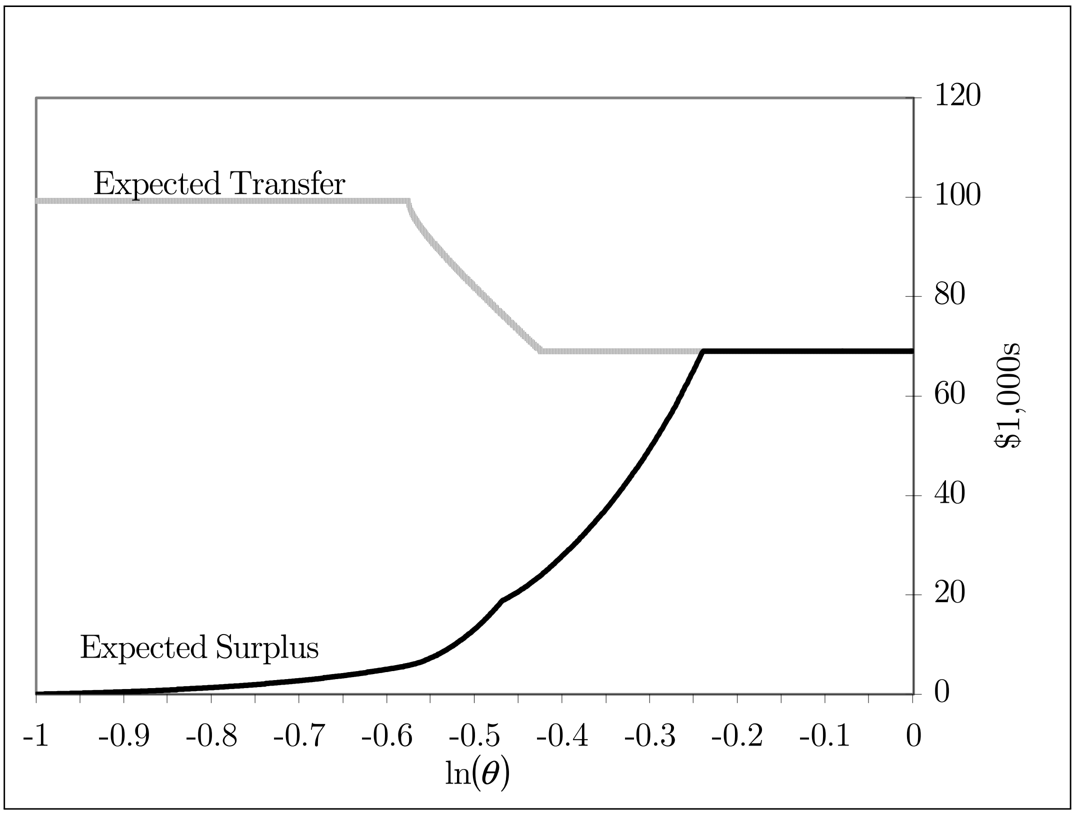


Figure 5.21: FAIR Act, With Environmental Constraint, Expected Payments by Type



analysis to a continuum of types does not alter the qualitative results. The optimal program consists of two contracts: either idle the maximum amount of land for a high payment, or idle no land for a lower payment. Types lower than -0.362 will accept the former, while higher types will accept the latter. Similar to Bourgeon and Chambers (2000) I obtain the result that some land idling is optimal, and "stop-and-go" agricultural policies are cost minimizing.

Allowing for two output prices changes the qualitative results. If contracting takes place before output price is known, the optimal program consists of three contracts. As before, lower-type farmers idle the maximum amount of land, and higher types idle no land. In this case, however, a central interval of types idles less than the maximum amount of land. The failure to successfully harness the countervailing incentives created by price uncertainty raises the expected cost of attaining the income target by about \$15,800 per farm (about 30 percent).

Because either program allows land idling to offset the information costs of the policy, both the *ex ante* and *ex post* programs are superior to a single contract lump-sum payment scheme. Production flexibility contracts required by the FAIR Act to attain the same income target in the absence of a CRP imply an average expected cost per producer approximately \$45,300 (88 percent) higher than the *ex ante* program.

With no environmental benefits, the *ex ante* program is about \$23,400 (85 percent) more expensive than a first-best program. However, if an accurate governmental survey of growing conditions could completely eliminate information asymmetries, it would be worth paying no more than \$11.70 per acre to conduct it.

Allowing for positive environmental benefits changes the qualitative nature of the programs. Rather than having one, two, or three contracts all three programs require a continuum of contracts ranging from zero to 1,575 acres idled. If idled acres yield a constant environmental benefit of \$71 per acre, the net benefits to the non-farm sector of attaining environmental and income targets range from $-\$51,200$ per producer for the FAIR Act to $\$9,000$ for the first-best. With the higher environmental benefits the difference between the *ex ante* and first best programs narrows significantly. The net benefits of the first best are about \$2,600 (41 percent) higher than the *ex ante* program, implying a potential gain of only \$1.3 per acre of collecting data that eliminates asymmetric information. The difference in benefits between the FAIR Act and the first-best, however could justify spending as much as \$30.10 an acre to collect the same data. The simulation indicates that the expected benefits to be gained by switching from the FAIR Act to an *ex ante* green payments program may be in the magnitude of \$56,600 per farm, or \$28.30 per acre.

It is also interesting to note the welfare effects of switching from the FAIR Act to an *ex ante* program. With or without environmental benefits, the FAIR Act gives the highest expected surplus payments to the more profitable producers. Under the *ex ante* program, however, expected surplus is eliminated for the higher types. (Compare Figures 5.7, 5.12, 5.16, and 5.21.) Therefore, from a political economy standpoint, one would expect opposition from the most profitable producers to proposals to switch from current policy to an *ex ante* green payments program.

Chapter 6

Conclusion

The objectives of this dissertation are twofold. The first is to apply modern mechanism design theory to agricultural policy. The second is to develop and implement an econometric framework through which mechanism design models can be evaluated empirically.

Regarding the first objective, I have shown that it is optimal for the government to link income support payments to participation in environmental programs. This result is contrary to current practice in the United States. Current policies seem to take a Tinbergen (1963) style two-objective, two-instrument approach. For the environmental objective, an auction process is used to idle environmentally sensitive land at least cost. For the income support objective non-distortionary lump sum payments are issued to farmers.

I have shown that this type of decoupled policy squanders information. Less-profitable producers have a lower opportunity cost of land. Therefore the degree to which a producer is willing to participate in a land set aside program can reveal information about his relative profitability. A decoupled program does not take advantage of this information.

However, it is not enough simply to link income support payments to land set aside. The relative importance of the two objectives changes with output price. A high output price increases the amount that must be paid to induce producers to idle land. At the same time, it reduces the amount that must be paid to ensure producers attain the minimum income threshold. If the income support objective is dominant, producers have an incentive to understate their profitability. If the environmental objective is dominant producers have an incentive to overstate their profitability (and hence the opportunity cost of idling land).

Uncertainty regarding future prices reduces the expected payoff to a producer of misrepresenting his true type. I have shown that a green payments program that takes place after price uncertainty is resolved does not take advantage of the countervailing incentives provided by price uncertainty. In order to minimize total expected cost, it is important that contracting take place before price uncertainty is resolved.

Although these theoretical results can give policy makers general guidance, they are not helpful in providing the details necessary to actually implement such a program. This lack of specific guidance is particularly worrisome given the multiplicity of possible solutions to the optimal contracting problem examined in Chapter 2. A gap in the literature exists with respect to how a policy maker can empirically evaluate a mechanism when some information is inherently hidden.

In Chapters 3 and 4, I develop and implement an approach to solving this problem by adapting techniques from stochastic frontier analysis. I start with a simple model of how a producer's type (profitability) explicitly enters the production process. From there I develop the implied cost frontier. Borrowing from stochastic frontier analysis, I choose a parametric family for the distribution of producer types. I then use generalized method of moments to econometrically estimate the parameters of the cost function and the parameters of the distribution of types. These estimates are used to simulate an optimal green payments mechanism and derive the optimal schedule of contracts.

The simulation in Chapter 5 shows that it is likely that a least-cost program is likely to involve pooling over a central interval of types. Such a result is impossible to achieve with the separated policies currently in use. For the region studied, the FAIR Act may be in the magnitude of 88 percent more expensive than the *ex ante* green payments program, even when idling land yields no environmental benefits. With environmental benefits of $71 per acre of land idled, the difference in net benefits between the FAIR act and the ex ante program are estimated to be about $56,600 per farm. Moreover, the *ex ante* program does a reasonable job of approximating the perfect information policy. Under the scenario of $71 per acre environmental benefits, it would only be worth $1.30 per acre to collect information regarding farm profits. Finally, the simulation shows that it is the most profitable farms that stand to lose from a switch from current policy to the optimal program.

The work in this dissertation represents a first approach to empirically evaluating mechanism design models. Restrictive assumptions were imposed in order to simplify the analysis. Work remains to be done with respect to generalizing the results enough to make it possible to design an optimal green payments mechanism at the detail necessary for actual policy implementation.

For example, a significant assumption is that all farms are the same size. It is obvious that this is not the case in reality. More work can be done to take farm size into account. Differing farm size can complicate the problem since size affects the marginal product of land. A policy that does not take this into account can give producers an incentive to change the size of their farm in order to get more government payments. It is of interest to see how allowing farm size to be endogenous might change the results of this analysis.

A second significant assumption is that input prices are constant and output price follows a simple binomial distribution. Since the optimal contract offers price contingent payments, practical implementation would require extending the model to a continuum of possible price states.

Finally, this work has possibilities to be extended to other fields outside of agricultural policy. Often, environmental objectives come into conflict with the welfare of politically important interest groups. For example, consider the case of a fishery. The government may wish to reduce fishing capacity, while protecting economically vulnerable fishermen. The analysis in the dissertation indicates that providing income support through payments not to fish may be a cost efficient way to achieve both objectives. Further gains in efficiency could be made if *ex ante* contracts make payments contingent upon fluctuations in the price of fish.

This dissertation can provide guidance to these types of policy problems in two ways. First, it is straightforward to extend the theoretical results to develop a general outline of the qualitative characteristics of an optimal solution. Second, it shows how one may use data available from producer surveys to empirically tailor a program that specifically fits the characteristics of the specific economic agents involved.

Appendix A

Empirical Results

A.1 Translog Cost Function

Table A.1: Translog Estimates Robust to Heteroskedasticity and County Clusters

	Expenditure Share Equation Eliminated					Expenditure Share Equation Eliminated			
	K	L	E	M		K	L	E	M
	Estimate Std. Err.	Estimate Std. Err.	Estimate Std. Err.	Estimate Std. Err.		Estimate Std. Err.	Estimate Std. Err.	Estimate Std. Err.	Estimate Std. Err.
δ_{97}	8.8173	11.1062	6.7709	7.0002	β_{LL}	0.0611	-0.5942	0.0386	0.0458
	1.8229	1.9099	1.8755	1.7443		0.0638	0.2674	0.0538	0.0532
δ_{98}	8.7557	11.0432	6.7404	6.9847	β_{LE}	-0.2116	0.0322	-0.1421	-0.3585
	1.8219	1.9092	1.8730	1.7430		0.0746	0.0901	0.0841	0.0695
δ_{99}	8.7301	11.0296	6.6905	6.9341	β_{LM}	-0.0227	0.2817	0.1874	0.4377
	1.8216	1.9094	1.8727	1.7417		0.1354	0.1524	0.1057	0.1334
δ_{00}	8.4505	10.7533	6.4196	6.6562	β_{LA}	0.2232	0.4539	0.2416	0.1586
	1.8192	1.9090	1.8744	1.7420		0.0524	0.0771	0.0368	0.0397
β_{A}	1.3088	2.9313	0.3415	0.6862	β_{LQ}	-0.3084	-0.5369	-0.3502	-0.2305
	0.6498	0.6822	0.5623	0.5817		0.0633	0.0845	0.0458	0.0484
β_{Q}	-1.2024	-2.4340	-0.3668	-0.5833	β_{EE}	-0.0092	-0.0065	-0.5225	-0.0515
	0.4572	0.5022	0.4105	0.4152		0.0436	0.0396	0.2590	0.0409
β_{K}	0.5541	-0.4916	0.6942	0.5979	β_{EM}	-0.0205	-0.0794	0.2031	0.1633
	0.7175	0.4742	0.4583	0.4566		0.0815	0.0702	0.1038	0.1207
β_{L}	2.5646	3.9057	2.9790	2.0183	β_{EA}	-0.1830	-0.1677	-0.3774	-0.2077
	0.4759	0.6234	0.3638	0.3676		0.0376	0.0397	0.0494	0.0404
β_{E}	-1.7295	-1.2569	-4.0618	-1.6435	β_{EQ}	0.2356	0.1915	0.5237	0.2436
	0.3234	0.3275	0.5145	0.3694		0.0433	0.0446	0.0572	0.0484
β_{M}	-0.3892	-1.1572	1.3886	0.0273	β_{MM}	0.1196	0.3437	0.3153	0.1873
	0.4583	0.4487	0.4157	0.6304		0.1221	0.0996	0.1025	0.2854
β_{KK}	-0.3381	0.2121	0.3282	0.6667	β_{MA}	-0.1213	-0.2232	0.0694	-0.0089
	0.3509	0.1209	0.1312	0.1691		0.0521	0.0515	0.0424	0.0729
β_{KL}	0.1731	0.2803	-0.0839	-0.1250	β_{MQ}	0.1272	0.2428	-0.1134	0.0348
	0.1537	0.1166	0.1174	0.1221		0.0621	0.0609	0.0526	0.0846
β_{KE}	0.2413	0.0537	0.4616	0.2466	β_{AA}	0.0774	0.1118	0.0886	0.0706
	0.1263	0.0806	0.1570	0.0928		0.0326	0.0333	0.0327	0.0317
β_{KM}	-0.0764	-0.5460	-0.7058	-0.7883	β_{AQ}	-0.1965	-0.3616	-0.1341	-0.1416
	0.1926	0.2013	0.2154	0.1684		0.0505	0.0570	0.0446	0.0461
β_{KA}	0.0811	-0.0631	0.0663	0.0580	β_{QQ}	0.1460	0.2387	0.0970	0.1072
	0.0827	0.0528	0.0498	0.0514		0.0305	0.0339	0.0268	0.0277
β_{KQ}	-0.0544	0.1026	-0.0600	-0.0480					
	0.0962	0.0632	0.0601	0.0613					

Table A.2: Translog Estimates Robust to Heteroskedasticity

	Expenditure Share Equation Eliminated					Expenditure Share Equation Eliminated			
	K	L	E	M		K	L	E	M
	Estimate Std. Err.	Estimate Std. Err.	Estimate Std. Err.	Estimate Std. Err.		Estimate Std. Err.	Estimate Std. Err.	Estimate Std. Err.	Estimate Std. Err.
δ_{97}	8.6454	9.3070	8.8522	9.0151	β_{LL}	0.2232	0.2379	0.2232	0.2013
	0.6686	0.6834	0.6618	0.6715		0.0196	0.0323	0.0208	0.0200
δ_{98}	8.5267	9.1868	8.7381	8.8910	β_{LE}	-0.1445	-0.1025	-0.2011	-0.1482
	0.6683	0.6827	0.6616	0.6710		0.0127	0.0164	0.0195	0.0128
δ_{99}	8.4944	9.1495	8.7017	8.8545	β_{LM}	0.0962	0.0054	0.1655	0.1445
	0.6672	0.6815	0.6606	0.6698		0.0185	0.0201	0.0196	0.0199
δ_{00}	8.2544	8.9098	8.4830	8.6056	β_{LA}	0.1747	0.2810	0.2301	0.1833
	0.6670	0.6823	0.6599	0.6699		0.0082	0.0146	0.0103	0.0086
β_{A}	1.0119	1.3326	1.0424	1.1748	β_{LQ}	-0.2698	-0.4096	-0.3412	-0.2798
	0.1882	0.1907	0.1871	0.1894		0.0098	0.0171	0.0121	0.0102
β_{Q}	-1.0004	-1.2853	-1.0537	-1.1492	β_{EE}	-0.0629	-0.0682	-0.0966	-0.0791
	0.1809	0.1845	0.1791	0.1816		0.0132	0.0105	0.0258	0.0118
β_{K}	-0.2206	-1.0857	-0.3903	-0.8133	β_{EM}	0.0688	0.1139	0.1157	0.1157
	0.0716	0.0848	0.0704	0.0759		0.0149	0.0136	0.0184	0.0160
β_{L}	2.4128	3.4653	2.9449	2.4817	β_{EA}	-0.1105	-0.1133	-0.2183	-0.0993
	0.0735	0.1292	0.0917	0.0767		0.0073	0.0078	0.0130	0.0066
β_{E}	-1.0788	-1.1029	-2.1677	-0.9825	β_{EQ}	0.1471	0.1506	0.2901	0.1335
	0.0646	0.0688	0.1166	0.0587		0.0085	0.0091	0.0152	0.0078
β_{M}	-0.1135	-0.2768	0.6131	0.3141	β_{MM}	0.4195	0.4070	0.4424	0.4255
	0.0640	0.0640	0.0776	0.0717		0.0436	0.0436	0.0459	0.0477
β_{KK}	0.6208	0.6102	0.7292	0.7717	β_{MA}	-0.0368	-0.0540	0.0357	0.0023
	0.0499	0.0513	0.0492	0.0510		0.0069	0.0070	0.0083	0.0077
β_{KL}	-0.1750	-0.1407	-0.1876	-0.1976	β_{MQ}	0.0604	0.0825	-0.0353	0.0060
	0.0221	0.0248	0.0215	0.0224		0.0085	0.0086	0.0102	0.0095
β_{KE}	0.1386	0.0569	0.1821	0.1116	β_{AA}	0.1835	0.1987	0.1849	0.1950
	0.0150	0.0146	0.0156	0.0155		0.0193	0.0196	0.0192	0.0194
β_{KM}	-0.5844	-0.5264	-0.7237	-0.6857	β_{AQ}	-0.1875	-0.2206	-0.1906	-0.2061
	0.0419	0.0434	0.0426	0.0453		0.0210	0.0213	0.0208	0.0210
β_{KA}	-0.0274	-0.1137	-0.0475	-0.0862	β_{QQ}	0.2700	0.3108	0.2761	0.2919
	0.0078	0.0093	0.0077	0.0083		0.0241	0.0246	0.0239	0.0242
β_{KQ}	0.0623	0.1764	0.0864	0.1403					
	0.0096	0.0113	0.0094	0.0101					

Table A.3: Translog Estimates Using 3SLS

	Expenditure Share Equation Eliminated					Expenditure Share Equation Eliminated			
	K	L	E	M		K	L	E	M
	Estimate Std. Err.	Estimate Std. Err.	Estimate Std. Err.	Estimate Std. Err.		Estimate Std. Err.	Estimate Std. Err.	Estimate Std. Err.	Estimate Std. Err.
δ_{97}	9.3502	9.0243	8.8744	9.6131	β_{LL}	0.2364	0.2591	0.2507	0.2523
	0.7831	0.7896	0.7700	0.7860		0.0205	0.0367	0.0220	0.0214
δ_{98}	9.2453	8.9248	8.7757	9.5031	β_{LE}	-0.1676	-0.1024	-0.2254	-0.1619
	0.7822	0.7882	0.7693	0.7850		0.0142	0.0193	0.0216	0.0141
δ_{99}	9.1896	8.8706	8.7203	9.4441	β_{LM}	0.1354	0.0493	0.1990	0.1576
	0.7803	0.7861	0.7675	0.7830		0.0201	0.0213	0.0213	0.0213
δ_{00}	8.9548	8.6108	8.5024	9.1878	β_{LA}	0.1873	0.2697	0.2295	0.1913
	0.7824	0.7893	0.7693	0.7854		0.0073	0.0133	0.0093	0.0076
β_{A}	1.4284	1.3301	1.2950	1.5135	β_{LQ}	-0.2840	-0.3893	-0.3393	-0.2893
	0.2033	0.2074	0.1979	0.2046		0.0088	0.0160	0.0111	0.0092
β_{Q}	-1.3352	-1.2314	-1.1891	-1.4225	β_{EE}	-0.0527	-0.0712	-0.0606	-0.0738
	0.2109	0.2145	0.2058	0.2121		0.0153	0.0122	0.0303	0.0136
β_{K}	-0.5558	-1.2414	-0.6564	-1.0536	β_{EM}	0.0863	0.1332	0.1142	0.1408
	0.0683	0.0785	0.0663	0.0702		0.0157	0.0142	0.0200	0.0174
β_{L}	2.5081	3.2873	2.9243	2.5479	β_{EA}	-0.1133	-0.1033	-0.2105	-0.1022
	0.0676	0.1229	0.0854	0.0706		0.0068	0.0073	0.0123	0.0062
β_{E}	-1.0398	-0.9459	-1.9839	-0.9352	β_{EQ}	0.1454	0.1327	0.2715	0.1313
	0.0627	0.0676	0.1128	0.0574		0.0082	0.0088	0.0146	0.0075
β_{M}	0.0875	-0.1000	0.7161	0.4410	β_{MM}	0.4216	0.3497	0.3907	0.3224
	0.0662	0.0660	0.0781	0.0734		0.0463	0.0462	0.0484	0.0504
β_{KK}	0.7135	0.6977	0.7562	0.7738	β_{MA}	-0.0141	-0.0342	0.0514	0.0232
	0.0562	0.0557	0.0548	0.0551		0.0071	0.0071	0.0084	0.0079
β_{KL}	-0.2042	-0.2060	-0.2243	-0.2480	β_{MQ}	0.0327	0.0581	-0.0517	-0.0150
	0.0240	0.0266	0.0232	0.0238		0.0088	0.0088	0.0103	0.0097
β_{KE}	0.1340	0.0404	0.1719	0.0949	β_{AA}	0.1741	0.1648	0.1613	0.1816
	0.0160	0.0156	0.0162	0.0161		0.0178	0.0181	0.0174	0.0179
β_{KM}	-0.6433	-0.5322	-0.7038	-0.6208	β_{AQ}	-0.2171	-0.2051	-0.2000	-0.2277
	0.0455	0.0461	0.0455	0.0472		0.0224	0.0229	0.0218	0.0225
β_{KA}	-0.0599	-0.1323	-0.0704	-0.1124	β_{QQ}	0.3133	0.2992	0.2928	0.3259
	0.0073	0.0085	0.0071	0.0075		0.0267	0.0272	0.0259	0.0268
β_{KQ}	0.1060	0.1984	0.1194	0.1730					
	0.0091	0.0103	0.0088	0.0093					

Table A.4: Translog Curvature Results

Error specification and expenditure share eliminated	Monotonicity satisfied (percent observations)	Probability of falsely rejecting Cobb-Douglas (Wald test)
HCR		
K	0.26	<0.01
L	0.27	<0.01
E	0.23	<0.01
M	0.45	<0.01
HR		
K	0.44	<0.01
L	0.39	<0.01
E	0.28	<0.01
M	0.45	<0.01
3SLS		
K	0.43	<0.01
L	0.41	<0.01
E	0.29	<0.01
M	0.45	<0.01

A.2 Cobb-Douglas Cost Function

Table A.5: Cobb-Douglas Estimates Robust to Heteroskedasticity and County Clustering

	Expenditure Share Equation Eliminated			
	K	L	E	M
	Estimate Std. Err.	Estimate Std. Err.	Estimate Std. Err.	Estimate Std. Err.
δ_{97}	1.5821	0.9918	0.8914	0.8426
	1.4357	1.4290	1.4352	1.4175
δ_{98}	1.6160	1.0432	0.9500	0.9035
	1.4371	1.4307	1.4368	1.4180
δ_{99}	1.5883	0.9795	0.8596	0.8060
	1.4384	1.4319	1.4377	1.4198
δ_{00}	1.2321	0.6430	0.5602	0.5002
	1.4316	1.4259	1.4319	1.4139
β_A	-1.0627	-0.8756	-0.8557	-0.8331
	0.4465	0.4438	0.4455	0.4395
β_Q	1.2023	1.2021	1.2072	1.2079
	0.0080	0.0079	0.0079	0.0065
β_K	0.3983	0.3906	0.3901	0.3974
	0.0149	0.0079	0.0082	0.0073
β_L	0.1593	0.1652	0.1500	0.1469
	0.0080	0.0141	0.0095	0.0074
β_E	0.0480	0.0443	0.0580	0.0422
	0.0093	0.0095	0.0133	0.0064
β_M	0.3944	0.3999	0.4019	0.4135
	0.0084	0.0084	0.0085	0.0128
β_{AA}	0.1289	0.1000	0.0958	0.0909
	0.0684	0.0680	0.0683	0.0674
σ_θ	…	0.4210	0.4252	0.3161

Table A.6: Cobb-Douglas Estimates Robust to Heteroskedasticity

	Expenditure Share Equation Eliminated			
	K	L	E	M
	Estimate Std. Err.	Estimate Std. Err.	Estimate Std. Err.	Estimate Std. Err.
δ_{97}	0.5323	0.4967	0.4659	0.5376
	0.2880	0.2868	0.2856	0.2883
δ_{98}	0.4209	0.3877	0.3557	0.4259
	0.2883	0.2871	0.2859	0.2886
δ_{99}	0.3922	0.3598	0.3286	0.3978
	0.2876	0.2863	0.2852	0.2879
δ_{00}	0.1454	0.1099	0.0764	0.1513
	0.2866	0.2853	0.2841	0.2869
β_A	-0.6492	-0.6429	-0.6332	-0.6508
	0.0875	0.0871	0.0867	0.0876
β_Q	1.1727	1.1742	1.1740	1.1727
	0.0068	0.0068	0.0068	0.0068
β_K	0.3743	0.3751	0.3734	0.3734
	0.0019	0.0019	0.0019	0.0019
β_L	0.1706	0.1674	0.1703	0.1706
	0.0012	0.0012	0.0012	0.0012
β_E	0.0401	0.0411	0.0415	0.0401
	0.0003	0.0003	0.0003	0.0003
β_M	0.4150	0.4164	0.4149	0.4159
	0.0020	0.0020	0.0020	0.0020
β_{AA}	0.0721	0.0709	0.0696	0.0724
	0.0133	0.0132	0.0132	0.0133
σ_θ	0.6748	0.6764	0.6825	0.6740

Table A.7: Cobb-Douglas Estimates Using 3SLS

	Expenditure Share Equation Eliminated			
	K	L	E	M
	Estimate Std. Err.	Estimate Std. Err.	Estimate Std. Err.	Estimate Std. Err.
δ_{97}	0.6646	0.6645	0.6643	0.6650
	0.1437	0.1437	0.1437	0.1437
δ_{98}	0.5666	0.5665	0.5661	0.5669
	0.1441	0.1441	0.1442	0.1441
δ_{99}	0.5082	0.5081	0.5077	0.5086
	0.1434	0.1434	0.1434	0.1434
δ_{00}	0.3136	0.3136	0.3136	0.3138
	0.1446	0.1446	0.1446	0.1446
β_A	-0.6464	-0.6463	-0.6462	-0.6465
	0.0368	0.0368	0.0368	0.0368
β_Q	1.1686	1.1686	1.1686	1.1686
	0.0105	0.0105	0.0105	0.0105
β_K	0.3802	0.3802	0.3802	0.3802
	0.0020	0.0020	0.0020	0.0020
β_L	0.1739	0.1739	0.1739	0.1739
	0.0015	0.0015	0.0015	0.0015
β_E	0.0417	0.0417	0.0417	0.0417
	0.0004	0.0004	0.0004	0.0004
β_M	0.4042	0.4042	0.4042	0.4042
	0.0021	0.0021	0.0021	0.0021
β_{AA}	0.0693	0.0693	0.0693	0.0693
	0.0059	0.0059	0.0059	0.0059
σ_θ	0.6352	0.6353	0.6355	0.6351

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