**PAYMENTS FOR ENVIRONMENTAL SERVICE CONTRACT DESIGN**

**WITH ASYMMETRIC INFORMATION**

by

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# ABSTRACT

Payments for environmental service contracts commonly suffer asymmetric information problems before and after a contract is signed between a regulator and private parties. Before a contract, private parties possess private information such as productivity and production cost, and they may lie on their cost to get higher payments. After a contract, private parties may avoid fulfilling their responsibility. These problems need to be considered by the regulator when designing the contract since they are fiscally inefficient. This article proposes to involve monitoring choices in the contract design scheme as a signal of cost type and develops a principal-agent framework to study the interaction of the two problems. We established a dichotomous optimization problem to quantify the optimal payment schedule under different contract scenarios.  We find that to design a feasible second-best contract, several conditions need to be met. Further analysis shows how the monitoring choices would affect the farmers' expected payoff and potential actions so that the regulator could direct the high-cost farms into the program with minimal or zero payment. We also find the interesting interaction between the hidden information and hidden action problem in a signal game which is a result of different signal levels. The significance of the signal would affect the distribution of the payment.

## Chapter 1

## INTRODUCTION

Payments for environmental services (PES), also known as payments for ecosystem services, are incentives offered to private parties in exchange for managing their land to provide some sort of environmental service. Compared with traditional approaches like regulatory restrictions, PES encourage private parties to carry out actions that will provide environmental benefits or stop negative externalities. There is a wide range of programs using PES. Among different forms[1], the bilateral contract technique is widely used. A leading example of contracting in the U.S. is the Conservation Reserve Program (CRP), which pays farmers to retire land. PES contracts also are used internationally. For example, the program in Costa Rica (Pagiola 2008) made substantial progress in transferring payments from environmental services (including water, biodiversity and carbon sequestrating) users to landowners.

A research question arises about the optimal design of PES contracts. Participation only occurs if the payment for PES equals or exceeds the private party's net cost of making the change. Asymmetric information problem arise when the private party has better information about their cost and may not fulfill their

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[1] PES could be realized by different schemes or market types. It could be a traditional subsidy paid by social planner. It could be a contract based on bilateral agreements. A trading market is also a kind of PES with a special feature that transactions are made between private parties while the social planner is only responsible for setting up the market.

responsibility because inadequate monitoring. This advantage may lead to adverse selection and moral hazard problems. There are potential applications of game theory under asymmetric information in PES contract design. Certain kinds of contracts can be worked out, such as Wu and Babcock (1995, 1996) who make farmers reveal their types. There will also be some kinds of trade-off between more monitoring and higher social net benefit (NSB), which means we may take a risk at certain level to trust the farmers, expecting them to underperform, and save some monitoring costs for some farms. In addition, since taxpayers provide these compensation payments and taxation itself incurs a deadweight loss, the regulator aims to pay compensation that covers the costs of compliance and no more.

## 1.1 Asymmetric Information

Asymmetric information comes in two major types in theory: hidden information and hidden action. See figure 1.1 for the relationship.

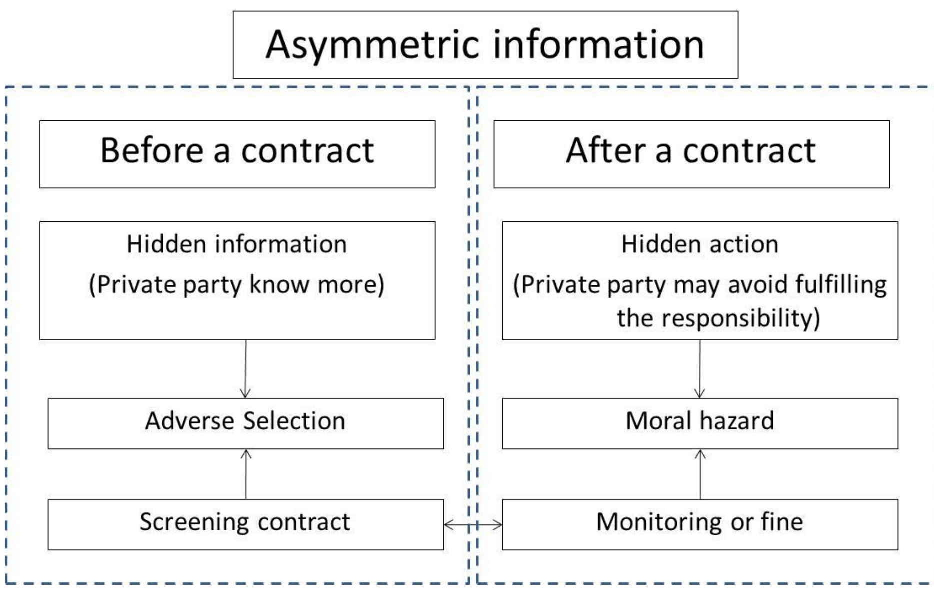

Figure 1.1: The structure of asymmetric information

### 1.1.1 Hidden Information and Relative Research

Hidden information arises when negotiating a PES contract if the private party has better information than the regulator. In a game, assume nature acts first to assign a value of talent[2] to a land manager or owner, which will affect land productivity and emission levels. A similar difference could be found in the unobservable land capabilities to deliver production or abatement. These differences result in the different costs for providing environmental services, which are unobservable to the regulator—in other words the PES market has an upward sloping supply curve. The problem is called adverse selection. One approach to solve the adverse selection problem is to get more information. But it is widely recognized that getting enough information is costly in time and in money. Furthermore, Wu and Bacock (1995) have argued that even if regulators could get enough information as private parties do, political pressure may preclude using it as the basis for policy formulation. In other words, a perfect-information scenario or first-best scheme is impossible or too costly to get. First-best means: the regulator figures out the exact cost of each farm and make specific payment level for each farm. Landowner compliance and monitoring would be costless. To make sure farmers' compliance with the contract, first-best would also require every farm to be costlessly monitored. But this will be unlikely.

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[2] By the word "talent" here, we use it to stand for all these hidden information that affects both farm production and externality. It includes unobservable land characteristics, equipment quality, etc.

The solution to the hidden information problem depends on the use of key information. Some researchers set the uncertainty of talent as the key information, such as Wu and Babcock (1995). They developed a second-best contract, which could induce landowners with different land quality to choose the specific contract designed for them and reveal their types. The contract could reduce budgetary cost under hidden information. However, Wu and Babcock (1995) simplified the problem with dichotomous types: a high-talent farm and a low-talent farm. Smith (1995) used a scalar-valued index, called an efficiency parameter, to represent the key information and characterized properties of a least-cost Conservation Reserve Program (CRP) by applying mechanism design theory. In a later paper, Wu and Babcock (1996) generalized and formalized the PES contract model by assigning continuous types for each farm as key information and derived the characteristics of an optimal contract. Others focused on the heterogeneity in cost directly, such as Moxey et al. (1999). They elaborate the information cost of establishing environmental contracts into selection cost, negotiation cost, and monitoring cost. Similar to the work by Wu and Babcock (1995, 1996), they constructed a principal-agent model and a simulated example to demonstrate how the negotiation costs could be avoided through the revelation principle and mechanism design.

There are also debates on whether a PES contract is an effective way to provide public benefits and which type of PES should the regulator use. Ferraro (2008) compared procurement auctions and screening contracts with the conclusion that auction is better than screening contracts because the later one is difficult to realize in the real world. But the comparison depends merely on verbal description and further empirical study is needed for the argument. On the contrary, Arnold, Duke, and

Messer (2013) also compare the effectiveness of screening contracts, auctions, and externality-correcting tax and show results that screening contracts yield higher social surplus than auctions. Arnold, Duke, and Messer (2013) also show that a tax instrument can achieve first-best, though it is less likely to be observed in practice. So based on the research above, I conclude that a second-best screening contract remains a promising instrument for delivering cost-effective PES.

### 1.1.2 Hidden Action and Relative Research

In contrast to hidden information, hidden action arises after a contract is signed and can lead to the moral hazard problem. A regulator may find monitoring-contract compliance costly and may be unable to verify compliance with certainty. For example, Spooner (1993) states that monitoring of land treatment and water quality should be multi-year before and after best management practice (BMP) implementation. Thus, private parties have an incentive to avoid fulfilling their contractual responsibilities with incomplete monitoring. If private parties "cheat" on agreed responsibilities, this is a form of efficiency loss.

Research on hidden action identifies the importance of private parties' risk preference with respect to their willingness to risk getting caught for cheating on the contract. For example Ozanne et al. (2001) find that if monitoring costs are negligible or fixed, or farmers are highly risk averse, the moral hazard problem can be eliminated. Peterson and Boisvert (2004) proposed a method to accommodate asymmetric information on farmers' preferences in policy design and showed that incentives would be inadequate for many risk-averse producers, if the regulator does not account for the diversity in risk preference. But work by Ozanne and White (2008) find different results. They analyzed the design of PES schemes based on monitoring and fines for risk-averse producers and, quite interestingly, they find that risk preferences play a relatively minor role in designing an efficient scheme. As such, they argue that regulators should focus on assessing producers' compliance cost because if the regulator adjusts the contract level to the producer's expectation, the optimal input and level of monitoring is determined by the profit function, instead of risk preference. The profit function is a kind of hidden information. So the conclusion leads the discussion back to the hidden information problem instead of hidden action.

### 1.1.3 Modeling both Hidden Information and Hidden Action

The best way to simulate reality is to consider both types of asymmetric information together because they exist in the real world simultaneously. Some recent works have sought to model both types of information asymmetry simultaneously such as Ozanne and White (2007). Based on the input quota work by Moxey *et al*. (1999) and input charge work by White (2002), they demonstrated that input charge and input quota approaches lead to identical outcomes, they also establish a general result that the presence of moral hazard may undermine attempts by the regulator to discriminate between producer types by differentiated contracts.

Such works are still scarce, and the most obvious reason for not considering the two types together is that the combination will make the model extremely complicated. In contrast, there are other approaches from empirical and theoretical literature that focus more on the value of information. Borisova et al. (2005) addresses the value of information for water quality control and compares the value of information for price and quantity instruments.

## 1.2 Using Monitor as a Signal in a Screening Contract

My review of the literature found no source that considered using monitoring as a signal in a screening contract. It is reasonable to take a farmer's choice of monitoring as a signal for several reasons. First of all, Spence (1973) introduced the idea of signaling into the education model in which education has no direct effect on improving a person's productivity, but the signal is useful for demonstrating ability to employers. Compared to the PES contract scenario here, we find that monitoring, which comes with a cost just like education, cannot help the private parties to increase their productivity, either. But monitoring can help farmers demonstrate their abilities to provide the environmental service, given that the regulator pays them for providing the service. So, those private parties with low abatement costs would have the incentive to accept monitor and thereby reveal their ability to deliver desired services from the PES program.

Based on the game theoretic contract design models presented in Rasmusen (2007), this paper develops PES contracts that fit the screening game framework and that an effective design could be cost-effective in certain situations. In addition, the treatment of monitoring as a signal could transfer the monitoring cost from regulators to private parties, so that it becomes internal to the private parties' decision making. This could largely simplify the asymmetric information problem. The existence of monitoring could help prevent PES participants from cheating and those low-abatement-cost participants would have the incentive to choose accept monitoring for a higher payment.

This study would contribute to the literature in several ways. First, in contrast to most previous studies of hidden information and hidden action, this study takes monitoring as a choice in the screening contract and also as a signal in the game and compares the results of the optimal contract under different assumptions to show the theoretical effectiveness of the screening contract. Second, by allowing different monitoring levels and probabilities of observing truth, we could see how the hidden information and hidden action interact theoretically.

### 1.3 Mechanism Design

In this incomplete information scenario where the regulator is uncertain about the farmer's effort level and compliance cost, we examine the use of monitoring as signal, or a choice variable, in the PES contract. On one hand, monitoring can help reveal the farmers' effort level to a certain extent so that the regulator could set up a payment schedule based on the revealed effort. On the other hand, through the choice of monitoring, the regulator gains information about farmers' compliance cost. By making farmers pay for the monitoring cost at first, as we predicted, all these farms with high compliance cost would choose low monitoring levels and low effort to get a baseline payment. Similarly, the low cost farms would choose high monitoring level and high effort so that they could not only get the baseline payment, but also extra payment based on the effort information shown by monitor.

The rest of the thesis is organized as follows. Chapter 2 sets up the assumptions and model. Chapter 3 shows analysis of the model. Chapter 4 lists and discusses results under different assumptions, and Chapter 5 contains the concluding remarks.

## Chapter 2

## MODELING THE PES CONTRACT PROGRAM

### 2.1 Game Structure

#### 2.1.1 Define Players and Types Assigned by Nature

The set of players is N={R, LF, HF} representing a Regulator (R), a Low-cost farm (LC), and a High-cost farm (HC)[3]. In other words, this simple game formulation consists of dichotomous types.

Farmer's best management practices (BMPs) provide environmental services, but they also come with a cost. As mentioned in the introduction part, the solution to the hidden information problem depends on the use of key information and researchers uses different kinds of key information such as type, talent, and cost. Here we follow Moxey et al. (1999) and assume heterogeneity in cost among different farms and consider the case of two farms[4] for simplicity. Let $C^{L}(x)$: $X \rightarrow \mathbb{R}$ denote the cost function of low-cost farms while $C^{H}(x)$: $X \rightarrow \mathbb{R}$ denotes the cost function of high-cost

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[3] Note that Nature is actually another player in the game and nature assigns the type to the farmers. But as nature only acts in the very first step, we omit it for simplicity, which will not affect the following interaction between regulator and farmers

[4] Extension of the two-type case to a continuum of farm types is relatively straightforward, but requires a more complicated structure and likely offers few additional analytical insights. Similar works are Wu and Babcock (1995), Moxey et al. (1999). As this is a first effort to combine hidden action and hidden information, we maintain this simplifying assumption.

farms. That is, for given effort level, $x \in X = \{0, 1\}$[5], where 0 means low effort and 1 means high effort, the relationship between the two different types' cost is: $C^H(x) > C^L(x)$. Under full information, first-best, a PES contract would offer a payment $s$ which just covers the farmer's compliance cost. However, the hidden information prohibits this optimal schedule since the government do not know the cost type. While knowing their own types, farmers may report a higher than true abatement cost to get more payment. To simplify the model, we assume that the government knows that there are two types of farms, but it cannot identify to which type a farm belongs. Thus, there is an asymmetric information (hidden information, adverse selection) problem because of the heterogeneity in compliance cost.

At the farm level, the unobservable effort cost function, $C(x)$, is defined as the difference between the unconstrained farm profit and the constrained profit. It is notable that the BMPs may change the profit function of the farm. A BMP not only brings extra costs (like labor, installment, and management cost) to the farm, but may also bring private benefits to the farm. For example, the use of cover crops may reduce the soil erosion and increase the nitrogen concentration of the soil. So there is a chance that $C(x) < 0$, which means the BMPs' private benefit exceeds private cost. Here, we only consider the case of positive $C(x)$. As we mentioned above, $C(x)$ is a kind of net cost, which has already taken the private benefits of BMPs into consideration.

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[5] We make an assumption here that $x$ is a dichotomous BMP practice and farmers could only choose between 0 and 1. We could extend the effort level $x$ to a continuous variable.

### 2.1.2 Define the Signal: Monitor

On the performance side, there is also asymmetric information (hidden action or moral hazard) because of the imperfection in observing or monitoring the true BMPs effort. We assume monitoring expenditures could potentially reveal the true effort. With monitoring devices or technology on the farm, there is a positive relationship between monitoring level (*m*) and the probability of knowing the true effort: Pr(*m*). The relationship depends on the type of the BMPs (see figure 2.1 for reference).

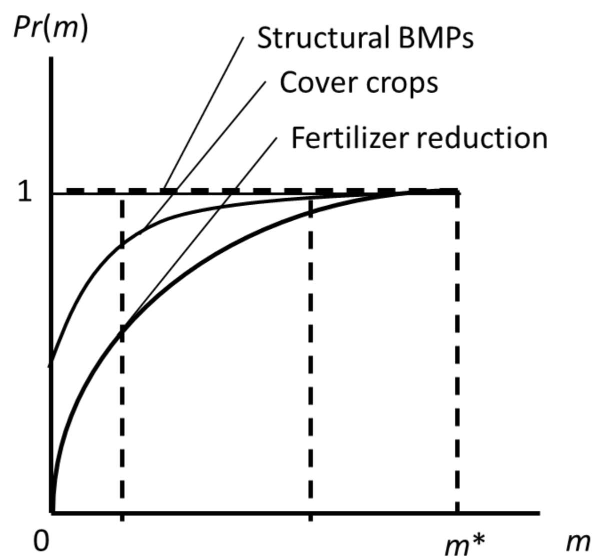



Figure 2.1: Monitor effort and the probability of reveal the true effort

For example, structural BMPs, such as forest buffer, may only need very low effort or even just one visit to reveal the effort because once installed, it is costly for farmers to remove or change structural BMPs. So, the probability would be a horizontal line at *Pr*(*m*) =1 (100%) as long as the monitoring effort is positive. Other

BMPs, like cover crops may need additional effort to monitor. The use of low level monitoring effort could result in a higher probability of capturing the true costs. There are also BMPs that requires high levels of monitoring, like fertilizer reduction, if the true level of farm effort is to be observed. In this case, low level monitoring would result in a low probability of capturing the true costs, because fertilizer use is flexible and easy to change. The latter two monitoring functions are assumed to be concave because initial monitoring effort is more productive than later monitoring effort.

Let $Pr\ (m)$: $M \rightarrow [0, 1]$ denote the corresponding probability of knowing the true effort BMP effort level given a monitor level $m$. Then $1 - Pr\ (m)$ represents the probability that the regulator get the wrong observed effort level. Since we made a dichotomous assumption of the true BMP effort, the wrong observed effort is easy to understand. For example, if a farmer chooses high BMP effort $x$=1 on his farm and a monitor level $m$. The regulator will observe the high effort with a probability of $Pr\ (m)$ and may also make a mistake, with a probability of $1 - Pr\ (m)$, to conclude that the farmer adopts low effort level. For simplicity here, we only consider a dichotomous monitor choice here, which means $m \in M = \{0, 1\}$, where 0 means low monitoring level and 1 means high monitoring.

## 2.2 Contract Design

The regulator's aim is to design a contract schedule over the observed effort level, monitoring choice, and payment level, $\{x_j, m, s_j\}$, $j=l, h$, where $x_j$ is the observed effort level, $m$ is the monitoring level choice and $s_j$ is the payment level base on the observed abatement such that social welfare is maximized. To get the payment, the farmers not only need to make a BMP effort $x_j$, but also need to pay for the monitoring cost by themselves at first. Let $K$: $M \rightarrow \mathbb{R}_{++}$ denote the monitoring cost based on the monitoring effort. Knowing that farmers would maximize their own payoff, the regulator needs to design the contract very carefully to get to the desired results. Based on the assumption of homogeneous benefit and heterogeneous cost, the regulator would want these LC farms to take more responsibility and supply the environmental services because they are relatively cost-effective compared to the HC farms, i.e., they could supply the same environment benefit with a relatively low cost. In another words, regulators would want LC farm to choose the “good” contract ($\{x_h$, 1, $s_h\}$ (high effort, high monitor level and high payment)). For the rest HC farms, it is not cost effective for them to supply environmental services because of their high cost. It is still necessary to encourage them to get into the program. So the regulator would want HC farm to choose the “bad” contract, $\{x_l, 0, s_l\}$ (low effort, low monitor and low payment).

This game starts with a screening-type contract. The regulator moves first by giving a contract menu to the two farmers. Since the type of the farmers is unobservable, the game tree contains an oval around the two nodes of LC farm and HC farm. Farmers are free to choose different contracts, but after they make a decision there is uncertainty about their payoffs because of the uncertainty of monitor results (figure 2.2).

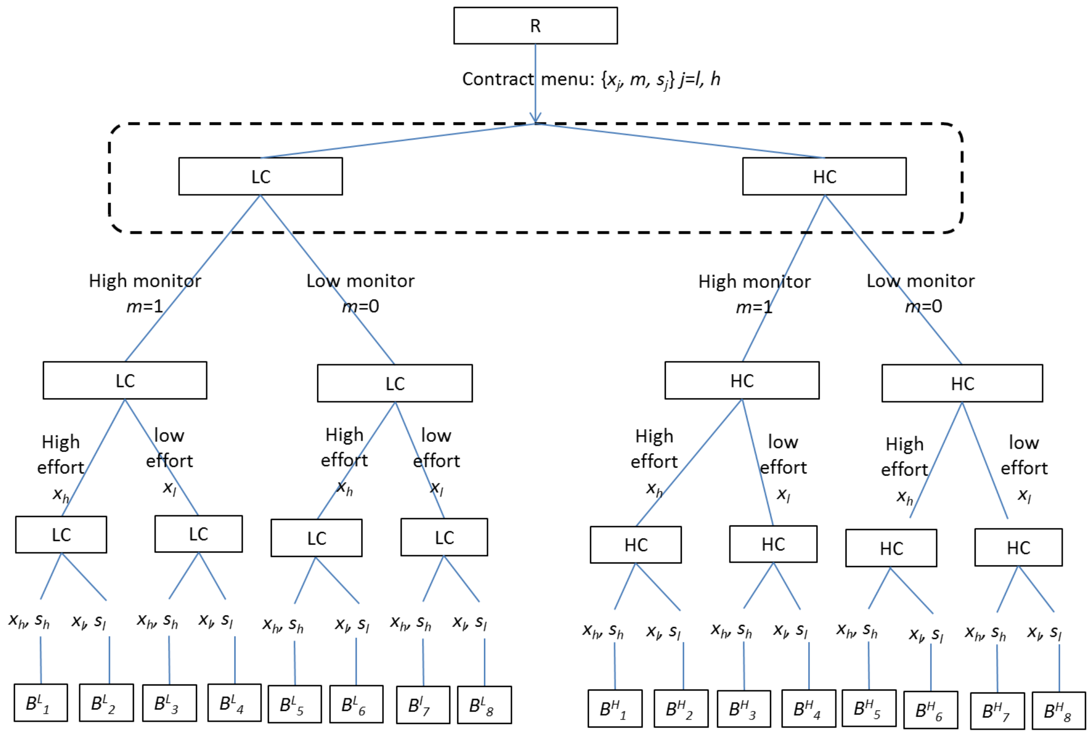



Figure 2.2: Game tree

Facing the contract menu {$x_j$, $m_k$, $s_j$}, $j$, $k$=$l$, $h$, farmers will make decision on monitor effort and true BMP effort individually. The strategies of farmers consist of a monitoring choice and a BMP effort choice. Assume farmers make choice on monitoring effort first. The choice set is

$$m_k = \begin{cases} 1 & if\ high\ monitor \\ 0 & if\ low\ monitor \end{cases}$$

One farmer could choose high monitoring level or low monitoring level, as we only consider the dichotomous situation here. After making a choice on monitoring effort, the farmers would make decisions on true BMP effort. They could choose between a high effort and a low effort.

$$\sigma = \begin{cases} x_h = 1 & if\ high\ BMP\ effort \\ x_l = 0 & if\ low\ BMP\ effort \end{cases}$$

We assume the payoffs for status quo or no participation is 0, which means that the payoffs from playing the BMP/monitoring game are deviations from the status quo. We use $B_n^i$ to represent payoffs under different choice where *i=L or H*, stands for low cost farm or high cost farm and *n* is just an ordinal number assigned to different scenarios for simplicity. Since there is a chance that the monitoring may be incorrect, the payoff to the farm involves uncertainty and a rational farmer will choose the strategies to maximize his expected payoff (the payoffs for a low-cost farm with different choices are shown in table 2.1. The payoffs for the high-cost farm is symmetric and could be derived easily by the same means).

Table 2.1: Payoffs to Low-Cost Farm Under Different Scenarios

| **Choice** | **Observe effort and payment** | **Payoff and corresponding probability** | **Expected payoff** |
|---|---|---|---|
| m=1 ; $x_h$<br>high monitor; high effort | $x_h$; $s_h$<br>high effort; high payment | $B^L_1=S_H-K(1)-C^L(x_h)$<br>*Prob: Pr(1)* | $E(B_{12})=Pr(1)\ B^L_1+[1-Pr(1)]\ B^L_2$ |
| | $x_l$ ; $s_l$<br>high effort; high payment | $B^L_2=s_l-K(1)-C^L(x_h)$<br>*Prob: 1-Pr(1)* | |
| m=1 ; $x_l$<br>high monitor; low effort | $x_h$ ; $s_h$<br>high effort; high payment | $B^L_3=s_l-K(1)-C^L(x_l)$<br>*Prob: Pr(1)* | |
| | $x_l$; $s_l$<br>low effort; low payment | $B^L_4=s_h-K(1)-C^L(x_l)$<br>*Prob: 1-Pr(1)* | |
| m=0 ; $x_h$<br>low monitor; high effort | $x_l$; $s_l$<br>low effort; low payment | $B^L_5=s_l-K(0)-C^L(x_h)$<br>*Prob: Pr(0)* | |

| | | | |
|---|---|---|---|
| | $x_h$ ; $s_h$<br>high effort; high payment | $B^L{}_6 = s_h - K(0) - C^L(x_h)$<br>*Prob: 1-Pr(0)* | |
| m=0 ; $x_l$<br>low monitor; low effort | $x_l$ ; $s_l$<br>low effort; low payment | $B^L{}_7 = s_l - K(0) - C^L(x_l)$<br>*Prob: Pr(0)* | $E(B_{78}) = Pr(0)\ B^L{}_7 + [1 - Pr(0)]\ B^L{}_8$ |
| | $x_l$; $s_h$<br>high effort; high payment | $B^L{}_8 = s_h - K(0) - C^L(x_l)$<br>*Prob: 1-Pr(0)* | |
| No participation | NA | 0 | 0 |

With an objective to maximize the overall social benefit by using the PES contract, society's goal could be expressed as：

$$\text{Max:}\, \pi = \sum es(x_j) + \{s_j - [C^i(x_j) + K(m)]\} - (1+e)s_j \qquad (1)$$

Where $es(x_j)$ is the value of the environmental service from BMP $x_j$ and we assume that It may save a lot of work if we simply assume that all ES values exceed the costs of the practices. I don't think this is too controversial. If you make this assumption, then the solution is much easier. $(1+e)s_j$ is the cost of transferring payment $s_j$. Further, $e$ is the deadweight loss of raising tax revenue to support government payments.

To make sure that farmers join the program voluntarily, the contract must satisfy the individual rationality constraint, i.e., the payment must exceed farmers' compliance cost and monitoring cost. Because of the uncertainty of monitoring results, the final payoff to the farmers will be in the format of expected net return as in this individual rationality constraint for the LC farm (IRC1):

$$\mathrm{E}(B_{12}^L) = Pr(1) \cdot B_1^L + [1 - Pr(1)] \cdot B_2^L \geq 0$$

which can be substituted according to table 2.1, revealing:

$$\Pr(1) \cdot [s_h - \mathrm{K}(1) - C^L(x_h)] + [1 - \Pr(1)] \cdot [s_l - \mathrm{K}(1) - C^L(x_h)] \geq 0$$

which simplifies to:

$$\Pr(1) \cdot s_h + [1 - \Pr(1)] \cdot s_l \geq \mathrm{K}(1) + C^L(x_h) \qquad (2)$$

Function (2) makes sure that the expected payoff of the LC farm to take the correct contract is non-negative. In another words, LC farms will be better off after taking the contract {$x_h$, *1*, $s_h$}. Similarly, the individual rationality constraint for the HC farm (IRC2):

$$\mathrm{E}(B_{78}^H) = Pr(0) \cdot B_7^H + [1 - Pr(0)] \cdot B_8^H \geq 0, \text{ or}$$

$$\Pr(0) \cdot [s_l - \mathrm{K}(0) - C^H(x_l)] + [1 - \Pr(0)] \cdot [s_h - \mathrm{K}(0) - C^H(x_l)] \geq 0$$

which reduces to:

$$\Pr(0) \cdot s_l + [1 - \Pr(0)] \cdot s_h \geq \mathrm{K}(0) + C^H(x_l) \qquad (3)$$

Equation (3) makes sure that the expected payoff of HC farm to choose {0, 0, $s_l$} is non-negative. In another words, high cost farms will be better off after taking the contract {$x_l$, 0, $s_l$}.

Also, to reveal the cost type of the farms, the contracts also need to make sure that farms of one type have no incentive to choose the option intended for the other type. This is called self-selection or incentive compatibility constraint. In functional form under our assumptions, it could be shown as this self-selection constraint for the LC farm (SSC1):

$$\mathrm{E}(B_{12}^L) \geq \mathrm{E}(B_{78}^L), \text{ or}$$

$$Pr(1) \cdot B_1^L + [1 - Pr(1)] \cdot B_2^L \geq Pr(0) \cdot B_7^L + [1 - Pr(0)] \cdot B_8^L$$

which reduces to:

$$[\Pr(1) + \Pr(0) - 1] \cdot s_h + [1 - \Pr(0) - \Pr(1)] \cdot s_l$$
$$\geq K(1) - K(0) + [C^L(x_h) - C^L(x_l)] \tag{4}$$

Equation (4) makes sure that the expected payoff of LC farm to choose {1, 1, $s_h$} is bigger than the Expected payoff to choose {0, 0, $s_l$}. The self-selection constraint for the HC farm (SSC2):

$$\mathrm{E}(B_{78}^H) \geq \mathrm{E}(B_{12}^H)$$

$$Pr(0) \cdot B_7^H + [1 - Pr(0)] \cdot B_8^H \geq Pr(1) \cdot B_1^H + [1 - Pr(1)] \cdot B_2^H$$

which reduces to:

$$[\Pr(1) + \Pr(0) - 1] \cdot s_h + [1 - \Pr(0) - \Pr(1)] \cdot s_l$$
$$\leq K(1) - K(0) + [C^H(x_h) - C^H(x_l)] \tag{5}$$

The HC farm is better off when choosing the intended contract over the good contract, which makes sure that the expected payoff of HC farm to choose {0, 0, $s_l$} is bigger than the Expected payoff to choose {1, 1, $s_h$}.

# Chapter 3

# ANALYSIS OF THE MODEL

To see how asymmetric information affects social benefit and the contract program, we analyzed the model with under three situations: the first-best scenario, second-best situation with no deadweight loss (*e*=0) and second-best situation with deadweight loss (*e*≠0).

## 3.1 First-Best Scenario

The first-best situation here leaves out 3 imperfections. When the asymmetric information problem does not exist (regulator knows the cost functions exactly for each farm and also there is no cheating), (1) there will be no incentive compatibility constraint beacuase the regulator could just assign the socially optimal choices to different farmers accurately. Also, (2) the monitoring effort is not necessary since no one is going to cheat. Finally, (3) there is no deadweight loss from transferring money from taxpayers to farmers. When the regulator pays each farm according to its type, then this is the objective function:

$$\underset{x_j}{\text{Max}}\!: \pi = \left[es(x_j) - C^L(x_j)\right] + \left[es(x_j) - C^H(x_j)\right] \qquad (6)$$

$$s.t.\!: s_h - C^L(x_j) \geq 0$$

$$s_l - C^H(x_j) \geq 0$$

$$s_h + s_l \leq min\{s_h + s_l\}$$

Note that the only constraints left here are individual rationality constraints that make sure the farmers will better off after accepting the contracts.

Note the payments themselves are cancelled out in the objective function and only appear in the participation constraint. While the regulator's aim to maximize the social benefit, it is also reasonable to assume that the regulator would like to achieve this goal with the least payment. This means that the regulator wants to pay as little as possible. This assumption leads to the third constraint in the optimization problem. Solving the maximization problem gives the solution that:

$$s_h = C^L(x_h) \; and \; s_l = C^H(x_l) \tag{8}$$

which is the same as a common conclusion that the optimal BMP level should be the point where the marginal benefit of BMP is equal to the marginal cost of BMP. And the payment should just cover the cost of installing the BMP.

### 3.2 2nd-Best Scenario with *e*=0

The second best solution takes individual rationality constraints and self-selection constraints into consideration because the regulator cannot observe farmer types. Starting with the situation when *e*=0, which means no deadweight loss, the optimization problem could be written as:

Max: $\pi = es(x_h) - \{[C^L(x_h) + K(1)]\} + es(x_l) - \{[C^H(x_l) + K(0)]\}$ (9)

*s.t.:*

$$\Pr(1) \cdot s_h + [1 - \Pr(1)] \cdot s_l \geq \mathrm{K}(1) + C^L(x_h) \tag{IRC1}$$

$$\Pr(0) \cdot s_l + [1 - \Pr(0)] \cdot s_h \geq \mathrm{K}(0) + C^H(x_l) \tag{IRC2}$$

$$[\Pr(1) + \Pr(0) - 1] \cdot s_h + [1 - \Pr(0) - \Pr(1)] \cdot s_l$$

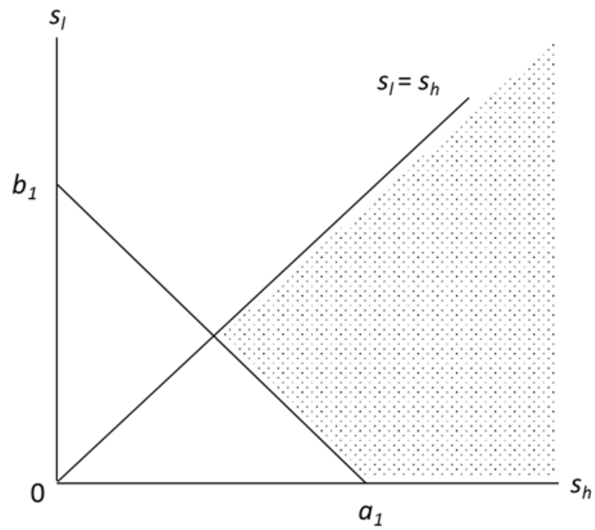
$$\geq K(1) - K(0) + [C^L(x_h) - C^L(x_l)] \quad \text{(SSC1)}$$

$$[\Pr(1) + \Pr(0) - 1] \cdot s_h + [1 - \Pr(0) - \Pr(1)] \cdot s_l \leq$$

$$K(1) - K(0) + [C^H(x_h) - C^H(x_l)] \quad \text{(SSC2)}$$

Note the constraints here are reduced form which is a simplification from function (2), (3), (4), and (5). IRC1 and IRC2 stands for the individual rationality constraints which make sure that farmers will better off after participation. SSC1 and SSC2 stands for the self-selection constraints which make sure that different types of farmers would choose the contract designed exactly for him.

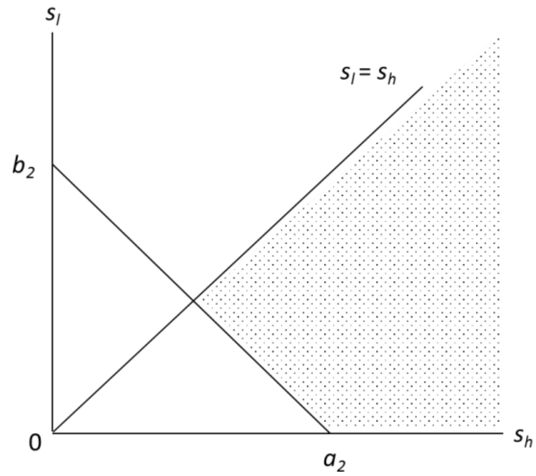
If all the above variables were continuous, the problem would be a constrained maximization problem. By using Kuhn-Tucker necessary conditions, one could solve the problem just as Wu and Babcock (1995) to reveal the optimal BMP efforts and monitor efforts for the problem. However, we made dichotomous assumptions for the variables in this thesis and have an idea about the optimal value that $x_h$*=1, $x_l$*=0. The problem here could be recast to find a range of $s_h$ and $s_l$ which leads to the optimal solution. We could solve the problem by constructing a two dimensional coordinate system by setting $s_h$ as the horizontal axis and $s_l$ as the vertical axis. Then the constraints form different ranges of feasible solutions in the coordinate system. A feasible solution is one in which an equilibrium contract could be written.




$$\left(\boldsymbol{a_1 = \frac{K(1)+C^L(1)}{\Pr(1)}, b_1 = \frac{K(1)+C^L(1)}{1-\Pr(1)}}\right)$$

Figure 3.1: Individual rational constraint for the LC-farm

Starting with IRC1, the possible combinations of $s_h$ and $s_l$ could be found by graphing the constraint in the two coordinate system. With equality, function $\Pr(1) \cdot s_h + [1 - \Pr(1)] \cdot s_l = \mathrm{K}(1) + C^L(x_h)$, could be described by a line as shown in figure 3.1 as $a_1b_1$ where $a_1$ is the intercept on the horizontal axis and $b_1$ is the intercept on the vertical axis. And from simple algebra, we can get that $a_1 = \frac{K(1)+C^L(1)}{\Pr(1)}$, $b_1 = \frac{K(1)+C^L(1)}{1-\Pr(1)}$. Then considering about the inequality, it gives the shaded area in figure 3.1. The shaded area shows the feasible ranges of $s_h$ and $s_l$ of individual rationality constraint for LC-farm combined with the underlying assumption that $s_h \geq s_l$. Since both the denominator and the numerator are positive, the intersection of the line and the axis are both positive, too. The slope of the constraint line is $k_1=Pr(1)/(Pr(1)-1)$.

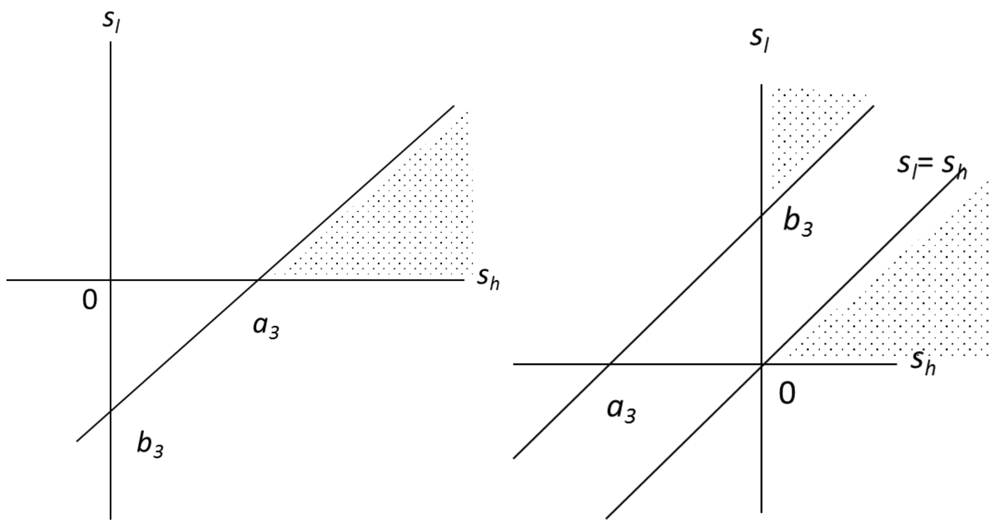



$$\left(\boldsymbol{a_2} = \frac{\boldsymbol{K(0)+C^H(0)}}{\mathbf{1-Pr(0)}}, \boldsymbol{b_2} = \frac{\boldsymbol{K(0)+C^H(0)}}{\mathbf{Pr(0)}}\right)$$

Figure 3.2: Individual rational constraint for the HC-farm

By the same means of figure 3.1 and IRC1, we can get that the shaded area in figure 3.2 shows the feasible ranges of $s_h$ and $s_l$ of individual rational constraint for HC-farm(IRC2), which is a result of the inequality constraint function (3). Since both the denominator and the numerator are positive, the intersection of the line and the axis are both positive, too. The slope of the constraint line is $k_2=Pr(0)/(Pr(0)-1)$.

From figure 3.1 and figure 3.2, one can derive the condition that $k_1-k_2=[Pr(0)-Pr(1)]/\{[Pr(1)-1][Pr(0)-1]\}<0$. So the constraint line in figure 3.1 is steeper than the constraint line in figure 3.2. Both sets are sets with positive infinity. So the intersection of the two constraints is non-empty.

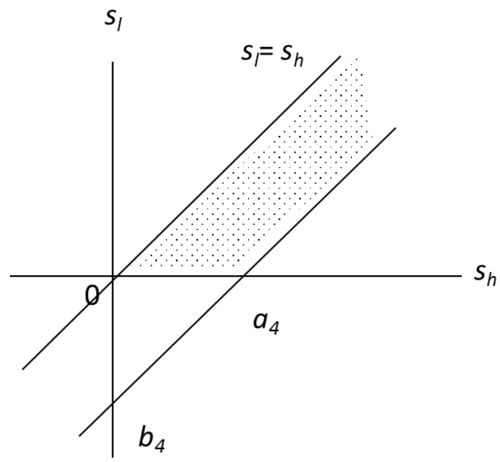



**(a)** **(b)**

$$\left(a_3 = \frac{K(1)-K(0)+C^L(1)-C^L(0)}{Pr(1)+Pr(0)-1},\ b_3 = \frac{K(1)-K(0)+C^L(1)-C^L(0)}{1-Pr(1)-Pr(0)}\right)$$

Figure 3.3: Self-selection constraint for the LC-farm.

The shades area in figure 3.3a or 3.3b shows the feasible ranges of $s_h$ and $s_l$ of self-selection constraint for LC-farm, which is a result of the inequality constraint equation (4). Note that the numerators of the intersections, $a_3$ and $b_3$ are always positive while the sign of the denominators depends on the value of [$Pr(0)+ Pr(1) - 1$]. When $Pr(0)+Pr(1) - 1>0$, the constraint line intersects with the positive part of the horizontal axis and the negative part of the vertical axis, which is the case of figure 3.3a. When $Pr(0)+Pr(1) - 1<0$, the constraint line intersects with the negative part of the horizontal axis and the positive part of the vertical axis, which is the case of figure 3.3b. But the feasible area could not satisfy the constraint that $s_h>s_l$. So we get the idea that $Pr(0)+Pr(1) - 1<0$ is not a feasible case.  Note the slope of the constraint line is $k_3=1$ in both cases.




$$\left(a_4 = \frac{K(1)-K(0)+C^H(1)-C^H(0)}{Pr(1)+Pr(0)-1}, b_4 = \frac{K(1)-K(0)+C^H(1)-C^H(0)}{1-Pr(1)-Pr(0)}\right)$$

Figure 3.4: Self-selection constraint for the LC-farm

The shaded area in figure 3.4 shows the feasible ranges of $s_h$ and $s_l$ of self-selection constraint for HC-farm, which is a result of the inequality constraint function (5).  Similar to figure 3.3, the intersection depends on the value of $[Pr(0)+Pr(1)-1]$. Since we get the idea that $Pr(0)+Pr(1) - 1>0$ always holds from figure 3.3, we do not need to consider the case that $Pr(0)+Pr(1) - 1<0$ here.  The constraint line intersects with the negative part of the horizontal axis and the positive part of the vertical axis, which is the case of figure 3.4a.  Note the slope of the constraint line is $k_4=1$, too.

The optimal solution of $s_l$ and $s_h$ must satisfy all the four above constraints at the same time, and also $s_l < s_h$.  To find this optimal solution, we could put all 4 constraint sets into the same graph and find the intersection of the 4 sets. The final solution set depends on the value of the individual constraint sets (which in graph, is the position of the shaded area.). Further parameterization and assumptions are needed to get these values because there are too many unknowns to derive a unique set of equilibria.

### 3.3 2nd-Best Scenario with *e*≠0

Further analysis takes the deadweight loss of transferring tax money into consideration. The optimization problem could be written as:

$$\max_{x_j, s_j}: \pi = es(x_h) - \{[C^L(x_h) + K(1)]\} + es(x_l) - \{[C^H(x_l) + K(0)]\} - \mathrm{e}(s_l + s_h) \tag{10}$$

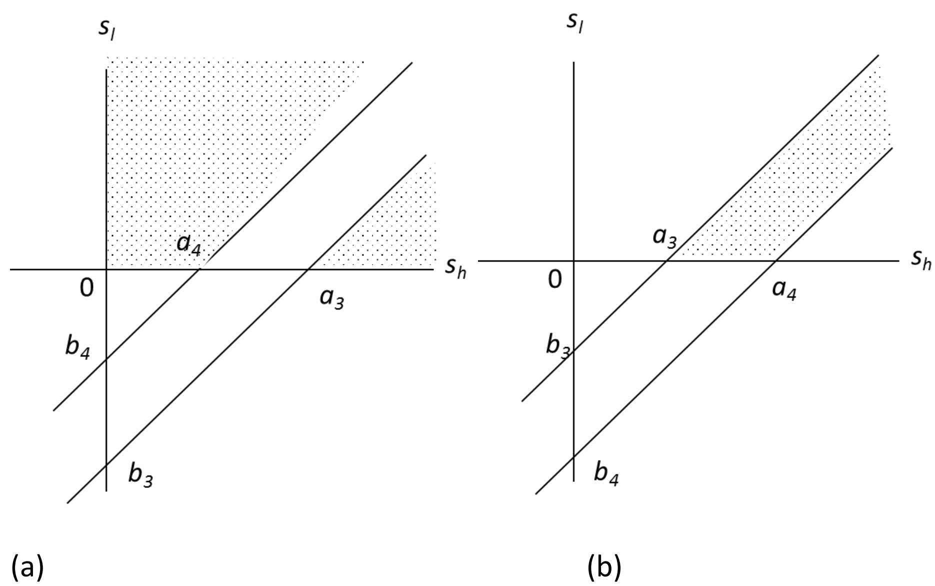
with the same two individual rationality constraints and two self-selection constraints. One interesting thing in this scenario is that the deadweight loss factor, *e*, only enters the objective function and would not affect farmers' decisions. It is actually a kind of constraint for which only the regulator would consider when determining whether it is socially optimal to write any contract. In the optimization problem, it has the same function as minimizing payment constraint. Since we will get the optimal payment level from the constraint sets, the final payment level would be exactly the same as results in section 3.2. The only difference is a lower social benefit caused by transferring money.

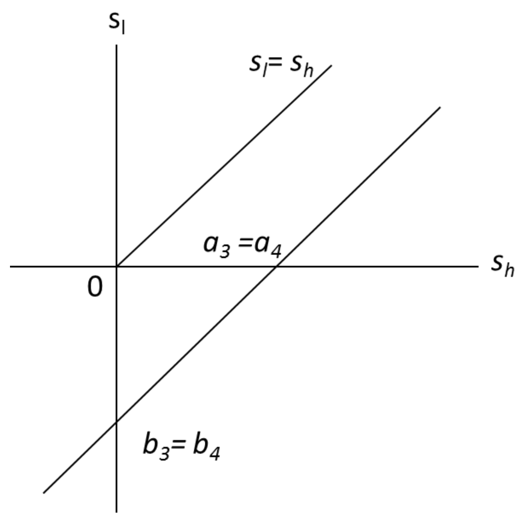
## Chapter 4

## RESULTS DISCUSSION

### 4.1 Proof of Non-Existence

When we graph the two self-selection constraints together in one figure, there will be different situations based on the relative value of $a_3$ and $a_4$.






(c)

Figure 4.1: Intersections of self-selection constraints

Note when $a_4<a_3$ (so that $b_4>b_3$), as figure 4.1a above, there is no intersection between the two sets, which means no optimal solution. We will get $a_4<a_3$ when

$$a_4 - a_3 = \frac{[C^H(1)-C^H(0)]-[C^L(1)-C^L(0)]}{\Pr(1)+\Pr(0)-1} < 0 \quad , \tag{11}$$

which is $[C^H(1) - C^H(0)] - [C^L(1) - C^L(0)] < 0$ (Since we have $Pr(0)+Pr(1) - 1>0$ always holds.). On the opposite side, as long as $[C^H(1) - C^H(0)] - [C^L(1) - C^L(0)] > 0$, which implies $a_4>a_3$, as figure 4.1b, the intersection between the self-selection constraints is non-empty with positive infinitive values. So the intersection of four constraint sets is non-empty, too. When $[C^H(1) - C^H(0)] - [C^L(1) - C^L(0)] = 0$, which is shown by figure 4.1c, the self-selection constraint set are the constraint line.

From the discussion of figure 3.3b above, one sees that cases with $Pr(0)+Pr(1) - 1<0$ are not feasible. So in certain circumstances, there is no equilibrium because it is impossible to write a second-best contract. Or in other words, the separating equilibrium is impossible here and only a pooling equilibrium (a single payment contract) might be obtained. With certain assumptions, we can compare the results between separating equilibrium and pooling equilibrium to see how much better do we do with separating equilibrium.

d

## 4.2 Parameterization for Second-Best Scenario with *e*=0

As we can see from the optimization problem, to get a precise and analytically useful final equilibrium more information of the above variables (BMP cost, monitor cost, probability of knowing the truth) needs to be acquired or assumed. For BMP cost here, we use cover crops as an example.

Table 4.1: Cover-Crop Cost/Payment Data

| **Cost study** | Range($/Acre) | Factors driving heterogeneity in cost |
|---|---|---|
| Tourte and Buchanan (2003) | [48, 163] | |
| Bergtold and Maddy (2008) | [62, 107] | CC type |
| Wieland, Parker et al. (2009) | [31.4, 37.3] | CC type, planting time, method and geology |
| SARE CTIC CC Survey Report (2012-2013) | 40 | Median value |
| MDA CC cost estimation (2014) | [56.63, 161.63] | CC type |
| Tyner and Pratt (2014) | [35.78, 69.81] | CC type |

| Payment Examples | | |
|---|---|---|
| Sussex Conservation District CC Program (2014) | {40, 50} | Planting dates |
| Maryland's CC program (2014-2015) | [45, 100] | Traditional CC, Planting dates and practices(manure, tillage, broadcast and so on) |
| | {25, 35} | Harvest CC, CC type |

Based on these cost studies, we assume cost estimation of $140 for a high-cost type farm using high BMP effort ($C^H(1)$=140), $100 using low BMP effort($C^H(0)$=100). Similarly, we assume $80 cost for low-cost type farm using high BMP effort ($C^L(1)$=80), $60 using low BMP effort($C^L(0)$=60). These assumptions satisfy the relationship that$[C^H(1) - C^H(0)] - [C^L(1) - C^L(0)] \geq 0$.

For monitoring costs, we assume *K*(1)=$80 and *K*(0)=$40 because the monitoring of cover crop is relatively low cost to the regulator, generally regulator could just pay a visit at certain time to eyeball the practice. Here low monitoring level could be interpreted as a one-time visit with a cost of $40 while high monitoring be visiting twice with a cost of $80.

The assumption on *Pr*(1) and *Pr*(0) needs to satisfy both *Pr*(1) > *Pr*(0) and *Pr*(1) +*Pr*(0)>1. Varying by 0.1 we get the possible combinations of *Pr*(1) and *Pr*(0) as:

Table 4.2: Possible Combinations of *Pr*(1) and *Pr*(0)

| *Pr*(1) | 0.6 | 0.7 | 0.8 | 0.9 |
|---|---|---|---|---|
| *Pr*(0) | 0.5 | 0.6 | 0.7 | 0.8 |
| | NA | 0.5 | 0.6 | 0.7 |
| | NA | 0.4 | 0.5 | 0.6 |
| | NA | NA | 0.4 | 0.5 |

| | | | | |
|---|---|---|---|---|
| | NA | NA | 0.3 | 0.4 |
| | NA | NA | NA | 0.3 |
| | NA | NA | NA | 0.2 |

Before we get the final results here, we need to make another assumption about the upper limit of the payment level. It is the rational regulator government. In the optimization model, the constraints work to drive different types of farmers to make the optimal choice. But no constraint is showed to limit the payment ability of the government. A rational regulator should pay no more than the net benefit results from the practices. In functional form, it should be note as:

$$s^*_h \leq es(x_h)\text{-}C^L(x_h)\text{-}K(1)$$

$$s^*_l \leq es(x_l)\text{-}C^H(x_l)\text{-}K(0)$$

We assume that the environment service value is high enough that the payment level is always lower that the net benefit of the practices.

Given above assumptions and parameterizations, we calculate the values of $a_n$ and $b_n$ (n=1, 2, 3, 4). Results are shown in table below. A binding constraint means the constraint holds with equality. In economics, this means that the farmer is indifferent between the choices made in the constraints.

Table 4.3: Simulation Results

| *Pr*(1) | *Pr*(0) | $s_h$ | $s_l$ | $s_h+s_l$ | Binding constraints |
|---|---|---|---|---|---|
| 0.6 | 0.5 | 600 | 0 | 600 | SSC1 |
| 0.7 | 0.6 | 259 | 29 | 288 | SSC1, IRC2 |
| 0.7 | 0.5 | 300 | 0 | 300 | SSC1 |
| 0.7 | 0.4 | 600 | 0 | 600 | SSC1 |
| 0.8 | 0.7 | 223 | 103 | 326 | SSC1, IRC2 |
| 0.8 | 0.6 | 259 | 59 | 318 | SSC1, IRC2 |
| 0.8 | 0.5 | 200 | 0 | 200 | SSC1, IRC1 |
| 0.8 | 0.4 | 300 | 0 | 300 | SSC1 |

| | | | | | |
|---|---|---|---|---|---|
| 0.8 | 0.3 | 600 | 0 | 600 | SSC1 |
| 0.9 | 0.8 | 208 | 123 | 331 | SSC1, IRC2 |
| 0.9 | 0.7 | 211 | 111 | 322 | SSC1, IRC2 |
| 0.9 | 0.6 | 211 | 91 | 302 | SSC1, IRC2 |
| 0.9 | 0.5 | 215 | 65 | 280 | SSC1, IRC2 |
| 0.9 | 0.4 | 233 | 0 | 233 | IRC2 |
| 0.9 | 0.3 | 300 | 0 | 300 | SSC1 |
| 0.9 | 0.2 | 600 | 0 | 600 | SSC1 |

For example, with $Pr(1)$=07, $Pr(0)$=0.6, we derive the relative values of $a_n$ and $b_n$ to graph the different constraints in figure 4.2. Then the shaded area is the solution set that satisfies all four constraints for a separating equilibrium. To find the optimal solution, note that we also have a constraint to minimize the total payment level, which is $s_h+s_l$. The dashed line stands for $s_h+s_l = P$ in the figure 4.2, and as the line moves to the right/up direction, $P$ will increase accordingly and decrease in the opposite direction. So as the total payment line moves out from the origin (0, 0) to the upper right direction and intersects the solution set, the first solution we could get is the lowest level of $P$, which is the optimal $s_h+s_l$ value. In this case, it is $s_h$= 259, $s_l$ =29 and $s_h+s_l=P$=288.

When we compare the different payment schedules in table 4.3 with first best payment schedule and actual cost to the farms, we find interesting results here. Based on our parameterization, $s_h= C^H(1)$=140 , $s_l = C^L(0)$=60 and $s_h+s_l=P$=200, the total payment is higher in our model but within a reasonable range. The extra payments come from the efficiency loss results from the asymmetric information. But there is a special case when $Pr(1)$=0.8, $Pr(0)$=0.5, such that $s_h$= \$*200* , $s_l$ =\$0 and $s_h+s_l=P$=\$200, which is identical to the first best case. This means no efficiency loss and second-best achieved the same results with first-best. Further, if we compare the payment level with the actual cost of farmers, we find something interesting. The actual cost for high cost farms are actually $C^H(1) + K(1)$=\$140+\$80=\$220, which is less than $s_h$ under corner solution cases but may be higher than other cases. And when we looked at the actual cost to low cost farms, $C^L(0) + K(0)$=\$60+\$40=\$120, it is actually higher than the payment schedules. This is a result of the expectation method we used in the model constraints.

In this case, there are two constraints binding, IRC1 and SSC1.

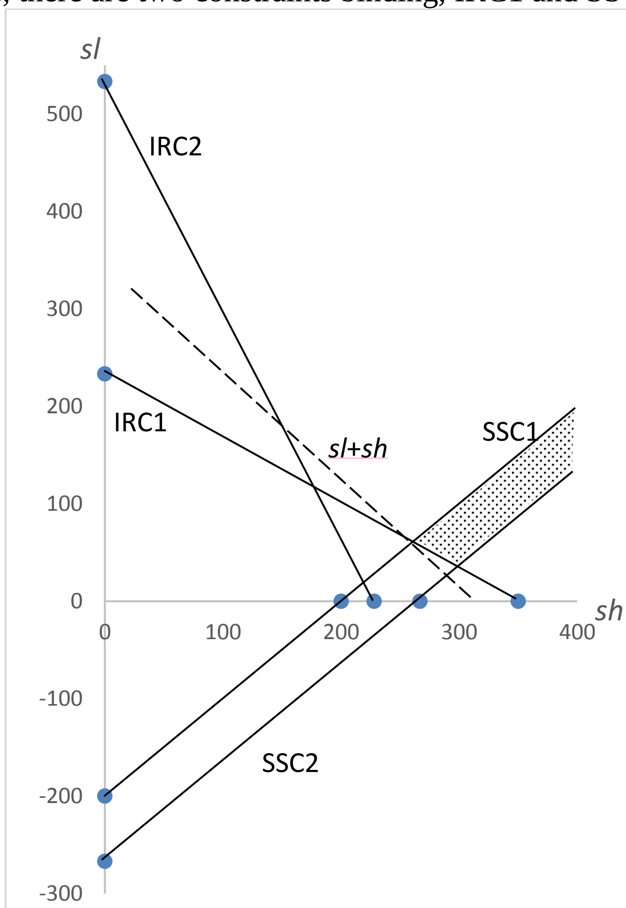



Figure 4.2: Optimal solution with *Pr*(1)=07, *Pr*(0)=0.6

Note that when $s_l$ is 0, it means a corner solution where the optimal solution happens to be on the horizontal axis. Just as shown in figure 4.3. In this case, there is only one constraint binding, the SSC1.

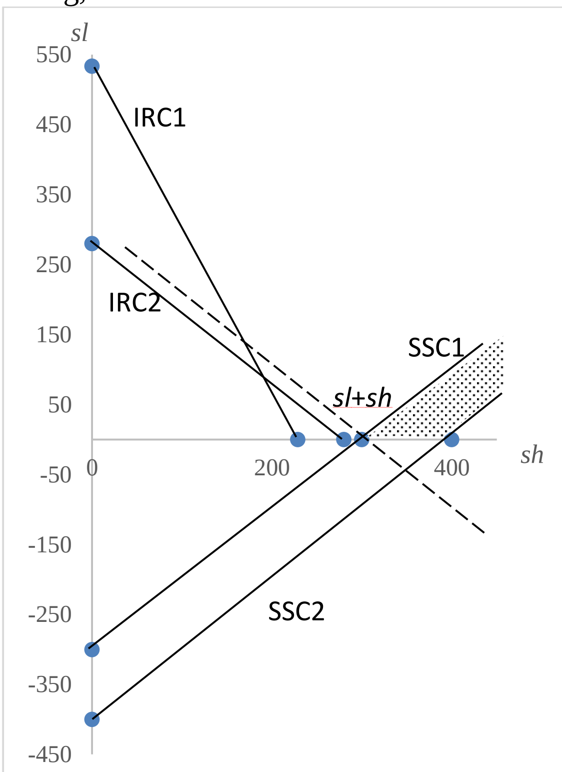



Figure 4.3: Example of a corner solution

## 4.3 Results Discussion

To find out how the final payment level would change according to different probabilities, we graphed the results of table 4.3 in figure 4.4. In the two graphs, the horizontal axis and vertical axis stands for the probability levels so each point in the coordinate system stands for a possible combination of the two monitor levels. Under each combination, there is an equilibria contract level derived. To show how the underlying assumptions and different probabilities affect the contract level, we use the size of the circle. The larger the circle, the higher of $s_h+s_l$, which is the total payment level.

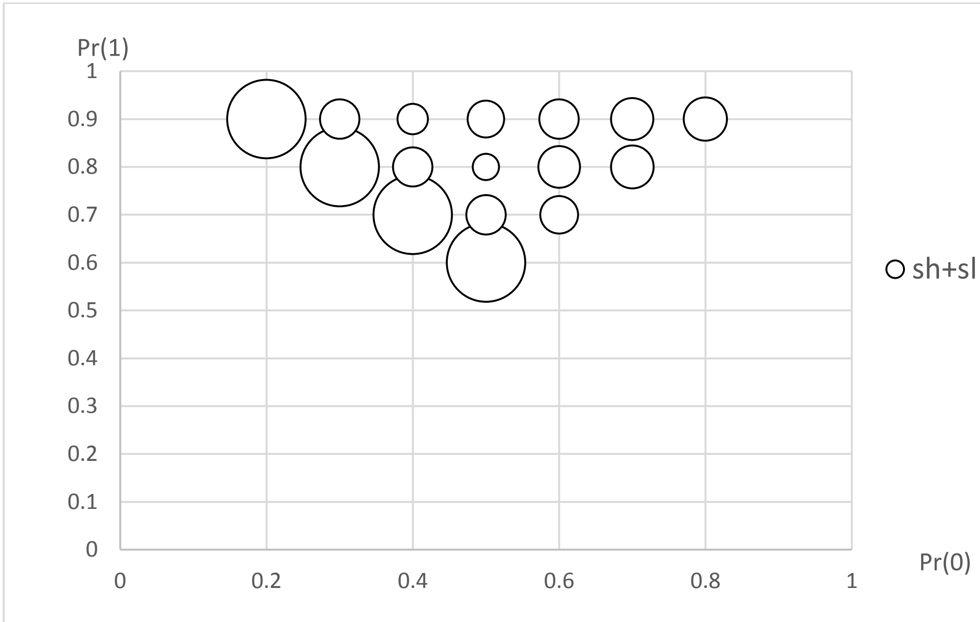



Figure 4.4: Equilibria contract levels

From the above figure, we can see that:

(1) Under the parameterization and assumptions we made, the corner solutions shows extreme results (larger payment than interior optimum). All these corner solutions result from the only binding constraint: SSC1. This occurs, theoretically, from the inequality of SSC1, we derive that an unreasonable high payment corner solution when $Pr(1)+Pr(0)-1$ is relatively small. The small value of $Pr(1)+Pr(0)-1$ blows up the SSC1 (higher payment schedule to make sure the LC farms to select the right contract) since $Pr(1)+Pr(0)-1$ is in the denominator. However, the value $Pr(1)+Pr(0)$ really does not make that much sense in the real world. Since the probability of different monitor choice is independent action and it's true that we can

compare monitoring probability by $Pr(1) - Pr(0)$ but summing up the different probability does not make any realistic sense.

Another interesting interpretation of the corner solution is that the HC farm would still join the program even the potential payment level, $s_l$, is 0. This seems unreasonable in the real world but it makes sense here and it could be explained by the expected payoff to the farmers. The expected payoff includes a chance that when HC farms invest a low effort and a low monitor on their farms, the regulator may observe the low effort as high effort by mistake and give them a high payment. Especially when $Pr(0)$ is relatively low, which means that the regulator is very likely to make the above mistake and $s_h$ is very high. This explanation matches the corner solution results since they come with low $Pr(0)$ and high $s_h$. So, by making $s_h$ really high, the regulator could trick the high cost farmers into the program.

(2) The highest total payment happens at corner solutions (which is the left lower bound of the range). High payments are not necessarily ineffient (unless there is deadweight loss), but they do affect the separating equilibrium. As the probabilities increase to the upper right corner, the total payment level decreases to the lowest at first but start increasing after that. This means, the regulator is worse off only if the deadweight loss factor $e \neq 0$. The more payment made by the regulator, the lower the total social benefit. If the regulator operates, however, in a constrained budget world, then this higher payment would mean lower enrollment.

(3) Results in (2) seems counter intuitive as the probability for knowing the truth increases, the actual total payment increases too. Why does this happen? One possible reason is that the interaction between the hidden information problem and the hidden action problem. Note that we introduced monitoring as a signal in this game

and the probabilities are reflections of monitoring. So, we could define the difference of *Pr*(1) and *Pr*(0) as the truth-revelation of the signal of the signal. The larger the difference, the more significant the signal is. When both *Pr*(1) and *Pr*(0) increase to the upper limit ( to the up-right corner of the quadrant), it is true that higher probability could make sure that the regulator could observe the real effort so that fix the hidden action or cheating problem. However, it will not help to distinguish the type or the heterogeneity in the cost. The regulator still wants to distinguish them so that he or she can customize the payment. As the difference in probabilities of truth-revelation of the signal, or *Pr*(1)－*Pr*(0), drops, the significance of the signal is not strong enough or the signals are so similar that it cannot distinguish the two types. In other words, the signal is not working anymore and the whole contract is heading to a single payment contract schedule (pooling equilibrium) and higher payments.

Another interpretation is that there might be higher information rent for these high cost type farms. To find out whether this is true, we need to see what is the distribution of payments for each type? Or what is the size of $s_h$ and $s_l$? How is the distribution going to change according to the change in probability and why? This could be seen from figure 4.5

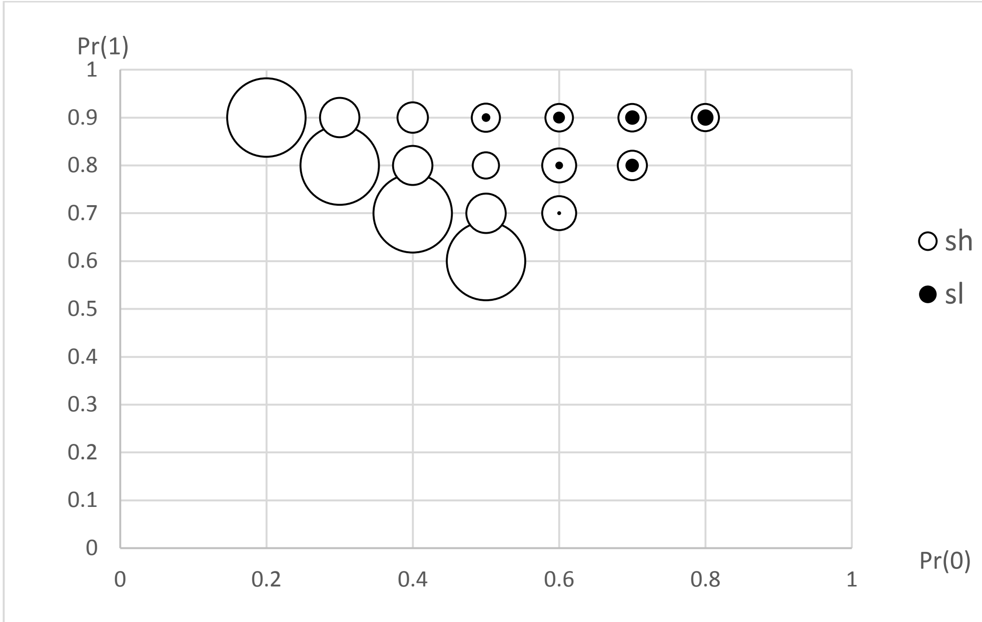



Figure 4.5: Distribution of optimal payment

When a corner solution happens, all the payments goes to $s_h$ so $s_l$ =0. But as long as $s_l \neq 0$, it shows a strictly increasing trend as either probability increases. The change in $s_h$ is relatively small when $s_l$ is not 0. Why? This result can be understood from two different perspectives.

Mathematically, the principal driver of the difference between these corner solutions and inner solutions is the binding constraints. From table 4.3, almost all the optimal solutions (except the specially case of $Pr(1)$=0.9, $Pr(0)$=0.4) have SSC1 binding. But the inner solutions all have one more binding constraint, which is IRC2. Therefore, the inner solutions are actually the result of solving the two binding equations set, which makes sure that the optimal point is in the positive quadrant. IRC2 is used to assure the expected net benefit of the HC farm which should get the payment $s_l$.

From another perspective, we could use an extreme case to understand the result. What if there is only a perfect monitoring choice, which is $Pr(1)$=$Pr(0)$=1? We take this special parameterization back in to the optimization functions which is:

$$\text{Max: } \pi = es(x_h) - \{[C^L(x_h) + K(1)]\} + es(x_l) - \{[C^H(x_l) + K(0)]\} \tag{12}$$

*s.t.:*

$$s_h \geq \mathrm{K}(1) + C^L(x_h) \tag{IRC1}$$

$$s_l \geq \mathrm{K}(0) + C^H(x_l) \tag{IRC2}$$

$$s_h - s_l \geq K(1) - K(0) + [C^L(x_h) - C^L(x_l)] \tag{SSC1}$$

$$s_h - s_l \leq K(1) - K(0) + [C^H(x_h) - C^H(x_l)] \tag{SSC2}$$

The objective function is still not affected and the constraints are largely simplified because of the extreme situation (the probability parameters is simplify to 1). The optimization problem is simplified to a simple hidden information problem similar to those in Wu and Babcock (1995, 1996) and the monitor cost works as a kind of fixed cost in the function. In this extreme situation, IRC2 assures that $s_l \geq \mathrm{K}(0) + C^H(x_l) = 140$. So we could conclude that starting from the corner solutions where $s_l$=0, as both $Pr(1)$ and $Pr(0)$ increases to the upper limit of 1, IRC2 shifted to the upper right and push the solution set to the extreme case.

### 4.4 Further Discussion on *e*

When $e \neq 0$, it affects the total social benefit but does not affect the results of payment schemes, since deadweight loss does not enter the constraints by which we get the results of total payments. But it is useful to show the net benefit of transferring payment. If *e* is so high that the cost of transferring money is higher than the benefits of BMP efforts, the system will collapse.  This could be verified by assuming a dollar amount of environmental service.

# Chapter 5

# CONCLUSION

This article has identified an optimal PES contract schedule by involving monitoring choice as a signal in the contract that aims to solve both the hidden information and hidden action problem faced by the regulator. By setting an optimal payment schedule, the regulator could tell which farm is a low-cost or high-cost farm and which one is a high-cost or low productive farm by their choice of monitoring level, since the farmers' expected net benefit is maximized only if he or she chooses the contract designed specifically for that farmer.

Although much literature has devised methods, such as auctions or trading, to reduce the potential information rents by inducing private parties to reveal voluntarily private information, our findings suggest that setting monitoring in the contract schedule could not only distinguish different types of agents but also reveal the true effort on site to keep the agents from cheating. This conclusion is built on assumptions of different monitor choice combination which may not hold in general because of the reality of imperfect monitoring, the proof of non-existence showed the cases when a separating contract is not working. . We find that under certain levels of probability to observe the true effort, which is based on the monitor level, it is impossible to write a separating contract.

In addition, the uncertainty of payment, which results from the uncertainty of monitoring results, would not only affect the payment schedule, but also affect the action of the agents. The regulator could set the low payment level to zero but set the high payment level really high so that he can motivate the high-cost type farms into the scheme since they believe that there is a chance for the regulator to make a mistake.

At last, the interaction between the hidden information and hidden action problem is significant and would affect the optimal payment level in certain ways. As we defined above, the significance of the signal, will affect the payment distribution. As both monitoring choices tend to perfect monitoring, the significance of the signal drops so that it is useless to tell the difference of different types, which leads to a normal hidden information problem and a higher total payment.

Of course a primary disadvantage of the model here is the largely simplified dichotomous case since the both the effort level and cost heterogeneity in the real word should be a viewed as a continuously changing factor. A limitation of our empirical analysis is that our Parameterization are based on other researchers and may vary significantly between the BMP choice, geographical region and many other factors. The result depends on the relative value of different variables in the model. Without further parameterizations on these variables, it is hard to find an optimal solution. This could limit the generalization our findings. Finally, the model structure is somewhat stylized, and does not apply to the current interactions between regulators and farmers.

## REFERENCES


1. Arguedas, C., and D.P. van Soest "Optimal Conservation Programs, Asymmetric Information and the Role of Fixed Costs." Environmental & Resource Economics 50 (2011):305-23.

2. Arnold, M.A., J.M. Duke, and K.D. Messer "Adverse Selection in Reverse Auctions for Ecosystem Services." Land Economics 89 (2013):387-412.

3. Baerenklau, K. "Green payment programs for nonpoint source pollution control: How important is targeting for cost-effectiveness?" Journal of Agricultural and Resource Economics 27 (2002):406-19.

4. Banerjee, S., S. Secchi, J. Fargione, S. Polasky, and S. Kraft "How to sell ecosystem services: a guide for designing new markets." Frontiers in Ecology and the Environment 11 (2013):297-304.

5. Bontems, P., G. Rotillon, and N. Turpin "Self-selecting agri-environmental policies with an application to the don watershed." Environmental & Resource Economics 31 (2005):275-301.

6. Borisova, T., J. Shortle, R. Horan, and D. Abler "Value of information for water quality management." Water Resources Research 41 (2005):W06004.

7. Elofsson, K. "Climate change and regulation of nitrogen loads under moral hazard." European Review of Agricultural Economics (2013):

8. Feng, H. "Green payments and dual policy goals." Journal of Environmental Economics and Management 54 (2007):323-35.

9. Ferraro, P.J. "Asymmetric information and contract design for payments for environmental services." Ecological Economics 65 (2008):810-21.

10. Hart, R., and U. Latacz-Lohmann "Combating moral hazard in agri-environmental schemes: a multiple-agent approach." European Review of Agricultural Economics 32 (2005):75-91.

11. Jeffrey M. Peterson, and Richard N. Boisvert "Control of Nonpoint Source Pollution Through Voluntary Incentive-Based Policies: An Application to Nitrate Contamination in New York." Agricultural and Resource Economics Review 30 (2001):127-38.

12. Moxey, A., B. White, and A. Ozanne "Efficient Contract Design for Agri-Environment Policy." Journal of Agricultural Economics 50 (1999):187-202.

13. Ozanne, A., T. Hogan, and D. Colman "Moral hazard, risk aversion and compliance monitoring in agri-environmental policy." European Review of Agricultural Economics 28 (2001):329-47.

14. Ozanne, A., and B. White "Equivalence of input quotas and input charges under asymmetric information in agri-environmental schemes." Journal of Agricultural Economics 58 (2007):260-8.

15. ———"Hidden action, risk aversion and variable fines in agri-environmental schemes*." Australian Journal of Agricultural and Resource Economics 52 (2008):203-12.

16. Pagiola, S. "Payments for environmental services in Costa Rica." Ecological Economics 65 (2008):712-24.

17. Peterson, J.M., C.M. Smith, J.C. Leatherman, N.P. Hendricks, and J.A. Fox "Transaction Costs in Payment for Environmental Service Contracts." American Journal of Agricultural Economics (2014):

18. Peterson, J., and R. Boisvert "Incentive-compatible pollution control policies under asymmetric information on both risk preferences and technology." American Journal of Agricultural Economics 86 (2004):291-306.

19. SMITH, R. "The Conservation Reserve Program as a Least-Cost Land Retirement Mechanism." American Journal of Agricultural Economics 77 (1995):93-105.

20. SPOONER, J., and D. LINE "Effective Monitoring Strategies for Demonstrating Water-Quality Changes from Nonpoint-Source Controls on a Watershed Scale." Water Science and Technology 28 (1993):143-8.

21. Tacconi, L. "Redefining payments for environmental services." Ecological Economics 73 (2012):29-36.

22. Wu, J., and B.A. Babcock "Contract Design for the Purchase of Environmental Goods from Agriculture." American Journal of Agricultural Economics 78 (1996):935-45.

23. ———"Optimal Design of a Voluntary Green Payment Program under Asymmetric Information." Journal of Agricultural and Resource Economics 20 (1995):316-27.