Cost Effectiveness of Conservation Auctions Revisited:
The Benefits of Information Rents

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Auctions are a common tool for reducing the costs of conservation programs, but a large literature questions whether existing alternative auction designs could be more cost effective. One of the most prominent examples, USDA's Conservation Reserve Program (CRP), is administered through a national, multi-unit, reverse auction and has enrolled, over the course of the past thirty years, contracts worth tens of billions of dollars. Since the environmental services being procured through the programs like CRP are not a uniform good, auction designs typically serve a second function in addition to reducing costs, namely encouraging higher quality contracts. This study examines the tradeoffs between cost reductions and benefit improvements. An econometric analysis of the five most recent CRP auctions reveals that the current program encourages higher quality offers in a way that results in information rents. Simulations of changes in the ranking score are based on a two-part model of bid structure that accounts for contract quality and rental rate. Efforts to reduce information rents related to environmental quality are shown to potentially increase information rents related to opportunity costs. Even when a change to the ranking score does result in reduced costs, it generally also involves a reduction in environmental benefits under the current auction structure.

Overview

USDA's Conservation Reserve Program (CRP) is one of several payments for environmental services (PES) programs that use an enrollment auction to reduce program costs (Wunder, Engel, and Pagiola 2008). For over 30 years, the CRP has enrolled environmentally sensitive cropland in long-term contracts that provide annual rental payments in exchange for the establishment and maintenance of approved conservation covers (Claassen, Cattaneo, and Johansson 2008). The majority of the land in the program has been enrolled through the General Signup, a multi-unit, sealed-bid, reverse auction that involves competition over both quality and cost. Participants can increase their ranking and improve the probability that their offer is accepted for enrollment by including improved conservation cover practices or by lowering the annual rental rate ($/acre).

Cost effectiveness is an important program goal for any government program. When looked at nationally, it is clear that CRP achieves a significant degree of cost control. The average annual rental payment in the most recent signup for accepted offers ($63 per acre) was about forty percent of the national cropland cash rental rate ($163). Part of this difference arises from the eligibility criteria, which restricts enrollment to the most environmentally sensitive and more marginal cropland, but the auction design is likely to be an important factor.

Since CRP is a pay-as-bid (own-price) auction, participants have an incentive to offer an annual rental rate that is higher than the minimum they would actually be willing to accept (i.e.: their reserve value). This is the reverse auction equivalent of bid shading (in forward auctions) and reflects the fact that the CRP general signup is not incentive compatible. The difference between their offered rental rates and their reserve value is general described as participants' information rent. A number of studies have found that alternative auction designs could reduce information rents in the CRP (Hellerstein, Higgins, and Roberts 2015; Hellerstein 2017; Kirwan, Lubowski, and Roberts 2005; Vukina et al. 2008).

In this study, we extend the prior research by examining what tradeoffs would be involved in changing the scoring method to reduce the information rents. The central underlying concept here is that the information rents provide a form of incentive-based targeting within the current program and that reducing those rents is likely to change program outcomes through several mechanisms.

There are three possible ways in which reducing information rents could potentially reduce public benefits of the program. The ranking effect is simply the fact that under many efforts to reduce information rents the relative ranking of offers will changes and so the composition of accepted offers will change even if we assume that the same offers are made and the bid structures are not changed. The self-selection effect occurs when efforts to reduce information rents leads to exit from the program and therefore changes the composition of the pool of offers. The bid structure effect occurs when reducing information rents changes either the conservation cover practices selected or the offered rental rates. The ranking effect and the bid structure effect take the existing mechanisms to control costs – bid caps and competition – into account

We develop an econometric model of bidding in USDA's Conservation Reserve Program (CRP). We use this bid structure model to simulate the tradeoffs that arise from efforts to reduce information rents. The core of our study is a novel treatment of the variation with the CRP ranking mechanism, joint models of bid cost and quality, and three sources of exogenous variation within the program: eligibility rules, county-level participation constraints, and shocks to field-level bid constraints.

To estimate our econometric model, we look at data from the 835,422 offers made in the program over the past twenty years. We model the rental rate decision similarly to previous studies, by estimating a Tobit model of the “bid down” decision. Over the past twelve signups, between 35 and 60 percent of offers have bid down below their bid caps by an average of 8 to 13 percent. This represents a savings to the program (relative to the bid caps) of more than one billion dollars over these two decades. Unlike prior literature, we also model the cover practice selection as a Tobit using the practice-based ranking points as the dependent variable. We use exclusion restrictions based on regional differences in the ranking criteria to estimate these two decisions jointly and find that there is a tradeoff between the two decisions. Offers that choose improved practices are less likely to bid down their rental rate. Our approach to modeling “exogenous” ranking points is similar to prior studies, but we disaggregate the ranking criteria in a much more precise manner. While prior research found that the bid down decision was influenced differently by different types of exogenous ranking points (Jacobs, Thurman, and Marra 2014), we find that in most signups the bid down and practice decisions respond similarly to different types of exogenous points.

To simulate the impact of changes in the ranking criteria, we make several additional innovations. To capture changes in competitive pressure we exploit the fact that the program is subject to county enrollment caps. When these caps are binding, offers essentially face a much smaller and more competitive auction relative to the national auction. Variation in the proportion of land eligible in each county criteria creates exogenous variation in the extent to which these caps can be binding since some counties can never hit their enrollment caps. In addition, variation in how the field-level bid caps are calculate based on county level data allows us to predict when enrollment caps are likely to be binding in all counties. Using this variation, we are able to estimate the impact of competitive pressure on bid structure, and we find that this mechanism is an important driver of the tradeoff between program cost and quality.

Literature

The basic structure of the CRP General Signup has been fairly consist over the history of the program (Claassen, Cattaneo, and Johansson 2008; Hellerstein 2017). Targeting, through the programs Environmental Benefit's Index (EBI), is at the core of the program. The EBI score increases when an offer has higher environmental benefits (across multiple criteria) and increases as the asking price of an offer (the requested per acre annual rental rate) declines. Some studies have suggested an alternative approach of ranking based on a benefit cost-ratio (Miao et al. 2016; Babcock et al. 1996; Babcock et al. 1997)), but the program has continued to use the additive EBI. While there are similar auctions in Australia (Rolfe, Whitten, and Windle 2017) and a similar fixed-price program in China (Uchida, Xu, and Rozelle 2005), CRP remains the largest and longest-standing effort to implement auctions in a conservation setting.

In addition to relying on the competitive pressure of an auction, the CRP general signup uses field-specific bid caps too control costs. This is similar to the use of reserve prices in forward auctions, which influence auction outcomes through multiple pathways and are therefore difficult to set optimally (Klemperer 2002). Experimental analysis of CRP-like auctions shows that bid caps that are too stringent can actually reduce cost-effectiveness by discouraging participation and reducing competitive pressure (Hellerstein and Higgins 2010).

Bidding behavior in CRP is often analyzed using the bid down on each individual offer, the percentage difference between the bid cap and the annual rental rate. When an offer to CRP have a rental rate at the bid cap, the bid down is zero, and the bid cap is binding in the sense that the land owner would likely prefer to ask for a higher rental rate. In a seminal paper that estimated a model of bid down choice in five of the CRP auctions from the 1990's, it was shown that land with a higher environmental score was less likely to bid down and, on average, bid down less than land with a lower score (Kirwan, Lubowski, and Roberts 2005). Using the estimated bid down model, Kirwan et al. simulate a counter factual in which all environmental points are zero (i.e.: where benefits are implicitly ignored for ranking purposes) and find that information rents account for about 10 to 40 percent total program costs in the 1999 and 2003 general signup auctions (less in three earlier auctions). The presence of such large information rents suggests that there may be opportunities to significantly reduce program costs while maintaining program benefits. A subsequent study with a more structural bid down model found that participants' environmental preferences were likely to influence their bidding behavior and, by inference, their opportunity cost (Vukina et al. 2008). In addition to farmer preferences, regional differences in the scoring function, specifically the designation of conservation priority areas, influences bidding decisions (Jacobs, Thurman, and Marra 2014). The general concept underlying these simulations is that under a budget constraint, the most cost-effective program will pay the reserve rate to each participant (Polasky et al. 2014; Ferraro and Simpson 2002)

Given the significance of information rents due to variable quality (benefits), one solution for reducing information rents is to withhold the information on how benefits are scored and ranked (Cason and Gangadharan 2004). A variety of theoretical models (Glebe 2013) and lab experiments (Banerjee, Kwasnica, and Shortle 2015; Messer et al. 2017; Conte and Griffin 2017) have found evidence that withholding ranking information with respect to benefits can improve cost effectiveness, although at least one study finds that revealing ranking information improves quality (Conte and Griffin 2017). Extensions of this later findings suggest that it can be important to consider the context when effort matters (Schilizzi and Latacz-Lohmann 2016) and that there is often a tradeoff between cost-effectiveness and meeting other program goals, such as in an auction for planting trees in Tanzania (Jindal et al. 2013). Over a broad set of experimental research, there is a general finding that cost effectiveness and other outcomes are quite sensitive to auction format and participant characteristics (induced values) (Schilizzi 2017). Other factors such as entry and exit (dynamic effects) (Fooks, Messer, and Duke 2015) and behavioral intentions (Wallander, Ferraro, and Higgins 2017) can also impact cost-effectiveness.

Theory

This study's model of bid structure is similar to earlier research (Kirwan, Lubowski, and Roberts 2005) but adds the decision about quality (cover practice), decomposes the ranking score (EBI) differently, and takes into account the competitive pressure due to county enrollment caps.

When submitting an offer to the program, a participant (with a field indexed by i) selects $rent_i$, the annual rental payment, subject to the bid constraint $rent_i \leq cap_i$. For the subsequent analysis, this decision can be represented as $biddown_i = 100 * (cap_i - rent_i)/cap_i$. The participant also selects a conservation practice, $cover_i$, from a list of approximately a dozen different options. An offer can combine multiple covers, using higher scoring and higher cost practices on a portion of the enrolled acreage. Rather than model $cover_i$ as a discrete choice, which would be challenging given the many options available, we model it using the continuous variable $coverEBI_i$, which the portion of the EBI score that is determined by the practice selection.

There are three types of costs associated with submitting an offer. A participant's reserve rate μ_i is their opportunity cost of being in the program, the minimum annual rental payment that they would accept. The reserve rate, which is known only by the participant, is likely close to the cash rental rate that the land would obtain in an annual crop production rental agreement. However, each individual's reserve rate would also include any other costs or benefits that the participant associates with CRP, such as wildlife benefits if they value hunting or a certainty equivalent benefit of having a fixed, ten-year contract if they face increased drought risk (Wallander et al. 2013). There is also a cost c_i associated with the choice of the cover practice selected, which is expressed net of the portion of the cost covered through the program's cost share payment. Lastly, we assume that there is a positive, sunk transaction cost k_i associated with making a bid. For ease of exposition, we implicitly treat the practice cost and transaction cost as annualized.

The benefits to participant of improving the offer quality through either choosing a lower rent or an improved practice are realized primarily through an increase in the probability that an offer is selected p_i. (The model does not currently include the possibility that a participant's reserve value is dependent upon the cover choice.) The probability that an offer is selected can be expressed in terms of the offer's ranking score (Environmental Benefits Index or ebi_i), the expected "cut-off" EBI (the minimum acceptable EBI score) that is determined after the auction has closed, and uncertainty around the cut-off EBI (or, equivalently, around the acceptance rate and the distribution of EBI scores for all offers). The EBI is an additive index composed of six factors and multiple subfactors. For the theory and empirical models, we decompose the EBI into four parts (table 1). Two parts, *coverEBI* and *biddownEBI*, are determined endogenously by the $cover_i$ and $rent_i$. The other two parts, $landEBI_i$ and *bidcapEBI*, are targeting factors and are determined exogenously by the land characteristic and program rules. These are the factors that have the potential to generate information rents. The $landEBI_i$ is increasing in several measures of environmental sensitivity. The $capEBI_i$ increases as the reserve price decreases and represents the number of points in the EBI cost factor that a given field would receive with zero bid down.

The farmer's optimization problem is to structure their bid so as to maximize the expected net benefits for field i. We write this maximization problem subject to a bid cap constraint (1.b) and a participation constraint (1.c)

$$\max_{rent_i, cover_i} = p_i * (rent_i - c_i(cover_i) - \mu_i) - k_i \quad (1.a)$$

$$s.t.: \quad rent_i \leq cap_i \quad (1.b)$$

$$p_i * (rent_i - c_i(cover_i) - \mu_i) \geq k_i \quad (1.c)$$

Substituting based on the EBI and expected acceptance functions, this model can be represented by the following Lagrangian incorporating slack variables (a_i^2 and b_i^2) on the two inequality constraints.

$$\mathcal{L} = p(\cdot) * [rent_i - c(\cdot) - \mu_i] - k_i + \lambda_i * \left(rent_i - cap_i - a_i^2\right) \quad (2)$$

$$+ \tau_i * \left\{p(\cdot) * [rent_i - c(\cdot) - \mu_i] - b_i^2\right\}$$

This formulation implies the following first-order Kuhn-Tucker conditions under optimal bid structure.

$$\frac{\partial \mathcal{L}}{\partial\, rent_i} = \frac{\partial\, p_i}{\partial\, ebi_i}\frac{\partial\, ebi_i}{\partial\, rent_i}[rent_i - c(\cdot) - \mu_i] + p(\cdot) + \lambda_i \quad (3)$$

$$+ \tau_i * \left\{\frac{\partial\, p_i}{\partial\, ebi_i}\frac{\partial\, ebi_i}{\partial\, rent_i}[rent_i - c(\cdot) - \mu_i] - p(\cdot)\right\} = 0$$

$$\frac{\partial \mathcal{L}}{\partial\, prac_i} = \frac{\partial\, p_i}{\partial\, ebi_i}\frac{\partial\, ebi_i}{\partial\, cover_i}[rent_i - c(\cdot) - \mu_i] - p(\cdot) * \frac{\partial\, c}{\partial\, cover_i} \quad (4)$$

$$+ \tau_i * \left\{\frac{\partial\, p_i}{\partial\, ebi_i}\frac{\partial\, ebi_i}{\partial\, cover_i}[rent_i - c(\cdot) - \mu_i] - p(\cdot) * \frac{\partial\, c}{\partial\, cover}\right\} = 0$$

$$\frac{\partial \mathcal{L}}{\partial\, a_i} = -2\lambda_i a_i = 0 \quad (5)$$

$$\frac{\partial \mathcal{L}}{\partial\, b_i} = -2\tau_i b_i = 0 \quad (6)$$

$$\frac{\partial \mathcal{L}}{\partial\, \lambda_i} = rent_i - cap_i - a_i^2 = 0 \quad (7)$$

$$\frac{\partial \mathcal{L}}{\partial\, \tau_i} = p(\cdot) * [rent_i - c(cover) - \mu_i] - b_i^2 = 0 \quad (8)$$

Rearranging equation 3 provides insight in the conditions for optimal rent.

$$rent_i = \mu_i + c(cover) + \frac{1}{\frac{\partial\, p_i}{\partial\, ebi_i}\frac{\partial\, ebi_i}{\partial\, rent_i}}\left[\frac{-p(\cdot) - \lambda_i}{(1+\ \tau_i)}\right]$$

This equation says that a participant's rent will be equal to their reserve price, plus their (annualized) practice costs, plus a third term which encapsulates the "information rent." To demonstrate how the information rent term captures incentives, let's consider the completely unconstrained case where both constraints are non-binding and so both Lagrangian constants are zero.

Econometrics

We estimate both of the bid structure equations using tobit models. For the rent decision, we model bid down, which is left censored at zero for those observations which have a binding bid cap. For the practice decision, *coverEBI* is also censored at zero for those offers which select the most basic practice (specified as a mixture of non-native grasses with no legumes).

Both decisions depend upon the endowment of exogenous EBI points due to the effect that those have on both the expected probability of acceptance ($p(\cdot)$) and, due to the non-linear nature of that probability, the effect that this endowment has on the marginal effect of an additional EBI point on that probability ($\frac{\partial\, p_i}{\partial\, ebi_i}$). We model the exogenous cost EBI points and the exogenous quality (land) EBI points separately because the cost points are not fully determined until after the auction closes.

The practice decision depends upon the marginal benefit of improving practices, the largest variation in which comes from the presence of conservation priority areas (CPA). The points awarded for some practices are much larger within CPAs. We also include CPA dummy variables in the bid down model as a potential cross price elasticity.

To capture the effects of county caps, we use a variable that reflects the total amount of eligible acreage that could be accepted within a county for each signup. The rules for the program stipulate that no more than 25 percent of cropland can be enrolled in a given county, although in some cases exemptions have been granted to slightly increase this cap for some counties. When a county hits the acreage cap, participants in that county essentially move from a nationally pooled auction to a county pooled auction and face a much more stringent cut-off EBI. The room under a cap is a function of the amount of land in a county that is eligible to enroll, the amount that is currently enrolled and not in expiring contract, and the amount of land that is in expiring contracts. In some counties, less than 25 percent of cropland is eligible and so it is always the case that 100 percent of eligible and unenrolled land can be accepted (if it is offered and scores at or above the national cutoff EBI). Therefore there is a considerable amount of both spatial and temporal variation in the extent to which local competitive pressure influences bids.

Data

Offers from the five most recent CRP General Signup auctions are used for the econometric estimation and simulations in this study. These five signups have occurred under the same ranking rules, which differ slightly from the prior signup by having eliminated points on offers that forego the cost share payments on practices. The EBI points are assigned by various subfactors. As noted above, we separate these subfactors into four parts, two exogenous parts, which are based on the land characteristics and do not change with bid structure, and two endogenous components, which vary depending upon the bid structure (table 1). The maximum points available for two parts of the cost factor vary because of variation in the field-specific bid caps.

Table 2 provides the summary statistics for the offer data from these five signups. There are total of 190,731 offers. The average annual rent rose from about $67 per acre in 2010 and 2011 to almost $112 per acre in 2016. Between 53 and 62 percent of offers across the signups bid down below the bid caps, and the average bid down for those offers was between 8.4 and 10.3 percent of the bid cap. Between 5 and 19 percent of the offers used the minimum (most basic) cover practice. For reporting the different categories of EBI points, we express them as the share of the maximum possible points. For the improvement of practice (*coverEBI*), the average score was between 8 and 10 percent of the maximum possible total EBI. For the exogenous environmental characteristics (*landEBI*), the average score was between 22 and 25 percent of the maximum EBI, which illustrates how much weight the targeting aspect of the EBI carries in the design of the program. For the exogenous portion of the cost factor (capEBI), which results from the bid caps, the average score was between 11 and 16 percent of the maximum EBI. Between 11 and 25 percent of offers were in a national conservation priority area (CPA), and between 33 and 51 percent of offers were in a state CPA. Being in a CPA can increase the marginal incentive (the change in EBI) for certain cover practices. Lastly, the measure of local competitive pressure, the percentage of eligible land that can be accepted under the county enrollment caps, is close to 40% in all signups.

The number of observations that have zero bid down are easily observed in a histogram of bid down, such as for the most recent signup (figure 1). The peak in zero bid down is, of course, the share of offers for which the bid cap is binding. The peaks in bid downs at 10 and 15 percent are likely related to the fact that a portion of the cost factor is non-linear, essentially creating a block price for *biddownEBI* points with discontinuities in the price at those two points. The peak in bid down at 5 percent does not have an obvious explanation within the program structure and may While the distribution of biddown is multimodal, the distribution of positive bid down is close to normally distributed with skewness between 0.2 and 1.4 and kurtosis between 2.7 and 10.8, varying by sign up.

For the two exogenous part of the EBI, *bidcapEBI* is the larger contribution to the exogenous EBI for move of the offers with total exogenous EBI between 100 and 200 points (figure 2). Few offers have less than 100 exogenous points total. Offers with 95 to 117 *bidcapEBI* have a bid cap of approximately \$52 to \$17 per acre, respectively. Offers with zero *bidcapEBI* have a bid cap of at least \$220 per acre. The most environmentally sensitive land, with the highest *landEBI*, is somewhat more likely to have mid-to-upper range bid caps and therefore mid-to-low range *bidcapEBI*.

Estimation Results

Table 3 presents the estimation results for the average bid down. Each signup is estimated separately because a variety of factors can impact the competitiveness of the national auction from year to year, including commodity prices, national acreage caps and the amount of land in expiring contracts. Despite these differences, the results are fairly consistent across years. As with previous research, we find that greater EBI endowments lead to less bid down (higher rents relative to the bid caps). The exogenous EBI points from the land *(landEBI*) have a similar magnitude effect as the exogenous points from the cost factor (*capEBI*). Being in a national CPA is associated with less bid down, which may reflect the fact noted above that being in a CPA can increase the incentive to improve the bid with practices. For most conservation practices, the same practice (and the same expenditure on that practice) will generate more *coverEBI* points when an offer is in a CPA. By substitution effects, this would be expected to decrease the incentive to bid down. There is also a potentially a second component to this substitution effect. To the extent that being in a CPA increases the likelihood of improved practices (discussed below), this would also increase the practice-related costs, which the theoretical model shows would lead to a higher optimal rents. However, the results for being in a state CPA are not consistent across sign ups, and in some years being in a state CPA is associated with more bid down. There appears to be an important interaction between the state CPA measure and the room under the county enrollment caps, because in the years when the state CPA has an (unexpected) positive sign the more room under the caps is associated with less bid down, as expected. The reverse is true in the two most recent signups.

Table 4 presents the estimation results for the average practice improvement. Again the results are fairly consistent across signups in terms of the direction of effects, but the magnitude of the effects vary. As with bid down, for practice selection there is a negative effect from the EBI endowments. Both exogenous EBI scores are associated with lower average endogenous practice score. Both national and state CPAs are associated with higher average practice scores, which could represent more actual practice improvement or could simply reflect the fact that the for some practices there is a higher score given for being in a CPA. In four of the five signups, a less locally competitive auction (more allowed acreage under the county cap) is associated with lower endogenous practice scores.

Simulations

The basic finding our econometric model corroborates prior research, which showed that bid down is lower on average when there is an "endowment" of higher exogenous EBI points. This suggests that there are information rents that could be reduced by lowering or eliminating these points and this endowment. We use simulation to estimate the likely impact of such an approach in the five most recent sign ups.

The exogenous EBI points are, as noted above, a targeting mechanism for the program to encourage the enrollment of land with higher environmental benefits. Our simulation capture the changes in this mechanism by recalculating the scores for all offers and then reapplying the same acceptance criteria used in each auction. We assume that the auction is constrained by an acreage enrollment cap (the million acres enrolled column in table 5), which varies by each auction according to how much land is currently enrolled and how much is in expiring contracts. It could also be the case that the program is budget constrained or quality constrained, which can lead to slightly different compositional changes when modelling the acceptance step (Wallander, Ferraro, and Higgins 2017).

The combination of the econometric model, which allows bid structure (both the bid down (rent choice) and the practice (as reflected in *coverEBI*)) to change in response to changes in the EBI, and the acceptance rule, means that we are modeling the ranking effect and the bid structure effects of changes in the targeting mechanisms. We decompose these in our model. We look at changes in program cost by taking the acreage-weighted average of the annual per-acre rental payment on accepted offers. We look at changes in environmental benefits by taking the acreage-weighted average of an environmental EBI that include the original *landEBI* score and either the original or the updated *coverEBI* score.

To isolate the ranking effect, we calculate the new EBI without the *landEBI* points, rescore the offers, and apply the acceptance criteria. This takes the original bid down and cover choices as given.

To isolate the bid structure effect, we estimate the updated environmental EBI and annual rental payments and then take the acreage-weighted average for the offers that were accepted in the baseline case. This effectively eliminates any ranking effect.

The results of the simulations are presented in table 6. Across all five sign ups, the effect of eliminating the *landEBI* points on the ranking of options does lead to a reduction in average program costs of between 2 and 27 percent. Since this is based on the original bid down decisions, this does not represent a reduction in information rents, per se. Rather, this results from the fact that the ranking criteria simply places significantly more weight on the cost factors. The tradeoff that results from this is that the ranking effect also results in a reduction in average environmental benefits (including the original *landEBI* score, which as noted above is ignored for purposes of ranking) of between 5 and 23 percent.

The bid structure effect results are a bit more mixed. The simulations show that the average annual rental payment changes between a reduction of 1 percent and an increase of 3 percent. The reason for this is that while information rents pertaining to *landEBI* are reduced, this is offset by increases in rents relating to *capEBI*. The effect on the environmental EBI, which now includes the changes in cover practice reflected in *coverEBI*, are similarly mixed. A future area of research would be to estimate simulation of an alternative EBI structure that increases the weight only on *coverEBI* and *biddownEBI*.

The combined effect of ranking and bid structure is more indicative of the ranking effect, showing a clear correlation between reduced costs and reduced benefits. In the first three sign ups, the reduction in costs is smaller in percentage terms than the reduction in benefits. This relationship reverses in the fourth sign up. In the most recent signup, the simulation actually reveal a large increase in the average rental payment. Part of this result may be due the fact that the much lower acceptance rate, which is due to the much tighter national acreage cap (table 5), leads to greater variation in expected rents, or it could results from the fact that the current econometric model does not capture a new national bid cap of $240 per acre that was binding for some offers in this signup.

Conclusions

Conservation auctions are an important tool for controlling the costs of enrolling environmentally sensitive farm land in voluntary programs like USDA's Conservation Reserve Program (CRP). Prior research has shown that standard conservation auction designs often create information rents by using ranking mechanisms that encourage more environmentally sensitive land to enroll, which reduces the incentive for that land to bid aggressively in the auction. These finding are usually taken as evidence that more cost-effective auction designs are possible, and attention on alternative designs often focuses on changes to the ranking score. This study estimates a bid structure model using data on more than 170,000 offers from the last five CRP auctions and finds evidence of information rents. However, simulations of changes to the ranking score based on this bid structure model reveal that reducing information rates is likely to result in a reduction in program benefits, which makes assessing the cost effectiveness of auction design changes much more difficult.

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Table 1: EBI Point Decomposition and Maximum Possible Points

Description	Environmental Score Subfactor	Exogenous Points **Land EBI**	Endogenous Points **Cover EBI**
N1 - Wildlife Benefits			
Cover type	N1a	3	47
Wildlife priority zone	N1b		30
Wildlife enhancements	N1c		20
N2 - Water quality Benefits			
Water quality area/zone	N2a	30	
Ground water quality	N2b	25	
Surface water quality	N2c	45	
N3 - Soil Erosion Benefits			
Erodibility Index	N3	100	
N4 - Enduring benefits			
Cover type	N4		50
N5 - Air quality benefits			
Wind erodibility	N5a	25	
Wind erosion soils	N5b	5	
Air quality zone	N5c	5	
Carbon sequestration	N5d		10
Description	**Cost Score Subfactor**	**Bid Cap EBI**	**Bid down EBI**
N6 - cost			
Annual rent	N6a	0 to 117	8 to 125
Amount below maximum rent	N6b		25
Maximum EBI points by category		238 to 355	190 to 307
Maximum total EBI		545	

Notes: All subfactors are additive in the final EBI score. Details on formulas for each subfactor can be found in the EBI fact sheets provided by FSA for each sign up (e.g.: https://www.fsa.usda.gov/Internet/FSA_File/gs43ebi.pdf). For this analysis, subfactor N1a includes 3 points in Land EBI because that is the minimum N1a points. The maximum value for N6a varies because, as described in the text, these points depend upon the field specific bid cap. The maximum for Bid cap EBI is 117 points because no field is assigned a zero dollar per acre bid cap.

Table 2: Summary Statistics

Signup	39	41	43	45	49
Year	2010	2011	2012	2013	2016
Offers (N)	50094	38715	47949	27817	26156
Drivers of Bid Structure			means		
Land EBI (share of max EBI)	0.22	0.23	0.24	0.25	0.23
Bid Cap EBI (share of max EBI)	0.15	0.16	0.15	0.12	0.11
National CPA (0/1)	0.11	0.21	0.25	0.23	0.22
State CPA (0/1)	0.51	0.48	0.46	0.42	0.33
Room under county cap (% of eligible acres)	41.8	39.59	39.46	38.43	38.64
Bid down outcome					
Mean Annual Rent ($/acre)	67.93	67.48	72.06	100.75	111.55
Share of offers with bid down	0.62	0.53	0.54	0.54	0.58
Average bid down (% if > 0)	10.32	9.8	9.59	8.42	8.39
Cover practice outcome					
Share of offers with most basic cover	0.07	0.19	0.19	0.14	0.05
Cover EBI (share of max EBI)	0.1	0.08	0.08	0.08	0.1

Notes: Exogenous EBI categories (landEBI and capEBI) are express here (and in the subsequent regressions) as the share of maximum possible EBI points, which is 545 for all five sign ups. The state and national conservation priority area (CPA) indicator variables are "1" for all contracts that have any acreage within one of these CPAs. The room under the county cap is the share of eligible and currently unenrolled acreage that can be accepted until the county cap (25 percent of cropland) is reached. Mean annual rent is larger than the numbers presented by USDA's FSA for each signup because these are straight averages and not acreage-weighted. The share of offers with the most basic cover represents those contracts with conservation practice CP1 (non-native grasses) without a legume.

Table 3: Bid down decision Tobit model results

Signup	39	41	43	44	49
Variable					
Land EBI (% max.)	-0.236***	-0.144***	-0.382***	-0.349***	-0.292***
	(-41.39)	(-26.00)	(-60.39)	(-43.16)	(-35.90)
Bid cap EBI (% max.)	-0.245***	-0.148***	-0.363***	-0.488***	-0.260***
	(-26.73)	(-15.53)	(-34.93)	(-48.22)	(-27.59)
National CPA (0/1)	-5.856***	-4.224***	-3.858***	-2.399***	-1.897***
	(-30.83)	(-21.75)	(-24.28)	(-11.82)	(-9.83)
State CPA (0/1)	1.187***	1.378***	1.311***	-0.0449	-1.194***
	(-10.73)	(-8.82)	(-9.62)	(-0.27)	(-7.27)
Share under county cap	-0.0212***	-0.0223***	-0.0198***	0.00608*	0.0216***
	(-12.55)	(-9.71)	(-9.46)	(-2.01)	(-6.91)
Constant	14.66***	9.748***	18.93***	17.71***	12.11***
	(-49.87)	(-26.28)	(-57.95)	(-47.39)	(-34.38)
Variance (e)	111.4***	136.2***	124.5***	122.0***	113.6***
	(-109.54)	(-86.18)	(-96.88)	(-72.71)	(-73.13)
N	50082	38652	47865	27746	26144

Notes: The t statistics are in parentheses (* $p<0.05$, ** $p<0.01$, *** $p<0.001$). The dependent variable is percentage bid down relative to the field-specific bid cap and is left-censored at zero.

Table 4: Cover practice EBI Tobit model results

Signup	39	41	43	44	49
Variable					
Land EBI (% max.)	-0.542***	-0.620***	-0.977***	-1.040***	-0.633***
	(-36.10)	(-38.38)	(-49.48)	(-48.69)	(-35.95)
Bid cap EBI (% max.)	-1.099***	-1.381***	-1.814***	-1.016***	-0.849***
	(-45.21)	(-49.38)	(-55.12)	(-38.65)	(-42.08)
National CPA (0/1)	17.99***	7.520***	10.58***	17.07***	13.60***
	(-37.15)	(-13.69)	(-21.28)	(-31.76)	(-31.81)
State CPA (0/1)	22.75***	19.27***	14.47***	17.82***	17.03***
	(-77.15)	(-42.16)	(-33.10)	(-38.90)	(-47.19)
Share under county cap	-0.0499***	0.0228***	-0.0582***	-0.0767***	-0.0881***
	(-11.18)	(-3.46)	(-8.91)	(-9.64)	(-12.82)
Constant	78.35***	83.88***	95.36***	83.86***	80.27***
	(-100.29)	(-76.96)	(-92.45)	(-83.99)	(-103.36)
Variance (e)	891.6***	1383.5***	1523.1***	1108.1***	685.9***
	(-148.89)	(-118.65)	(-132.39)	(-104.78)	(-109.8)
N	50082	38652	47865	27746	26144

Notes: The t statistics are in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the EBI score for the cover practice and is left-censored at zero.

Table 5: Historical Participation and Acceptance

Signup	Offers	Contracts	Acceptance Rate	Million Acres Enrolled	Million $ Annual Rent
39 (2010)	50,094	45,862	91.6%	4.34	200.16
41 (2011)	38,715	29,878	77.2%	2.83	136.20
43 (2012)	47,934	42,010	87.6%	3.88	198.60
45 (2013)	27,821	24,213	87.0%	1.68	108.25
49 (2016)	26,279	4,842	18.4%	0.41	25.48
Total	190,843	146,805	76.9%	13.14	668.69

Note: Numbers from official USDA FSA sign-up summary reports.

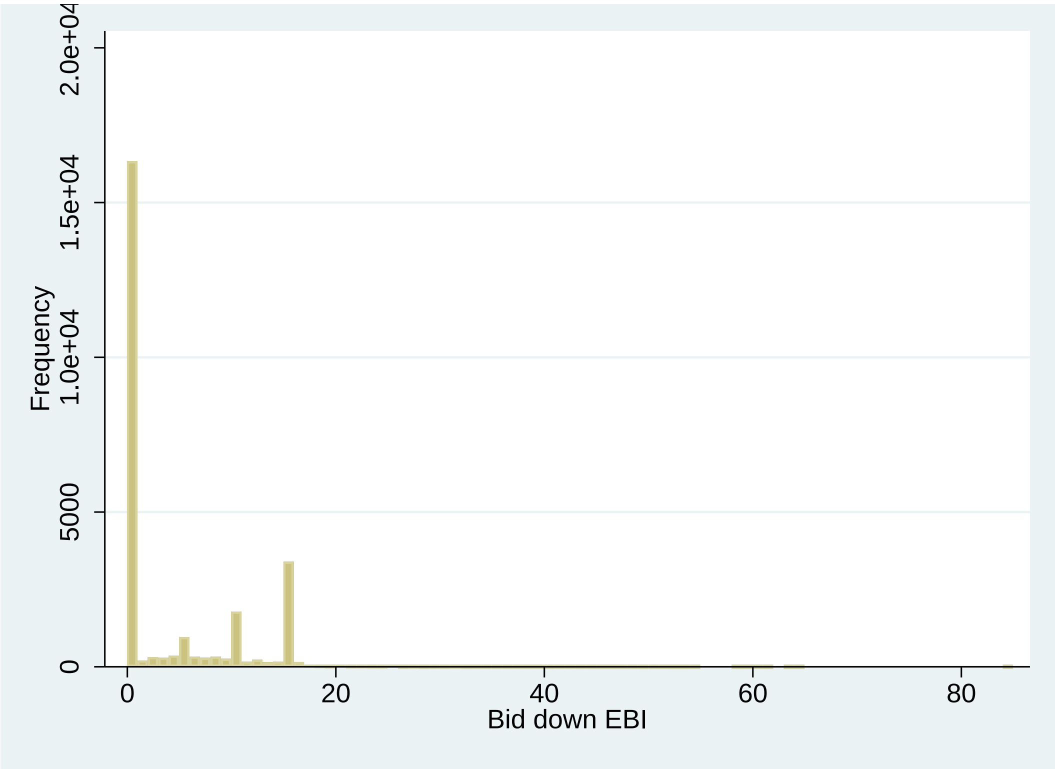
Table 6: Simulation impact of elimination of all exogenous environmental points

	Baseline		Ranking Effect		Bid Structure Effect		Combined Effect	
Signup	Rental Rate	Enviro. EBI	Rental Rate	Environ. EBI	Rental Rate	Enviro. EBI	Rental Rate	Enviro. EBI
39	45.75	172.6	40.45	163.81	46.5	165.83	42.63	158.29
41	50.11	184.42	48.98	174.02	51.69	168.04	46.77	155.4
43	51.03	174.77	43.48	161.69	50.54	164.41	46.63	151.92
45	63.12	175.81	52.93	163.45	62.66	186	54.73	173.28
49	62.03	224.08	45.25	172.77	62.68	220.83	72.69	168.66

	Ranking Effect		Bid Structure Effect		Combined Effect	
Signup	Rental Rate	Environ. EBI	Rental Rate	Enviro. EBI	Rental Rate	Enviro. EBI
39	-11.6%	-5.1%	1.6%	-3.9%	-6.8%	-8.3%
41	-2.3%	-5.6%	3.2%	-8.9%	-6.7%	-15.7%
43	-14.8%	-7.5%	-1.0%	-5.9%	-8.6%	-13.1%
45	-16.1%	-7.0%	-0.7%	5.8%	-13.3%	-1.4%
49	-27.1%	-22.9%	1.0%	-1.5%	17.2%	-24.7%

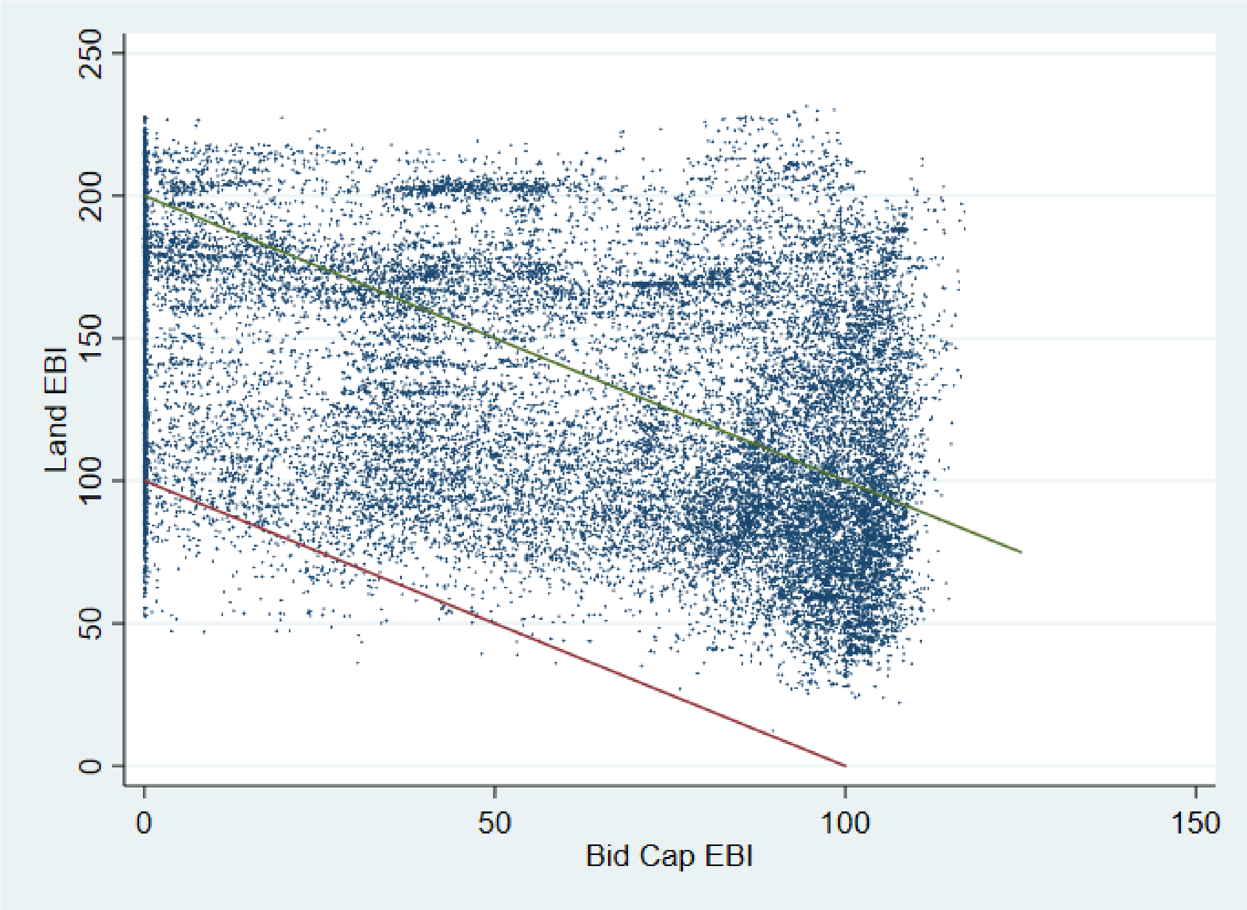
Notes: Rental rate is the acreage-weighted average for all accepted offers. Environmental EBI is the acreage-weighted average for all accepted offers. The baseline is for all offers accepted in the actual sign up. The ranking effect is for all offers that would be accepted under a re-ranking without landEBI points and subject to accepted no more acres than were originally accepted and using the original bid down and environmental (landEBI+coverEBI) points. The bid structure effect is for all offers that were originally accepted using the new bid down and environmental (original landEBI and new coverEBI) points. The combined effect is for all offers that would be accepted under the re-ranking without landEBI and using the new bid down and environmental points. The second table shows the percentage change from the baseline to the new scenario.

Figure 1:Bid down distribution for signup 49



Notes: Histogram is for all offers in sign up 49 with a bin width of one percentage point.

Figure 2: Exogenous EBI points for CRP sign up 49.



Notes: Plot of EBI points for all offers in sign up 49, subject to a random jitter of up to 0.5 points to provide a better visual representation of the density of the joint distribution. Bid cap EBI is between 0 points (a bid cap of >= $220 per acre) and 117 points (a bid cap of about $17 per acre). The diagonal red line is the isoquant of 100 total exogenous EBI points. The green diagonal line is the isoquant of 200 total EBI points.