The role of contract attributes in purchasing environmental services from landowners*

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Abstract

Payment for environmental services (PES) contracts are a common means of acquiring public ecosystem goods or services from private landowners. Aside from the well-studied incentive problems with these contracts, such as hidden action and hidden information, a sparsely studied complication is the role of transaction costs in contract initiation and enforcement. This paper quantifies both the individual and aggregate impacts of the transaction costs that arise from nonprice contract attributes, including the time requirements for contract enrollment and compliance procedures during the contract period. Individual agents were found to incur widely varying transaction costs from these attributes, but on average transaction costs comprised a significant portion of contract willingness-to-accept. At the aggregate level, transaction costs were found to create a significant drain on the cost-effectiveness of contracting, similar in magnitude to the inefficiency created by hidden information.

1 Introduction

A common approach to acquire ecosystem goods or services from landowners is to contract with them to implement practices in exchange for a payment. Such payment for environmental service (PES) contracts are widely used in agriculture and forestry programs in several countries and also serve as the foundational commodity in environmental markets, including markets for soil carbon sequestration and water quality improvements.

Several researchers have studied these contracts in a principal-agent framework, in which the government authority or market buyer is the principal and the landowner is the agent. Ferraro (2008) provides a review of this literature. Two types of incentive problems have been identified, both of which will hamper the cost-effectiveness of obtaining the desired services. First, the principal

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cannot perfectly observe the agents' actions (e.g., Choe and Fraser, 1999; Ozanne, 2001; Fraser, 2002; Hart, 2005; Ozanne and White, 2008). This leads to a moral hazard problem in which the agent has an incentive to shirk on his contractual responsibilities. Second, agents hold private information on their cost of practice adoption (e.g., Spulber, 1988; Chambers, 2007; Fraser, 1995; Latacz-Lohmann and Van der Hamsvoort, 1997; Wu and Babcock, 1995, 1996; Peterson and Boisvert, 2001, 2004). If contracts offer a fixed price and are available to all agents, the price paid by the principal will exceed at least some agents' willingness to accept (WTA).

The gap between the payments and agents' WTA is known as an information rent, which represents a potential savings in payment expenditures to the principal. If the principal had complete information on each agent's WTA and could price discriminate on this basis, then the same environmental services could be acquired at a reduced overall cost. In practice, price discrimination in PES contracts rarely occurs in its pure form because of the difficulty in acquiring private information accurately. Economists have proposed several modifications to the contracting scheme that creates an incentive for agents' to reveal their hidden WTA. One strategy includes incentive-compatible auctions, where agents submit bids to enroll (e.g., Selman et al., 2008; Connor et al., 2008; Ortega-Pacheco et al., 2009). Another possibility is selection design, where agents select contracts from an announced menu of alternatives that vary by price and by contract requirements. Under certain conditions, the menu can be designed so that agents with relatively low WTA are attracted to contracts offering low prices (e.g., Wu and Babcock, 1995, 1996; Peterson and Boisvert, 2001, 2004). However, for a finite number of groups these schemes can eliminate only a portion of information rents and some agents will still receive a price exceeding their WTA.

While information rents have been found to be a significant drain on the cost-effectiveness of PES contracts (Ferraro, 2008), other frictions in the contracting process have been only sparsely studied. In part because of concern about moral hazard, most PES contracts involve requirements beyond adopting the practice itself, such as an application process before entering into a contract and consent to being monitored during the contract period and to pay fines in the case of noncompliance. These nonprice attributes of contracts generate transaction costs that may differ widely across agents depending on their preferences and perceived costs of the contractual requirements. While these strategies are recognized as responses to the hidden action problem, they may have unanticipated effects on the participation levels and gains among contract enrollees.

Transaction costs have been shown to influence the distributional and efficiency outcomes of environmental markets and government programs in general (e.g., Colby, 1990; Stavins, 1995; Netusil and Braden, 2001; Falconer et al., 2001; McCann and Easter, 1999; McCann, 2009; Vernimmen, 2000), yet relatively few studies have considered the transaction costs in contracting. Hudson and Lusk (2004) conducted choice experiments to assess farmers' perceived transaction costs of different types of contracts to produce a commodity in a vertically coordinated production chain. Farmers were asked to choose from among hypothetical contract alternatives with varying rules, such as the length of the contract and the level of producer autonomy, which were then modeled as components of transaction costs. While not cast as transaction costs, nonprice features of PES contracts have been studied in more recent literature where choice experiments are applied to predict landowners' preferences for different contract designs (Horne, 2006; Espinosa-Goded et al., 2010; Ruto and Garrod, 2009; Christensen et al., 2011; Vedel et al., 2010). Typical findings in these studies are that farmers have very heterogeneous preferences toward nonprice features, and that such features strongly influence the WTA for contracts among a significant subset of individuals.

The preferences toward nonprice attributes has not been explicitly modeled as transaction costs in contracting alongside information rents. If nonprice features can be changed to reduce agents' transaction costs, then the principal could enroll the same acreage with a lower uniform price, resulting in a reduced aggregate expenditure on payments. As such, the transaction costs from nonprice features – designed at least in part to mitigate hidden action problems – may themselves create a drain on the cost-effectiveness of contracting. If these transaction costs are large relative to information rents, then as an alternative (or complement) to obtaining WTA information, the principal may obtain larger savings overall by changing nonprice features in ways that are more attractive to landowners, possibly even at the cost of reduced contract compliance. Further, the use of agent-specific information to discriminate eligibility or payments is often politically infeasible while reducing transaction costs is likely to be more palatable.

In this paper we develop a principal-agent setting that explicitly incorporates the frictions from nonprice contract features. Each agent's WTA for a contract is decomposed into adoption cost and transaction cost components. Heterogeneity in these cost components across agents leads to an upward-sloping supply curve of contracts, which identifies the potential savings in aggregate contract payments by eliminating information rents and from eliminating transaction costs.

Our empirical analysis estimates these cost components from stated choice data from potential sellers in a water quality trading (WQT) market in the U.S. Great Plains. Several such trading programs have been adopted worldwide (Selman et al., 2009), based in part on evidence that nonpoint sources can reduce nutrient loading at a much lower cost than point source polluters in many watersheds (Faeth, 2000). While such a gap in costs suggests potential gains from trading, a commonly noted feature of existing programs is low trading volume; none of the programs have had extensive trading activity and many have had no trading at all (Hoag and Hughes-Popp, 1997). As in the recent literature on PES choice experiments, contract alternatives presented to subjects vary by price and by nonprice attributes. The data are analyzed with a mixed logit model. Consistent with the results of other studies, we find significant heterogeneity in adoption costs and in preferences toward contract attributes.

In addition, we model the full set of correlations between adoption costs and the cost of each nonprice feature, allowing us to determine changes in the shape and position of the contract supply relationship under different contract configurations. We then conduct a series of microsimulations of our model to characterize the range of possible outcomes of plausible contracting schemes. The simulations are structured to quantify the variation in results due to the uncertainty in the estimated parameters as well as in the heterogeneity of costs and preferences. The results indicate that uniform-price contracts have low cost-effectiveness as a means of acquiring landowners' environmental services; less than 30% of aggregate payments covers the cost of practice adoption while the rest covers agents' transaction costs or becomes information rent. The potential savings in payments from transaction costs was found to be large and of a comparable magnitude to information rents. Independent of any efforts to acquire better WTA information, the cost-effectiveness of contracting can be improved dramatically by changing contractual terms to reduce transaction costs.

2 Conceptual framework

Consider a region comprised of a large number of landowners (agents) who own farms of equal size. A government agency or environmental credit aggregator (the principal) offers all landowners environmental contracts where each contract requires adopting a specified practice on the landowner's entire farm. All contracts have identical terms specified by the predetermined vector $(b, \mathbf{x})$, where

b is the (farm-level) subsidy or contract payment and $\mathbf{x}$ is a set of nonprice attributes including enrollment, monitoring, and other provisions.

A landowner's utility from signing a contract is specified as

$$U(b, \mathbf{x}) = \alpha(b - c) - \phi(\mathbf{x}), \tag{1}$$

where $\alpha > 0$ is the marginal utility of income, c is the monetary adoption cost of the contracted practice, and $\phi(\mathbf{x})$ represents the disutility of the nonprice attributes. The function $\phi(\cdot)$ is defined such that $\phi(\mathbf{0}) = 0$; a landowner's reservation utility from not contracting is thus $U(0, \mathbf{0}) = 0$. Both c and $\phi(\cdot)$ may vary across landowners.

If contract enrollment is voluntary, a landowner will enroll in a contract if and only if $U(b, \mathbf{x}) \geq 0$. From (1) this condition implies

$$b \geq c + \phi(\mathbf{x})/\alpha = \text{WTA} \tag{2}$$

where WTA is the landowner's willingness to accept or minimum acceptable subsidy. Equation (2) implies that an agent's WTA has two components: the explicit cost of practice adoption, c, and the implicit costs of the nonprice attributes, $\phi(\mathbf{x})/\alpha$. The second component can be regarded as transaction costs because it reflects a gap between the agent's cost of generating the practice (c) and the price that the principal must pay to obtain it (WTA).

In much of the agency literature, transaction costs are assumed to be absent, the special case where $\phi(\mathbf{x}) = 0$ and WTA $= c$. A landowner will then enroll in a contract as long as there is a positive difference between contract benefits and adoption costs ($b - c > 0$), a gap we refer to as the contract margin. In the agency literature the contract margin is interpreted as an information rent, a pure gain to the landowner arising from the principal's lack of information on each landowner's adoption cost.

Consider now the case where $\phi(\mathbf{x}) > 0$ so that WTA has both adoption and transaction cost components. Assuming that $b > c$ so that enrollment would have occurred without transaction costs, there are two possible cases. If $b <$ WTA the landowner will not accept the contract, so that no environmental benefits will be generated and the landowner gains nothing. Transaction costs have the expected effect of preventing some otherwise gainful contracts from being executed.

If $b >$ WTA, then the landowner will still enroll and will earn an information rent, but the rent is no longer equal to the contract margin. From the equality in (2), the contract margin can be written as

$$b - c = b - \text{WTA} + \phi(\mathbf{x})/\alpha, \tag{3}$$

implying it is now comprised of two parts: the information rent ($b -$ WTA) and transaction costs ($\phi(\mathbf{x})/\alpha$). A second effect of transaction costs, then, is that they diminish cost-effectiveness of contracting schemes independent of any information effects. Even if information rents can be eliminated by some revelation mechanism on adoption costs, the inefficiency due to transaction costs will remain.

We now consider the aggregate effects of transaction costs from the principal's perspective and compare them to the aggregate effects of information rents. These effects are illustrated in Figure 1, where agents' adoption costs are assumed to be uniformly distributed across farms in the range $[\underline{c}, \bar{c}]$. This variation is depicted as the upward sloping line labeled c, where the horizontal axis arrays the agents in ascending order of adoption costs. Transaction costs, $\phi(\mathbf{x})/\alpha$, are uncorrelated with adoption costs and, for simplicity, we initially assume them to be constant at t across landowners. The WTA curve is the sum of adoption and transaction costs, identifying the contract revenue needed to enroll the last agent at any given quantity of contracts.

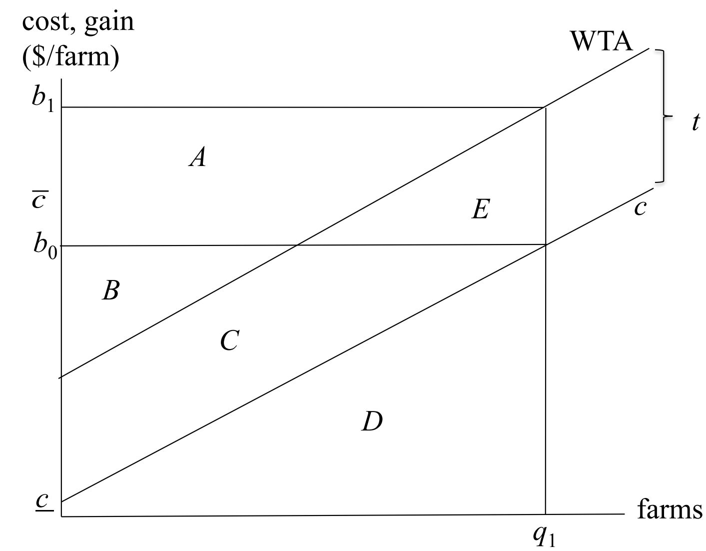

Figure 1 Aggregate effects of transaction costs, no correlation

If the principal offers a price of b_1 then q_1 acres will be enrolled at an aggregate expenditure on payments of $A + B + C + D + E$. Of the aggregate payments, only area D compensates agents for the cost of adopting practices.Information rents (IR) are equal to area $A + B$, representing the aggregate gains between the uniform price of b_1 and the privately-known WTA for each farmer who enrolls; the principal could eliminate the IR portion of payments if he had complete information on individual WTA and could price discriminate on this basis. If individual WTA information is not (or cannot be) collected but transaction costs can be reduced to zero instead, the principal could enroll the same acreage by offering a lower uniform price, namely b_0. Aggregate expenditures can then be reduced by area $A+E$ (which, in the case of constant transaction costs, is equal to $C+E$). Let TC denote the amount of potential payment savings from eliminating transaction costs.

In the case of constant transaction costs across agents, the potential payment savings in payments from information rents (IR) and from transaction costs (TC) are independent. For example, if transaction costs were completely eliminated, then $\text{IR} = B + C$, which by construction is identical to IR when transaction costs are present $(A + B)$. Alternatively, if information rents were first eliminated through price discrimination, the remaining gain from eliminating transaction costs on each contract would be $\text{TC} = C + E$, which as noted above, is equal to TC when information rents exist $(A + E)$.

If agent-level transaction costs are not constant and are correlated with adoption costs, there are interaction effects between the two types of payment savings. Such correlations are plausible because some of the unobserved factors affecting agents' adoption costs (e.g., managerial skill) may also affect their transaction costs from nonprice attributes. Figure 2) depicts the case of positive correlation – i.e., where transaction costs are large for agents with large adoption costs – which reveals that the interaction effects are negative: IR is smaller when transaction costs are eliminated $(B+C < A+B)$ and TC smaller if information rents were eliminated $(C+E < A+E)$. In the case of negative correlation (Figure 3), the interaction effects are positive and the opposite inequalities hold; the gain from eliminating one type of expenditures is enhanced if the other type is eliminated first. In general, the potential payment savings from eliminating information rents are bounded between $B+C$ and $A+B$ while the potential payment savings from eliminating transaction costs are bounded between $C+E$ and $A+E$. A primary goal of the empirical analysis that follows is to find and quantify the upper bounds on IR and TC and to compare their relative magnitudes.

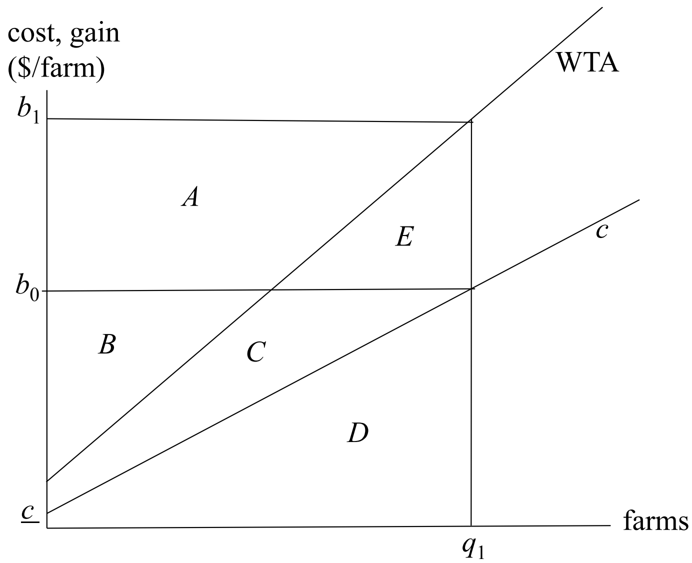

Figure 2 Aggregate effects of transaction costs, positive correlation

3 Data

Our data for the empirical analysis were obtained from stated choice experiments conducted with landowners, in which the contracts would generate water quality credits in a hypothetical WQT market. Our experimental subjects were presented with a 'point-nonpoint' trading scheme, where municipal wastewater treatment plants would be allowed to meet their nutrient emission limits by contracting with landowners to implement practices that improve water quality.

After reviewing the operations of existing programs and consulting with Extension staff and a focus group of farmers, we identified the contract attributes in Table 1 that are likely to influence farmers' enrollment decisions. *AppTime* is the amount of time a potential seller would have to spend to establish his eligibility to enter into a WQT contract. This time would be expended on such activities as meeting with the staff of the entity managing the market, compiling data on the field to be enrolled, and completing enrollment paperwork. *AppTime* would vary depending on the complexity of the program and the desires of the buyer in the contract. We set this attribute to vary from 4 to 40 hours to enroll a 100-acre field for a 10-year period, a range we assumed was large enough to capture a wide range of contract complexity.

The second attribute is the monitoring method, coded as the binary variable (*Annual*). If *Annual*$=1$, then farmers selling a contract would be visited at an unannounced time each year to ensure they are meeting their contractual obligations. If *Annual*$=0$, the monitoring method is a spot check system, specified here as a 10% probability that each field would be visited each year. *Penalty* is a one-time fine to be paid if the seller is found in violation of the contract.

The Best Management Practice (BMP) attribute has four categorical levels that vary along two

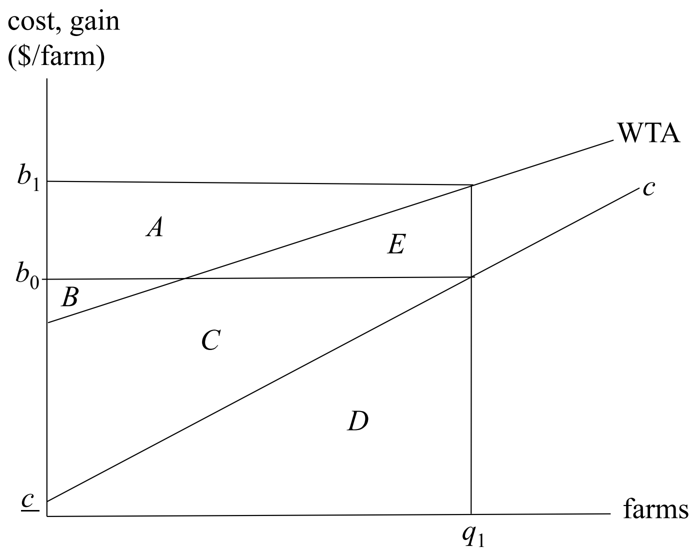

Figure 3 Aggregate effects of transaction costs, negative correlation

Table 1 Choice experiment attributes and levels

Attribute name	Description	Levels
AppTime	Application time (to enroll a 100-acre field; hours)	4, 16, 24, 40
Annual	Annual versus spot check monitoring	1 = Annual, 0 = Spot check
Penalty	One-time fine for contract violation ($/acre enrolled)	50, 100, 250, 500
FS	Type of practice required	1 = Filter strip, 0 = No-till
FShay	Haying/grazing allowed on filter strip	1 = Yes, 0 = No
NTrot	Rotational no-till allowed	1 = Yes, 0 = No
Revenue	Annual contract payment ($/acre enrolled)	3, 7, 15, 25

You have two opportunities to sell credits in a Water Quality Trading market, given by Option A and Option B below. Your choices are to enroll your entire 100-acre field in one of these options (but not both) or neither of them.

	Option A	Option B	Option C
Application time (hours)	24	40	
Monitoring method	Annual verification	Annual verification	
Penalty for violations ($/acre enrolled)	100	100	
Best Management Practice (BMP)	Filter strip (with haying/grazing)	Rotational no-till	Do Not Enroll
Price and Cost information			
Offer price per credit ($/credit/year)	$2.50	$1.40	
Credits generated per acre enrolled	6	5	
Credit Revenue ($/acre/year)	**$15.00**	**$7.00**	

Which option would you choose?
(mark one box only) ☐ ☐ ☐

Figure 4 Sample choice set presented to farmers

dimensions. The first dimension is the type of practice — the farmer must either install a filter strip or implement no-till. The second dimension is the level of flexibility the farmer would have in meeting his contract obligations. In the case of filter strips the more flexible option would allow farmers to hay and/or graze the filter-designated area. For no-till, flexibility comes in the form of frequency of use; "rotational no-till" allows for some other tillage practice in 5 out of the 10 years under contract.

The final attribute is trading revenue, or the price per credit multiplied by the number of credits generated from the BMP. We varied trading revenue from $3/acre/year to $25/acre/year, based on the ranges used by Cooper and Keim (1996) and Cooper (1997). Each BMP was assumed to generate a fixed number of credits, and the price per credit was calculated in each scenario so that price times credits equaled the specified revenue level.[1] The assumed variation in credits across practices combined with the variation in revenue produced a range in the price per credit of $0.25 to $5.00.

Different combinations of the above attributes define the contract alternatives presented to our subjects. Subjects were shown a series of choice scenarios, each of which contained three choices: a contract to implement a filter strip (option A), a contract to implement no-till (option B), and a "do not enroll" alternative (option C). Fixing filter strip and no-till contracts to the labels A and B, respectively, created visual consistency across choice sets and also reduced the number of levels of the BMP attribute from four to two. A sample scenario is in Figure 4. To facilitate comparison, subjects were told that all contracts had a 10-year duration and that the field being considered for enrollment was 100 acres in size. In addition, subjects were told to assume that (1) the land quality

[1] The assumed number of credits generated (per enrolled acre per year) for the modeled practices were: 12 for filter strip (no haying/grazing), 6 for the filter strip (with haying/grazing), 9 for 100% no-till, and 5 for rotational no-till. The way these assumptions were combined with price information in the choice sets is illustrated in figure 4. For Option A in that figure, our experimental design called for a revenue of $15/acre/year and a BMP of filter strip (with haying/grazing), which generates 6 credits. The price per credit was then calculated as $15/6 = $2.50.

of the field was representative of their farm, (2) the most recent tillage practice was minimum tillage (not no-till or conventional tillage), and (3) the recent cropping pattern followed their typical crop rotation.

To construct the choice scenarios, we used the SAS %MktRuns and %MktEx macros (Kuhfeld, 2005) to find the smallest orthogonal main effects design varying all five attributes across the two contract alternatives (Adamowicz et al., 1994). The smallest such design contained 32 scenarios, which were blocked into two sets of 16, giving us two versions of the experiment that were randomly assigned across subjects.

Data were gathered from groups of farmers attending Extension meetings at four locations in the Great Plains, described in more detail by Peterson et al. (2007). Subjects were recruited at each meeting via a pre-registration mailing and an announcement at the opening conference session. The choice experiment itself was then conducted during a 1-hour session, typically scheduled with the help of the meeting organizers as a parallel session in a one-day program.

The procedures and instruments used in our data collection sessions were refined with feedback from a focus group of 12 farmers before the first meeting. Special attention was paid to ensuring that the range of attribute levels induced sufficient variation in choices across the three alternatives. Our final data collection session was a sequence of six activities. First, the concept of WQT was explained in a brief presentation. Second, subjects were introduced to the hypothetical context of the stated choice experiments: they were asked to imagine that a WQT program had been developed where different buyers offered different types of contracts varying by the attributes described above. Third, instructions on how to complete the choice experiment were provided, including the presentation of a practice choice set. Fourth, the subjects completed a booklet containing 16 choice scenarios; each page of the booklet contained one choice set and an open-ended question asking, "Why did you make this choice?" Fifth, each subject completed a four-page questionnaire eliciting information on his/her farm operation, his/her attitudes toward water quality issues and policies, and demographic data. Lastly, each subject was paid an honorarium of $50 in cash. Usable data were collected from 137 subjects across the four locations, providing a total of 2,177 usable choice observations.

The analysis of all the quantitative data (choice responses) are described below. Qualitative data were also available in the form of the responses to the open-ended follow-up question to each choice task. Content analysis of these responses were strongly suggestive of preference heterogeneity. For example, many of the responses for scenarios where one of the alternatives had a much higher *Penalty* than the other were similar to one of the following examples:

> . . . I am assuming that I am going to comply and so I am not concerned with the penalty . . .

> . . . Payment is great per acre . . . but penalty is very high and checked [*sic*] every year. Sure I probably would not violate but don't want to take the chance . . ....

The subjects who gave responses similar to the first one tended to choose the contract with the higher penalty, while those giving responses similar to the second avoided that contract. This variety of responses suggests heterogeneity in subjects' preferences. A similar spectrum of preferences was found from the follow-up responses to scenarios where *AppTime* was large in one of the alternatives. In these cases some farmers avoided the alternative with a long application time, noting their distaste for "paperwork" and "hassle." Others chose the alternative with the long application time, noting they felt the other attributes were favorable, that they are accustomed to similar application processes from other government programs, and/or that they would be irrational to let a one-time cost of applying prevent a significant income stream.

4 Econometric model

Our econometric analysis is built on a random utility framework. The choice scenarios presented to each subject are indexed by $s = 1, \ldots, 16$, while the alternatives in each choice set are indexed by $j \in \{A, B, C\}$, corresponding to the labels in Figure 4. In the random utility formulation of (1), a subject's expected utility from choosing alternative j in scenario s is

$$\begin{aligned} U_{js} =& \alpha(b_{js} - c_{js}) - \phi(\mathbf{x}_{js}) + \epsilon_{js} \\ =& V_{js} + \epsilon_{js} \end{aligned} \tag{4}$$

where V_{js} is known as the nonrandom or modeled portion of utility and ϵ_{js} is a disturbance term reflecting factors known to the subject but unobserved and treated as random by the researcher. We impose the normalization restriction that $V_{js} = 0$ for $j = C$; i.e., the modeled portion of utility equals zero for nonenrollment.

The variable b_{js} in (4) is the value of *Revenue* in alternative j and scenario s from the choice experiments. The function $\phi(\mathbf{x})$, measuring the disutility of nonprice attributes, is specified as

$$\phi(\mathbf{x}) = -\boldsymbol{\beta}'\mathbf{x}, \tag{5}$$

where $\boldsymbol{\beta}$ is a vector of marginal disutilities. The nonprice attributes themselves are $\mathbf{x} = (\mathit{AppTime}, \mathit{Epen}, \mathit{Annual})$, where *Epen* is the expected penalty if a contract is violated:

$$\mathit{Epen} = (\mathit{Annual})(\mathit{Penalty}) + (1 - \mathit{Annual})(0.1)(\mathit{Penalty}). \tag{6}$$

Epen is a derived attribute that captures the inherent interaction between *Annual* and *Penalty*; landowners consider the penalty to a lesser degree in scenarios with spot check monitoring ($\mathit{Annual} = 0$), when a violator would pay a penalty with probability 0.1.

We did not directly observe adoption costs, c_{js}, in our experiments but we can estimate these costs by exploiting the fact that subjects perceive them as differing across practices. In particular, we parameterize c_{js} as

$$c_{js} = -\frac{1}{\alpha}(\gamma_j + \delta_A \mathit{FShay}_{js} + \delta_B \mathit{NTrot}_{js}), \tag{7}$$

where γ_j is an alternative-specific constant (ASC) and the δ_j's reflect shifts in the ASC's for different practices within an alternative. As described above, alternative $j = A$ requires installation of a filter strip and alternative $j = B$ requires adoption of no-till, but the practice required in each case varies across scenarios. The filter strip can either allow haying/grazing ($\mathit{FShay} = 1$) or not ($\mathit{FShay} = 0$), while no-till can be on a rotational ($\mathit{NTrot} = 1$) or continuous ($\mathit{NTrot} = 0$). Table 2 shows the result of equation (7) for each practice, which is identified by a unique combination of j and the dummy variables.

Substituting (5) and (7) into (4), the estimated utility function becomes

$$V_{js} = \gamma_j + \delta_A \mathit{FShay}_{js} + \delta_B \mathit{NTrot}_{js} + \alpha \mathit{Revenue}_{js} + \boldsymbol{\beta}'\mathbf{x}_{js}, \qquad j = A, B. \tag{8}$$

Let $\boldsymbol{\theta} = (\boldsymbol{\gamma}, \boldsymbol{\delta}, \alpha, \boldsymbol{\beta})$ denote the full set of coefficients to be estimated. Given estimates of these coefficients, $\hat{\boldsymbol{\theta}}$, we can derive estimates of WTA for particular contracts. For a contract requiring a practice from Table 2 and having nonprice attributes of $\mathbf{x}$, the point estimate of WTA is

$$\text{WTA} = \hat{c} - \frac{1}{\hat{\alpha}}\hat{\boldsymbol{\beta}}'\mathbf{x}, \tag{9}$$

Table 2 Derived adoption costs, by practice

Practice	Adoption costs
Filter strip (no haying/grazing)	$-\gamma_A/\alpha$
Filter strip with haying/grazing	$-(\gamma_A+\delta_A)/\alpha$
Continuous no-till	$-\gamma_B/\alpha$
Rotational no-till	$-(\gamma_B+\delta_B)/\alpha$

where $\hat{c}$ is the derived estimate of adoption cost for the practice in question. Further, the way that WTA responds to a change in the k^{th} attribute, or marginal WTA (mWTA_k), can be estimated as

$$\text{mWTA}_k \equiv \frac{\partial \text{WTA}}{\partial x_k} = -\frac{\hat{\beta}_k}{\hat{\alpha}}. \tag{10}$$

While point estimates are of interest, the uncertainty in these estimates from estimation error and from any variation in the coefficients across subjects, is also relevant. Below, we describe estimation and simulation methods that account for both these sources of variation.

4.1 Mixed logit specification

The utility parameters in (8) were estimated with a mixed logit (MXL) model (Train, 1998, 2003), which allows us to capture any heterogeneity in preferences across subjects and any correlation among the coefficients determining adoption and transaction costs. We apply a random coefficients MXL formulation, in which the utility coefficients vary across subjects following a specified density, $f(\boldsymbol{\theta};\boldsymbol{\lambda})$, where $\boldsymbol{\lambda}$ is the set of distributional parameters (e.g., means and dispersions of the coefficients).

The mixed logit model is described in detail by Train (2003). Estimation is based on the probability that alternative j is a subject's utility-maximizing choice in scenario s, conditional on a particular value of $\boldsymbol{\theta}$. Assuming that the error, ϵ_{js}, has an extreme-value type I distribution, this probability is given by the logit formula (McFadden, 1974):

$$P_s(j|\boldsymbol{\theta}) = \frac{\exp(V_{js})}{1+\sum\limits_{j\in\{A,B\}}\exp(V_{js})}. \tag{11}$$

Let $Y_s \in \{A,B,C\}$ denote the subject's observed choice in scenario s and let $\mathbf{Y} = \{Y_1,\ldots,Y_S\}$ denote the sequence of his choices across all scenarios. From equation (11), the probability of observing the sequence $\mathbf{Y}$, conditional on a particular value of $\boldsymbol{\theta}$, is $P(\mathbf{Y}|\boldsymbol{\theta}) = \prod_s P_s(Y_s|\boldsymbol{\theta})$. The unconditional choice probability across all possible realizations of $\boldsymbol{\theta}$ is then (Train, 2003)

$$P(\mathbf{Y}) = \int P(\mathbf{Y}|\boldsymbol{\theta}) f(\boldsymbol{\theta};\boldsymbol{\lambda}) d\boldsymbol{\theta}. \tag{12}$$

The estimated parameters in a mixed logit model are the distributional parameters of the mixing density, $\boldsymbol{\lambda}$.

While the parameters of $f(\cdot)$ are estimated, its form must be specified by the researcher. Common specifications in the literature include the normal, triangular, and lognormal. One advantage of the lognormal is that its support spans only the non-negative real numbers, so that the coefficients for the entire population can be restricted in sign (a negative sign can be imposed by premultiplying an entry of $\mathbf{x}$ by -1). A triangular distribution is a common choice if both the lower and upper bounds of the support are known. A normal distribution is appropriate when the support has no known bounds.

Here, we specify a joint distribution for the coefficients that is lognormal in the coefficients with a theoretically expected sign and a normal in the coefficients of theoretically indeterminate sign. The lognormal distribution is inherently asymmetric with the bulk of its probability mass over the relatively small realizations and a long tail spread over the larger realizations. While not suitable for all applications, this property is appropriate for our data, which (for the coefficients with a known sign) contains a few subjects with a strong aversion to certain contract features, implying large marginal disutilities on those attributes. Most of the subjects, however, have more a modest aversion to contract features, implying a clustering of marginal utilities close to zero. The problem with specifying a symmetric distribution for a coefficient that is expected to be negative is that subjects with large marginal disutilities (i.e., those in the in the left tail extending into the negative domain) would artificially inflate the probability in the right tail extends into the positive domain, even if there are no subjects producing observations in the right tail to justify probability mass in that region.

The distributional assumption of each coefficient is in the first column of Table 3. The coefficients $\boldsymbol{\gamma}$ and $\boldsymbol{\delta}$, along with α, determine the adoption costs of the various practices (equation (7) and Table 2). In general, one would expect adoption cost to be positive, implying negative signs on $(\boldsymbol{\gamma})$ given that $\alpha > 0$. Accordingly we specify a lognormal distribution for $\gamma_A < 0$, implying positive adoption costs for filter strips. For no-till, however, there are costs as well as offsetting benefits that may result in negative costs for some farmers; no-till farming reduces expenses on tillage operations and in some settings generates higher average crop yields. To allow for this possibility we specify γ_B to be normal with unrestricted sign. δ_B and δ_A are specified as fixed (i.e., nonrandom) coefficients that simply shift the distribution of adoption costs if a 'flexible' version of each practice is contracted. We do not restrict the sign of these coefficients although they are expected to be positive empirically – i.e., flexible practices are expected to be cost-reducing. The lognormal assumptions for $\beta_1 < 0$, $\beta_2 < 0$, and $\alpha > 0$ impose utility to be decreasing in enrollment time (which is assumed to have an opportunity cost), decreasing in expected penalties, and increasing in contract income. β_3 is specified as normal with unrestricted sign because of recent literature indicating that farmers may incur costs as well as perceive some benefits from more frequent monitoring depending on their preferences.[2]

As noted in the theoretical section, any correlation between adoption and transaction cost components will alter the welfare effects of contracts. Such correlations are plausible if the same unobserved factors (e.g., managerial skill) affect both kinds of costs. To allow for this possibility, we specify the most general joint distribution of coefficients where all pairwise correlations are estimated.

[2]Both experimental and field evidence have revealed that monitoring of actions in principal-agent settings is viewed favorably by some agents (Vedel et al., 2010). For the landowner contracts, an agent's cost would include the opportunity cost of time and administrative costs during additional monitoring visits, in addition to disutility from viewing monitoring as intrusive or as a signal of mistrust. Benefits would be perceived by farmers with socially-oriented preferences, who may regard monitoring as a means to uphold social norms of fairness (e.g., Nyborg, 2000) or as supporting conscientious behavior (e.g., Frey and Jegen, 2001).

4.2 Estimation

The procedures to estimate a combination of correlated normal and lognormal random coefficients via maximum likelihood are described by Greene (2007). We note some of the key features of estimation here, as they involve transformations that affect the interpretation of our results. First, the lognormal coefficients are estimated as their log transforms. Let θ denote a generic lognormal coefficient. By definition its log transform, $\theta^* = \ln\theta$ is normally distributed, which becomes the random coefficient entering estimation. During estimation, each occurrence of θ in the logit formula (equation (11)) is computed as e^{θ^*}.

Second, the coefficient vector is partitioned as $\boldsymbol{\theta} = [\boldsymbol{\delta}, \boldsymbol{\theta}^*]$, where $\boldsymbol{\theta}^*$ contains all the normal coefficients and the transforms of the lognormals. $\boldsymbol{\theta}^*$ follows a multivariate normal distribution whose mean vector, $\boldsymbol{\mu}^*$, and the covariance matrix, Σ^*, contain the underlying parameters to be estimated along with the nonrandom coefficients, $\boldsymbol{\delta}$. Another transformation is that the elements of Σ^* are estimated indirectly using a Cholesky decomposition; i.e., the estimated covariance parameters are the elements of L, the lower triangular matrix such that $LL' = \Sigma^*$.

The objective of estimation is to maximize the log of the likelihood function, constructed by taking the log of equation (12) and summing across subjects in the sample. However, the integral in (12) cannot be written in closed form and must be computed with a discrete approximation. This process is known as maximum simulated likelihood (MSL) (Train, 2003). We implemented the MSL estimator in NLOGIT 4.0 (Greene, 2007), which approximates the integral by averaging across a sequence of draws from the mixing density at each iteration of the optimization routine. We set the number of draws to 150.

5 Regression results

The results of the MSL estimation are difficult to interpret directly because of the transformations noted above. For completeness the raw results are reported in table 9 in the appendix, but we focus here on the estimates of utility coefficients, adoption costs, and marginal WTA.[3] Several of these estimates are derived by simulation techniques as described in more detail below. These simulations distinguish between the *coefficient distribution*, which reflects preference heterogeneity across subjects, and the *parameter distribution*, which reflects the statistical error around the point estimates of the parameters. In general, the parameters of interest are measures of the first and second moments of the coefficient distributions.

Table 3 reports the estimated parameters of the utility coefficient distributions. The estimates for the normally distributed coefficients are from the raw output in Table 9, while those for the lognormal coefficients were derived from a Krinsky-Robb simulation; empirical point estimates and standard errors of those parameters were computed from R independent draws of the estimated parameter distribution.[4] In this and all other simulations we used $R = 10,000$ draws. Most of the parameters were estimated with high statistical precision, providing evidence that the marginal co-

[3] The MSL estimation resulted in the following goodness-of-fit statistics: McFadden Pseudo $R^2 = 0.3802$, AIC=1.388, BIC=1.464.

[4] Again let θ denote a generic lognormal coefficient and $\theta^* = \ln\theta$ its log transform entering estimation. For each draw of the estimated mean, μ^*, and standard deviation, σ^*, of θ^*, the associated mean and standard deviation of θ are $\mu = \exp(\mu^* + \sigma^{*2}/2)$ and $\sigma = \sqrt{\exp(\sigma^{*2} + 2\mu^*)(\exp(\sigma^{*2}) - 1)}$, respectively (Weisstein, 2011). Averages of these computed parameters across the R draws produces the point estimates in Table 3 while the sample standard deviations across draws are the estimated standard errors.

Table 3 Utility coefficient estimates

Coefficient (Distribution)[a]	Variable	Mean	Standard Deviation
γ_A (L^-)	ASC:A	-1.6825^{***}	1.6741^{***}
		(0.4871)	(0.7162)
γ_B (N)	ASC:B	-1.976^{***}	1.4821^{***}
		(0.1804)	(0.1491)
δ_A (F)	*FShay*	0.7729^{***}	
		(0.1340)	
δ_B (F)	*NTrot*	0.9988^{***}	
		(0.1145)	
β_1 (L^-)	*AppTime*	-0.1475^{*}	0.5395
		(0.0882)	(0.5604)
β_2 (L^-)	*Epen*	-0.0071^{**}	0.0119
		(0.0028)	(0.0073)
β_3 (N)	*Annual*	0.8043^{***}	0.5651^{***}
		(0.1586)	(0.1846)
α (L^+)	*Revenue*	0.2377^{***}	0.1657^{***}
		(0.0227)	(0.0227)

[a] Distribution codes are F = fixed (nonrandom), N = normal, L^- = lognormal in the negative domain, L^+ = lognormal in the positive domain.

Figures in parentheses are estimated standard errors (Krinksy-Robb standard errors for lognormal coefficients). Asterisks denote p-values below * 0.1, ** 0.05, and *** 0.01.

efficient distributions are all centered away from zero and have significant dispersion across subjects. The estimated standard deviation parameters for the distributions of β_1 and β_2 were estimated with the least precision.

The mean of the ASC for no-till contracts, γ_B, was found to be negative, as expected. However, the estimated standard deviation was almost equal to the mean, suggesting that adoption costs of no-till are negative for a substantial share of subjects. Also as expected, the fixed dummy coefficients, δ_A and δ_B, were positive, indicating that filter strips are less costly when haying and grazing is allowed, and that no-till is less costly when it can be used on a rotational basis. We discuss the distribution of adoption costs and the implication of negative costs in more detail below.

The remaining parameter of indeterminate sign, the mean of β_3, was estimated to be positive. This result implies that, holding all other attributes constant including expected penalties, the average subject prefers annual monitoring over a 10% spot check system, perhaps because it is seen as enforcing fairness and conscientious behavior. Vedel et al. (2010) obtained a similar result for Danish landowners. The estimated mean and standard deviation of this distribution ($\beta_2 \sim N(0.8043, 0.5651^2)$) implies that only about 7.4% of subjects prefer the spot check system, *ceteris paribus*.

Table 4 shows the derived distributional statistics for adoption costs and the marginal willingness to accept (mWTA) of the nonprice attributes. These estimates were obtained from the simulation procedure of Hu et al. (2005), which is similar to the Krinsky-Robb method except that for each of the R draws from the parameter distribution, a set of N draws from the implied coefficient distribution is simulated to compute the statistics of the derived cost or mWTA distribution.[5] The 'inner' simulation is needed here because, unlike the parameters of the log transforms in Table 3, the adoption costs and mWTA are more complicated transforms of correlated normal and lognormal coefficients for which closed-form expressions of the distributional statistics are not available.

The estimated distributions of adoption costs are quite dispersed, with large standard deviations relative to the means and medians. The standard deviation of the filter strip cost distributions were estimated with low precision; we discuss the sources and implications of this model uncertainty below. The dispersion of the no-till cost distributions, however, were estimated quite precisely, and together with the estimated means they imply that the cost of adopting continuous (rotational) no-till is less than zero for about 16% (37%) of landowners. This suggests that some concern about additionality of no-till (particularly rotational no-till) contracts is warranted; a certain number of contracts will be paying landowners who would have adopted the practice in any case.

The filter strip cost distributions are quite skewed to the right, with means substantially larger than the medians. The low statistical precision of the estimated standard deviation of those distributions is likely related to their skewness. By definition there are relatively few observations in the long right tail from which its position can be determined. However, the position of the left 'bulge' in the distribution (as measured by the means and medians) is estimated with much more precision. This portion of the distribution is the most relevant for the contract market simulations to follow, as a contract offering a given revenue level will, by definition, screen out the high-cost landowners.

The mWTA distributions are also significantly dispersed. Similar to the reasoning of filter strip

[5] We set $N = R = 10,000$. For each draw of the parameters in the outer simulation, the mean, median, and standard deviation across the N inner draws are computed for adoption costs (Table 2) and the marginal WTA of each nonprice attribute (equation (10)). Empirical point estimates and standard errors are then computed for each of these statistics over the outer draws as in the standard Krinksy-Robb method.

Table 4 Derived distributions of adoption costs and marginal WTA

Item	Mean	Median	Standard Deviation
Adoption costs	$ per enrolled acre per contract year		
Filter Strip (no haying/grazing)	12.47^{***}	5.19^{***}	28.59
	(4.30)	(1.49)	(19.01)
Filter strip with haying/grazing	8.67^{**}	1.40	28.58
	(4.11)	(1.50)	(19.01)
Continuous no-till	9.68^{***}	9.60^{***}	9.65^{***}
	(1.37)	(1.37)	(1.32)
Rotational no-till	4.78^{***}	4.74^{***}	9.62^{***}
	(1.18)	(1.18)	(1.32)
Marginal WTA			
Application Time (hrs/contract)	0.66	0.13^{**}	3.22
	(0.46)	(0.053)	(4.27)
Expected Penalty ($/acre enrolled)	0.0167^{**}	0.0135^{***}	0.0119^{*}
	(0.0066)	(0.0051)	(0.0063)
Annual Monitoring (1=yes)	-3.96^{***}	-3.91^{***}	1.76^{**}
	(1.05)	(1.05)	(0.88)

Figures in parentheses are Krinksy-Robb standard errors. Asterisks denote p-values below * 0.1, ** 0.05, and *** 0.01.

costs, the distribution of the mWTA for *AppTime* is highly skewed and its dispersion is estimated with low precision. The median farmer would need \$0.13/acre in additional annual income to be compensated for an extra hour of application time at contract inception. Given that a contract would enroll a 100-acre field and the payments would be received annually over a 10-year period, this estimate translates to a median hourly compensation of about \$105 per hour assuming a discount rate of 0.05. This value seems large, but may partly reflect landowners' expected time commitments during the contract period. To the extent that landowners saw enrollment time as an indicator of administrative time requirements during the contract, then the expected cost of the future time commitments would be incorporated in the estimated mWTA.

The mWTA for *Epen* is mildly skewed. Under certain conditions this value can be interpreted as a landowner's subjective probability of violating contractual terms. To see this, first note that by equations (9) and (10) the WTA for a given contract can be expressed as $\text{WTA} = \hat{c} + \sum_k \text{mWTA}_k x_k$. If agents are risk neutral, then the term in the sum reflecting expected penalties ($\text{mWTA}_{Epen} Epen$) must be equal to the expected cost of penalties, or $p \times Epen$, where p is the agent's ex-ante subjective probability of violating contractual terms. Thus, for risk neutral agents, $\text{mWTA}_{Epen} = p$. For a variety of reasons, farmers may be ex-ante uncertain about their own ability to comply with a contract, particularly a multi-year contract requiring an unfamiliar practice (Vedel et al., 2010). This interpretation implies that the median (risk neutral) landowner is estimated to place a small but significant probability (about 1.4%) on violating contractual terms and having to pay an expected penalty.

As discussed above, farmers were found to prefer annual monitoring over a spot check system. In monetary terms this preference translates to a WTA discount of about \$4 for the average (and median) landowner. This value varies somewhat across landowners, although the estimated parameters imply it is a negative value for an estimated 98.5% of individuals.

Finally, the estimated correlation parameters indicate that farmers' preferences for certain pairs of attributes are correlated. Table 5 reports the estimated correlation coefficients among adoption costs of the two practices and the mWTA of the nonprice attributes. The adoption costs of the two practices were found to be positively correlated with each other, while the adoption costs of both practices were positively correlated with the mWTA of *AppTime*. Apparently, farmers who can adopt the practices at low cost anticipate that they can also go through enrollment procedures at a relatively low cost as well. The other remaining correlations were small and not statistically significant. Nevertheless, as presented in the next section, the correlation between adoption costs and the mWTA for *AppTime* are sufficient to generate positive correlations between transaction costs as whole and the adoption costs of both types of practices.

Table 5 Estimated correlation coefficients

	Adoption Costs		Marginal WTA	
Item	Filter Strip	No-till	*AppTime*	*Epen*
Adoption costs				
No-till	0.242^{***}			
	(0.080)			
Marginal WTA				
AppTime	0.260^{*}	0.248^{**}		
	(0.144)	(0.075)		
Epen	0.051	0.134	−0.0004	
	(0.121)	(0.150)	(0.059)	
Annual	−0.069	−0.130	−0.026	−0.179
	(0.098)	(0.096)	(0.064)	(0.392)

Figures in parentheses are Krinksy-Robb standard errors. Asterisks denote p-values below * 0.1, ** 0.05, and *** 0.01.

6 Contract simulations

To quantify the aggregate effects of transaction costs, we exercised our estimated model to simulate the enrollment patterns and resulting welfare measures under contracts with varying attributes. We simulated the contracting outcomes for a hypothetical but representative region with 1 million eligible acres of cropland, made up of 10,000 fields, each 100 acres in size. While this setting is hypothetical, the simulated agents owning the fields are populated with WTA distributions defined by our estimated parameters (Table 3), so that the results reveal the aggregate outcomes implied by the estimated model.

In each of our simulated scenarios, an identical contract for a single practice is offered to all agents, so that the agent owning each field simply makes a binary choice between enrolling in or declining the specified contract. We simulated two sets of scenarios, one where the contracted practice is a filter strip without haying/grazing and one where it is continuous no-till. The results for filter strips with haying/grazing and rotational no-till reveal the same patterns as they simply involve a downward shift in the adoption cost curves from the simulations shown below.

The scenarios within each set consider four different profiles of contact attributes, shown in Table 6. The first scenario in each set is the null contract with zero transaction costs, which serves as a benchmark against which we compare the remaining results. The other scenarios represent low, medium, and high transaction costs, respectively. Contract revenue per enrolled acre was set to \$10 for the filter strip scenarios and to \$15 for the no-till scenarios. These revenue levels are in the middle of the range in our choice experiments and are similar to the prices offered in existing contracts in the Environmental Quality Incentives Program in the Great Plains (Smith, 2011). In what follows, we refer to a given scenario with a three-letter code, where the first two letters indicate the type of practice (FS = filter strip, NT = no-till) and the third letter indicates the level of transaction costs (0, L, M, and H corresponding to the column headings in Table 6).

Table 6 Contract Attributes for Simulation Scenarios

	Contract-Level Transaction Costs			
Attribute	Zero	Low	Medium	High
AppTime (hrs)	0	8	16	40
Epen (\$/ac. enrolled)	0	100	250	400
Annual (1=yes)	0	0	0	1
Revenue-FS (\$/ac. enrolled)	10	10	10	10
Revenue-NT (\$/ac. enrolled)	15	15	15	15

The simulations involved repeated draws from the estimated parameter distribution to quantify the effect of uncertainty from estimation error. Similar to the procedures described above, $R = 10,000$ draws were taken from the parameter distribution in an outer simulation. For each of these draws a distribution of agents is generated by computing WTA (equation (9)) at each of $N = 10,000$ inner draws from the implied coefficient distribution. Figures 5 and 6 display the WTA distributions averaged over the outer R parameter draws, plotted in the same manner as the cost curves in Figure 1.

The WTA curves for the null contracts (FS-0 and NT-0) represent the adoption costs of the two practices, while the gap between each of these curves and any other scenario in the same graph represents transaction costs in that scenario. For example, the transaction costs associated with the NT-H contract are the gap between the NT-H and NT-0 curves, an amount which grows from less than \$5/acre at 0.1 million acres to over \$15/acre at 0.7 million acres. While the estimated transaction cost gap depends on the scenario as expected, its magnitude is substantial compared to adoption cost even with relatively low levels of nonprice attributes. In the FS-L and NT-L scenarios, transaction costs account for an estimated 52% and 39%, respectively, of overall WTA at a quantity of 0.3 million acres and for 37% and 26% of WTA, respectively, at 0.7 million acres. A notable feature of the no-till WTA curves (Figure 6) is that they cross the horizontal axis. The negative values at the bottom of these curves reflects the problem of additionality; no-till is a profitable practice for some producers and would be adopted on a certain percentage of fields even without contract incentives.

In all scenarios, simulated transaction costs increase along with adoption costs as more acreage is enrolled, which reflects a positive estimated correlation between the two types of costs. The correlation coefficient between adoption and transaction costs are reported in the last column of Table 7. Point estimates for the correlation coefficients vary within a fairly narrow range of 0.22 to 0.24 across scenarios, although the confidence intervals are somewhat wider for the FS contracts. McCann and Easter (2000) also found a positive relationship between transaction and abatement costs for compliance with Natural Resource Conservation Service programs. As discussed in the model section, a positive correlation implies that the aggregate information rents from contracting will be larger than the would be otherwise.

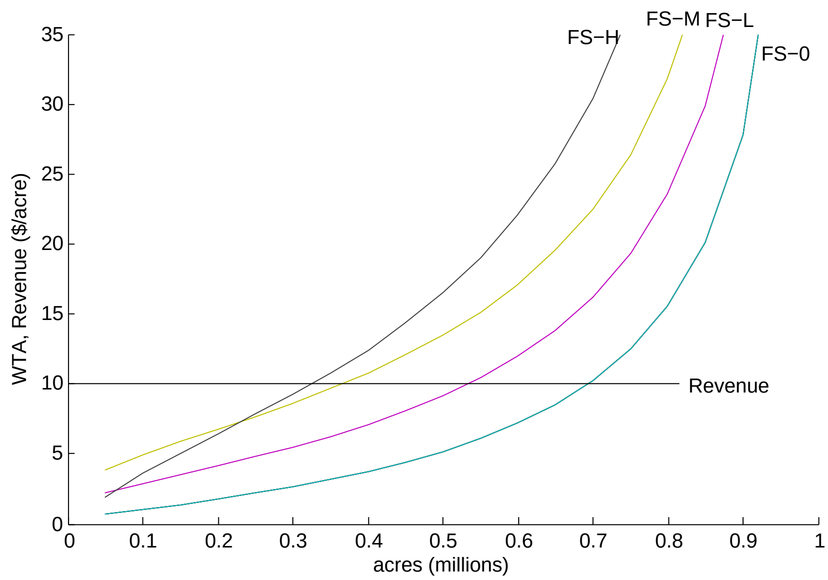

Figure 5 Simulated WTA curves for filter strip contracts

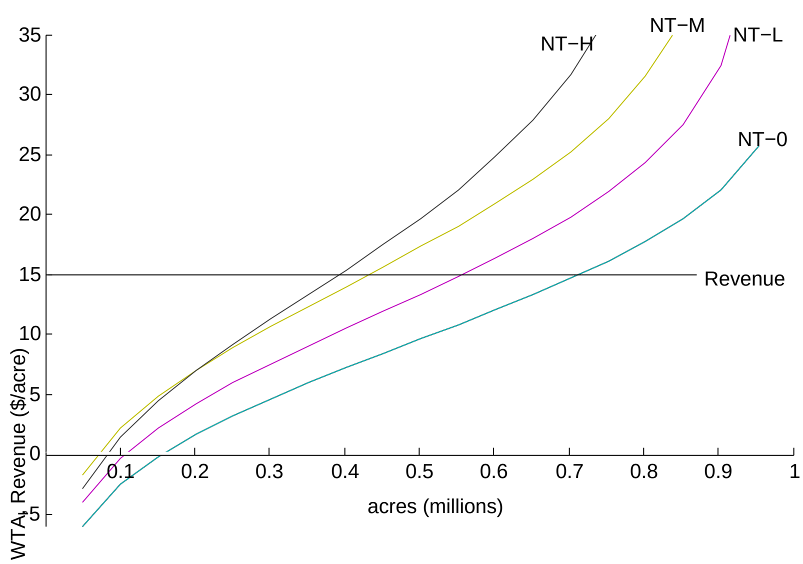

Figure 6 Simulated WTA curves for no-till contracts

For visual clarity, the estimation errors surrounding each of the curves in Figures 5 and 6 are not shown. Table 7 reports the point estimates and accompanying confidence intervals for five specific acreages along each WTA curve. As noted above, the confidence intervals are relatively narrow near the bottom of each WTA curve and widen considerably for large acreage levels, reflecting the large estimation uncertainty surrounding the high cost fields. The relatively narrower intervals at and below the specified contract revenue ($10 for FS and $15 for NT) help the precision of the estimated aggregate impacts, which are areas between curves in the graph and/or between a given curve and the revenue line.

Table 7 Simulated Adoption Costs and WTA

	Area enrolled (million acres)					Adopt. Cost
Scenario	0.1	0.3	0.5	0.7	0.9	Correlation
	$ / acre enrolled					
FS-0	1.02	2.65	5.19	10.26	27.83	—
	[0.43, 2.04]	[1.37, 4.66]	[2.88, 8.66]	[5.74, 16.88]	[14.11, 49.80]	
FS-L	2.89	5.48	9.15	16.23	40.55	0.242
	[1.74, 4.56]	[3.52, 8.25]	[5.99,13.48]	[10.51,24.10]	[24.05,65.24]	[0.059, 0.489]
FS-M	4.92	8.64	13.49	22.51	53.86	0.243
	[2.95, 7.85]	[5.46,13.12]	[8.71,20.09]	[14.59,33.54]	[31.71,89.41]	[0.059, 0.489]
FS-H	3.62	9.24	16.5	30.45	83.07	0.240
	[-0.19, 8.52]	[4.14,16.58]	[9.04,27.45]	[17.60,50.44]	[42.80,159.06]	[0.055, 0.488]
NT-0	-2.57	4.62	9.6	14.63	22.03	—
	[-5.61, 0.21]	[2.48, 6.94]	[7.09,12.46]	[11.32,18.53]	[17.16,27.73]	
NT-L	-0.36	7.52	13.34	19.8	32.39	0.226
	[-3.49, 2.69]	[4.72,10.90]	[9.64,17.92]	[14.52,26.65]	[22.55,48.29]	[0.104, 0.367]
NT-M	2.12	10.66	17.29	25.25	44.51	0.228
	[-1.57, 6.28]	[6.73,16.00]	[12.01,24.55]	[17.62,36.31]	[27.55,75.98]	[0.104, 0.371]
NT-H	1.42	11.26	19.69	31.65	72.48	0.221
	[-3.54, 7.40]	[5.60,19.23]	[11.84,31.04]	[19.26,51.33]	[34.78,150.85]	[0.102, 0.355]

Ranges in brackets are Krinksy-Robb 95% confidence intervals.

Outcomes of the contracting scheme were computed for each field in each simulated population. A field was assumed to be enrolled if contract revenue exceeds the simulated WTA. Among a given population of simulated agents $i \in 1, \ldots, N$, let $S = \{i : WTA_i \geq \textit{Revenue}\}$ denote the subset of agents who enroll in contracts. Table 8 reports the point estimates and confidence intervals across the R outer population draws for several aggregate measures of contract enrollees, including the total contracted acreage ($q = 100(\#S)$), total contract payments ($q \times \textit{Revenue}$), adoption costs ($\sum_{i \in S} \hat{c}_i$), equal to area D in Figures 1-3), and the upper bounds on the potential payment savings from information rents and transaction costs (IR and TC, respectively). As described in the model section, the potential payment savings have both upper and lower bounds, but we focus here only on the upper bounds as the most relevant measure of *potential* savings. Note that the figures in Table 8 can be equivalently interpreted as aggregate measures in millions of units or as average values per eligible acre.

Because of the positive correlation between adoption and transaction costs (Table 7), the upper bounds for IR and TC correspond to areas $A+B$ and $A+E$ in Figure 2, respectively. Accordingly, IR in Table 8 is calculated as the sum of information rents on enrolled contracts: IR $= \sum_{i \in S}(\textit{Revenue}-$

WTA_i).[6] To obtain TC, the contract revenue needed to enroll q acres after eliminating transaction costs (b_0 in Figure 2) was first found by sorting the WTA_i's in each population and TC was computed as $\text{TC} = q(\textit{Revenue} - b_0)$.

Table 8 Aggregate Performance Measures of Contracting

Scenario	Area enrolled	Total payments	Adoption cost	Potential payment savings IR	Potential payment savings TC
	share of acres	——— $ per eligible acre ———			
FS-L	0.539	5.39	1.52	2.62	2.24
	[0.379, 0.683]	[3.79, 6.83]	[1.03, 2.03]	[1.47, 3.79]	[1.17,3.43]
FS-M	0.375	3.75	0.86	1.43	2.4
	[0.182, 0.556]	[1.82, 5.56]	[0.35, 1.40]	[0.48, 2.57]	[1.33,3.43]
FS-H	0.337	3.37	0.86	1.73	2.52
	[0.136, 0.531]	[1.36, 5.31]	[0.28, 1.57]	[0.45, 3.41]	[1.09,3.31]
NT-L	0.564	8.46	1.81	5.26	1.38
	[0.418, 0.716]	[6.27,10.75]	[0.39, 3.26]	[3.68, 6.93]	[0.92, 1.94]
NT-M	0.442	6.63	0.77	3.83	2.02
	[0.276, 0.613]	[4.14, 9.19]	[-0.44, 2.15]	[2.17, 5.61]	[1.48, 2.63]
NT-H	0.404	6.07	0.78	3.91	1.38
	[0.223, 0.592]	[3.35, 8.89]	[-0.43, 2.33]	[1.81, 6.26]	[0.28, 2.24]

Ranges in brackets are Krinksy-Robb 95% confidence intervals.

As one would expect, increasing transaction costs decreases enrollment rates and aggregate payments. In the low transaction cost scenarios (FS-L and NT-L), enrollments exceed 50% of eligible acreage for both types of contracts, but enrollment rates fall to 34% and 40% in the FS-H and NT-H scenarios, respectively. As enrollment rates fall, aggregate payments fall correspondingly given the assumption of constant revenue per contract. In all scenarios, a relatively small share of aggregate payments compensates for the actual cost of practice adoption. While aggregate payments range from about $3 to $5/eligible acre (hereafter, el.ac.) for FS contracts and from about $6 to $8/el. ac. for NT contracts, adoption costs range from $0.8 to $1.8/el. ac. across all scenarios. The share of adoption costs to total payments ranges from 0.23-0.28 for FS contracts and from 0.12-0.21 for NT contracts. These results imply that there is a large potential to improve cost-effectiveness of contracting by reducing information rents and/or transaction costs.

The last two columns of Table 8 are the potential payment savings from eliminating information rents and transaction costs, respectively. Information rents were found to be substantial across all scenarios, ranging from $1.4 to $5.2/el. ac. As a percentage of initial payments in each scenario, these values represent potential savings ranging from 38% to 64%. The cost-effectiveness of contracting could be substantially improved through the collection and use of better information on individual WTA.

The potential payment savings from eliminating transaction costs is of a comparable magnitude to that of information rent. The potential savings from transaction costs are larger for FS contracts ($2.2 to $2.5/el. ac.) than for NT contracts ($1.4 to $2/el. ac.). While the aggregate savings

[6] As shown in Figure 6, the WTA for NT contracts was negative for some simulated agents, but information rents here were computed in the same manner; IR should be interpreted to include any profits earned from no-till for the agents who would have adopted without contracts.

are fairly constant across scenarios within the FS contracts and within the NT contracts, they are more variable as a percentage of initial payments; as one might expect the percentage of potential savings is much larger when transaction costs per contract are high. For example, the potential savings in the FS-H scenario represents 75% of initial payments compared to a potential savings of 42% in the FS-L scenario. Across all scenarios the potential savings on a percentage basis ranges from 16% to 75%.

In sum, the estimated parameters imply that uniform-price, voluntary contracts are a quite cost-inefficient means of acquiring environmental services, and that transaction costs contribute significantly to the low cost-effectiveness. Ignoring any administrative costs, the principal can potentially eliminate as much as 75% of payments through modifications to the contracting process that reduce information rents and/or transaction costs.

7 Conclusions

This paper has estimated the impacts of transaction costs in PES contracts at both the individual and aggregate levels. Individual agents' willingness-to-accept for contracts were found to vary widely due to differing costs of providing environmental services and to differing preferences toward nonprice contract attributes. For many agents, the transaction costs induced by the nonprice attributes are a more important driver of contract WTA than the cost of adopting the environmental practice. At the aggregate level, the nonprice attributes have a significant impact on the overall cost effectiveness of the contracting mechanism. The potential gain in cost effectiveness from reducing transaction costs is roughly as large as that from eliminating information rents.

Naturally, the estimated effect of nonprice attributes depends on the levels of those attributes in a given contracting scheme. Little research has been conducted on the costs incurred from these attributes by agents in existing PES schemes, although the available evidence suggests that our simulations capture the relevant range from similar programs. McCann (2009) found that livestock producers in Iowa and Missouri spend an average of 16.6 hours developing comprehensive nutrient management plans. Falconer et al. (2001), Fang et al. (2005) and McCann and Easter (2000) all found transaction costs in the range of 30%-40% of total costs for farmer involved in contracting and technical assistance schemes, which are within the range of our estimates.

For existing contracting programs and environmental markets, our results suggest that the past focus on mechanisms to recover agents' hidden WTA is warranted, but that an equal focus on reducing transaction costs is also warranted. Reducing transactions costs appears to be at least as fruitful as eliminating information rents if the goal is to improve cost-effectiveness. Moreover, transaction costs due to the nonprice features of PES contracts offers one explanation for the low participation rates observed in some nonpoint trading markets and voluntary environmental programs.

Future research can identify modifications to PES schemes that effectively reduce the inefficiencies due to transaction costs. Such modifications are a potentially complex issue because the nonprice attributes are created to secure a property right for the environmental service in the first place. For example, the enrollment process allows the government agency or environmental credit buyer to verify that the contracted practice is feasible and will provide environmental service on the agent's land, while the penalties for any violations are intended to deter cheating and ensure that the contracted service will be provided.

When agents are heterogeneous, the nonprice attributes need not be constant across agents to obtain equally secure property rights across contracts. An agent may be willing to take a significantly lower contract price for less stringent terms, which will still be a sufficient incentive to fulfil the contract obligations. Like the selection designs to mitigate the lack of information on adoption costs, similar approaches might be used to offer contracts that are differentiated on the basis of nonprice attributes. For instance if a 'simple' contract, with streamlined application compliance procedures and a lower payment, could be offered alongside the 'standard' contract that has more stringent terms and a higher payment. Under conditions that must be evaluated, the attributes and payment levels in these contracts can be designed so that the same enrollment can be achieved with smaller overall payment expenditures.

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Appendix

Table 9 Mixed logit estimation results

Coefficient	Variable	Estimate	Standard Error	p-value
Means of random coefficients				
γ_A^*	ASC:A	.02256707	.19083459	.9059
γ_B	ASC:B	-1.97640790	.18037668	$< .0001$
β_1^*	*AppTime*	-3.66357824	.24620164	$< .0001$
β_2^*	*Epen*	-5.94923660	.26558733	$< .0001$
β_3	*Annual*	.80425571	.15858816	$< .0001$
α^*	*Revenue*	-1.58202290	.06174437	$< .0001$
Nonrandom coefficients				
δ_A	*FShay*	.77286812	.13402153	$< .0001$
δ_B	*NTrot*	.99884506	.11446075	$< .0001$
Diagonal values in Cholesky matrix, L				
γ_A^*	ASC:A	.93699243	.16633983	$< .0001$
γ_B	ASC:B	1.48057371	.15063883	$< .0001$
β_1^*	*AppTime*	1.60367497	.26681423	$< .0001$
β_2^*	*Epen*	.20376050	.18725605	.2765
β_3	*Annual*	.24273953	.23347031	.2985
α^*	*Revenue*	.03841567	.07616341	.6140
Below diagonal values in L matrix				
(γ_A^*, γ_B)		.06744777	.19492148	.7293
(β_1^*, γ_A^*)		.40192801	.17954939	.0252
(β_1^*, γ_B)		-.64219555	.18227174	.0004
(β_2^*, γ_A^*)		.67669508	.16845625	.0001
(β_2^*, γ_B)		-1.01696656	.19191277	$< .0001$
(β_2^*, β_1^*)		.49071347	.25254291	.0520
(β_3, γ_A^*)		.26158051	.19022661	.1691
(β_3, γ_B)		-.29851423	.18013180	.0975
(β_3, β_1^*)		.21617268	.19617720	.2705
(β_3, β_2^*)		-.23688837	.17863022	.1848
(α^*, γ_A^*)		.09500450	.07994330	.2347
(α^*, γ_B)		.00256756	.05877640	.9652
(α^*, β_1^*)		.14089397	.08222341	.0866
(α^*, β_2^*)		-.44930739	.06128752	$< .0001$
(α^*, β_3)		-.14647314	.07926943	.0646
Standard deviations random coefficients				
γ_A^*	ASC:A	.93699243	.16633983	$< .0001$
γ_B	ASC:B	1.48210921	.14912205	$< .0001$
β_1^*	*AppTime*	1.77362191	.27615917	$< .0001$
β_2^*	*Epen*	1.33208681	.17209875	$< .0001$
β_3	*Annual*	.56507018	.18463680	.0022
α^*	*Revenue*	.50367731	.06626144	$< .0001$

$*$ denotes normal transforms of lognormal coefficients