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Do farmers value the environment? Evidence from a conservation reserve program auction ☆

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Abstract

The paper uses data from one Conservation Reserve Program (CRP) auction to elicit farmers' attitudes toward the environment by analyzing their bids. The CRP pays farmers to remove chosen plots of land from agricultural production and put them to a conservation use. An interesting aspect of this auction is that winners are determined by a combination of low bids and environmental scores of individual plots. Using decision theoretic approach to model this auction we show that farmers condition their bids on the strength of their environmental scores and that they value environmental benefits, especially those that increase future soil productivity of their land.

JEL classification: D44; D81; Q51; Q58

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1. Introduction

In this paper, we study the strategies of bidders in an auction sponsored by the U.S. Department of Agriculture (USDA) to determine participants in the Conservation Reserve Program (CRP). The CRP pays farmers to remove land from production and put it to a conservation use. Farmers wishing to participate bid the price per acre they will receive if accepted into the program. In addition, an environmental score is calculated which attempts to measure the potential environmental benefits of idling the offered parcel. The score is the sum of six separate categories each expressing different environmental attributes such as wildlife habitat, water quality or soil erosion reduction. This score is then combined with the farmer's bid via a formula established by USDA at the end of the bidding period to obtain an index which provides the ranking used to decide program participants.

The main objective of this paper is to understand how farmers formulate optimal bidding strategies when competing in the CRP auctions. Since individual environmental scores measure different potential environmental benefits, some of which could affect long term farm profitability and land values whereas others are more of a public goods nature, exactly how farmers condition their bids on those individual categories should reveal information about farmers' preferences towards conservation and protection of the environment.

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There are several papers that examine CRP auction data in the literature. For example, Shoemaker (1989) examined the results of early bidding behavior on land values and argued that asymmetric information about farmer risk aversion and farmers learning the bid cap (the maximum acceptable bid, which was not revealed in the early sign-up periods) caused bids to approach the bid cap. Similarly, Reichelderfer and Boggess (1988) found that when conservation contracts are sold in sequential auctions, farmers can analyze the results of the preceding rounds and increase their bids. Miranda (1992) used bid data from the first CRP sign-up to test if landowners consider in their bidding behavior the soil productivity gains from placing land in the CRP. She found a strong positive relationship between the opportunity cost of placing land in the CRP and the bid, but a much weaker relationship between the bid and future on-farm productivity gains. Finally, Kirwan, Lubowski and Roberts (2005) estimated the premium received by CRP participants above their reservation rents and found that in sign-ups 20 and 26 those premiums amounted to 10–40% of the CRP total payments.

This paper differs from the earlier CRP literature in that by modeling a new generation of CRP auctions in which environmental scores and bids are *jointly* used to determine the winners, we accomplish two things: first, explain how bidders formulate bids given differences in the environmental characteristics of their land, and second uncover farmers' preferences towards different categories of environmental benefits.

The CRP auctions are significantly different from the institutions typically studied in the auction literature. First, in the CRP auctions winners are determined by a combination of low bids and high environmental scores rather than the bids only. Second, the winner determination rule and the number of units offered in the auction (number of parcels that will be accepted into the program) are not revealed to the bidders when they bid. Finally, the number of potential bidders in each of the CRP auctions are in the thousands, while typical auctions deal with no more than a few dozen potential bidders. These important differences prevent us from using a structural approach based on the game theoretic auction models (e.g. Guerre et al., 2000) to empirically analyze the auction data.[1] Instead, we model farmers' optimal bidding strategy using decision theoretic approach reminiscent of the early empirical works on auctions (e.g., Friedman, 1956; Capen et al., 1971).[2] Our model provides the unique solution to the optimal bid which separates the measurement of the farmer's agricultural production values and environmental benefits from the strategic effect resulting from the program scoring rules. An increase in an individual environmental score has two effects on the optimal bid: it raises a farmer's total score which increases the probability a bid is accepted (a positive-strategic effect) and it raises a farmer's long run profit/utility thereby lowering the opportunity cost of CRP participation (a negative-environmental effect). The model identifies these two effects even when the trade-off between environmental scores and bids is unknown.

The empirical analysis is carried out using the individual contract data for the 15th sign-up CRP auction from North Carolina. This is the first auction following the major changes in the program structure where bidders were first made aware of the environmental scoring rules before the sign-up period. The results show that farmers do in fact condition bids on the strength of their environmental scores and that they consistently value environmental improvements, especially the long-term benefits of enhanced soil productivity beyond the contract period.

The rest of the paper is organized as follows: the next section describes the institutional details of the CRP and the auction data. The third section presents the decision theoretic model of the farmers' bidding behavior when they hold heterogenous beliefs, while the fourth section builds on the theory to formulate an econometric model. The fifth section presents and discusses the empirical results emphasizing the dual effect of the scoring rules on the equilibrium bid. The sixth section concludes with a discussion of the policy implications of the empirical results.

2. Program description and data

The US Conservation Reserve Program was introduced in the Food Security Act of 1985 (the 1985 Farm Bill). According to the program, a farmer can bid qualified land into the program and, if the bid is accepted, contract to receive annual rental payments equal to the value of the submitted bid in exchange for removing the land from agricultural production and putting it to a conservation use. In addition to an annual per-acre rental payment, the farmer may request a one-

[1] Prominent examples of empirical research on auctions that involve government agencies as auctioneers such as the CRP include the series of papers examining the auctions for outer continental shelf (OCS) oil exploration tracts (e.g., Hendricks and Porter, 1988; Leland, 1978), U.S. Forest Service timber auctions (e.g., Athey and Levin, 2001; Haile, 2001), Federal Communications Commission spectrum auctions (Ausubel et al., 1997), and government procurement auctions (e.g. Thiel, 1988; Levin and Smith, 1990).

[2] For an excellent survey of this literature see Laffont (1997).

time cost share payment to partially offset the cost of conservation practices she promised to install on her land. This contract is generally for 10 or 15 years. USDA periodically announces sign-up periods when farmers can offer bids to place land into the program.

The 1996 Federal Agricultural Improvement and Reform Act (the 1996 Farm Bill) made some fundamental changes to the CRP. It placed additional restrictions on qualifying land and the total acreage that could be accepted into the program (36.4 million acres nationally, 10% of each state's total cropland and 25% of the county's total cropland). It also required for the first time an upper limit on acceptable bids. The maximum acceptable bid (cap) was now equal to the average land rental rate for each soil type in the county where the proposed CRP land is located, plus a $5 per acre maintenance allowance (USDA, 1997a). The Bill also provided for continuous sign-up periods for particular partial-field practices, such as riparian buffer strips, that involve a small amount of acreage, but provide a disproportionately large environmental benefit.[3]

Thirty-three sign-up periods have been held since the CRP's inception. Bids in sign-up periods 1–9 were not ranked according to the potential environmental benefits the parcel would provide. Beginning with the 10th sign-up period an Environmental Benefits Index (EBI) was calculated for each parcel offered but this information was not shared with farmers prior to the submission of bids. Finally, beginning with the 15th sign-up period producers were made aware of most of the scoring rules making up the EBI before the sign-up period. The data used in this study comes from the 15th sign-up period in North Carolina, which was held in 1997. The definitions of individual environmental scores are presented in Table 1. A more detailed summary of the scoring rules is presented in Table 2.

In order to rank bidders, the EBI combined the environmental scores (N1–N6) that measure the potential environmental benefits of an offered parcel with the cost factor (N7).[4] Of the six environmental scores, N3 (on-farm benefits from reduced wind and water erosion) and N4 (long term benefits of cover beyond the contract period) measure benefits that are largely concentrated on the farm in the form of increased future productivity of land once the retired land comes back into agricultural service. In addition, the CRP provides environmental benefits that are spread across a larger area beyond the farm borders such as wildlife habitat (N1), water quality (N2) and air quality benefits (N5). Finally, score N6 (benefits from enrollment in conservation priority area) does not correspond to any plot-specific environmental potential. All parcels located in a given geographical area, in our case the long leaf pine priority area, automatically earn 25 points regardless of their environmental characteristics. N6 is most easily interpreted as a geographic control for some unmeasured environmental potential. The cost factor (N7) is obtained by converting a farmer's dollar bid (rental rate offered) into EBI points using a particular transformation scheme (see formulae in the bottom two rows of Table 2). For example, if in the 15th sign-up a farmer submitted a bid of $40/acre and requested no cost-share money, $N7 = 190 - \left(\frac{40 \cdot 190}{165}\right) + 10 = 153.94$. If she submitted a bid of $30, her N7 would increase to 165.45.

Table 1
Components of the environmental benefits index — 15th sign-up

EBI components	Max. points
N1: Wildlife habitat	100
N2: Water quality benefits from reduced water erosion, run-off and leaching	100
N3: On-farm benefits from reduced wind and water erosion	100
N4: Long-term benefits of cover beyond the contract period	50
N5: Air quality benefits from reduced wind erosion	25
N6: Benefits from enrollment in conservation priority areas	25
N7: Cost factor	200
Total:	600

Source: USDA (1997b).

Environmental scores are computed by the personnel of two USDA agencies in each county: the Farm Service Agency (FSA) and the Natural Resource Conservation Service (NRCS). Points are assigned in each environmental category for each offered parcel as prescribed by the handbook which lists specific details on how points are to be assigned for each conservation practice and land characteristic (USDA, 1997b). The bidding process has become much more transparent since the 1996 Farm Bill was enacted. There has been a concerted effort to see that all bidders have the same information about how their EBI is determined. Each bidder is given a fact sheet about the scoring rules for each environmental category, and FSA and NRCS personnel review the sheet with the applicant. Before submitting a bid, each bidder knows

[3] In a continuous sign-up, if the land is eligible and the bid is at or below the bid cap, plus an incentive payment of up to 25% of the cap, the land is accepted automatically into the CRP. As such, continuous sign-ups are not interesting for the types of questions we address in this paper.

[4] The EBI has changed since. For instance, carbon sequestration has been added as an environmental category; see e.g., Kirwan, Lubowski and Roberts (2005).

Table 2
Scoring rules for the CRP — 15th sign-up

Main Categ.	Sub-category (allocated points)					
N1	Cover factor (50)	Proximity to wetland (10)	Proximity to prot. area (10)	Upland-wetland ratio (10)	Endang. spec. area (15)	Contract area (5)
N2	Priority area (30)	Ground water quality (20)	Surface water quality (40)	Cropped wetland conversion (10)		
N3	Erodibility index (100)					
N4	Long-term tree, shrub, and wetland retention (50)					
N5	Wind erosion (25)					
N6	N.E. cape fear for wildlife habitat (25)					
N7	$N7=190-(\text{bid}/165)*190^{a}$ (200)					

Source: USDA (1997b).
[a] Additional 10 points contingent on declining a cost share.

the number of points earned in each environmental category, the total environmental score and the applicable bid cap for the parcel under consideration, but not the value of the cost factor N7. This information (N1–N6) is entered on the "Conservation Reserve Program Worksheet" which is signed by the bidder (USDA, 1997b).

The formula for converting monetary bids into the cost factor (N7) points as well as the weight of N7 in the total EBI *were not known* to farmers prior to the submission of bids. Bidders in the 15th sign-up were told only that a lower bid would improve their chances of acceptance, but were not told exactly how lowering their bid would affect their cost factor (N7). Additionally, requesting a cost share would lower the EBI by 10 points. The N7 formula and its weight in the total EBI were then determined by the Secretary of Agriculture after all the bids had been received in Washington. This final decision was made on a national basis, taking total EBI scores, total program cost and the county, state, and national acreage caps into account and communicated to growers through the FSA county offices. All bidders knew their respective bid caps.

The empirical analysis in this paper is performed with the individual CRP contracts data that contain the following variables: acres offered, rental rate offered (bid), maximum pay rate (cap), total cost share, environmental scores (N1–N6), cost factor (N7) and the total EBI ($\sum_{k=1}^{7} Nk$).[5] Summary statistics for the entire data set are given in Table 3. Note the small values of environmental scores for air quality (N5) and conservation priority areas (N6) relative to their maximal levels. According to the EBI, air quality is not an environmental concern in rural North Carolina. The average size of N5 is 0.003, whereas the maximum number of points that could have been earned in this category was 25. The number of plots eligible for receiving *N*6 points was also very small. Notice that the number of North Carolina farmers interested in participating in the program was 2915. The minimum EBI score needed to win acceptance into the program was 259, and the percentage of successful bidders was 68%.

3. A simple optimal bidding model

The most common approach in the auction literature is to specify bidders' beliefs according to a game theoretic solution concept such as a Bayesian Nash equilibrium in which each bidder correctly accounts for the effects of their own bids on the bids of others. That is, one farmer's belief about the bids of others is a function of her own bid (see, for example, Laffont, 1997). In this paper, we do not pursue a game theoretic

Table 3
Summary statistics for all observations in 15th sign-up

Variable	Mean	S.D.
Number of bids	2915	
Bid ($)	43.42	7.69
Bid cap ($)	46.50	8.36
EBI	280	41.15
EBI cut-off	259	
Accepted bids	68.2%	
N1	9.95	15.6
N2	47.8	18.4
N3	65.1	28.2
N4	8.4	8.7
N5	0.0	0.2
N6	0.2	2.4

[5] To conform to privacy rules, the NRCS stripped each individual bid of any information that could possibly identify a farmer, which effectively precludes any economic analysis that would require bidders' socio-economic characteristics. On the other hand this data set is unique in that it contains the records on all submitted bids, i.e. those accepted as well as the rejected bids.

approach because we don't believe farmers consider the strategic effect of their bids on the bids of others due to the fact that the number of potential bidders is large and they are geographically dispersed. As seen from Table 3, there are 2,915 bidders for one CRP auction in our data set and they are spread across the entire state. Moreover, the acceptance into the program is based on the nationally determined EBI cut-off score so in effect an individual farmer-bidder is competing against farmers from the entire country.

Based on these institutional features, we propose a simple decision theoretic model where economic agents (farmers) maximize profit/utility in a perfectly competitive framework. We assume that farmers are risk neutral and each of them is endowed with a piece of land of a given size and fixed characteristics which can be either farmed or enrolled in the CRP in its entirety. By assuming exogenous, fixed characteristics and land endowments, we avoid the problems of dealing with the farmer's decision of which parcel of land to enroll and whether to install certain conservation practices that may increase the EBI score and for which cost-share money is available.[6] Participation in the CRP generates a stream of conservation payments from the government, imposes certain costs caused by an immediate loss of farming income and creates non-stochastic environmental benefits.

When placing a bid, farmer i holds private expectations about the stream of discounted future profits from farming y_i and environmental benefits caused by idling the land under the CRP contract e_i. Both y_i and e_i are measured relative to the *status quo* of leaving the land in agricultural production. The discounted future stream of government payments to program participants is denoted by b_i. From a farmer's point of view, the cost of program participation can be defined as the net agricultural cost of retired land (including both current costs and future benefits) $C_i = y_i - e_i \geq 0$. The net benefits of enrolling the land into the program are simply $b_i - C_i$.

Consider the problem of the farmer deciding on the bid b that she is going to submit to the program for a parcel with environmental score $s_i = \sum_{k=1}^{6} Nk$.[7] A significant feature of the CRP auctions is that farmers do not know the trade-off between bids and the cost factor ($N7$). Ex post, the trade-offs have been linear (see the bottom row in Table 2), but ex ante, they are (and continue to be) unknown. Farmers are only told that lower bids and hence higher scores improve their chances of acceptance. Therefore, we assume that $P_i(b_i)$, the farmer's belief about the probability of being accepted into the program when he bids b_i, is continuous and decreasing on the support $[0, \bar{\beta}_i]$ where $\bar{\beta}_i$ is the maximum allowable bid (cap), that is, $\frac{\partial P_i(b_i)}{\partial b_i} < 0$. This captures the fact that the higher the bid, the lower the acceptance probability will be. It is also assumed that $P_i(\bar{\beta}_i) > 0$ as there is also a probability that a bid at the cap $\bar{\beta}_i$ will be accepted. In our setting, farmer i's beliefs P_i are affected by two factors: her beliefs about the unknown CRP scoring rules and her beliefs about the strength of her environmental score s_i. In the rest of the paper, we assume that farmers share common beliefs about CRP scoring rules but differ systematically conditional on their own environmental scores, that is, the heterogenous beliefs across farmers stem from their environmental scores. Therefore, the probability P_i is conditioned on s_i, that is $P(b_i|s_i)$.

To solve the model, we need to consider three possible scenarios. First, a bidder with $C_i > \bar{\beta}_i$ would not bother to participate, so in our data we only observe bidders with $0 \leq C_i \leq \bar{\beta}_i$. Second, a bidder with $C_i = \bar{\beta}_i$ should be indifferent between participating and not participating and if she chooses to participate, she would bid $b_i = \bar{\beta}_i$. Finally, a bidder with $0 \leq C_i < \bar{\beta}_i$, would surely participate and would determine her optimal bid by solving the expected profit maximization problem[8]

$$\max_{0 < b_i \leqq \bar{\beta}_i} (b_i - C_i) P(b_i|s_i). \tag{1}$$

The Kuhn–Tucker solution is

$$C_i = b_i^* + \frac{P(b_i^*|s_i)}{P'(b_i^*|s_i)} \text{ if } b_i^* < \bar{\beta}_i \tag{2}$$

$$b_i^* + \frac{P(b_i^*|s_i)}{P'(b_i^*|s_i)} \leq C_i < \bar{\beta}_i \text{ if } b_i^* = \bar{\beta}_i \tag{3}$$

with the second order condition

$$2P'(b_i|s_i) + P''(b_i|s_i)(b_i - C_i) < 0.^{9} \tag{4}$$

[6] These simplifications are not overly restrictive because a) the choice of parcel is somewhat restricted by the eligibility rules (USDA 1997b), and b) the cost share requests are not very common, accounting for only 11% of the total submitted bids in the 15th sign-up.

[7] This is a simplification because the actual bids submitted by farmers are per acre annual rental rates B_i whereas $b_i = \sum_{t=0}^{T} \delta^t B_i$ is the present value of the stream of submitted bids (annual CRP payments) over the length of the contract period T.

[8] Since we do not observe any bid with $b_i = 0$, when solving the model we ignore the possible corner solution of $b_i = 0$.

[9] $P'(b_i|s_i) = \frac{\partial P(b_i|s_i)}{\partial b_i}$ and $P''(b_i|s_i) = \frac{\partial^2 P(b_i|s_i)}{\partial b_i^2}$.

The formula for the interior solution optimal bid (2) indicates that bidders mark-up their bids above the cost of program participation C_i by $-\frac{P(b_i^*|s_i)}{P'(b_i^*|s_i)} \geq 0$.[10] It is also apparent that given fixed beliefs P_i, the potential for environmental improvement (either through increased future productivity of land or a more pleasant environment) reduces the cost of program participation and hence the bid.

3.1. Comparative statics results

Applying the implicit function theorem to the first order condition (2) holding C_i constant, we can show that the optimal bid varies with s as follows:

$$\frac{db_i^*}{ds_i} = -\frac{\frac{\partial P(b_i^*|s_i)}{\partial s_i} + \frac{\partial P'(b_i^*|s_i)}{\partial s_i}(b_i^* - C_i)}{2P'(b_i^*|s_i) + P''(b_i^*|s_i)(b_i^* - C_i)} \tag{5}$$

The sign of (5) is theoretically ambiguous. Since the denominator is negative by the second order condition, $\frac{db_i^*}{ds_i}$ is going to be positive as long as the numerator is positive. This would mean that the optimal bid increases with an increase in the environmental score of the plot, an intuitively plausible result. The optimal bids would always increase in environmental scores as long as:

$$\frac{\partial P(b_i^*|s_i)}{\partial s_i} > -\frac{\partial P'(b_i^*|s_i)}{\partial s_i}(b_i^* - C_i). \tag{6}$$

Intuitively, (6) restricts the farmers' beliefs about the probability of being accepted from changing too slowly as s_i changes. In order for $\frac{db_i^*}{ds_i}$ to be positive, the probability a bid is accepted must change at least at some bounded rate.[11]

Applying the implicit function theorem to (2) holding s_i constant, we obtain another comparative statics result describing how the optimal bid varies with net agricultural costs of retired land:

$$\frac{db_i^*}{dC_i} = \frac{P'(b_i^*|s_i)}{2P'(b_i^*|s_i) + P''(b_i^*|s_i)(b_i^* - C_i)} \tag{7}$$

Since the denominator is negative by the second order condition and the numerator is negative by our previous assumption, the optimal bid is always increasing in the net agricultural costs C_i. Since $C_i = y_i - e_i$ is decreasing in environmental benefits, it follows that the optimal bid must be decreasing in environmental benefits.

4. The Econometric Model

Although the theoretical model above does not provide a closed form solution for the optimal bid, it does establish a behavioral relationship between bids and measures in our data. The Kuhn–Tucker conditions (2) and (3), together with the fact that a bidder with $C_i = \bar{\beta}_i$ would bid $b_i = \bar{\beta}_i$ if she chooses to participate, yield estimating equations

$$b_i^* = C_i - \frac{P(b_i^*|s_i)}{P'(b_i^*|s_i)} \text{ if } b_i^* < \bar{\beta}_i \text{ is observed} \tag{8}$$

$$\bar{\beta}_i + \frac{P(\bar{\beta}_i|s_i)}{P'(\bar{\beta}_i|s_i)} \leq C_i \leq \bar{\beta}_i \text{ if } b_i^* = \bar{\beta}_i \text{ is observed} \tag{9}$$

that can be estimated with the available data.

A suitable estimation technique for the problem at hand is the nonlinear least squares (NLLS) method that uses (8) as the moment condition. The NLLS method is chosen because a closer examination of the estimating equations reveals that with $C_i \geq 0$, the lower support of b_i equals $-\frac{P(b_i^*|s_i)}{P'(b_i^*|s_i)}$, which clearly indicates its dependence on the parameters to be estimated through $P(\cdot|s_i)$ and $P'(\cdot|s_i)$.[12] This violates the regularity conditions of the classical maximum likelihood estimation (Donald and Paarsch, 1993, 1996; Chernozhukov and Hong, 2004; Hirano and Porter, 2003) and hence prevents us from using a standard tobit type estimator that would accommodate both the interior solution (8) and the corner solution (9) of the auction model. The NLLS method is easy to implement and does not suffer from such a problem. Its drawback is that the estimation uses only the portion of the data set where the submitted bids are less than the bid cap. As a result, the estimation

[10] The magnitude of the mark-up can thought of as the information rent earned by the farmers due to their private information about the opportunity cost of their land. In fact, the asymmetry of information between the farmers and the CRP administrators is the principal reason for designing such an elaborate auction scheme. In the absence of such asymmetric information problem, the CRP could simply pay the farmers their true reservation price for the respective plots and the entire auctioning mechanism would be superfluous.

[11] We acknowledge that if the second order condition for profit maximization does not hold, then multiple optima or no optimum in the bidding strategy are possible. As shown later when estimating the model, we choose a specification for $P(b)$ such that (4) is automatically satisfied. On the other hand, the condition that $\frac{db_i^*}{ds_i} > 0$ from (6) will be checked empirically after estimation.

[12] The upper support for b_i is $\bar{\beta}_i$.

yields consistent but less efficient estimates relative to the case where the entire data set were used.

The next problem stems from the fact that the individual opportunity costs of program participation C_i are not directly observable. To address this problem we rely on the fact that the maximum bid cap is determined by the auctioneer for each submitted plot as the average rental rate for the county and soil type in which the submitted plot belongs. Therefore, the individual opportunity cost of the CRP participation can be approximated with some linear combination of the maximum bid cap $\overline{\beta}_i$ and the measurements of the parcel's potential environmental benefits given by its individual categories of the EBI score N1 through N6:

$$C_i = a_0 + \alpha\,\overline{\beta}_i + \sum_{k=1}^{6} \gamma_k N_{ik}. \tag{10}$$

In addition, as our model requires $P'(\cdot|s_i)<0$, $P(\overline{\beta}_i|s_i)>0$, and $0 \le P(b_i|s_i) \le 1$, for $b_i \in (0, \overline{\beta}_i]$ (the last relationship is due to the fact that P is defined as probability), we specify the probability $P(b_i|s_i)$ as

$$P(b_i|s_i) = \frac{M}{(\theta_0+\theta_1 s_i)^2}\exp\left[-\frac{b_i}{(\theta_0+\theta_1 s_i)^2}\right] \tag{11}$$

where $M>0$ is a normalizing constant that guarantees $P\,(b_i|s_i) \le 1$ for $b_i \in (0, \overline{\beta}_i]$. This specification satisfies all the restrictions imposed by the properties of $P(\cdot|s_i)$ and some other requirements of the theoretical model. In particular, this specification guarantees that the second order condition (4) holds and hence the optimal bid represents the unique maximum of the farmers' objective function.[13] Finally, we also assume that the optimal bid b_i^* in (8) is observed with error u_i with the property $E(u_i)=0$.

With these assumptions, (8) and (10) yield the moment condition expressed in terms of the observed bids b

$$E(b_i) = a_0 + \alpha\,\overline{\beta}_i + \sum_{k=1}^{6} \gamma_k N_{ik} + (\theta_0+\theta_1 s_i)^2 \tag{12}$$

with the restriction

$$0 \le C_i = a_0 + \alpha\,\overline{\beta}_i + \sum_{k=1}^{6} \gamma_k N_{ik} < \overline{\beta}_i - (\theta_0+\theta_1 s_i)^2. \tag{13}$$

[13] Note that M is not identified as it drops out of the first order condition. But this does not affect any of our empirical results.

Collecting all the unknown parameters in φ, the NLLS estimator $\widehat{\varphi}$ is defined as

$$\widehat{\varphi} = \arg\min_{\varphi} \frac{1}{N}\sum_{i=1}^{N}\left[b_i - a_0 - \alpha\,\overline{\beta}_i - \sum_{k=1}^{6}\gamma_k N_{ik} - (\theta_0+\theta_1 s_i)^2\right]^2 \tag{14}$$

where N is the sample size.[14] Following Wooldridge (2002), the asymptotic variance of the NLLS estimator can be obtained as follows

$$\widehat{A\text{var}}\,(\widehat{\varphi}) = \left(\sum_{i=1}^{N} \nabla_\varphi \widehat{m}_i' \nabla_\varphi \widehat{m}_i\right)^{-1} * \left(\sum_{i=1}^{N} \widehat{u}_i^2 \nabla_\varphi \widehat{m}_i' \nabla_\varphi \widehat{m}_i\right) * \left(\sum_{i=1}^{N} \nabla_\varphi \widehat{m}_i' \nabla_\varphi \widehat{m}_i\right)^{-1} \tag{15}$$

where $\widehat{m}_i = \widehat{a}_0 + \widehat{\alpha}\,\overline{\beta}_i + \sum_{k=1}^{6}\widehat{\gamma}_k N_{ik} + \left(\widehat{\theta}_0 + \widehat{\theta}_1 s_i\right)^2$, $\widehat{u}_i = b_i - \widehat{m}_i$, and $\nabla_\varphi \widehat{m}_i = \partial\frac{\widehat{m}_i}{\partial\varphi}$.

After estimation, we can decompose the bid into the program participation cost

$$\widehat{C}_i = \widehat{a}_0 + \widehat{\alpha}\,\overline{\beta}_i + \sum_{k=1}^{6}\widehat{\gamma}_k N_{ik} \tag{16}$$

where $\frac{\partial C_i}{\partial Nk_i} = \widehat{\gamma}_k$, and the strategic component

$$-\frac{P(b_i|s_i)}{P'(b_i|s_i)} = \left(\widehat{\theta} + \widehat{\theta}_1 s_i\right)^2. \tag{17}$$

Therefore, an increase in an individual environmental score N_k has two effects on the optimal bid. First, it raises farmer's long run benefits either through increased future soil productivity or a more pleasant environment thus lowering the optimal bid (the direct environmental effect). Second, it raises a farmer's environmental score s which increases the probability that a bid will be accepted, which in turn (if (6) is satisfied) increases the optimal bid (the indirect strategic effect). Hence, the marginal effect of an increase in any component of the environmental score on the equilibrium bid, that is, $\frac{\partial b^*}{\partial N_k}$ can be disentangled into two effects: a) the effect on future farmer's profit/utility given by the increased future soil productivity and better environment, and b) the increase in payments accruing

[14] In practice, we estimate the NLLS model without constraint (13) and then check whether (13) holds using parameter estimates for each observation. Estimating the NLLS model with constraint (13), which is nonlinear, is extremely difficult.

to the bidder as a result of her land being perceived by the CRP as environmentally more valuable thereby commanding a higher environmental score. The former component (16) represents the farmer's valuation of environmental benefits at the margin, whereas the latter component (17) can be interpreted as the marginal information rent.

5. Estimation results

Prior to estimation, the data (bids and scores) have been scaled (divided) by 100 for numerical reasons. Therefore, the estimate of a_0 is scaled down by 100, θ_0 is scaled down by 10, θ_1 is scaled up by 10, whereas other parameters are not affected. The estimation includes only environmental scores $N1$–$N4$. This is because in North Carolina, very few farmers obtained nonzero values for the remaining two scores and even if the scores are nonzero, there is very little variation in the data. For N5 (air quality benefits) only 1 out of 1738 observations with interior bids have a nonzero score. For N6 (conservation priority areas), only 10 out of 1738 observations with interior bids have a nonzero score and the score is the same for all of these observations (Table 4).

The estimation results are presented in Table 5. Before looking and the statistical and economic significance of the estimated parameters, we first checked whether the condition $\overline{\beta}_i-(\theta_0+\theta_1 s_i)^2>C_i\geq 0$ is satisfied for the interior bids as required by our model (8). This is satisfied for 1731 out of 1738 observations. To assess how well the model fits the data, we compare the observed bids with their model predictions. As seen from Table 6, the forecasted bids fit the actual bids pretty closely for all percentiles of the bid distribution indicating that our model fits the data very well.

Looking at the estimated coefficients one can see that they all have meaningful magnitudes and some of them are statistically significant. For example, the estimate of α indicate that an increase in a bid cap by $1 would increase the bid by roughly 76 cents. The coefficients on $N1$–N4 scores are small relative to α, and all except N2 are negative indicating that farmers value environmental benefits and are willing to decrease their bids in the anticipation of environmental benefits that the program will produce. For example, an increase in N4 score (long term benefits of cover beyond the contract period) by 1 point, will decrease the average optimal bid by about 5 cents per acre per year. The magnitudes of the remaining two negative coefficients (N1 — wildlife habitat, and N3 — on-farm benefits from reduced wind and water erosion) are tiny and the parameters are not statistically significant. The coefficient on the remaining environmental score, N2 (water quality benefits), is actually positive and significant. A 1-point increase in N2 would increase the equilibrium bid by 2 cents, indicating that in this case farmers demand compensation for the provision of environmental benefits.

The highlighted results provide evidence that farmers tend to value more the environmental benefits which directly affect future productivity of their land than those benefits which focus on larger geographical areas or enhance the environment in a public good sense. Given the fact that N4 basically reflects the increased soil productivity caused by idling the land during the contract period that farmers can appropriate through increased future yields, the estimated marginal effects seem to indicate that farmers are willing to shade their

Table 4
Summary statistics for observations with interior bids

Variable	Mean	Stand. Dev.
Number of bids	1738	
Bid ($)	42.70	7.23
Bid cap ($)	47.86	8.18
N1	9.67	15.51
N2	45.69	19.80
N3	65.65	27.19
N4	8.72	8.52
N5	$5.75*10^{-5}$	0.24
N6	0.14	1.89

Table 5
Estimation results

Parameter	Estimate	*t*-statistic
a_0	0.0546	5.7776
α	0.7633	65.4084
γ_1	−0.0003	−0.0219
γ_2	0.0225	2.3748
γ_3	−0.0051	−0.5379
γ_4	−0.0481	−3.0533
θ_0	−0.0163	−3.1480
θ_1	0.0597	1.8588

Table 6
Model fit: comparison of observed and predicted bids

Percentiles	Observed bids ($)	Predicted bids ($)
10	34	34.32
20	35	36.86
30	40	38.33
40	40	41.08
50	44	43.11
60	45	44.67
70	46.96	46.06
80	50	47.91
90	50	50.04
mean	42.70	42.43

bids more if they anticipate future soil productivity gains. This result differs from Miranda (1992) who found differences in the relationship between the bid and future on-farm productivity gains across regions. With the exception of the Corn Belt and Lake States, farmers in that study either did not understand or were failing to act on the on-farm productivity effects caused by soil erosion. With minor exceptions, in all other areas (including Southeast) landowners did not systematically take the soil productivity effects into consideration when formulating their land management strategies. To the extent that dynamic inefficiencies associated with soil degradation come from farmers' disregard for future soil productivity, our results show that farmers in fact behave non-myopically.

In addition to the relationship between the opportunity cost of program participation and the optimal bid, our econometric model also enables the quantification of the strategic component of the optimal bid. The decomposition of the bid into the cost component (16) and strategic component (17) has been done in Table 7. As seen from the results, the cost component amounts to \$42.27 per acre per year, or 99% of the total bid, and the strategic component on average amounts to \$0.43 or 1%. This indicates that the CRP auctions are pretty competitive as the mark-up only accounts for a very small part of the bid.

The obtained results show that farmers condition their bids on their total environmental scores. As indicated in the final row of Table 7, for each point increase in their total score s farmers increased the strategic component of their bid by an average of 73 cents. This marginal effect of a 1-point increase in s on the strategic component of the bid would amount to the same marginal increase in the optimal bid provided that C is held constant. However, interestingly enough, when empirically checking condition (6) that guarantees that the optimal bid is increasing in the environmental score s, it turns out that it is satisfied for only 732 out of 1738 observations.

The environmental effect and the strategic effect can be added together to obtain the total effect of a 1-point increase in any of the environmental scores on the equilibrium bid. For example, a 1-point increase in N4 would have a direct negative environmental benefits effect on equilibrium bid of 4.81 cents and an average positive marginal strategic effect of 73 cents.[15] Therefore the total effect is 68.19 cents, meaning that a 1-point increase in N4 score would cause the farmer to increase her bid by 68.19 cents.

Table 7
Average quantities of economic interest

Item	15th sign-up
Bid	\$42.70
Cost component C_i	\$42.27
Strategic component $-\frac{P(b_i^*\vert s_i)}{P'(b_i^*\vert s_i)}$	\$0.43
Effect of 1 point increase in s_i on $-\frac{P(b_i^*\vert s_i)}{P'(b_i^*\vert s_i)}$	\$0.73

6. Conclusions

In this paper, we examine the behavior of bidders in a CRP auction where winners are determined by the monetary bids and the environmental scores reflecting the environmental benefits that the submitted parcel of land can potentially generate. The framework is of a more general interest for analyzing other similar programs where the number of potential entrants is large enough to eliminate the need to cast the problem in a game-theoretic framework. Such auctions are being used or contemplated for other conservation programs such as the floodplain swine farms buy-out program in North Carolina and a water conservation land buy-back along the Flint River in Georgia. This paper is a first attempt to quantify and test bidding behavior in such a setting.

Modeling this unique institution allows us to explain how bidders formulate bidding strategies using their beliefs about how valuable their parcel is from the perspective of the auctioneer and to elicit farmers' preferences towards different types of environmental goods. Based on our theoretical model we stipulate that farmers should condition their bids positively on higher environmental score and negatively on the individual components of the score. The empirical findings, based on the 15th sign-up CRP auction in North Carolina where the EBI score was known to the bidders, are generally supportive of the theoretical predictions of our model. In particular, we found that: a) farmers condition bids on their environmental score and b) farmers care about the environment, but seem to value more those environmental benefits that directly affect the productivity of their land and less those benefits which resemble public goods.

These results may have valuable public policy implications. For example, if the goal of the program is to maximize the enrolled acreage subject to the fixed budget constraint, our results indicate that there may be room for improvement. Farmers are seen to internalize those benefits which positively affect future productivity of their land (i.e., reduced soil erosion) and hence

[15] There is a subtle difference in the way the marginal effects have been estimated. The marginal environmental effects are the estimated parameters of the model so there is one parameter estimate for the entire sample. On the other hand, the strategic effect is calculated for each individual farmer in the sample, so the result presented in Table 7 is the average over all farmers.

including these categories in an environmental scoring procedure may distort incentives. Since the strategic effect is on average shown to be positive, including on-farm environmental benefits into the scoring formula compensates farmers for something they would have done anyway by simply inflating the strategic component of their bids. On the other hand, the auction is shown to be rather competitive as indicated by the fact that the bidder mark-up is very small. Hence, redesigning the auction rules along the suggested lines may not save much money to the program.

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