# Additionality and Asymmetric Information in Environmental Markets: Evidence from Conservation Auctions

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**Abstract**

Voluntary, market-based mechanisms encourage the delivery of environmental services at low cost, but targeting payments to participants whose behavior is affected by the incentive is complicated by information asymmetry. We explore solutions to this market-design challenge in the context of the US Conservation Reserve Program, one of the oldest and largest payment-for-ecosystem services programs in the world. Using a regression discontinuity around the winning bid, we first document the presence of the market failure commonly referred to as the challenge of "additionality": we estimate that three of four marginal bidders would have counterfactually retired land in the absence of the incentive. A positive correlation between low bids and counterfactual land retirement demonstrates the presence of adverse selection in the market. We then develop and estimate a joint model of bidding and land use to quantify welfare under counterfactual market designs. We find that feasible procurement schemes that discriminate based on observable predictors of additionality generate substantial welfare gains relative to the status quo and other naive pricing schemes. Finally, we investigate the performance of a counterfactual decentralized offset market mechanism. Adverse selection limits trade and reduces welfare, but feasible, differentiated pricing restores the social optimum. Our results highlight that, especially when well-designed, markets for environmental services can deliver welfare gains, even in the presence of substantial non-additionality.

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# 1 Introduction

Land-use change contributes 9% of global greenhouse gas emissions (Le Quéré et al., 2015) and leads to substantial biodiversity loss, water pollution, and erosion (Dirzo et al., 2014; Vörösmarty et al., 2010; Borrelli et al., 2017). In theory, pricing environmental services on private lands can address environmental degradation by aligning social and private incentives for the preservation of public goods (Samuelson, 1954; Anderson and Libecap, 2014; Teytelboym, 2019). In practice, however, many argue that voluntary market mechanisms for environmental services are doomed to fail (Anderson, 2012; Filewod, 2017; Maron et al., 2016). Criticisms of these markets center on the issue of "additionality" — achieving gains from trade is complicated if only some participants' behavior are affected by the incentive. This market failure potentially undermines the widespread adoption of environmental incentive programs (Salzman et al., 2018) and rapidly growing offset markets (Kossoy et al., 2015)[1]. Changes to land management practices present some of the lowest-cost strategies available to mitigate damages due to climate change (Griscom et al., 2017; McKinsey & Company, 2013): can these gains be realized, or will the challenge of additionality unravel their potential?

We address this question by leveraging the observation that the issue of additionality is a manifestation of information asymmetry: landowners possess, and potentially act upon, private information about the likelihood that the incentive will impact behavior and deliver environmental value (Jack and Jayachandran, 2019). This makes clear both the fundamental challenge, as information asymmetry can drive markets to failure (Akerlof, 1970; Manelli and Vincent, 1995), and opportunity for market design, which can utilize a well-developed set of theoretical and empirical tools to evaluate the welfare consequences of and policy instruments to address this market failure. The principal goal of this paper is therefore to test for and quantitatively evaluate the welfare consequences of additionality and to assess the impact of alternative market designs that address this challenge.

We focus on the empirical setting of the Conservation Reserve Program (CRP), administered by the United States Department of Agriculture, which is one of the largest Payments for Ecosystem Services (PES) programs in the world.[2] The CRP incentivizes the retirement

[1] In offset markets, private buyers purchase contracts that "offset" any environmental degradation acre-for-acre, ton-for-ton, or dollar-for-dollar. Markets for offsets have emerged across a range of settings, due to direct implementation from regulators (wetlands and air pollution), to allow for gains from trade between regulated and unregulated industries (California's AB-32), between countries to provide flexibility in meeting international emissions commitments (the Clean Development Mechanism and REDD+), and due to the exploding volume of voluntary net-zero commitments among firms (McKinsey Sustainability, 2021, 2022).

[2] Integrated over its scale and history, the CRP is the single largest PES program in the world. Within a given year, the CRP is second to China's Sloping Land Conversion Program.

of agricultural land and the adoption of conservation activities via procurement auctions of conservation contracts. We assemble a dataset that links each participant's bid with a panel of land use outcomes that measures the incentivized activity via high-resolution satellite imagery.

The CRP setting presents several advantages to address key challenges to research. First, estimating additionality — or the probability that a participant changes behavior in response to the incentive — requires knowledge of an unobserved counterfactual (Rubin, 1974) and therefore a credible empirical design to evaluate treatment effects. The design of the CRP enrollment mechanism presents such an opportunity, as we exploit the sharp discontinuity in contracting around the winning bid in a Regression Discontinuity (RD) design. Second, evaluating the welfare consequences of information asymmetry requires a quantitative economic framework that captures the joint distribution of landowners' costs and expected additionality. The detailed information in revealed preferences in bidding behavior — which can then be linked to estimates of additionality measured with land-use outcomes — provides an ideal environment for both testing and quantitative welfare analysis of information asymmetry (Athey and Haile, 2006). Finally, insights from the CRP are broadly applicable and are derived from a sophisticated, mature market. The CRP structures contracts similarly to other PES programs,[3] to contracts traded in global offset markets (Engel et al., 2008), and to private, decentralized agricultural offsets markets in the US, which have attracted substantial private sector and policy interest.[4]

We begin by formalizing the challenge of additionality and its welfare consequences in both procurement settings and decentralized offset markets, building on the generalized Roy model of Eisenhauer et al. (2015) and the graphical welfare framework of Einav et al. (2010). Potential participants differ in both their willingness-to-accept (WTA) a contract and their additionality. Following Jack and Jayachandran (2019), who highlight the importance of multiple dimensions of private costs that jointly determine a landowner's WTA, namely, costs of conservation and costs associated with program participation, we allow for an unrestricted relationship between WTA and additionality. A positive correlation between WTA and additionality generates adverse selection in the market, but the existence and extent of this correlation is an empirical question.[5]

[3] China's Sloping Land Conversion Program and the U.K.'s Environmental Stewardship Program are notable examples. See citations in Kinzig et al. (2011).

[4] The Growing Climate Solutions Act of 2021 calls for the creation of a USDA-regulated agricultural offsets market. As of 2021, at least ten companies had attempted to create an agricultural offset market. See `https://www.congress.gov/bill/117th-congress/senate-bill/1251` and Stubbs et al. (2014) for more details.

[5] Indeed, Jack and Jayachandran (2019) do not detect evidence of adverse selection, despite its clear theoretical possibility.

We highlight three implications of additionality for the design of environmental markets, all of which are standard ideas in classic applications of selection markets but are frequently not incorporated in status quo market mechanisms for environmental services. First, incentives must be differentiated by the expected additionality, or Marginal Treatment Effect (MTE) of each type, in order to align social and private incentives. This can be achieved either via differentiation across observable characteristics or across contract types to leverage self-selection. Second, the adverse selection generated by landowners' private information about additionality can in principle make it impossible for a regulator to offer a surplus-increasing market at all, despite the existence of regions of surplus. Finally, adverse selection can limit trade and yield additional welfare losses in decentralized offset markets, as buyers take expectations over the expected additionality of *all* market participants, not only the individual contracting at the margin (Akerlof, 1970). The quantitative importance of these implications depends on the magnitude of additionality and landowners' WTA, their relationship, and the extent to which additionality can be explained by observable characteristics.

Our first empirical task tackles the first of these objects: what is the extent of non-additionality? While a key input into the design and evaluation of environmental markets, credible evidence on the extent of additionality, particularly in large-scale, mature markets, is scarce. We use the discontinuity in contracting around the winning bid to document both substantial effects of the program on land use — bidders substitute away from row-crop agriculture to natural vegetation and grasslands — and substantial non-additionality. Only 27% of participants change behavior, or conversely, three quarters of participants would have counterfactually engaged in the incentivized activity. Non-additionality is quantitatively important in this setting.

Next, we turn to testing for a relationship between additionality and landowner WTA that can further complicate the design of environmental markets via adverse selection. We use the observation that for rejected bidders, we possess both an $i-$specific estimate of additionality and an $i-$specific bid, and we examine the relationship between the two to test for adverse selection in the spirit of Chiappori and Salanie (2000). We document a strong relationship between bids and additionality: the highest bidders are nearly five times as additional than the lowest bidders after conditioning on characteristics already incorporated in the mechanism. This highlights the presence of adverse selection in the market. This adverse selection is in part mediated by heterogeneity across contract types — certain contracts, e.g. tree planting, are much more adversely selected than others — and via observable characteristics, including estimates of soil productivity, which are highly predictive of additionality.

To evaluate the impact of these descriptive patterns on welfare, and the performance of counterfactual designs, we leverage the controlled strategic environment of the auction, and specify a joint model of bidding and treatment effects that rationalize these patterns and the RD estimates of additionality. In the CRP mechanism, bidders submit multi-dimensional bids consisting of both a conservation action — e.g. grass or tree planting, habitat restoration — and a bid amount which are aggregated into a score. The existence of a menu of contracts provides an opportunity to test if and how the design of this menu can be leveraged to screen types based on their additionality. However, specifying and estimating an auction model with multi-dimensional types and bids presents a challenge. We build on Asker and Cantillon (2008) and characterize bidders' strategies in two separable steps: an "inner" choice of the optimal action-bid combination, conditional on score, and an "outer" choice of score, given expectations over the distribution of competing scores. We estimate this model using optimality conditions in both steps and policy variation in the scoring rule that shifts the relative returns to actions. The estimated distribution of costs — which yields a distribution of contract-specific WTA for each landowner — is based solely on optimal bidding behavior.

We combine this model of bidding, and the estimated distribution of WTA, obtained via revealed preference, with a "downstream" model of treatment effects that links additionality to observable characteristics and the unobserved costs that determine WTA. We maintain complete flexibility regarding the relationship between WTA and additionality. We estimate the Marginal Treatment Effect function, or expected additionality as a function of observable characteristics and unobserved costs, that rationalizes (i) the observed levels of additionality, on average and across observable characteristics, and (ii) the relationship between additionality and endogenous bidding behavior, both of which were the focus of the reduced form analyses in the first half of the paper. We then scale our estimates of additionality with estimates of the social value of CRP activities from the literature and relative values across bidders and contracts implied by the scoring rule, both of which — importantly — assume full additionality (Claassen et al., 2018).[6]

Consistent with the documented positive correlation between bids and additionality, we estimate a strong correlation between additionality and WTA: the highest-WTA decile of bidders have treatment effects that are over two times as large as the lowest-WTA bidders. This correlation is indicative of the classic "lemons" problem in Akerlof (1970): the first to select into the program generate the least value because bidders with poor outside options, who may have kept their land retired in the absence of the program, have the lowest WTA. We also observe substantial heterogeneity in WTA across bidders and across the additional conservation actions, suggesting the possibility of improved outcomes by setting differentiated

[6] "Benefit-cost indices are used to rank applications for acceptance in all major USDA conservation programs... Existing indices, however, implicitly assume full additionality." (Claassen et al., 2018)

prices or having bidders self-select among contracts.

We use our estimates in three sets of counterfactual exercises, motivated by the results from our theoretical framework. We begin by examining the performance of uniform price instruments in the presence of selection in the simple graphical analysis of Einav et al. (2010). First, we document welfare losses of 10% to 36% when a regulator fails to set incentives based on expected additionality — as is the case in most status quo policy interventions — when setting optimal uniform prices. Second, consistent with our estimates of correlated WTA and additionality, we find evidence that trade in decentralized offset markets will be limited without corrective subsidies: quantities and prices traded will be 25% and 50% below efficient levels, respectively, reducing welfare by 3%. The small effect on welfare masks important convexity: if the value of environmental services increases — as global concern about climate change rises — the welfare costs of adverse selection in offset markets may increase. These counterfactuals highlight a key finding of this paper: though the descriptive extent of both (1) non-additionality and (2) adverse selection are substantial, in fact, the market *can* be offered by a regulator and *does not unravel* completely in private markets. This conclusion highlights the importance of moving beyond testing to quantify the welfare implications of information asymmetry to understand the performance of environmental markets in the presence of non-additionality.

Next, we turn to more sophisticated policy instruments that differentiate across types according to their expected additionality in posted prices, offset trade, and finally, in auction settings. We find that setting feasible, differentiated prices across participants generates large welfare gains, achieving just under three quarters of the difference in welfare between pricing that does not condition on expected additionality at all and a first-best benchmark in which private costs are observed. Setting differentiated prices, though ambiguous ex-ante, also reduces the welfare costs of adverse selection by 90%. These two results underscore the gains to collecting detailed information about participants and setting differentiated incentives. We find that setting differentiated incentives is far more effective than designing the menu of conservation actions to induce self-selection among additional types. Finally, returning to the auction setting of the CRP, we implement these ideas in a series of efficient auctions, in which truthful reporting of costs is incentivized via a discriminatory VCG mechanism. Holding total acreage enrolled and the set of bidders fixed, we show that changing the auction design to efficiently incentivize contracting across heterogeneous bidders and contracts could increase welfare by over 90%, or almost $1 billion per auction.

**Related Literature** First, our conceptual framework characterizing selection and treatment effects brings together the literature on Roy-selection and policy-relevant treatment effects (Heckman and Vytlacil, 2001, 2005; Eisenhauer et al., 2015; Ito et al., 2021) with the welfare framework for analyzing selection markets pioneered by Einav et al. (2010) and Einav and Finkelstein (2011). We also relate to a recent empirical literature analyzing screening problems of agents with multi-dimensional hidden types (Chade et al., 2022; Gaynor et al., 2023) as well as theoretical work on contracting under asymmetric information in our specific context of PES (Li et al., 2022; Mason and Plantinga, 2013).

Second, our paper contributes to a recent literature that evaluates market designs based on their impact on treatment effects, rather than revealed-preference measures of participant welfare. These ideas have been applied empirically to organ allocation problems (Agarwal et al., 2020), foster care (Robinson-Cortés, 2019), and education (Kapor et al., 2022; Otero et al., 2021; Larroucau and Rios, 2023), and typically require estimating a relationship between revealed preference choices and downstream outcomes, as we do in our setting. In the auction context, a large body of theoretical work has examined how incorporating downstream outcomes impacts the design of procurement mechanisms (Manelli and Vincent, 1995; Laffont and Tirole, 1987; Che, 1993; Asker and Cantillon, 2008, 2010; Lopomo et al., 2023). However, this has received more limited empirical attention, with Lewis and Bajari (2011), Decarolis (2014), and Carril et al. (2022) notable exceptions.

Methodologically, our auction model leverages the separability between the "inner" and "outer" bidding problem as analyzed theoretically in Asker and Cantillon (2008) and the general identification results of Agarwal et al. (2023). In doing so, we contribute to a recent empirical literature analyzing scoring auctions in infrastructure procurement (Bolotnyy and Vasserman, 2023) and for resolving failed banks (Allen et al., 2023), and on the empirical analysis of multi-dimensional auctions more generally (Kong et al., 2022).

Most directly, our paper contributes to our understanding of payments for ecosystem services and offset market design (Aronoff and Rafey, 2022). These papers have focused primarily on estimating average treatment effects of incentive payments (Alix-Garcia et al., 2015; Jack, 2013; Jayachandran et al., 2017; Jack and Jayachandran, 2019; West et al., 2020; Calel et al., 2021; Rosenberg et al., 2022). Others have highlighted the possibility of adverse selection, though evidence detecting selection thus far has been mixed (Montero, 1999; Jack, 2013; Jack and Jayachandran, 2019). Our primary contribution builds on this literature in two ways. First, we leverage the rich empirical environment of the CRP to provide credible estimates of additionality — not just treatment effects, but treatment effects relative to enrollment — and to test for adverse selection in a large-scale, mature market. Second, more importantly, we develop a framework to evaluate the welfare and market design consequences of these descriptive facts in both procurement and offset market settings. Though our specific application is most narrowly related to conservation incentives, this framework applies broadly to ubiquitous incentive-based "voluntary" environmental regulation (Allcott and Greenstone, 2017; Borenstein and Davis, 2016; Boomhower and Davis, 2014).

# 2 Theoretical Framework

In this section, we present a model of heterogeneous private landowners supplying environmental services. We use the model to highlight sources of inefficiency in environmental payments programs and trade-able offset markets and to discuss potential solutions. In Section 2.1, we set up our framework, and in Sections 2.2 and 2.3 we discuss welfare and policy under the two distinct market structures in which environmental services from private landowners are contracted: direct procurement by a regulator and trade in competitive offset markets.

## 2.1 Set-up: costs and welfare

We develop a generalized Roy model to characterize selection and treatment effects. We begin with a simple setting, a binary decision to contract and a binary potential outcome, and subsequently enrich the set of contracts available. Let $D_i$ be a random variable that indicates whether or not $i$ selects into supplying a PES contract, and let $(Y_{i0}, Y_{i1})$ be the potential outcomes without and with the contract, respectively. In our setting, $Y_i$ denotes whether or not $i$ conserved ($Y_i = 1$) or cropped ($Y_i = 0$) her land, with:

$$Y_i = D_i \cdot Y_{i1} + (1 - D_i) \cdot Y_{i0} \tag{1}$$

The contracted outcome is $Y_i = 1$, so under perfect compliance, $Y_{i1} = 1$ for all $i$. However, counterfactual behavior without the contract, $Y_{i0}$, may be heterogeneous across participants.

**Private welfare: suppliers** Let $v_i$ be the cost of choosing $D_i = 1$, or a landowner's willingness-to-accept (WTA) the contract. $v_i$ (WTA) includes *both* the differences in private payoffs between the outcomes $Y_{i1}$ and $Y_{i0}$ — e.g. the lost option value to crop during the contract — *and* any additional hassle costs or preferences associated with contracting (Jack and Jayachandran, 2019). Private welfare under $D_i = 1$ versus $D_i = 0$ is $p_i - v_i$, so the selection equation is:

$$D_i = \mathbb{1}\{p_i - v_i > 0\} \tag{2}$$

for some incentive $p_i$ that can (potentially) vary across some observable dimensions of $i$; in the absence of any program or market, $p_i = 0$.

**Social welfare** The action $Y_i = 1$ has value $B$ that private landowners do not internalize, derived from avoided negative externalities such as pollution and erosion, and the provision of public goods such as open space and wildlife habitat.[7] This externality motivates the existence of the incentive program or offset market, as a buyer – a social planner or a consumer who values reductions in environmental harm – values the gross surplus generated by the action at $B \cdot (Y_{i1} - Y_{i0})$. The contribution of each individual $i$ to social welfare can be written as

$$B \cdot (Y_{i1} - Y_{i0}) - v_i - \lambda \cdot p_i \tag{3}$$

where $\lambda \geq 0$ is a cost of funds that is non-zero if a government is financing these contracts via distortionary taxation. A key realistic feature of our set-up is that private costs are paid upon contracting, either due to the existence of hassle costs in $v_i$[8] or a cost of funds.

We now define a key object: the Marginal Treatment Effect (MTE) at observable characteristics $\mathbf{z}$ and WTA $v$ (Heckman and Vytlacil, 1999, 2005):

$$\tau(\mathbf{z}, v) = \mathbb{E}\left[Y_{i1} - Y_{i0} | \mathbf{z_i} = \mathbf{z}, v_i = v\right] \tag{4}$$

This object captures the expected additionality of any $(\mathbf{z}, v)$ type. Under an assumption of perfect compliance, we can simplify (4) further as $\tau(\mathbf{z}, v) = 1 - \mathbb{E}\left[Y_{i0} | \mathbf{z_i} = \mathbf{z}, v_i = v\right]$. Substituting in, the welfare contribution of choosing $D_i = 1$ for each individual $i$ with characteristics $\mathbf{z}_i$ and cost $v_i$ is:

$$\underbrace{B \cdot \tau(\mathbf{z_i}, v_i)}_{\text{Social WTP}} - \underbrace{v_i}_{\text{private costs}} - \underbrace{\lambda \cdot p_i}_{\text{cost of funds}} \tag{5}$$

We make no restriction on the relationship between $v$ and potential outcomes, a defining

[7] We assume here for simplicity that $B$ is uniform across potential participants, but $B$ could vary flexibly across observable characteristics if the environmental benefits of land retirement varies across space. In our empirical application, we allow $B$ to vary based on observable characteristics such as erodibility, distance to bodies of waters, and wildlife sensitivity.

[8] In the language of Eisenhauer et al. (2015), $v_i$ can include "subjective costs of treatment," or costs or preferences that are unrelated to potential outcomes but are incurred when selecting into treatment. This is a key differentiating feature between a generalized Roy model and the original Roy (1951) model.

characteristic of the generalized Roy model (Eisenhauer et al., 2015).

**Enriching the menu of contracts** With this simple set-up, we can now enrich the set of contracts to include a menu of potential projects or actions that a supplier can undertake that yield some additional productive value beyond $Y_i = 1$. We will refer to these as "top up" actions above the base contract of retiring land, which include, in our setting, establishing pollinator habitats or planting and maintaining trees. We assume that these "top-up" projects are always bundled with the base contract to align with our empirical setting.

Individuals now make a choice not only to enroll, but to enroll with a given action $j$, denoted by the indicator $D_i^j$. Each individual has an incremental cost of providing each of the actions, $\kappa_{ij}$, with $\kappa_{ij} = 0$ for the base action. We define an individual's cost type as $\theta_i = (v_i, \kappa_i)$. Our modified selection equation now involves an individual $i$ choosing among the set of $j$ potential actions plus the outside option to not participate

$$D_i^j = \mathbb{1}\left\{ j = \arg\max_{j'} p_{ij'} - v_i - \kappa_{ij'} \right\} \tag{6}$$

We make the assumption that agents provide none of the incremental actions, e.g. establishing pollinator habitats or trees, in the absence of the incentive and perfectly comply with the chosen action under the incentive. This assumption simplifies the analysis significantly, aligns with what we are able to observe in the data, and is consistent with the fact that many of the incremental actions in our empirical setting are unlikely to be supplied under the status quo. This assumption allows us to focus on only the one key dimension of unobserved counterfactual behavior.

Under the additional assumption of perfect compliance on the base action, i.e. $Y_{i1} = 1$ for all $i$, we can simplify and write social welfare for contracting $i$ to do action $j$ as:

$$\underbrace{B \cdot \tau(\mathbf{z}_i, \theta_i)}_{\text{Social WTP for land retirement}} + \underbrace{B^j}_{\text{Social WTP for additional actions}} - \underbrace{(v_i + \kappa_{ij})}_{\text{private costs}} - \underbrace{\lambda \cdot p_i^j}_{\text{cost of funds}} \tag{7}$$

This richer set-up, as well as the simplified version with only a single contract in Equation (5), present the core challenge in this setting. Marginal treatment effects $\tau(\mathbf{z}, \theta)$ determine social surplus, as they capture the additionality of each type, but may depend on unobservable characteristics. Moreover, $\tau(\mathbf{z}, \theta)$ is a causal object that may be difficult to learn about or estimate in practice. Individuals self-selecting into their most preferred contract can lead to inefficient choices if prices cannot be set to exactly reflect the WTP for contracting with each individual based on $B \cdot \tau(\mathbf{z}, \theta)$.

## 2.2 Procurement by a government regulator

We first consider the optimal pricing strategy of a regulator. The regulator solves:

$$\max_{\{\mathbf{p}_z\}} \int \left(B \cdot \tau(\mathbf{z}, \theta) + B^j - v - \kappa_{ij} - \lambda \cdot p_z^j\right) \cdot D^j\left(\mathbf{p}_z; \mathbf{z}, \theta\right) \, dF\left(\mathbf{z}, \theta\right) \tag{8}$$

where $\{\mathbf{p}_z\}$ is a set of $J-$dimensional price vectors differentiated by characteristics $\mathbf{z}$. We begin with optimal pricing under the simplest contracting set-up, where there is only a single base contract to retire land at cost $v$, so we simplify the notation and set $\theta_i = v_i$.

**Proposition 1.** *(Optimal Incentives for a Single Contract) Consider a regulator solving (8) for the single base contract for which $\kappa_{ij} = 0$. Then:*

1. ***No cost of public funds:*** *If $\lambda = 0$, the optimal price schedule equals the expected environmental benefit of the marginal enrollee, or*

$$p_z^* = B \cdot \tau(\mathbf{z}, p_z^*) \tag{9}$$

   *with $p_z^* = 0$ if $\int \left(B \cdot \tau(\mathbf{z}, p_z^*) - v\right) \cdot D\left(p_z^*; \mathbf{z}, \theta\right) \, dF\left(\mathbf{z}, \theta\right) < 0$.*

2. ***Ramsey-Boiteux pricing under a cost of public funds:*** *If $\lambda > 0$, the optimal price schedule sets:*

$$p_{\mathbf{z}} = B \cdot \tau(\mathbf{z}, p_{\mathbf{z}}) \cdot \frac{1}{\lambda \cdot \left(1 + \frac{1}{\epsilon(\mathbf{z}, p_z^*)}\right) + 1} \tag{10}$$

   *where $\epsilon(\mathbf{z}, p_z^*)$ is the price elasticity of supply for participants with characteristics $\mathbf{z}$, with $p_z^* = 0$ if $\int \left(B \cdot \tau(\mathbf{z}, p_z^*) - v - \lambda \cdot p_z\right) \cdot D\left(p_z^*; \mathbf{z}, \theta\right) \, dF\left(\mathbf{z}, \theta\right) < 0$.*

*Proof.* See Appendix A. □

The first part of Proposition 1 is the classic condition that the optimal subsidy should equal the expected social WTP for the marginal enrollee without a cost of funds. In the presence of a cost of funds, the second part derives the classic Ramsey (1927)-Boiteux (1956) pricing equation, where optimal prices are differentiated both with respect to $\tau(\mathbf{z}, v)$ and the price elasticity of supply for participants of different characteristics.

Proposition 1 also highlights that, depending on the shape of the $\tau(\mathbf{z}, \theta)$ function, it may not be optimal to offer the market *at all*. We demonstrate this pricing problem in Figure 1a. Figure 1a includes the three key objects from Proposition 1: the value of $B$, the CDF of $v$, which makes up the supply curve, and the social WTP curve, $B \cdot \tau(\mathbf{z}, v)$, which incorporates the relationship between $v$ and additionality at each point along the supply curve. We include two example $\tau(\mathbf{z}, v)$ curves, both *upwards-sloping*, reflecting the possibility that at higher prices, participants with more profitable outside options select in, yielding a greater likelihood of changing behavior and a higher $\tau(\mathbf{z}, v)$. However, our framework is agnostic about the relationship between $\tau(\mathbf{z}, v)$ and $v$: variation in costs can be driven by $Y_i$-relevant factors or preferences and hassle costs orthogonal to potential outcomes. The shape of the $\tau(\mathbf{z}, v)$ curve is an empirical question.

This is a crucial empirical question, as different shapes of the $\tau(\mathbf{z}, v)$ curve yield dramatically different conclusions for a regulator's optimal pricing problem and the gains that can be achieved in the market, as illustrated in Figure 1a. The solid social WTP curve increases less steeply than the supply curve, while the dashed social WTP curve increases more steeply. Under the solid line, the socially optimal price is equal to B and the area of triangle ABC represents social welfare gains. Under the dashed line, the region of surplus lies above point B, in triangle BEF, whereas triangle CBD represents social costs. In this region, low levels of additionality make social WTP less than $v$. Under the economy represented by the dashed line, the highest welfare that a regulator can achieve is to set prices equal to zero, and not offer the market at all. Without additional information, any mechanism that achieves the gains in triangle BEF must suffer the costs of triangle CBD. And because triangle CBD is larger than BEF, net welfare from offering the market will always be negative. In this economy, adverse selection makes it impossible for a regulator to offer a market, despite the existence of gains from trade.

Figures 1b plots an alternative relationship between WTA and $\tau(\mathbf{z}, v)$, in which treatment effects are characterized by a simple threshold rule: landowners are not additional if $v = 0$ and are additional if $v > 0$. This would be the case if landowners had perfect foresight about future activities and there were no costs at all from participating in the program beyond the difference in payoff from $Y_i = 1$ and $Y_i = 0$. All of the economies depicted in Figures 1a and 1b are possible, lead to substantially different conclusions, and depend on the the distribution of $v$ and the shape of $\tau(\mathbf{z}, v)$.

**Welfare losses from pricing at $B$** To achieve the optimal pricing schedule in Proposition 1 , the regulator must know the population distribution of $\tau(\mathbf{z}, v)$. In practice, learning the distribution of marginal treatment effects may be difficult and costly. Many programs make miscalibrated assumptions about the value of $\tau(\mathbf{z}, v)$, often assuming that eligibility requirements are set stringently enough to ensure that $\tau(\mathbf{z}, v) = 1 \;\forall\, (\mathbf{z}, v)$ and set prices at

$B$ instead of $B \cdot \tau(\mathbf{z}, v)$.[9]

Figure 1a illustrates the welfare loss from this form of pricing. Consider the economy described by the solid social WTP curve. Optimal uniform pricing leads to welfare gains in triangle ABC, while pricing at $B$ yields welfare losses from triangle BFG. If the area of triangle BFG is larger than the area of triangle ABC, the existence of an incorrectly-priced incentive scheme can reduce welfare.

**Welfare losses from uniform pricing** Even if a regulator knows the distribution of treatment effects, it may be difficult to collect information and set differentiated prices based on $\mathbf{z}$. If there is heterogeneity in preferences to participate or compliance or enrollment costs, uniform pricing will lead to welfare loss, as illustrated in Figure 1c.[10]

**Menu design** The discussion thus far has ignored the presence of higher-quality "top-up" action choices on top of land retirement. Now, we return to our richer cost distribution, $\theta_i = (v_i, \kappa_i)$. The welfare implications of introducing "top-up" actions are two-fold. First, they add socially productive value — the social benefit of an a acre of forest might be higher than an acre of fallow land with grasses (captured by $B^j$ in Equation (7)). Second, prices for different actions can be used as additional instruments to separate "good types" with high $B \cdot \tau(\mathbf{z}, \theta)$ from "bad types" with the same base cost $v_i$, if the costs of providing top-up actions are correlated with $\tau(\mathbf{z}, \theta)$. The choice of the vector of action prices in (8) is a multi-dimensional screening problem without intuitive expressions like Proposition 1. In Appendix A, we discuss the mechanics of these screening actions with an illustrative example.

The prospect of using a menu of contracts to select types in environmental payment settings is an influential idea (Jack and Jayachandran, 2019), particularly if observable characteristics that influence $\tau(\mathbf{z}, \theta)$ are difficult to collect or learn about. However, this tool's promise is ultimately an empirical question that depends on the distributions of marginal treatment effects $\tau(\mathbf{z}, \theta)$ and costs $\theta$.

## 2.3 Adverse selection in offset markets

We now turn to the second market structure in which PES contracts are supplied: competitive offset markets. In offset markets, buyers, instead of a regulator, seek to purchase the

[9] Even if program designers acknowledge the existence of some individuals for whom $\tau(\mathbf{z}, v) \neq 1$, they may still price at $B$ if they invoke the simplifying assumptions on the relationship between costs and treatment effects described in Proposition 1 Part 2 and illustrated in Figure 1b.

[10] This idea of heterogeneity in treatment-effect type conditional on cost type is related to the idea of cost-type-heterogeneity condition on preferences in insurance markets (Bundorf et al., 2012).

gross surplus of environmental services produced by landowners. We assume for simplicity and expositional ease that private and social valuations of this surplus align, i.e. that there exists a mass of uniform price-taking buyers, each willing to pay $B \cdot \tau(\mathbf{z}_i, \theta_i) + B^j$ for $i$ to undertake action $j$ under complete information. We maintain the assumption that buyers have rational expectations about $\tau(\mathbf{z}, \theta)$ — recent evidence shows that there is demand for "additionality" in offset schemes (Conte and Kotchen, 2010; Rodemeier, 2023) — though realistic departures from this benchmark, via miscalibrated $\tau(\mathbf{z}, \theta)$, can have additional welfare impacts, as in the regulator's case.

Although offset buyers and the social planner value the gross surplus of each action under complete information identically, the same friction that makes policy design from a regulator's standpoint non-trivial, imperfect information about $\tau(\mathbf{z}, \theta)$, can generate additional welfare loss in a decentralized offset market equilibrium, as illustrated in Proposition 2.

**Proposition 2.** *(Offset Market Equilibrium) In a perfectly competitive offset market, in which price-taking buyers know the distribution of $\tau(\mathbf{z}, \theta)$ but not each individual $\theta_i$:*

1. *WTP for a contract $j$ from a landowner with characteristics $\mathbf{z}$ is*

$$\mathbb{E}[B \cdot \tau(\mathbf{z}, \theta) + B^j | D^j(\mathbf{p_z}; \mathbf{z}, \theta) = 1] \tag{11}$$

2. *The equilibrium price vector $\mathbf{p_z}$ is determined by the following condition:*

$$p_z^j = \mathbb{E}[B \cdot \tau(\mathbf{z}, \theta) + B^j | D^j(\mathbf{p_z}; \mathbf{z}, \theta) = 1] \tag{12}$$

   *for each contract $j$.*

3. *If private costs are correlated with potential outcomes, socially optimal and competitive prices can diverge.*

*Proof.* See Appendix A. □

The key idea of Proposition 2 is that the possibility of any selection into trade via the dependence of $\tau(\mathbf{z}, \theta)$ on private costs $\theta$ generates a welfare loss from adverse selection (Akerlof, 1970). Buyers demand the expected value of offsets supplied, so equilibrium prices are determined by the *average* treatment effect (the ATE) among landowners in the market, conditional on $\mathbf{z}$, instead of the treatment effect of the *marginal* landowner (the MTE), which yields the socially optimal allocation.

Figure 1d illustrates this welfare loss, following the graphical analysis of Einav et al. (2010) and Einav and Finkelstein (2011) for the simple case of only the base contract. In the adversely selected market illustrated in Figure 1d, the private WTP curve, which depends on the ATE for each $v < p$ (Equation (11)), has a shallower slope than the upwards-sloping social WTP curve, which depends on the MTE at each point $p = v$. The competitive equilibrium price, where the private WTP curve intersects the supply curve is lower than the socially optimal price, resulting in a welfare loss of triangle DEB of efficient conservation that does not occur due to adverse selection. As in any other selection market, a regulator could achieve the efficient outcomes by subsidizing (or, if there is advantageous selection, taxing) offset contracts.

Proposition 2 highlights why concerns about additionality are particularly prevalent in decentralized offset markets. Private information about $\tau(\mathbf{z_i}, \theta_i)$, even when buyers have rational expectations about its distribution, generates additional welfare losses from adverse selection that can be so extreme as to completely unravel a market, as illustrated in Figure A.1. A key empirical question is whether offset markets are or will remain small because of adverse selection, and the scope for policy to efficiently expand the market.

In a decentralized offset market, the welfare effects of differentiated versus uniform pricing are no longer straightforward, as it was in the regulator's problem. Absent corrective subsidies, setting differentiated prices based on $\mathbf{z}$ can either restore the first-best outcome if there is no residual private information conditional on $\mathbf{z}$, or reduce welfare if the pooled equilibrium is more efficient than a separating one.[11]

## 2.4 Empirical questions

The welfare effects of any incentive scheme depend on the extent to which $\tau(\mathbf{z}, \theta)$ can be priced or separated via a menu of contracts and the relationship between $\tau(\mathbf{z}, \theta)$ and unobservables $\theta$. The goal of our empirical analysis is to assess these welfare effects and the scope for alternative market or policy designs to ameliorate welfare losses. To do so, we must estimate the joint distribution of costs $\theta = (v, \kappa)$ and marginal treatment effects $\tau(\mathbf{z}, \theta)$ that determine equilibrium outcomes and social welfare.

[11] This is the case because the pooled welfare loss triangle CDE in Figure 1a need not be smaller than the weighted welfare loss triangles conditional on $\mathbf{z}$ (Einav and Finkelstein, 2011).

# 3 Empirical Setting and Data

## 3.1 The Conservation Reserve Program

Our empirical setting is the Conservation Reserve Program (CRP), a Payments for Ecosystem Services (PES) scheme incentivizing conservation on agricultural land administered by the United States Department of Agriculture (USDA). Established in 1985, the CRP pays landowners approximately two billion dollars per year to retire highly erodible and other environmentally sensitive cropland and adopt additional conservation activities for a contract duration of 10-15 years. The structure of the CRP and its incentivized activities are similar to other government financed PES schemes,[12] to offset contracts traded in voluntary markets,[13] and most specifically, to a burgeoning private agricultural offset market in the US.[14] There is substantial policy interest in growing this market – the Growing Climate Solutions Act of 2021 included provisions for the creation of a USDA-regulated agricultural offset market, in which CRP-style contracts would be traded by private actors.[15]

Under the CRP's General Enrollment mechanism, eligible landowners bid for contracts in a discriminatory, asymmetric, scoring auction.[16] Bids are scored according to a known scoring rule, the Environmental Benefits Index (EBI), that awards landowners points for the level of environmental sensitivity — based on erodibility, importance for habitats, potential for water pollution, and carbon sequestration potential — of their land, for the quality of the actions they choose to provide, and for a bid rental rate that they would be willing to accept to retire their land and adopt the bid actions. These actions include planting specific grass mixes, planting specific trees, and establishing or restoring pollinator or rare habitats. Rental rates are subject to a bid cap (the Soil Rental Rate) based on the average land rental rate in the county and soil productivity estimates.

The aggregate acreage enrolled in an auction is determined by Congress in the Farm Bill which in turn determines the threshold score to be accepted in the program. All bidders

[12] China's Sloping Land Conversion Program and the U.K.'s Environmental Stewardship Program are notable examples. See citations in (Kinzig et al., 2011).

[13] Over 50% of contracts traded in voluntary offset markets are land use and management contracts. See `https://gspp.berkeley.edu/research-and-impact/centers/cepp/projects/berkeley-carbon-trading-project/offsets-database` for more details.

[14] As of 2021, at least 10 companies had established platforms for the trade of agricultural offset contracts(Stubbs et al., 2014)

[15] See `https://www.congress.gov/bill/117th-congress/senate-bill/1251` for more details.

[16] In addition to the General Enrollment mechanism, the CRP also has a posted-price Continuous Enrollment mechanism for highly targeted lands and environmental benefits, including wetlands restoration. The General Enrollment mechanism accounts for approximately 75 percent of the land enrolled in the CRP (Hellerstein, 2017).

with scores above the threshold score are accepted into the CRP with a contract equal to their bid rental rate and action choice.[17] The uncertain acreage threshold, in combination with with uncertainty over opposing bidders' characteristics, makes the threshold score ex-ante uncertain to bidders. Bids are prepared with the assistance of staff at Farm Services Agency county offices, who helps participants understand the win probabilities with different action-bid combinations.[18]

These auctions, called sign-ups, occur once every 1-4 years. Landowners are eligible to bid if they meet erosion standards, are in a national or state conservation priority area, and either had cropped at least four years in a 5-10 year window preceding the sign-up or are re-enrolling CRP land. Bidders face steep penalties — refunding all payments since enrollment plus a 25-percent penalty — if they exit early or fail to comply with the rules of the program.[19]

Research quantifying the value of the CRP has documented improvements in wildlife habitat, erosion control, water quality, and carbon sequestration from cropland retirement (Allen and Vandever, 2012; Hansen, 2007; Hellerstein, 2017; FAPRI-MU, 2007; Johnson et al., 2016). However, these analyses are typically conducted using models that ignore counterfactual land use. In research, policy, and cost-benefit analyses of the CRP, it is assumed that all land would crop in the absence of the program. Because the primary environmental gains from the CRP accrue by avoiding the harmful environmental effects of row-crop agriculture, the fact that some landowners might conserve in the absence of the program presents the core additionality concern in this setting.

## 3.2 Data

The key feature of our dataset is that we are able to links bids from the CRP enrollment mechanism to land use outcomes $Y_i$.

**Data on bids, contracts, and the scoring rule** We obtain data on all components of the bid, including the bid rental rate — the amount a landowner will be paid, per acre, per year, if she wins — her chosen conservation action, and the exogenous characteristics of the land that impact the score. Our data cover all 8 auctions that occurred from 2009 to 2021.

[17]There is an additional constraint that no more than 25% of any county's total acreage can be enrolled in the CRP, but this essentially never binds.

[18]There is one category worth only few points that is determined only after all bids are submitted, but the rule has remained almost constant over our study period, so we consider it as known.

[19]The USDA has occasionally allowed for voluntary contract extensions or automatic re-enrollment, most notably between 2007 and 2011 . No such initiatives were implemented during our main period of study.

Each bidder owns a collection of fields, delineated by Common Land Units, defined as the smallest geographic unit with a common land use. When bidders participate in the CRP, they typically enroll only a subset of their total fields. Our bid data include the identity and geolocation of the bidder for all auctions, as well as for specific bid fields for the 2016 auction.

In addition to the bids submitted, we use the Environmental Benefits Index (EBI) Fact Sheets for each year's sign-up to construct the scoring rule. We also obtain data on all CRP contracts to validate that winning bidders enroll and losing bidders do not.

**Data on land use outcomes** We use the tract and field identifiers and geolocations of bidders to link bids, and for the purposes of comparison, agricultural non-bidders, to a panel of land use outcomes. The primary land use outcome of interest is whether land is cropped versus retired, as this is the behavior incentivized by the CRP. We make use of three complementary datasets.

Our primary dataset is the Cropland Data Layer (CDL), a remote-sensing product from the National Agricultural Statistics Service (NASS). The CDL provides land cover classifications, including over 50 crop and 20 non-crop classifications, at 30m by 30m resolution (roughly a quarter acre) from 2009-2020. The CDL is more accurate when differentiating across aggregate categories (crop versus non-crop) than more narrow categories and is more accurate at categorizing row-crop agriculture (corn, soybeans, etc.) than other crops. For our main outcome of interest — crop versus non-crop — the CDL has been been shown to be extremely accurate at a nation-wide scale (Lark et al., 2021), though as in other satellite-derived products, non-classical measurement error can generate biases in assessing land-use change (Torchiana et al., 2022; Alix-Garcia and Millimet, 2022). Appendix B discusses measurement error in the CDL in more detail.

Our second land use dataset is field-level administrative data on land use that all agricultural landowners report to the USDA in "Form 578" for 2013-2019. These data are highly accurate and comprehensive for cropped land because crop insurance payouts are dependent on these reports. The primary strength of the Form 578 data relative to the CDL is that it is not subject to non-classical measurement error; indeed, it is part of the "ground truth" on which the CDL is trained.[20] The two weakness of the Form 578 data are that (1) all landowners in the CRP are mechanically coded as enrolled in the CRP, making it difficult to confirm compliance when enrolled, and (2) non-crop land-use outcomes, for example, natural

[20] See CDL metadata here: https://www.nass.usda.gov/Research_and_Science/Cropland/metadata/meta.php

vegetation or grassland classifications, are much more limited. Due to the complementary strengths between these two datasets, we will use the CDL and Form 578 data together throughout the paper.

Our final land-use dataset is a completely un-processed collection of high-resolution satellite imagery (0.6m to 1m) of CRP-enrolled land collected under the National Agriculture Imagery Program (NAIP) from 2017-2021. We use these to observe fields' compliance with CRP rules.

While highly accurate in assessing agricultural land use and retirement — the main incentivized activity of the CRP — these datasets cannot convincingly differentiate among the different conservation "top-up" actions incentivized by the program, e.g. native (versus non-native) grasses and trees, or pollinator habitats. This is one reason that, as discussed in Section 2, we assume these actions are not provided absent the program, and that there is perfect compliance with undertaking the actions.

**Summary statistics** Table 1 presents summary statistics for the bidding tracts in our sample, the specific bid fields, and for all agricultural tracts in the US, which includes both tracts that are eligible and ineligible for the CRP. Panel A presents land use outcomes in the year prior to bidding, using both the satellite (CDL) and administrative (Form 578) data. Approximately 21% of bidding tracts are cropped prior to bidding (15-18% on bid fields), compared to approximately 30% nation-wide, with the majority of the remainder accounted for by natural vegetation and grassland. Corn and soybeans cultivation account for two-thirds of all cropping. Our satellite and administrative measures of land use generally align, but do not match exactly. Of course, bidders are not incentivized to report land that is in natural vegetation or grassland to the USDA, so we only obtain this outcome from the CDL.

Panel A already provides evidence suggestive of a correlation between costs, based on bidders' willingness to select into bidding, and marginal treatment effects, as CRP-bidding tracts and fields are less likely to be counterfactually cropped than the average tract. These patterns of selection are also reflected in the difference between estimated soil productivities (Panel B), which are constructed based on the composition of soil types on each tract.

CRP tracts are approximately 250 acres, larger than the average tract (160 acres) and are positively selected on environmental sensitivity, as measured by the Environmental Benefits Index (EBI), which denotes the points awarded for land-based characteristics in the mechanism's scoring rule. This is likely driven in part by positive selection, and in part by eligibility requirements that columns (1) and (2) are not conditioning on.

The average bidder in our sample offers 84.1 acres into the CRP (33% of the total tract) for a rental rate per acre per year of $83. Almost two-thirds of bidders offer one of a menu of grassland-planting related categories, 20% choose a wildlife habitat option, and 10% choose a tree-planting option. As the CRP is one of the oldest PES programs in the world, 70% of bidders are re-enrolling after their initial 10-year contract expired.[21] 80% of bidders are accepted across the sign-ups in our sample, with the average sign-up including 36,763 bidders.

# 4 Regression Discontinuity Evidence on Additionality

As highlighted by our conceptual framework in Section 2, the treatment effect of the CRP on land use — or the additionality of the incentive — is a crucial input into market design and welfare analysis. Despite the importance of estimates of additionality to both the evaluation and design of environmental markets, credible evidence on this policy parameter, particularly for large-scale, mature markets, is scarce. This is due to the fundamental challenge of identifying research designs to credibly estimate a counterfactual.

In this section, we make progress on this challenge by leveraging the sharp discontinuity in CRP acceptance and payment at the winning score threshold, $\underline{S}$, to evaluate the treatment effect of the CRP for the marginal bidder in a regression discontinuity (RD) design. We then compare the magnitude of the treatment effect to the magnitude of enrolled (and compensated) land to compute an estimate of additionality on the margin. In the notation of our framework in Section 2, we will estimate the magnitude of $\tau(\mathbf{z}, \theta)$ at the point $S = \underline{S}$.

**Empirical strategy** Our RD specification pools all auctions in our sample, normalizes each bidder's score relative to that auction's acceptance threshold, and evaluates how incentivized land use outcomes differ around this threshold. Our main outcome of interest is whether land is cropped or retired, the primary incentivized activity of the CRP ($Y_i$ in the notation of Section 2).

Our main specification takes advantage of the panel nature of our dataset and estimates the following estimating equation, for bidder $i$, in auction $s$, and year relative to auction $r$:

$$y_{ist} = \sum_r \beta_r \cdot 1\{S_{is} \geq \underline{S_s}\} \cdot 1\{r' = r\} + f_r(S_{is} - \underline{S_s}) + \epsilon_{ist} \tag{13}$$

where $\beta_r$ are the dynamic RD coefficients of interest, and $f_r(S_{is} - \underline{S_s})$ are relative-year-specific flexible functions. In our baseline specification, we set $f_r(S_{is} - \underline{S_s})$ as local-linear regressions in the MSE-optimal bandwidth (Calonico et al., 2014). We also estimate and provide corresponding RD figures for the following pooled specification:

[21] Re-enrolling bidders are treated identically to new bidders by the scoring rule.

$$y_{isr} = \beta_{r\leq 0} \cdot 1\{S_{is} \geq \underline{S_s}\} + \beta_{r>0} \cdot 1\{S_{is} \geq \underline{S_s}\} + f_{r\leq 0}(S_{is} - \underline{S_s}) + f_{r>0}(S_{is} - \underline{S_s}) + \epsilon_{ist} \quad (14)$$

with $\beta_{r\leq 0}$ providing a test of validity, as there should be no discontinuity at the threshold before enrollment, and $\beta_{r>0}$ providing an estimate of the pooled treatment effect.

We estimate Equations (13) and (14) at the bidder level. This allows for the possibility of spillovers across fields that are offered into the CRP and other, non-offered fields, as bidders typically only offer a subset of all of their land into the CRP mechanism. We cluster standard errors at the bidder level.

**Validity** The validity of the RD design hinges on randomness in the *ex-post* location of the winning score threshold. Specifically, we assume that while bidders possess information *ex-ante* about the distribution of the threshold, which they use to construct their bids, they do not know the threshold's precise location and choose to locate just above it. Testing this assumption translates to standard smoothness and manipulation tests for RD analyses. If (certain) bidders are able to predict the exact location of the score threshold, then we would observe bunching in the distribution of scores. We may also observe differences in land use before the auction that reflect bidders sorting around the threshold.

Figure 2 presents a histogram of the score distribution normalized to the acceptance threshold, $S_{is} - \underline{S_s}$, or the running variable of the RD. Bidders with positive values are accepted, and bidders with negative values are rejected. Figure 2 confirms the lack of bunching at the threshold. In Figure 3a, we present our pooled (across years and auctions) RD plot on *pre-period* land-use, i.e. we plot the raw data and fit parameters from Equation (14), restricted to only $r \leq 0$. We see no evidence of differential land use at the discontinuity before the auction, providing further support for the validity of our RD design.

The second assumption necessary for interpretation of Equations (13) and (14) is that that being above the score threshold is highly predictive of receiving a CRP contract, relative to being below the score threshold, i.e. we require an estimate of the magnitude of the first stage. Figure 3b plots the share of bidders with a CRP contract after the auction around the threshold, $S_{is} - \underline{S_s}$, estimating Equation (14) for $r > 0$, and demonstrates a first stage close to one. Based on Figure 3b, we will interpret the RD coefficients in Equations (13) and (14) as reflecting the impact of receiving a CRP contract.

**Results** Figures 4 and 5 and Table 2 present results.

Figure 4a presents raw data and fit parameters corresponding to the treatment effect of the CRP, estimating Equation (14) for $r > 0$. As the CRP's primary goal is to incentivize agricultural land retirement, our outcome of interest is the share of each bidder's land that is cropped. The discontinuity in land use outcomes – winning fields crop 8% less of their land – rejects the null hypothesis of no treatment effect of the program ($\tau = 0$). This land is instead put into natural vegetation and grassland (trees, shrubs, wetlands and grasses), as incentivized by the CRP (Figure 4b). Because we present estimates at the bidder level, cropping outcomes do not go to zero for winners, who typically only enroll a subset of their land into the CRP. These effects therefore could in theory be comprised of changes in activities on both offered and non-offered fields. These clear treatment effects reject the most pessimistic views of environmental markets: that no participants change behavior, leading to no scope for welfare gains from incentivizing the provision of environmental services.

We next turn to our estimates of additionality. To achieve this, we estimate our main dynamic RD specification in Equation (13) and present coefficient estimates in Figure 5. We present estimates using both the satellite-based data (used in Figures 3a and 4) and the administrative data to ensure that results are not driven by the limitations associated with either dataset. We also include on the graph a $\tau = 1$, or "full additionality" benchmark. This is calculated as the share of each marginal bidder's land that is offered into the CRP. If the CRP induced 100% of bidders to change land use completely — the definition of a full additionality benchmark — we would observe treatment effects equivalent to the $\tau = 1$ line on Figure 5. Dashed lines indicate the 10-year average of the $\beta_r$ coefficient estimates — reflecting the full contract duration — for both the satellite and administrative datasets.

Four facts emerge from the estimates presented in Figure 5. First, in line with the pre-period placebo test in Figure 3a, we see no effects at the discontinuity before the auction. Because Figure 5 is a year-by-year RD, pre-period effects are identified in levels and in trends and are zero in both. Second, encouragingly, post-period effect sizes and time-trends are similar using both datasets, confirming that our results are not driven by either non-classical measurement error in the satellite data or mis-reporting in the administrative data (see the discussion in Section 3.2). Third, while treatment effects grow in the first few years, reflecting land in transition, treatment effects are fairly constant over the ten year contract period, reflecting the fact that opportunities to rebid — which would cause treatment effects to decrease over time — are not driving down the average treatment effects in the pooled RD figures. Indeed, we see little evidence of substantial rebidding at all: Appendix Figure C.3 plots the hazard rate of rebidding following an failed initial bid: even five years following the initial bid, after which bidders have had multiple opportunities to rebid, only approximately 20% of losers have rebid and fewer than 15% have won.

Finally, our main result from Figure 5 is that over the 10-year contract, the magnitude of the effect size is substantially less than the $\tau = 1$ full additionality benchmark. Figure 5 demonstrates that approximately 27% of bidders are additional, or conversely, that 73% of bidders are non-additional, or do not generate value from land retirement upon contracting. This highlights that non-additionality does indeed pose a potentially severe challenge to the performance and design of environmental markets.

Our estimate of 27% additionality has clear welfare and policy implications in the context of the conceptual framework presented in Section 2. First, the social WTP curve must be deflated substantially — setting incentives based on $B$ alone could lead to inefficient selection and welfare loss, substantiating the controversy and debates surrounding additionality in environmental markets.

A second, more subtle implication of our result of 27% additionality at the margin of acceptance, is that costs and behavior cannot be summarized by a simple one-dimensional index, in which bidders with positive costs of conservation are additional, and bidders with negative costs of conservation — and therefore zero costs of enrolling in the CRP — are non-additional, as illustrated in Figure 1b.[22] Under this simple model, at the margin, additionality should be either zero, if the threshold hits the part of the bid distribution where costs of enrolling in the CRP are zero, or one, if the threshold instead falls in the part of the bid distribution where costs are positive. The fact that we observe robust evidence of an interior measure of additionality — 27% — is illustrative of a more complex relationship between costs and potential outcomes. This interior estimate of additionality could be due to multiple dimensions of private costs, e.g. costs related to both cropping profitability and to hassle costs of or preferences for participating in the CRP, as highlighted in other markets for ecosystem services (Jack and Jayachandran, 2019). This underscores the possibility of inefficient selection and the necessity of setting differentiated incentives based on $\tau(\mathbf{z}, \theta)$. It will also motivate our flexible modeling approach in Section 6.

Table 2 summarizes results from Figures 3, 4, and 5, presenting estimates for the pooled (Equation (14)) specifications in both datasets for our primary outcome of interest, $Y_i$, or whether the land is cropped (Panel A), as well as other land use outcomes (Panel B), e.g. specific crops, fallow land, and conserved land in natural vegetation and grasslands. Appendix Figures C.1 and C.2 present additional corresponding RD figures.

[22]Technically, because there exist bidder characteristics (asymmetry) and additional action choices that shift the score, and because we pooled sign-ups with different thresholds, the RD results in Figure 4 and Table 2 could be estimating a mixture of purely marginal ($\tau = 0$) and purely inframarginal ($\tau = 1$) types. We rule this out in Appendix Table C.1, which presents RD estimates split by the location of the threshold — parameterized by the amount a bidder would need to bid for the base contract to achieve $\underline{S}$ — and finds that $0 < \tau < 1$ across groups.

**Mechanisms: leakage and non-compliance** We argue that our estimates are driven by unobserved differences in potential outcomes specifically on the land offered into the mechanism. In Panel C of Table 2 (and Appendix Figures C.1d and C.2d), we document the absence of any positive or negative spillovers onto non-offered fields on bidding tracts. This could occur either via a leakage mechanism, by which landowners reduce cropping substantially on offered fields but increase it on other fields, or if there are complementarities to cropping multiple fields such that retiring some fields makes it less likely to crop others. We see no evidence of either of these hypotheses.[23]

In theory, the lack of additionality could be two-sided, driven by both conservation without a CRP contract and cropping with a CRP contract (non-compliance). We assess the CRP's compliance regime by systematically inspecting ultra-high resolution (0.6-1m) aerial photographs of over 1,000 enrolled fields.[24] We chose to use aerial photographs instead of either the processed satellite imagery or the administrative data because measurement error in the satellite data will mechanically bias toward finding non-compliance, and the administrative data will never record non-compliance as participants will never be incentivized to report rule-breaking. As described in more detail in Appendix F, we find no evidence of non-compliance.

Together, these two results — no leakage, and no non-compliance — highlight that the substantial non-additionality documented in Figure 5 is driven by unobserved differences in counterfactual land use, absent a CRP contract, among offered fields. This means that, for rejected bidders, we can "read off" each bidder's additionality by observing their land use decisions following the auction. We leverage this observation in the next section.

# 5 Testing for Adverse Selection

Section 4 provided clear evidence that concerns over additionality are warranted in this setting and likely complicate the design of environmental markets. The RD analysis in Section 4 investigated additionality at one point in the distribution. However, a key insight of Section 2 is that additionality may vary across bidders, based on either observable characteristics or unobserved costs. This creates both challenges for the performance of markets, if bidders

[23]The lack of evidence of increased cropping on non-enrolled fields is in contrast to evidence of so-called "slippage" effects in earlier periods, such as Wu (2000)'s analysis of the CRP in the 1990s. Relative to Wu (2000)'s analysis, we focus on spillovers at the bidder level, as opposed to cross-sectional regressions across regions based on total CRP enrollment.

[24]Specifically, we hired two MIT undergraduate research assistants to blindly classify high resolution images of both CRP fields and a set of non-CRP (cropped) fields.

possess private information about additionality that can lead to adverse selection, and opportunities, if incentives can be differentiated based on observable predictors of treatment effects or if contract features can be used to screen additional types via menu design. The key point in Section 2 is that in the presence of non-additionality, environmental markets are — potentially — selection markets. In this section, we test for this possibility of selection directly.

**Empirical strategy** We leverage the results of Section 4, which demonstrated a lack of leakage, and our validation of the compliance regime, to obtain $i-$specific measures of additionality among all losing bidders. Combining $i-$specific measures additionality with the rich choice set of the auction environment, in which we observe an $i-$specific bid, allows for an unusually rich environment to test for the existence of asymmetric information about additionality and the nature of the relationship between costs — which govern selection — and additionality — which governs value to a buyer.

We examine selection using a test inspired by the positive correlation test (Chiappori and Salanie, 2000) applied to our auction setting. Specifically, we estimate versions of the following regression specification:

$$y_i = \beta \cdot \mathbf{b_i} + \pi \cdot \mathbf{z_i} + f\left(\mathbf{z_i^t}\right) + \epsilon_i \tag{15}$$

where $y_i$ is a measure of $i$'s additionality, or the share of $i$'s bid fields that are cropped, observed only conditional on being rejected by the auction, $\mathbf{b}_i$ represents characteristics of $i$'s bid, either the bid amount, or the bid action from the menu of possible contracts, $f\left(\mathbf{z_i^t}\right)$ are flexible controls for characteristics that enter the scoring rule, and $\mathbf{z}_i$ are characteristics that may be predictive of additionality but that are not included in the status quo scoring rule. A positive correlation between bids and additionality is indicative of adverse selection.[25]

We estimate Equation (15) in the one auction in which we observe the exact fields offered into the CRP (the 2016 auction). This allows us to directly read off estimates of additionality from land use outcomes among rejected bidders. This auction is also the most restrictive auction in our data. We observe $y_i$ for 82% of bidders.

**Results** First, Figure 6a presents a binned scatterplot of the correlation between additionality and bid amount, or the dollar amount requested per acre per year, residualized

[25] Often tests of adverse selection of this form are confounded by moral hazard, but the absence of moral hazard in my setting makes the relationship between bids and additionality more easily interpretable as pure adverse selection.

of characteristics that are "priced" as asymmetries in the scoring rule. Figure 6a demonstrates a striking positive relationship between higher bids — reflective of higher costs — and additionality. Figure 6a illustrates that higher cost bidders have higher costs in part because of their private information about land use in the absence of the CRP contract. The results in Figure 6a provide clear evidence of the challenge of market design in the presence of non-additionality: the market can be adversely selected.

Figure 6b takes the analysis in Figure 6a one step further and shows that bids remain correlated with additionality even conditional on information that *could be*, but is not currently, priced on, namely prior land use decisions interacted with estimates of the soil productivity of the offered land. The extent of the relationship is weaker, but Figure 6b documents the possibility of adverse selection even conditional on a rich set of characteristics.

Figure 6c leverages the fact that in the rich CRP auction environment, bidders are not only bidding a single bid amount, but rather bidding on a menu of contracts, each incentivizing a different conservation activity. Figure 6c tests for selection on actions, or contract features, by replacing $\mathbf{b_i}$ with a vector of chosen action indicators. The most striking feature of Figure 6c is the strong evidence of adverse selection on tree-planting contracts, relative to the base category of introduced grasses. Selection on action costs presents both challenges and opportunities. The challenge is that certain contracts may be highly adversely selected, making it difficult for a regulator to offer these contracts or prevent trade from unravelling in decentralized offset markets. The opportunity is that these heterogeneous action costs can provide information to better differentiate, and induce favorable selection, among additional and non-additional types.

Finally, Figure 6d turns from testing for heterogeneity across unobservables to heterogeneity that can be captured by observable characteristics. Figure 6d plots the relative additionality by decile of predicted soil productivity, conditional on $f(\mathbf{z_i^t})$ but excluding any endogenous bid choices from the regression specification. These estimates of soil productivity are collected by the USDA and are designed to approximate the amount that a landowner would be able to earn on a given parcel of land. These characteristics serve as ideal predictors of additionality in theory, and in practice, we see in Figure 6d that this characteristic is strongly predictive of additionality, though it is not currently incorporated into the scoring rule. Figure 6d highlights the promise of improving welfare by differentiating across types using highly predictive observable characteristics.

**Discussion** The results in Figure 6 document substantial heterogeneity in additionality across (multiple dimensions of) unobserved costs, the potential for adverse selection, and the promise of leveraging observable characteristics to set differentiated incentives for more additional types. In order to quantify the welfare effects of the status quo or alternative market designs, we must move beyond testing and specify a joint model of costs, which governs choices, and potential outcomes, which governs additionality and therefore the social value of contracting.

# 6 A Model of Bidding and Potential Outcomes

In this section, we build on Asker and Cantillon (2008) to develop a model of optimal bidding in response to the rules of the CRP scoring auction. Choices of actions and scores allow us to estimate the population distribution of costs, or $(v, \kappa)$, by revealed preference. We then use our linked land-use data to estimate the distribution of treatment effects $\tau(\mathbf{z}, \theta)$ as a function of observable characteristics and unobserved costs. Finally, we monetize the value of land retirement and top-up actions using social preferences implied by the scoring rule and estimates of the social value of CRP-incentivized activities from the literature.

## 6.1 Supply: a model of optimal bidding

Each bidder $i$ prepares a two-part bid $\mathbf{b_i} = (r_i, \mathbf{a_i})$. $\mathbf{a_i}$ is an action vector, chosen from a menu of actions, with $a_{ij} = 1$ if the $j$-th action is chosen and $a_{ij} = 0$ otherwise. $r_i$ is the rental rate (per acre, per year) a bidder is willing to accept to retire land for the duration of the 10-year contract and undertake the chosen action $\mathbf{a_i}$. Bidders make a single discrete choice among the menu of actions, so $\sum_j a_{ij} = 1$, and submit a single bid. If $i$ wins and enrolls, $\mathbf{b_i} = (r_i, \mathbf{a_i})$ describes the terms of her CRP contract.

Each bid $\mathbf{b_i}$ is converted into a score $S$ according to a known scoring rule that takes as arguments the bid $\mathbf{b_i}$ and exogenous characteristics $\mathbf{z_i^t}$, where $\mathbf{z_i^t}$ denotes the subset of observable characteristics that are incorporated into the scoring rule: $S = t\left(\mathbf{b_i}, \mathbf{z_i^t}\right)$. All bidders above a winning threshold score $\underline{S}$ are accepted into the program. Each bidder $i$ solves:

$$\mathbf{b_i^*} = \underset{(r,\mathbf{a})}{\operatorname{argmax}} \left\{ \underbrace{(r - v_i - \mathbf{a} \cdot \kappa_\mathbf{i})}_{\text{Payoff to } i \text{ conditional on bid } (r,\mathbf{a})} \times \underbrace{\left(\Pr\left\{t\left(\mathbf{b}, \mathbf{z_i^t}\right) \geq \underline{S}\right\}\right)}_{\text{Probability of } i \text{ winning with bid } (r,\mathbf{a})} \right\} \tag{16}$$

where a bidder chooses her optimal $\mathbf{b_i} = (r_i, \mathbf{a_i})$ that maximizes her payoff conditional on winning given her type $\theta_i = (v_i, \kappa_\mathbf{i})$, $r_i - v_i - \mathbf{a_i} \cdot \kappa_\mathbf{i}$, multiplied by the probability of winning given the scoring rule $t\left(\mathbf{b_i}, \mathbf{z_i^t}\right)$ and expectations about the location of the winning threshold $\underline{S}$.

We briefly note two assumptions in this formulation of the bidder's problem. First, we assume bidding is costless; we do not model a bid preparation cost or selection into bidding.[26] Second, we model bidding as static, reflecting the fact that the vast majority of bidders do not re-bid (see Figure C.3). In a dynamic framework, the cost parameters estimated from the formulation in (16) can be interpreted as *pseudo-costs* that are the result of mapping a dynamic program with sequential auctions into a static game (Jofre-Bonet and Pesendorfer, 2003).[27]

#### 6.1.1 Separability of the bidder's problem

Our formulation of the bidder's problem in (16) embeds a key result used in the analysis of scoring auctions (Asker and Cantillon, 2008; Bolotnyy and Vasserman, 2023): though bidder types and strategies are multi-dimensional, bidder scores are sufficient statistics for equilibrium behavior. This implies that optimal bid decisions can separated into two sub-problems, corresponding to the separable multiplicative structure of (16). For any score, a bidder must optimally choose the highest payoff $(r_i, \mathbf{a_i})$ bid satisfying $t\left((\mathbf{r_i}, \mathbf{a_i}), \mathbf{z_i^t}\right) = S$:

$$\mathbf{b}^*(S) = \arg\max_j \quad \underbrace{t^{-1}(S, \mathbf{a^j}, \mathbf{z_i^t})}_{\text{payoff for choosing action } j} - \underbrace{v_i}_{\text{base cost}} - \underbrace{\kappa_{ij}}_{\text{incremental cost of action } j} \tag{17}$$

where $t^{-1}(S, \mathbf{a^j}, \mathbf{z_i^t})$ is the inverse of the scoring rule at score $S$ when choosing action $j$ with characteristics $\mathbf{z_i^t}$. Define $\pi(S; \mathbf{z_i^t}, \theta) = \max_j t^{-1}(S, \mathbf{a^j}, \mathbf{z}_i^t) - v_i - \kappa_{ij}$ as the maximum payoff for $i$ associated with score $S$.

Then, given optimal $(r_i, \mathbf{a_i})$ component choices for every $S$, a bidder chooses a score given expectations over the probability of winning with a given score:

$$\max_S \pi(S; \mathbf{z_i^t}, \theta) \cdot \Pr\left\{t\left(\mathbf{b}^*(S), \mathbf{z_i^t}\right) \geq \underline{S}\right\} \tag{18}$$

[26]This is a simplifying assumption, as Hellerstein (2017) makes the point that many eligible landowners (as many as 90%) do not bid. We will assume that non-bidders are invariant to changes in the mechanism.

[27]Interpreting these cost parameters as pseudo-costs will require some nuance to how exactly we specify our counterfactuals. However, as noted in the main text, the fact that only a small share of bidders ultimately re-enroll makes us comfortable mapping a dynamic setting into a static game.

### 6.1.2 Sources of uncertainty

Each bidder faces uncertainty about whether or not she will win the auction with a given score $S$. We assume that $i$ does not observe either the number or the observable characteristics of her competitors. This assumption is consistent with the operation of the CRP, where bidding is decentralized and involves thousands of bidders across dozens of states. $i$ instead forms expectations about her probability of winning at any score $S$, $\Pr\{t(\mathbf{b}^*(S), \mathbf{z_i^t}) \geq \underline{S}\}$, based on expectations over uncertain realizations of two distributions. The first is expectations over $i$'s competitors, specifically the joint distribution of the scores, size (acres offered), and number of competing bidders. The second source of uncertainty is over the magnitude of the acreage limit determined by Congress in the Farm Bill, which governs the amount of acres accepted into the CRP. The acreage limit and the number and composition of bidders jointly determines the equilibrium winning score threshold $\underline{S}$. We assume that each bidder does not condition on her own characteristics (observed $\mathbf{z_i^t}$ or unobserved $\theta$) when forming expectations about the distribution of $\underline{S}$. Under these assumptions, all participants have the same information about the distribution of opposing scores and therefore the probability of winning at a given score, $G(S)$.

Because the number of bidders is large — the average auction in our sample has over 36,000 bidders — the uncertain acreage limit, which varies across years, is a key driver of randomness in $\underline{S}$. Appendix Figure E.1 provides empirical support for the assumption of quantity uncertainty: the distributions of submitted scores are essentially identical across sign-ups with large differences in acreage limits.

### 6.1.3 Identification

The revealed preference action-score combinations yield inequalities that generate identified sets containing the true population distribution of $(v, \kappa)$ given observable characteristics $\mathbf{z}$ (Agarwal et al., 2023). We obtain inequalities, rather than point-identification as in standard first-price auctions (Guerre et al., 2000), because of the discrete nature of the action choices. With a choice shifter, in this case, variation in the mechanism that shifts returns to actions, $t^{-1}(S, \mathbf{a^j}, \mathbf{z^t})$, these bounds can be tightened. In the limit, sufficient variation in $t^{-1}(S, \mathbf{a^j}, \mathbf{z^t})$ can be used to completely "trace out" the distribution of $(v, \kappa)$ and achieve point identification. In the following section, we develop an econometric model that uses the "inner" and "outer" optimal bidding conditions in equations (17) and (18) to estimate $\theta = (v, \kappa)$.

## 6.2 Econometric model for cost parameters

### 6.2.1 Constructing menus and payoffs implied by $t\left(\mathbf{b}(S), \mathbf{z_i^t}\right)$

We first specify the relative "prices" for each action $j$, for bidder $i$, at each score $S$, across the set of feasible action choices, $j \in \mathcal{J}_i(S)$. These relative prices are implicit in the scoring rule and generate a bidder- and score-specific menu, from which bidders make optimal action choices as specified in (17). Relative payoffs for different action-score combinations depend on $\mathbf{z_i^t}$ and constraints on bids (bid-caps at the top, and a non-negativity constraint at the bottom) which make some action choices infeasible for certain bidders at certain target scores. Thus, the menu of actions is $i$-specific.[28]

We construct the menus using the EBI Fact Sheets for each sign-up in our sample. These Fact Sheets are published by the USDA to provide potential bidders information about the relative returns to various actions: they delineate the points that accrue from unchangeable characteristics of the land, from action choices, and from reductions in the bid. We use these Fact Sheets to construct the $t^{-1}(S, \mathbf{a^j}, \mathbf{z_i^t})$ function and validate it in Appendix Figure D.2, which demonstrates that our construction of $t^{-1}(S, \mathbf{a^j}, \mathbf{z_i^t})$ predicts true $r_i$ at the chosen action and score with an $R^2$ of over 99%. Appendix D provides more detail about the scoring rule and our construction of $t^{-1}(S, \mathbf{a^j}, \mathbf{z_i^t})$.

Table 3 presents the menu of all possible actions available to bidders and their average "prices," based on $t^{-1}(S, \mathbf{a^j}, \mathbf{z_i^t})$, and market shares. Each bidder must choose one of the 36 actions listed in Table 3. These actions are divided into into 12 primary covers, in aggregate categories of grasses, trees, and habitat provision, which are provided on the entire parcel of land offered into the CRP, and three upgrade choices, no upgrade, establishing a wildlife food plot, and establishing a pollinator habitat, which cover a smaller area. Table 3 also presents the average rental rate required to achieve the threshold score $\underline{S}$ across each of the 36 action choices, or $\frac{1}{N}\sum_i t^{-1}(\underline{S}, \mathbf{a}, \mathbf{z_i^t})$, demonstrating how the mechanism trades off action choices and bid amounts.

[28] In the most straightforward scoring auction formats like the quasi-linear scoring auctions considered in Asker and Cantillon (2008), the optimal action choice is separable from the choice of target score.

#### 6.2.2 Parameterizing $\kappa_{ij}$

Based on the structure of the action menu, we parameterize the cost of choosing action $j$ for bidder $i$ with observable characteristics $\{z_i^k\}$ as follows:

$$\kappa_{ij} = \underbrace{\beta_{p(j),s} + \beta_{u(j),s}}_{\text{additive primary + upgrade costs}} + \underbrace{\sum_k \left(\alpha^k_{p(j)} z_i^k + \alpha^k_{u(j)} z_i^k\right)}_{\text{obs. cost heterogeneity}} + \underbrace{\epsilon_{ij}}_{\text{i.i.d. shock}} \tag{19}$$

We allow for separate mean costs for each of the twelve primary covers $p(j)$ and three upgrades $u(j)$ that can vary by sign-up $s$, but assume that these costs are additively separable. This rules out complementarities between doing certain base and upgrade actions, which could be accommodated in a richer specification. We allow for observable heterogeneity in each of these costs as mean cost shifters. In our baseline specification, we allow costs to vary according to the following observable characteristics $z_i^k$: prior CRP status, deciles of estimated soil productivity, bidder size, and by five USDA-delineated regions (West, Plains, Midwest, South, and Atlantic). Finally, we allow bidders to have an idiosyncratic cost shock, $\epsilon_{ij}$, which we assume is drawn from a Type 1 Extreme Value distribution with dispersion $\sigma$ that is common across bidders.

#### 6.2.3 Choice shifters

We make use of two policy experiments that change the payoffs to different actions and provide variation in $t^{-1}(S, \mathbf{a^j}, \mathbf{z_i^t})$. Without imposing any parametric assumptions, this variation narrows the bounds on the distribution of $\kappa_{ij}$ conditional on characteristics $\mathbf{z}$. With our parameterization, this variation helps estimate the dispersion of idiosyncratic action costs.

First, between the 2010 and 2011 sign-ups, points for bidders in Wildlife Priority Zones[29] changed from being unconditional (i.e. asymmetric points) to being conditional on choosing a subset of actions, generating variation over time and across WPZ and non-WPZ bidders in the relative returns to actions.

Second, in the 2021 sign-up, a mid-mechanism policy change occurred. After bids were initially collected, a policy change introducing Climate Smart Practice Incentives — additional action payments dependent on actions' carbon sequestration potential — were announced. Bids were re-collected, and we obtained data on the bids submitted in both the interim and final mechanisms, yielding variation in $t^{-1}(S, \mathbf{a^j}, \mathbf{z_i^t})$ across actions within the same bidder

[29]Wildlife Priority Zones, or WPZs, are determined by state governments to focus conservation efforts on habitats of certain species or certain environmentally sensitive land, like wetlands.

and for the same exact contract period. Figure 7 illustrates the variation induced by each of these policy changes in the relative returns to actions.

A useful feature of this unusual "re-bidding" policy experiment is that we can directly test that bidders are indeed competing on the quality of contracts offered. We observe that the *same bidder* changes her optimal action under the new scoring rule, for the same contract period, 8% of the time.

### 6.2.4 Estimation

Our estimation approach proceeds in two step.

**Step 1: Estimate** $G(S) = \Pr\{S \geq \underline{S}\}$ First, we estimate the win probability $G(S)$ by simulation, following Hortaçsu and McAdams (2010). We assume that bidders form expectations of win probabilities at each score consistent with (1) the joint distribution of the scores and sizes (acres offered) within a given sign-up, and (2) the number of bidders and the distribution of possible aggregate acreage amounts across sign-ups in our sample. We implement this by first fitting Beta distributions to the number of bidders and acreage limits observed in our data. For fitting this distribution, we use additional historic data on acreage thresholds and the numbers of bidders for all sign-ups starting in 2000. Then, we simulate each auction 1000 times, drawing numbers of bidders and acreage thresholds from our fit distributions, and re-sampling from the observed joint distribution of the scores and sizes of bidders within each sign-up. Appendix Figure E.2 plots our estimates of $G(S)$ for each sign-up.

**Step 2: Estimate the distribution of** $(v, \kappa)$ Given estimates of $G(S)$, we estimate $(\beta, \alpha, \sigma)$ and the distribution of $v_i$ by imposing the "inner" and "outer" optimality conditions in Equations (17) and (18). Specifically, we estimate $(\beta, \alpha, \sigma)$ by Maximum Likelihood at the equilibrium scores. This takes advantage of the fact that the optimal bid-action combinations must be optimally chosen for every score, including the equilibrium score. Then, conditional on $(\beta, \alpha, \sigma)$, we simulate a distribution of $v_i$ that rationalizes optimal score choices using the following first order condition, following Guerre et al. (2000):

$$v_i = t^{-1}(S, \mathbf{a^0}, \mathbf{z_i^t}) + \tilde{\pi}(S; \mathbf{z_i^t}, \kappa_i) + \frac{G(S)}{g(S)} \cdot \frac{d\tilde{\pi}(S; \mathbf{z_i^t}, \kappa_\mathbf{i})}{dS} \tag{20}$$

where $\tilde{\pi}(S; \mathbf{z_i^t}, \kappa_i) = \pi(S; \mathbf{z_i^t}, \theta) + v_i - t(S, \mathbf{a^0}, \mathbf{z_i^t})$, or the incremental payoff of optimally chosen $j$, relative to the base contract with $\kappa_{ij} = 0$,[30] and $g(S) = \frac{dG(S)}{dS}$, which we calculate via our simulation in Step 1.[31]

### 6.3 Estimating marginal treatment effects $\tau(\mathbf{z}, \theta)$ and social WTP

As highlighted in Section 2, in addition to $(v, \kappa)$, we require an estimate of the $\tau(\mathbf{z}, \theta)$ curve to relate additionality to costs. To obtain social WTP, we also require valuations of land retirement to appropriately value any change in behavior described by $\tau(\mathbf{z}, \theta)$, as well as the value of each of the conservation actions, $B^j$. We enrich social preferences relative to our simple framework in Section 2, allowing for heterogeneity in benefits based on observable characteristics that determine the environmental sensitivity of the land.

We estimate $\tau(\mathbf{z}, \theta)$ using the same patterns as in our reduced form analysis. We again leverage the two assumptions of no leakage and no non-compliance to obtain $i-$specific estimates of additionality. Armed with our model of bidding, we can now rationalize both the level of additionality — which we estimated in the RD — and relationship between bids and additionality among all rejected bidders, which we examined in Section 5.

The remaining challenge, is that even in our most restricted auction, $i-$specific estimates of additionality are masked for the 20% of bidders who win. Because we observe a selected distribution, $Y_{i0}$ for $S_i < \underline{S}$, we invoke a standard Heckman-style solution to arrive at the unselected distribution of $Y_{i0}$. We estimate a selection equation and an outcomes model jointly, with an exclusion restriction on characteristics entering the selection equation. Our selection equation incorporates all determinants of equilibrium choices of $S_i$: our estimates of $v_i$, observable determinants of $\kappa_{ij}$, and all bidder characteristics incorporated in the scoring rule, $\mathbf{z_i^t}$. We split $\mathbf{z_i^t}$ into two categories: $\mathbf{z_i^{t1}}$ are characteristics in the scoring rule that are allowed to influence $Y_{i0}$ and $\mathbf{z_i^{t2}}$ are characteristics that are excludable from $Y_{i0}$. $\mathbf{z_i^{-t}}$ are characteristics not included in the status quo scoring rule that may influence outcomes. The exclusion restriction that we impose is that decision to crop when not enrolled in the program is conditionally independent of characteristics $\mathbf{z_i^{t2}}$:

$$Y_{i0} \perp \mathbf{z_i^{t2}} \mid \left(\mathbf{z_i^{t1}}, \mathbf{z_i^{-t}}, \theta\right) \tag{21}$$

[30]This formulation is related to the idea of pseudo-types in Asker and Cantillon (2008), who show that the optimal action choice is separable from the score choice when the bid can be adjusted freely to reach any action-score combination. In our setting, we construct related objects while accounting for a more complicated menu of action-score combinations.

[31]We operationalize this via accept-reject sampling, i.e. we simulate $\kappa_{ij}$ draws, calculate the $v_i$ consistent with the chosen score, and keep only simulation draws where the optimal action matches the action observed in the data. In future drafts, we will estimate $(\beta, \alpha, \sigma)$, the distribution of $v_i$, and $\tau(\mathbf{z}, \theta)$ jointly via method of simulated moments.

We use as excluded instruments $\mathbf{z_i^{t2}}$ whether a bidder is in a wildlife priority zone and an air quality zone, as these characteristics are reasonably excluded from potential outcomes given a rich vector of characteristics including soil productivity, lagged land use outcomes, and estimated land retirement costs, $v_i$. Indeed, in a test motivated by Angrist and Rokkanen (2015), in Appendix Figure F.3, we show that after residualizing potential outcomes on $\left(\mathbf{z_i^{t1}}, \mathbf{z_i^{-t}}, \theta\right)$, the score is no longer predictive of potential outcomes $Y_{i0}$ among bidders with $S_i < \underline{S}$.

We estimate $\tau(\mathbf{z}, \theta)$ among offered fields in the sign-up with the lowest acceptance rate, 2016, and assume that the relationship we estimate is constant over time.

### 6.3.1 WTP for land retirement and conservation actions

The final object necessary to estimate willingness-to-pay for a given contract is the valuation (in dollars) of land retirement and the top-up conservation actions, given the probability that $i$ changes her behavior. Recall from Section 2 that, under perfect compliance and our assumption that actions are not provided absent the incentive payment, WTP for a contract with action $j$ is given by $B_{z^t} \cdot \tau(\mathbf{z}, \theta) + B^j_{z^t}$. We have now indexed $B_{\mathbf{z^t}}$ and $B^j_{\mathbf{z^t}}$ by $\mathbf{z^t}$, allowing benefits to vary across observable characteristics of the land that determine the land's environmental sensitivity, and therefore the social value of retiring the land and adopting certain conservation activities, already incorporated in the scoring rule.

We make two assumptions to yield valuations for $B_{\mathbf{z^t}}$ and $B^j_{\mathbf{z^t}}$. First, we assume that the scoring rule reflects the regulator's relative valuations across bidders and across actions, assuming $\tau(\mathbf{z}, \theta) = 1$, reflecting discussion on the development of the CRP scoring rule in Ribaudo et al. (2001). To pin down levels, we scale $B_{\mathbf{z^t}}$ and $B^j_{\mathbf{z^t}}$ such that overall benefits of enrolled lands match estimates from the literature quantifying the aggregate impact of the CRP, using simulation studies that again assume $\tau(\mathbf{z}, \theta) = 1$ (Johnson et al., 2016; Feather et al., 1999; Hansen, 2007). The exact valuation — and the degree to which the CRP's scoring rule aligns with estimates of social WTP for an acre of the different conservation actions — is not the focus of our paper. We simply use these estimates to scale $\tau(\mathbf{z}, \theta)$, which is our primary focus.

# 7 Parameter Estimates

## 7.1 Distribution of land retirement costs $v_i$

Figure 8a plots the estimated distribution of $v_i$ and highlights that most bidders have positive costs. This reflects the fact that enrollment into the CRP involves giving up the option value of cropping over ten years and other hassle costs of program administration. A large mass of bidders have costs below \$50 per acre, per year with a tail of bidders with much higher costs. We note the 19.6% of bidders with negative land retirement costs; these are bidders who choose costly action-score combinations even when they are almost certain to win, which can only be rationalized with negative $v_i$.

Consistent with the correlation between bids and additionality presented in Section 5, Figure 9a illustrates that $v_i$ correlates with cropping outcomes among losing bidders, where $Y_{i0}$ is observed.[32] Figure 9b demonstrates that this relationship between potential outcomes and land retirement costs is robust to accounting for selection.

## 7.2 Distribution of action costs $\kappa_{ij}$

Figure 8b presents a kernel density plot of our estimated distribution of $\kappa_{ij}$ across all bidders, auctions, and top-up actions (the pink dashed line), and for two example actions, a tree planting primary cover and a pollinator habitat upgrade. As Figure 8b demonstrates, the costs of top-up actions are dispersed across both bidders and and actions. Table 4 summarizes our estimates, averaged across all sign-ups in our data. For readability, we aggregate the primary cover categories into three aggregate categories, grasses, trees, and habitats, and present costs for trees and habitats relative to the grasses category. Estimated costs are similar in rank and in magnitude to administrative data on action costs submitted to the USDA (see Appendix E for more details).

Table 4 demonstrates substantial unobserved dispersion and observable heterogeneity in action costs. Former CRP bidders have generally similar costs to the overall population, but bidders on more productive farms (as measured by soil productivity) appear to also have a substantial productivity advantage at higher-point (trees, habitat) actions. However, it is not the case that bidders differ on a single dimensional "productivity" level shift: larger

[32] Estimates of $v_i$ are derived from bidding behavior *alone*; our estimation procedure imposes no relationship between outcomes and costs. Thus, in addition to providing descriptive support for the selection mechanism explored in Section 2, the intuitive patterns in Figure 9a suggest that our revealed preference estimates of $v_i$ capture real heterogeneity across bidders that influence land use outcomes.

tracts have higher costs for some actions, relative to average, and lower costs for others. Appendix Table E.2 tabulates in detail the parameter estimates for the primary covers and upgrades and illustrates substantial regional heterogeneity in costs as well.

Systematic heterogeneity in action costs suggest the possibility of screening using the conservation actions. However, this will only be quantitatively meaningful if $\tau(\mathbf{z}, \theta)$ varies substantially with $\kappa_{ij}$, otherwise, it will not be valuable to a designer to distort incentives away from $B^j_{\mathbf{z^t}}$. This is difficult to assess from descriptive correlations alone as in Figure 6. Figures 9c and 9d shows the screening gains along the $\kappa_{ij}$ distribution (residualized of differences in $v_i$) for the two example actions from Figure 8b. While there is a residual correlation between costs of these top-up actions and expected marginal benefit from land retirement $B \cdot \tau(\mathbf{z}_i, \theta_i)$, as suggested by the descriptive evidence in Figure 6, the magnitude is small relative to the increase in costs of providing the action. Of course, these figures only examine two actions and do not consider how choices will change as the complete vector of prices changes. However, Figures 9c and 9d provide suggestive evidence that descriptively promising correlations may mask quantitatively small screening gains from menu design. Our policy counterfactuals will address this point directly.

### 7.3 Estimates of marginal treatment effects $\tau(\mathbf{z}, \theta)$

In Table 5, we present estimates of $\tau(\mathbf{z}, \theta)$. As we move from column (1) to column (4), we parameterize $\tau(\mathbf{z}, \theta)$ more flexibly and impose more conservative exclusion restrictions.

In column (1), we allow $v_i$, a linear function of estimated soil productivity, former CRP status, quartiles of bidder size, and region fixed effects to enter $\tau(\mathbf{z}, \theta)$; in column (2), we control for soil productivity more flexibly. In both columns (1) and (2), we impose that all characteristics in the scoring rule are excluded instruments. In columns (3) and (4), our preferred specifications, we allow $\mathbf{z^{t1}}$ to enter $\tau(\mathbf{z}, \theta)$, relying only on our exclusion restrictions on wildlife priority zone and air quality zone indicators ($\mathbf{z^{t2}}$).

Two main results emerge from the parameter estimates in Table 5. First, the private information contained in the bids remains predictive of marginal treatment effects $\tau(\mathbf{z}, \theta)$ even conditional on rich covariates, including estimates of soil productivity, former CRP status, and prior land use. This highlights the potential for adverse selection, even conditional on a rich set of predictors of $\tau(\mathbf{z}, \theta)$. Second, conditional on $v_i$, other characteristics are highly predictive of outcomes, highlighting the potential for gains from differentiated pricing. Appendix Table F.2 shows that the results in Table 5 are robust to alternative measurements of land use outcomes.

We scale the marginal treatment effects $\tau(\mathbf{z}, \theta)$ by the valuation of benefits described in Section 6.3.1 to generate WTP curves. See Appendix F for more details.

# 8 Welfare and Policy Counterfactuals

We use our estimates to investigate differences in welfare across alternative market structures and pricing regimes, to explore the performance of policy instruments, and to quantify the impact of alternative auction designs.

## 8.1 Welfare under alternative market and pricing structures

We first focus on only the base contract (i.e. with no additional "top-up" conservation actions) to illustrate how selection impacts market outcomes and welfare.

### 8.1.1 Graphical welfare analysis

In Figure 10, we plot the empirical version of our graphical welfare analysis of uniform pricing in Section 2. We plot curves residualized of the information contained in $\mathbf{z^t}$, as these attributes are already priced. Figure 10 illustrates two main conclusions.

First, though there would be inefficient selection under a $\tau = 1$ pricing benchmark (triangle CFG), this is outweighed by efficient behavioral changes (triangle ABC). Therefore, even when a regulator prices at the value of the *level* of the incentivized outcome — ignoring counterfactual behavior — as in many status quo policies,[33] including our setting of the CRP, the existence of this market for ecosystem services increases welfare.[34]

Second, Figure 10 documents evidence of adverse selection, as the WTP curve is upwards-sloping. This is driven by the positive correlation between marginal treatment effects $\tau(\mathbf{z}, \theta)$ and land retirement cost $v$ illustrated in the previous section. In an offset market, in which buyers are willing to pay for the expected value of a contract, this phenomenon would lead to too few trades: equilibrium prices and quantities would be at point D, substantially lower than the social optimum at point C. This suggests that status quo offset markets may indeed

[33] This occurs either because policymakers assume that their eligibility requires are strict enough such that $\tau(\mathbf{z}, \theta) = 1$ for everyone ("miscalibrated"), or if they operate under a simple Roy (1951) model in which even if $\tau(\mathbf{z}, \theta) \neq 1$ for everyone, $\tau(\mathbf{z}, \theta) = 1$ for the marginal enrollee, under which pricing at WTP for the *level* of conservation would still achieve efficiency.

[34] It is striking that almost all land is enrolled under the $\tau = 1$ pricing benchmark. This is due to the specific population we are studying: those who are eligible for and who select into bidding in the CRP.

be too small due to adverse selection. Without corrective instruments, this would lead to a welfare loss of triangle CED, capturing efficient conservation that does not occur.

The convexity of the social WTP curve in Figure 10 is of note: at low costs, the market does not appear adversely selected at all. This helps prevent the market from completely unravelling. However, this suggests that if WTP for land retirement increases, perhaps if social costs of environmental degradation are revised upward, or if markets are implemented in more environmentally sensitive locations, such as the Amazon rainforest, the welfare costs of adverse selection could increase substantially.

### 8.1.2 Quantifying the effects of alternative pricing regimes

Table 6 quantifies the triangles in Figure 10 and investigates the gains from heterogenous pricing under three different environments. The first is a social planner with no cost of funds (Panel A); this regime is illustrated in the social WTP curve in Figure 10. In Panel B, we add a cost of funds. In Panel C, we investigate outcomes under a decentralized offset market structure, illustrated in the private WTP curve in Figure 10. In the first column of Table 6, we report a first-best benchmark in which a social planner sets personalized prices for each potential participant equal to the minimum of their welfare gains and the costs associated with enrolling them. Columns (2)-(8) report outcomes under alternative, feasible pricing counterfactuals.

**Uniform pricing** We begin by quantifying the conclusions illustrated in Figure 10. The welfare costs of setting prices based on the *level* of conservation — rather than accounting for counterfactual behavior — are substantial, reducing welfare by 29% of the first-best benchmark with no cost of funds ($\lambda = 0$) and 53% with a positive cost of funds ($\lambda = 0.15$), though the existence of the market remains welfare-increasing under both regimes (column (2) versus column (1)). This is the pricing regime reflected in the pink line FH in Figure 10. Knowledge of the $\tau(\mathbf{z}, \theta)$ function that allows for setting the optimal uniform price — point C in Figure 10 — yields substantial gains, and achieves 79% ($\lambda = 0$) and 74% ($\lambda = 0.15$) of the first-best surplus (column (4)).

In Panel C, we investigate the magnitude of the welfare losses from adverse selection illustrated in Figure 10. As Figure 10 demonstrates, comparing uniform pricing regimes in Panel C to Panel A yields prices and quantities that are only 51% and 75% of the uniform-price social optimum, respectively. This results in a welfare loss of 3%, relative to the optimal uniform price, corresponding to triangle CED. Though modest, this welfare loss is high enough for a subsidy to be welfare-improving, even with a cost of funds.[35]

**Differentiated pricing** Figure 10 collapses all heterogeneity in $\tau(\mathbf{z},\theta)$ at each point along the supply curve, but as illustrated in Figure 1c, this can lead to inefficient selection if $\tau(\mathbf{z},\theta)$ is heterogeneous within each of these points, as suggested by the estimates in Section 7.3. We next turn to the welfare gains from differentiated pricing. We begin with the most limited change to the status quo, simply setting incentives that re-weight the components of the scoring rule to reflect the correlation between those attributes and $\tau(\mathbf{z},\theta)$. This yields only modest welfare gains of 2%, relative to the optimal uniform price. By contrast, incorporating additional predictors of $\tau(\mathbf{z},\theta)$ into the pricing scheme, simply by adding an additional $\hat{\tau}(\mathbf{z})$ component linearly into the incentive, increases welfare by 24-26%. Two thirds of those gains can be achieved without using predictors of prior land use, which may induce perverse dynamic incentives. Put differently, setting feasible differentiated prices by estimates of $\tau(\mathbf{z},\theta)$ can yield substantial welfare gains of 30% ($\lambda = 0$) to 82% ($\lambda = 0.15$), relative to status quo pricing based on the *level* of conservation (pricing with $\tau(\mathbf{z},\theta) = 1$).

Though theoretically ambiguous, we observe welfare in offset markets increase as predictors of $\tau$ are priced, reducing the welfare loss from adverse selection to only 14 cents per bidder-acre-year. Encouraging the collection and pricing of information in offset contracts yields much larger welfare gains (\$12.35), relative to subsidizing uniformly priced contracts (\$1.25). This suggests that a regulator may want to direct more resources to estimating $\tau(\mathbf{z},\theta)$ and enforcing differentiated pricing based on it rather than simply subsidizing offset markets. Our results indicate that large-scale efforts currently underway by firms and governments to "estimate additionality" — i.e. create reasonable counterfactuals for vastly heterogeneous offset projects and thereby flexibly estimate the marginal treatment effects $\tau(\mathbf{z},\theta)$ — are encouraging developments for the performance of these markets.[36]

## 8.2 Comparing methods of screening

Given the welfare gains associated with incorporating predictors of $\tau(\mathbf{z},\theta)$ into the pricing mechanism, a market designer may be interested in achieving these gains without needing to collect and price on observable characteristics (Jack and Jayachandran, 2019; Li et al.,

[35]The modest welfare loss from adverse selection is consistent with other work documenting small welfare costs of adverse selection in insurance markets (Einav and Finkelstein, 2011; Bundorf et al., 2012; Wagner, 2022).

[36]All of the largest private procurers of clean energy, such as Google and Microsoft, have outlined methodologies to calculate the "additionality" of the energy project. Other firms are developing products to "estimate additionality" among privately owned forests, like NCX.

2022). In this section, we investigate the extent to which screening via the menu of productive top-up actions can substitute for pricing based on observable characteristics.

Table 7 enriches the set of contracts to include the actions available to CRP participants. We focus on the regime with a cost of public funds, $\lambda = 0.15$. Moving from column (1) to column (2) shows that the productive gains from incentivizing more "ambitious" conservation actions are large, representing about half the surplus from the mechanism. This underscores the gains from incentivizing additional quality investments on conserved land. In column (3), we set action prices optimally to reflect both their productive (illustrated in column (2)) *and* screening value to investigate the gains from using self-selection to increase welfare. We find welfare gains of only 10 cents per bidder-acre-year. This is only 7% of the gains that can be achieved by optimally re-weighting the score (column (4)), and less than 2% of the gains from incorporating additional predictors of $\tau$ (column (5)).

The limitations of using self-selection to screen types occur even in a setting in which we (1) observe a correlation between marginal treatment effects and the costs of top-up actions $\kappa_{ij}$, and (2) have at our disposal a rich menu of (potentially) screening actions. However, in practice, the correlations between costs and treatment effects must be very strong to yield large gains, as it must outweigh the destruction of productive surplus from distorting prices away from the social benefits of each of the actions. This analysis underscores the limitations to descriptive correlations informing the performance of screening contracts: to evaluate the potential for self-selection, we must account for various incentive compatibility constraints and destruction of productive surplus that accompany using any additional actions to screen types. Our results suggest that, at least based on the menu of contracts we observe in this setting, there is no substitute to collecting information to set differentiated prices based on predicted marginal treatment effects $\hat{\tau}(\mathbf{z})$.

### 8.3 Re-designing the CRP: welfare under alternative auctions

In the prior two sections, we considered a posted prices regime to clearly exposit the economics of the setting, in accordance with our simple model in Section 2. In this section, we return to our empirical setting, in which quantities (acreage limits) are fixed and enrollment is administered via an auction. We implement the insights from the previous section to improve allocative efficiency by re-designing the enrollment mechanism.

Figure 11 presents outcomes under alternative enrollment regimes. We hold aggregate quantity fixed except in the right-most column, which provides a first-best benchmark at efficient quantities. We compare the status quo auction to a number of efficient auctions, which can be implemented via a Vickrey-Clarke-Groves (VCG) mechanism, in which each bidder $i$ is paid her positive externality from participating. Specifically, we rank each bidder according to the social surplus that she generates, conducting her most efficient action. VCG incentive payments are determined by paying each bidder $i$ the difference between social WTP net of costs for the top $K$ bidders, including $i$, and the social WTP net of costs for the top $K$ bidders, excluding $i$.[37]

We first observe that the status quo enrollment mechanism achieves positive surplus and increases welfare relative to a uniform efficient auction, implemented with VCG incentive payments treating all actions and bidders symmetrically. We next consider a $\tau$-ignorant efficient benchmark: a VCG auction that incorporates heterogeneous social WTP across conservation actions, and across bidders, based on the environmental sensitivity of their land, but ignores heterogeneity in $\tau$. This comparison isolates the performance of the design of the CRP mechanism without considering the "additionality" channel as a driver of welfare losses. Even this "naive" benchmark raises surplus substantially, reflecting poor design of the status quo auction as score-independent bid caps distort action decisions. These bid caps were introduced to control costs (Hellerstein, 2017), but Figure 11b shows that the $\tau$-ignorant VCG benchmark can achieve this substantial increase in welfare while holding spending and aggregate acreage constant.

Finally, we investigate the performance of VCG auctions that incorporate heterogeneity in $\tau(\mathbf{z}, \theta)$ across bidders based on observable characteristics and the costs that each $i$ truthfully reports via the VCG mechanism. Incorporating information about $\tau$ into the VCG mechanism increases surplus by 7% relative to a $\tau$-ignorant mechanism. While these gains are not as large relative to the switch from the status quo mechanism to a VCG mechanism incorporating the same information (a 72% increase), they are still substantial, reflecting gains of over \$130 million per auction, and represent a larger increase then the incremental gains from switching to the efficient quantity (a 4.5% increase).

However, Figure 11b plots the costs associated with implementing each of these mechanisms, and shows that achieving the efficient mechanism comes at substantial costs, driven by the fundamental nature of selection in this market: high-surplus bidders have higher costs. This fact perhaps motivates governments' increased interest in promoting private offset markets, in which private actors coordinate to preserve natural capital, rather than relying on (potentially costly) government expenditures. However, as our analysis in the previous sections discussed, these markets must be carefully regulated to ensure their success in the presence of adverse selection.

[37] In this section, we abstract away from heterogeneity in size.

# 9 Conclusion

We examine the performance and design of environmental markets in the presence of concerns about non-additionality. We cast the controversy around additionality as a classic problem of asymmetric information, and apply insights from a well-developed theoretical and empirical toolkit for the analysis and design of selection markets. We conduct our analysis using a unique dataset from the Conservation Reserve Program, one of the largest voluntary environmental market mechanisms in the world.

We demonstrate that the additionality problem is descriptively severe: only 27% of participants are additional. Moreover, descriptive analyses of the market highlight the existence of adverse selection.

To quantify these forces, analyze welfare, and explore the performance of alternative market designs, we develop and estimate a joint model of bidding and potential outcomes. We document that despite the existence of both substantial non-additionality and adverse selection — features of this market thought to doom them to failure — the market can deliver welfare gains under both procurement settings and in decentralized offset markets using feasible mechanisms. Moreover, we find large gains to conditioning payments on participants' expected additionality using readily available covariates.

Our analysis focused primarily on the impact of supply-side frictions, namely private information among landowners, on inefficiencies and market design. Understanding demand-side frictions, how they interact with adversely selected offset contracts, and the incentives of private platforms and certifying agencies that facilitate trades in offset markets is a fascinating avenue for future research.

# References


**Agarwal, Nikhil, Charles Hodgson, and Paulo Somaini**, "Choices and Outcomes in Assignment Mechanisms: The Allocation of Deceased Donor Kidneys," November 2020.

_ **, Paulo Somaini, and Pearl Li**, "On the General Structure of Revealed Preference Identification Arguments," February 2023.

**Akerlof, George A.**, "The Market for "Lemons": Quality Uncertainty and the Market Mechanism," *The Quarterly Journal of Economics*, 1970, *84* (3), 488–500. Publisher: Oxford University Press.

**Alix-Garcia, Jennifer and Daniel Millimet**, "Remotely Incorrect? Accounting for Nonclassical Measurement Error in Satellite Data on Deforestation," *Journal of the Association of Environmental and Resource Economists*, December 2022. Publisher: The University of Chicago Press.

**Alix-Garcia, Jennifer M., Katharine R. E. Sims, and Patricia Yañez-Pagans**, "Only One Tree from Each Seed? Environmental Effectiveness and Poverty Alleviation in Mexico's Payments for Ecosystem Services Program," *American Economic Journal: Economic Policy*, November 2015, *7* (4), 1–40.

**Allcott, Hunt and Michael Greenstone**, "Measuring the Welfare Effects of Residential Energy Efficiency Programs," May 2017.

**Allen, Arthur W. and Mark W. Vandever**, "Conservation Reserve Program (CRP) contributions to wildlife habitat, management issues, challenges and policy choices–an annotated bibliography," USGS Numbered Series 2012-5066, U.S. Geological Survey, Reston, VA 2012.

**Allen, Jason, Robert Clark, Brent Hickman, and Eric Richert**, "Resolving Failed Banks: Uncertainty, Multiple Bidding, and Auction Design," *The Review of Economic Studies*, 2023.

**Anderson, Kevin**, "The inconvenient truth of carbon offsets," *Nature*, April 2012, *484* (7392), 7–7. Number: 7392 Publisher: Nature Publishing Group.

**Anderson, Terry L. and Gary D. Libecap**, *Environmental Markets: A Property Rights Approach*, New York: Cambridge University Press, May 2014.

**Angrist, Joshua D. and Miikka Rokkanen**, "Wanna Get Away? Regression Discontinuity Estimation of Exam School Effects Away From the Cutoff," *Journal of the American Statistical Association*, October 2015, *110* (512), 1331–1344. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/01621459.2015.1012259.

**Aronoff, Daniel and Will Rafey**, "Conservation priorities and environmental offsets: Markets for Florida Wetlands," October 2022.

**Asker, John and Estelle Cantillon**, "Properties of scoring auctions," *The RAND Journal of Economics*, 2008, *39* (1), 69–85. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1756-2171.2008.00004.x.

**_ and _** , "Procurement when price and quality matter," *The RAND Journal of Economics*, 2010, *41* (1), 1–34. Publisher: [RAND Corporation, Wiley].

**Athey, Susan and Philip A. Haile**, "Empirical Models of Auctions," in Richard Blundell, Torsten Persson, and Whitney K. Newey, eds., *Advances in Economics and Econometrics: Theory and Applications, Ninth World Congress*, Vol. 2 of *Econometric Society Monographs*, Cambridge: Cambridge University Press, 2006, pp. 1–45.

**Azevedo, Eduardo M. and Daniel Gottlieb**, "Perfect Competition in Markets With Adverse Selection," *Econometrica*, 2017, *85* (1), 67–105. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA13434.

**Boiteux, M.**, "Sur la gestion des Monopoles Publics astreints a l'equilibre budgetaire," *Econometrica*, 1956, *24* (1), 22–40. Publisher: [Wiley, Econometric Society].

**Bolotnyy, Valentin and Shoshana Vasserman**, "Scaling Auctions as Insurance: A Case Study in Infrastructure Procurement," March 2023.

**Boomhower, Judson and Lucas W. Davis**, "A credible approach for measuring inframarginal participation in energy efficiency programs," *Journal of Public Economics*, May 2014, *113*, 67–79.

**Borenstein, Severin and Lucas W. Davis**, "The Distributional Effects of US Clean Energy Tax Credits," *Tax Policy and the Economy*, January 2016, *30* (1), 191–234. Publisher: The University of Chicago Press.

**Borrelli, Pasquale, David A. Robinson, Larissa R. Fleischer, Emanuele Lugato, Cristiano Ballabio, Christine Alewell, Katrin Meusburger, Sirio Modugno,**

**Brigitta Schütt, Vito Ferro, Vincenzo Bagarello, Kristof Van Oost, Luca Montanarella, and Panos Panagos**, "An assessment of the global impact of 21st century land use change on soil erosion," *Nature Communications*, December 2017, *8* (1), 2013. Number: 1 Publisher: Nature Publishing Group.

**Bundorf, M. Kate, Jonathan Levin, and Neale Mahoney**, "Pricing and Welfare in Health Plan Choice," *American Economic Review*, December 2012, *102* (7), 3214–3248.

**Calel, Raphael, Jonathan Colmer, Antoine Dechezlepretre, and Mattieu Glachant**, "Do carbon offsets offset carbon?," November 2021.

**Calonico, Sebastian, Matias D. Cattaneo, and Rocio Titiunik**, "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs," *Econometrica*, 2014, *82* (6), 2295–2326. Publisher: [Wiley, The Econometric Society].

**Carril, Rodrigo, Andres Gonzalez-Lira, and Michael S. Walker**, "Competition under Incomplete Contracts and the Design of Procurement Policies," March 2022.

**Chade, Hector, Victoria R. Marone, Amanda Starc, and Jeroen Swinkels**, "Multidimensional Screening and Menu Design in Health Insurance Markets," October 2022.

**Che, Yeon-Koo**, "Design Competition Through Multidimensional Auctions," *The RAND Journal of Economics*, 1993, *24* (4), 668–680. Publisher: [RAND Corporation, Wiley].

**Chiappori, Pierre-Andre and Bernard Salanie**, "Testing for Asymmetric Information in Insurance Markets," *Journal of Political Economy*, 2000, *108* (1), 56–78. Publisher: The University of Chicago Press.

**Claassen, Roger, Eric N. Duquette, and David J. Smith**, "Additionality in U.S. Agricultural Conservation Programs," *Land Economics*, February 2018, *94* (1), 19–35. Publisher: University of Wisconsin Press Section: Articles.

**Conte, Marc N. and Matthew J. Kotchen**, "Explaining the price of voluntary carbon offsets," *Climate Change Economics*, August 2010, *01* (02), 93–111. Publisher: World Scientific Publishing Co.

**Decarolis, Francesco**, "Awarding Price, Contract Performance, and Bids Screening: Evidence from Procurement Auctions," *American Economic Journal: Applied Economics*, January 2014, *6* (1), 108–132.

**Dirzo, Rodolfo, Hillary S. Young, Mauro Galetti, Gerardo Ceballos, Nick J. B. Isaac, and Ben Collen**, "Defaunation in the Anthropocene," *Science*, July 2014, *345* (6195), 401–406. Publisher: American Association for the Advancement of Science.

**Einav, Liran, Amy Finkelstein, and Mark R. Cullen**, "Estimating Welfare in Insurance Markets Using Variation in Prices*," *The Quarterly Journal of Economics*, August 2010, *125* (3), 877–921.

_ **and** _ , "Selection in Insurance Markets: Theory and Empirics in Pictures," *Journal of Economic Perspectives*, March 2011, *25* (1), 115–138.

**Eisenhauer, Philipp, James J. Heckman, and Edward Vytlacil**, "The Generalized Roy Model and the Cost-Benefit Analysis of Social Programs," *Journal of Political Economy*, 2015, *123* (2), 413–443. Publisher: The University of Chicago Press.

**Engel, Stefanie, Stefano Pagiola, and Sven Wunder**, "Designing payments for environmental services in theory and practice: An overview of the issues," *Ecological Economics*, May 2008, *65* (4), 663–674.

**FAPRI-MU**, *Estimating Water Quality, Air Quality, and Soil Carbon Benefits of the Conservation Reserve Program* 2007.

**Feather, Peter, Daniel Hellerstein, and LeRoy T. Hansen**, "Economic Valuation of Environmental Benefits and the Targeting of Conservation Programs: The Case of the CRP," *Agricultural Economic Reports*, 1999. Number: 34027 Publisher: United States Department of Agriculture, Economic Research Service.

**Filewod, Ben**, "Why REDD will Fail," *Journal of Forestry*, July 2017, *115* (4), 323.

**Gaynor, Martin, Nirav Mehta, and Seth Richards-Shubik**, "Optimal Contracting with Altruistic Agents: Medicare Payments for Dialysis Drugs," *American Economic Review*, 2023.

**Griscom, Bronson W., Justin Adams, Peter W. Ellis, Richard A. Houghton, Guy Lomax, Daniela A. Miteva, William H. Schlesinger, David Shoch, Juha V. Siikamäki, Pete Smith, Peter Woodbury, Chris Zganjar, Allen Blackman, João Campari, Richard T. Conant, Christopher Delgado, Patricia Elias, Trisha Gopalakrishna, Marisa R. Hamsik, Mario Herrero, Joseph Kiesecker, Emily Landis, Lars Laestadius, Sara M. Leavitt, Susan Minnemeyer, Stephen Polasky, Peter Potapov, Francis E. Putz, Jonathan Sanderman, Marcel Silvius,**

**Eva Wollenberg, and Joseph Fargione**, “Natural climate solutions,” *Proceedings of the National Academy of Sciences*, October 2017, *114* (44), 11645–11650. Publisher: Proceedings of the National Academy of Sciences.

**Guerre, Emmanuel, Isabelle Perrigne, and Quang Vuong**, “Optimal Nonparametric Estimation of First-Price Auctions,” *Econometrica*, 2000, *68* (3), 525–574. Publisher: [Wiley, Econometric Society].

**Hagerty, Nick**, “Adaptation to Surface Water Scarcity in Irrigated Agriculture,” November 2022.

**Hansen, LeRoy**, “Conservation Reserve Program: Environmental Benefits Update,” *Agricultural and Resource Economics Review*, October 2007, *36* (2), 267–280. Publisher: Cambridge University Press.

**Heckman, James J. and Edward J. Vytlacil**, “Local Instrumental Variables and Latent Variable Models for Identifying and Bounding Treatment Effects,” *Proceedings of the National Academy of Sciences of the United States of America*, 1999, *96* (8), 4730–4734. Publisher: National Academy of Sciences.

_ **and Edward Vytlacil**, “Policy-Relevant Treatment Effects,” *The American Economic Review*, 2001, *91* (2), 107–111. Publisher: American Economic Association.

_ **and** _ , “Structural Equations, Treatment Effects, and Econometric Policy Evaluation,” *Econometrica*, 2005, *73* (3), 669–738. Publisher: [Wiley, Econometric Society].

**Hellerstein, Daniel M.**, “The US Conservation Reserve Program: The evolution of an enrollment mechanism,” *Land Use Policy*, April 2017, *63*, 601–610.

**Hortaçsu, Ali and David McAdams**, “Mechanism Choice and Strategic Bidding in Divisible Good Auctions: An Empirical Analysis of the Turkish Treasury Auction Market,” *Journal of Political Economy*, October 2010, *118* (5), 833–865. Publisher: The University of Chicago Press.

**Imbens, Guido and Karthik Kalyanaraman**, “Optimal Bandwidth Choice for the Regression Discontinuity Estimator,” *The Review of Economic Studies*, July 2012, *79* (3), 933–959.

**Ito, Koichiro, Takanori Ida, and Makoto Tanaka**, “Selection on Welfare Gains: Experimental Evidence from Electricity Plan Choice,” January 2021.

**Jack, B. Kelsey**, "Private Information and the Allocation of Land Use Subsidies in Malawi," *American Economic Journal: Applied Economics*, July 2013, *5* (3), 113–135.

_ **and Seema Jayachandran**, "Self-selection into payments for ecosystem services programs," *Proceedings of the National Academy of Sciences*, March 2019, *116* (12), 5326–5333. Publisher: Proceedings of the National Academy of Sciences.

**Jayachandran, Seema, Joost de Laat, Eric F. Lambin, Charlotte Y. Stanton, Robin Audy, and Nancy E. Thomas**, "Cash for carbon: A randomized trial of payments for ecosystem services to reduce deforestation," *Science*, July 2017, *357* (6348), 267–273. Publisher: American Association for the Advancement of Science.

**Jofre-Bonet, Mireia and Martin Pesendorfer**, "Estimation of a Dynamic Auction Game," *Econometrica*, 2003, *71* (5), 1443–1489. Publisher: [Wiley, Econometric Society].

**Johnson, Kris A., Brent J. Dalzell, Marie Donahue, Jesse Gourevitch, Dennis L. Johnson, Greg S. Karlovits, Bonnie Keeler, and Jason T. Smith**, "Conservation Reserve Program (CRP) lands provide ecosystem service benefits that exceed land rental payment costs," *Ecosystem Services*, April 2016, *18*, 175–185.

**Kapor, Adam, Mohit Karnani, and Christopher Neilson**, "Aftermarket Frictions and the Cost of Off-Platform Options in Centralized Assignment Mechanisms," July 2022.

**Kinzig, A. P., C. Perrings, F. S. Chapin, S. Polasky, V. K. Smith, D. Tilman, and B. L. Turner**, "Paying for Ecosystem Services—Promise and Peril," *Science*, November 2011, *334* (6056), 603–604. Publisher: American Association for the Advancement of Science.

**Kong, Yunmi, Isabelle Perrigne, and Quang Vuong**, "Multidimensional Auctions of Contracts: An Empirical Analysis," *American Economic Review*, May 2022, *112* (5), 1703–1736.

**Kossoy, Alexandre, Grzegorz Peszko, Klaus Oppermann, Nicolai Prytz, Noemie Klein, Kornelis Blok, Long Lam, Lindee Wong, and Bram Borkent**, *State and Trends of Carbon Pricing 2015*, Washington, DC: World Bank, September 2015.

**Laffont, Jean-Jacques and Jean Tirole**, "Auctioning Incentive Contracts," *Journal of Political Economy*, 1987, *95* (5), 921–937. Publisher: University of Chicago Press.

**Lark, Tyler J., Ian H. Schelly, and Holly K. Gibbs**, "Accuracy, Bias, and Improvements in Mapping Crops and Cropland across the United States Using the USDA Cropland

Data Layer," *Remote Sensing*, January 2021, *13* (5), 968. Number: 5 Publisher: Multidisciplinary Digital Publishing Institute.

_ , **Richard M. Mueller, David M. Johnson, and Holly K. Gibbs**, "Measuring land-use and land-cover change using the U.S. department of agriculture's cropland data layer: Cautions and recommendations," *International Journal of Applied Earth Observation and Geoinformation*, October 2017, *62*, 224–235.

**Larroucau, Tomas and Ignacio Rios**, "Dynamic College Admissions," 2023.

**Lewis, Gregory and Patrick Bajari**, "Procurement Contracting with Time Incentives: Theory and Evidence," *The Quarterly Journal of Economics*, 2011, *126* (3), 1173–1211. Publisher: Oxford University Press.

**Li, Wanyi Dai, Itai Ashlagi, and Irene Lo**, "Simple and Approximately Optimal Contracts for Payment for Ecosystem Services," *Management Science*, February 2022. Publisher: INFORMS.

**Lopomo, Giuseppe, Nicola Persico, and Alessandro T. Villa**, "Optimal Procurement With Quality Concerns," *American Economic Review*, 2023.

**Manelli, Alejandro M. and Daniel R. Vincent**, "Optimal Procurement Mechanisms," *Econometrica*, 1995, *63* (3), 591–620. Publisher: [Wiley, Econometric Society].

**Maron, Martine, Christopher D. Ives, Heini Kujala, Joseph W. Bull, Fleur J. F. Maseyk, Sarah Bekessy, Ascelin Gordon, James E.M. Watson, Pia E. Lentini, Philip Gibbons, Hugh P. Possingham, Richard J. Hobbs, David A. Keith, Brendan A. Wintle, and Megan C. Evans**, "Taming a Wicked Problem: Resolving Controversies in Biodiversity Offsetting," *BioScience*, June 2016, *66* (6), 489–498.

**Mason, Charles and Andrew J. Plantinga**, "The additionality problem with offsets: Optimal contracts for carbon sequestration in forests," *Journal of Environmental Economics and Management*, 2013, *66* (1), 1–14. Publisher: Elsevier.

**McKinsey & Company**, "Pathways to a Low-Carbon Economy: Version 2 of the Global Greenhouse Gas Abatement Cost Curve," Technical Report 2013.

**McKinsey Sustainability**, "A blueprint for scaling voluntary carbon markets to meet the climate challenge," Technical Report January 2021.

_ , "The net-zero transition: what it would cost, what it could bring," Technical Report 2022.

**Montero, Juan-Pablo**, "Voluntary Compliance with Market-Based Environmental Policy: Evidence from the U.S. Acid Rain Program," *Journal of Political Economy*, October 1999, *107* (5), 998–1033. Publisher: The University of Chicago Press.

**Otero, Sebastian, Nano Barahona, and Dobbin Caue**, "Affirmative Action in Centralized College Admission Systems: Evidence from Brazil," November 2021.

**Quéré, C. Le, R. Moriarty, R. M. Andrew, J. G. Canadell, S. Sitch, J. I. Korsbakken, P. Friedlingstein, G. P. Peters, R. J. Andres, T. A. Boden, R. A. Houghton, J. I. House, R. F. Keeling, P. Tans, A. Arneth, D. C. E. Bakker, L. Barbero, L. Bopp, J. Chang, F. Chevallier, L. P. Chini, P. Ciais, M. Fader, R. A. Feely, T. Gkritzalis, I. Harris, J. Hauck, T. Ilyina, A. K. Jain, E. Kato, V. Kitidis, K. Klein Goldewijk, C. Koven, P. Landschützer, S. K. Lauvset, N. Lefèvre, A. Lenton, I. D. Lima, N. Metzl, F. Millero, D. R. Munro, A. Murata, J. E. M. S. Nabel, S. Nakaoka, Y. Nojiri, K. O'Brien, A. Olsen, T. Ono, F. F. Pérez, B. Pfeil, D. Pierrot, B. Poulter, G. Rehder, C. Rödenbeck, S. Saito, U. Schuster, J. Schwinger, R. Séférian, T. Steinhoff, B. D. Stocker, A. J. Sutton, T. Takahashi, B. Tilbrook, I. T. van der Laan-Luijkx, G. R. van der Werf, S. van Heuven, D. Vandemark, N. Viovy, A. Wiltshire, S. Zaehle, and N. Zeng**, "Global Carbon Budget 2015," *Earth System Science Data*, December 2015, *7* (2), 349–396. Publisher: Copernicus GmbH.

**Ramsey, F. P.**, "A Contribution to the Theory of Taxation," *The Economic Journal*, 1927, *37* (145), 47–61. Publisher: [Royal Economic Society, Wiley].

**Ribaudo, Marc O., Dana L. Hoag, Mark E. Smith, and Ralph Heimlich**, "Environmental indices and the politics of the Conservation Reserve Program," *Ecological Indicators*, August 2001, *1* (1), 11–20.

**Robinson-Cortés, Alejandro**, "Who Gets Placed Where and Why? An Empirical Framework for Foster Care Placement," November 2019.

**Rodemeier, Matthias**, "Willingness to Pay for Carbon Mitigation: Field Evidence from the Market for Carbon Offsets," February 2023.

**Rosenberg, Andrew B., Bryan Pratt, and David Arnold**, "Land Use Impacts of the Conservation Reserve Program: An Analysis of Rejected CRP Offers," January 2022.

**Roy, A. D.**, "Some Thoughts on the Distribution of Earnings," *Oxford Economic Papers*, 1951, *3* (2), 135–146. Publisher: Oxford University Press.

**Rubin, Donald B.**, "Estimating causal effects of treatments in randomized and nonrandomized studies," *Journal of Educational Psychology*, 1974, *66*, 688–701. Place: US Publisher: American Psychological Association.

**Salzman, James, Genevieve Bennett, Nathaniel Carroll, Allie Goldstein, and Michael Jenkins**, "The global status and trends of Payments for Ecosystem Services," *Nature Sustainability*, March 2018, *1* (3), 136–144. Number: 3 Publisher: Nature Publishing Group.

**Samuelson, Paul A.**, "The Pure Theory of Public Expenditure," *The Review of Economics and Statistics*, 1954, *36* (4), 387–389. Publisher: The MIT Press.

**Scott, Paul T.**, "Dynamic Discrete Choice Estimation of Agricultural Land Use," December 2013.

**Stubbs, Megan, Katie Hoover, and Jonathan Ramseur**, "Agriculture and Forestry Offests in Carbon Markets: Background and Selected Issues," Congressional Research Service Report August 2014.

**Teytelboym, Alexander**, "Natural capital market design," *Oxford Review of Economic Policy*, January 2019, *35* (1), 138–161.

**Torchiana, Adrian L., Ted Rosenbaum, Paul T. Scott, and Eduardo Souza-Rodrigues**, "Improving Estimates of Transitions from Satellite Data: A Hidden Markov Model Approach," December 2022.

**Vörösmarty, C. J., P. B. McIntyre, M. O. Gessner, D. Dudgeon, A. Prusevich, P. Green, S. Glidden, S. E. Bunn, C. A. Sullivan, C. Reidy Liermann, and P. M. Davies**, "Global threats to human water security and river biodiversity," *Nature*, September 2010, *467* (7315), 555–561. Number: 7315 Publisher: Nature Publishing Group.

**Wagner, Katherine R. H.**, "Adaptation and Adverse Selection in Markets for Natural Disaster Insurance," *American Economic Journal: Economic Policy*, August 2022, *14* (3), 380–421.

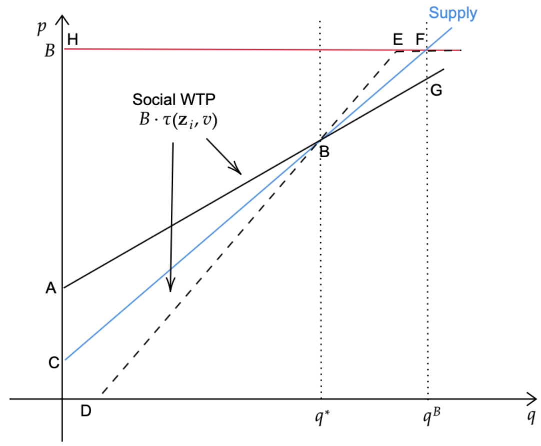
**West, Thales A. P., Jan Börner, Erin O. Sills, and Andreas Kontoleon**, "Overstated carbon emission reductions from voluntary REDD+ projects in the Brazilian Amazon," *Proceedings of the National Academy of Sciences*, September 2020, *117* (39), 24188–24194. Publisher: Proceedings of the National Academy of Sciences.

**Wu, JunJie**, "Slippage Effects of the Conservation Reserve Program," *American Journal of Agricultural Economics*, 2000, *82* (4), 979–992. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/0002-9092.00096.

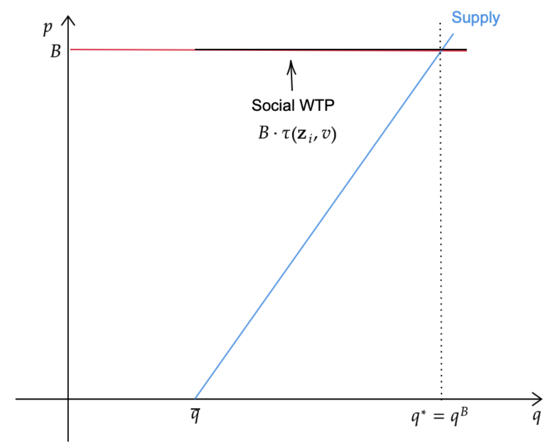
# Figures and Tables

Figure 1: Graphical welfare analysis

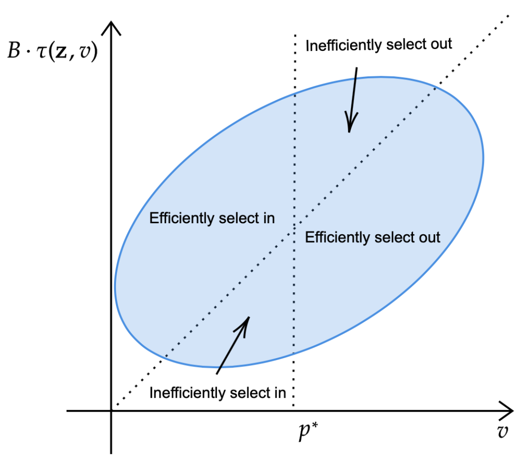
(a) Pricing under two possible social WTP curves



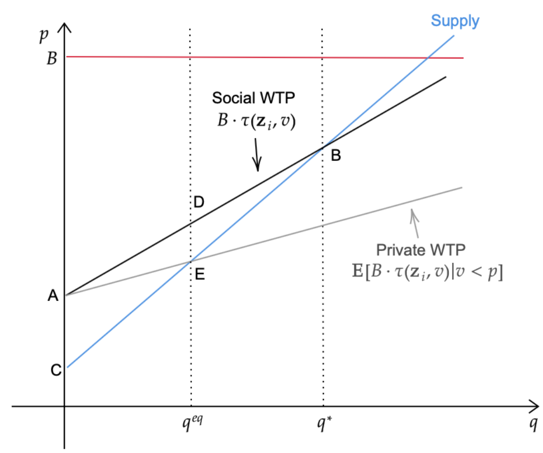

(b) A simple relationship between supply and social WTP




(c) Welfare losses under uniform pricing

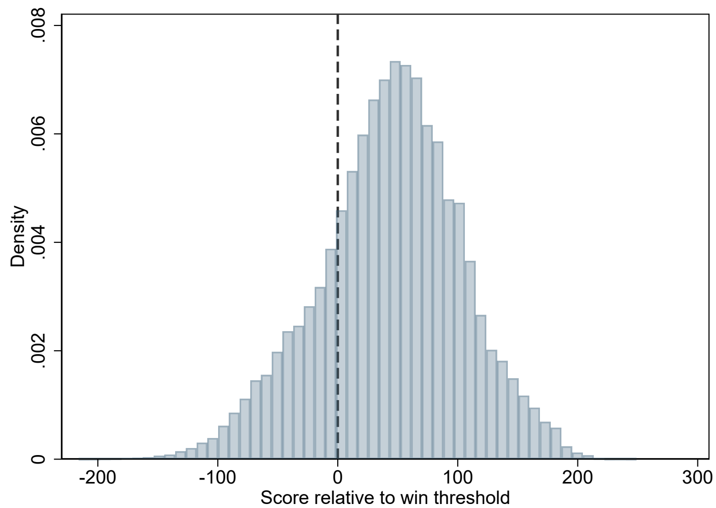



(d) Welfare losses in decentralized offset markets




*Notes:* Figure illustrate welfare-relevant objects: supply curves, social WTP curves, and private WTP curves for the base contract of retiring land at cost $v$. Figure 1a plots the supply curve (the CDF of $v$) and social WTP curves under two different potential relationships between $v$ and $\tau(\mathbf{z}, v)$. Under the dashed line, low $v$ types yield negative social surplus and a regulator cannot achieve the region of surplus BEF. Figure 1b shows a restrictive but commonly considered relationship between marginal treatment effects $\tau(\mathbf{z}, v)$ and costs $v$. Figure 1c plots WTP against costs for each participant to illustrate the welfare losses from even an optimal chosen uniform price when there is not a one-for-one relationship between treatment effects and costs. Figure 1d illustrates the welfare losses in decentralized, competitive offset markets, in which demand is based on expectations of the treatment effect of all landowners in the market (represented by the Private WTP curve). This leads to equilibrium outcomes that are lower than the social optimum and a welfare loss of triangle DEB.

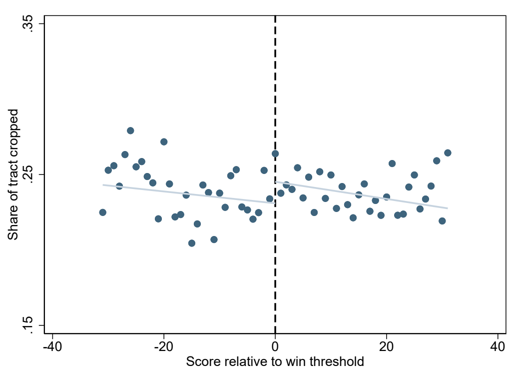
Figure 2: Histogram of the normalized bid distribution



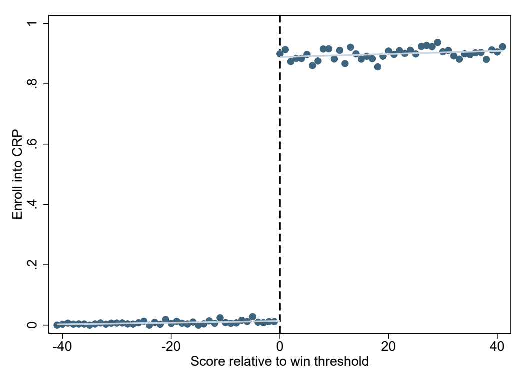

*Notes*: Figure presents a histogram of bidders' score relative to the win threshold (the running variable for the RD analysis), pooling signups 39 (2009), 41 (2011), 43 (2012), 45 (2013), and 49 (2016). Bidders above zero win and enroll in the CRP.

Figure 3: RD validity and first stage

(a) Pre: share of tract cropped




(b) First stage: enrollment

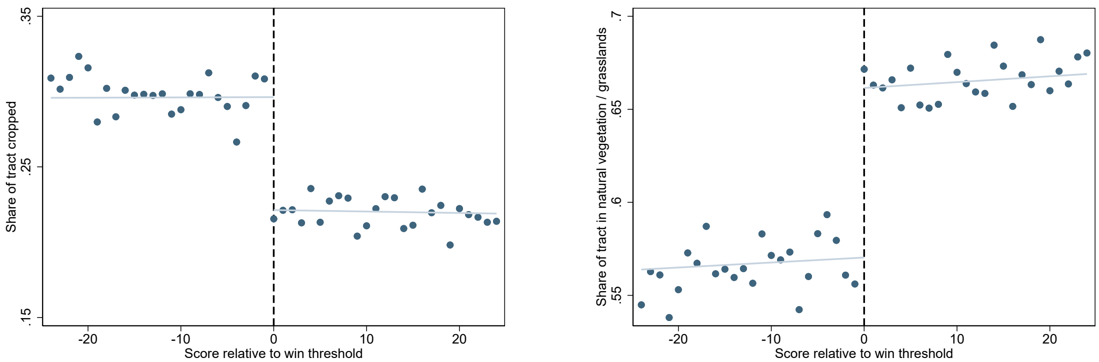



*Notes*: Sub-figures (a) and (b) present raw data and estimated parameters from Equation (14) with a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Calonico et al., 2014). Panel (a) is estimated for only $r \leq 0$ (pre-auction), and panel (b) is estimated for only $r > 0$ (post-auction). Sub-figure (a) presents a placebo RD plot examining land-use outcomes, measured as the share of the bidding tract that is cropped in the satellite data, in all years before enrollment. Sub-figure (b) plots the share of bidders that obtain a CRP contract. The running variable is the difference between each bidder's score and the threshold score. Positive numbers in the RD figures correspond to winning, negative numbers correspond to losing. Each observation is a bidder.

Figure 4: RD evidence: the effect of CRP payments on land use outcomes

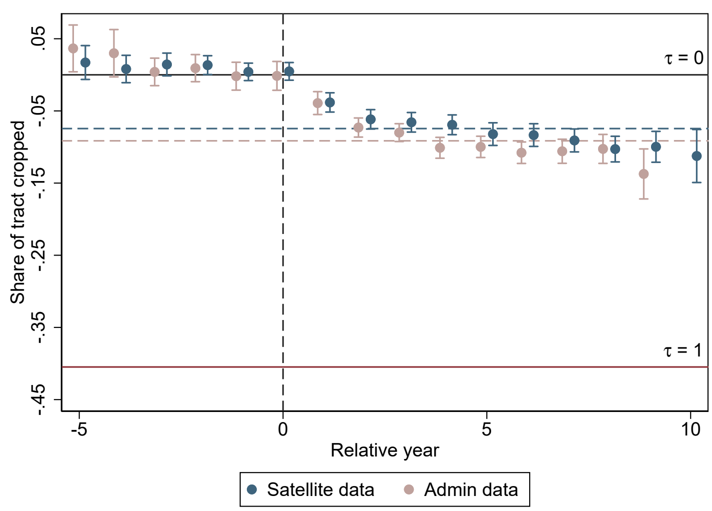
(a) Post: share of tract cropped

(b) Post: share of tract in natural vegetation




*Notes*: Sub-figures (a) and (b) present raw data and estimated parameters from Equation (14) with a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Calonico et al., 2014) for $r > 0$ (post-auction). Land-use outcomes are measured as the share of the bidding tract that is cropped in the satellite data (a) and the share of the bidding tract that is in natural vegetation (trees, grassland, shrubs, and wetland) in the satellite data (b). The running variable is the difference between each bidder's score and the threshold score. Positive numbers in the RD figures correspond to winning, negative numbers correspond to losing. Each observation is a bidder.

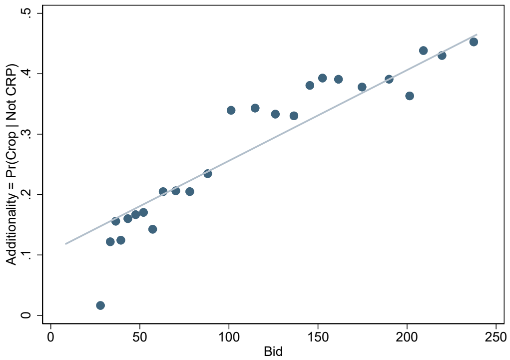
Figure 5: Estimating additionality



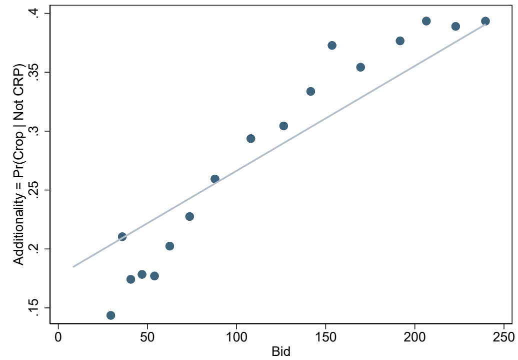

*Notes*: Figure plots coefficients from Equation (13), using a local linear specification in the MSE-optimal bandwidth (Calonico et al., 2014), on the outcome of cropped land, measured with both satellite and administrative (Form 578) dataset. Dashed lines indicate the long-run average treatment effects. The black line at 0 and red line at -.40 indicate the effect sizes if no one changed behavior, and if everyone changed behavior, respectively. Standard errors are clustered at the bidder level. Positive numbers in the RD figures correspond to winning and enrolling into the CRP. Positive years in Figure (d) correspond to post-auction years. Each observation is a bidder. $\tau = 1$ represents the "full additionality" benchmark and is calculated as the total acreage offered into the CRP mechanism among marginal bidders.

Figure 6: Heterogeneous treatment effects and selection on additionality

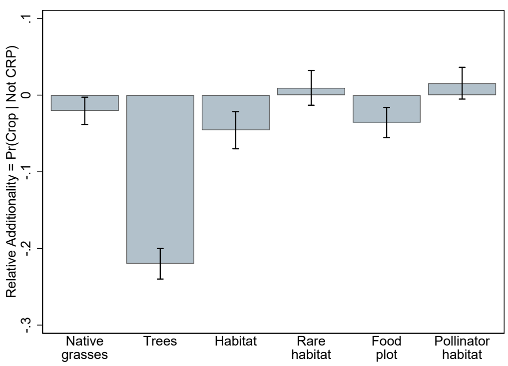
(a) Resid. of scoring rule characteristics



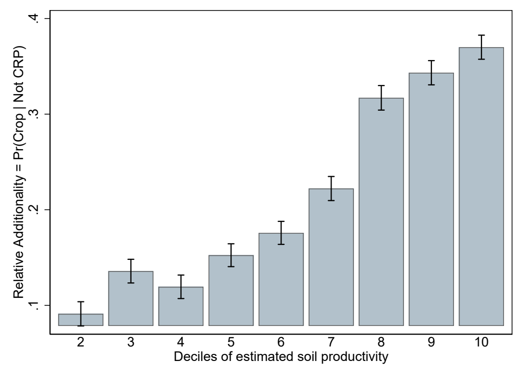

(b) Resid. of scoring rule characteristics and $\mathbf{z_i}$




(c) Selection on action costs



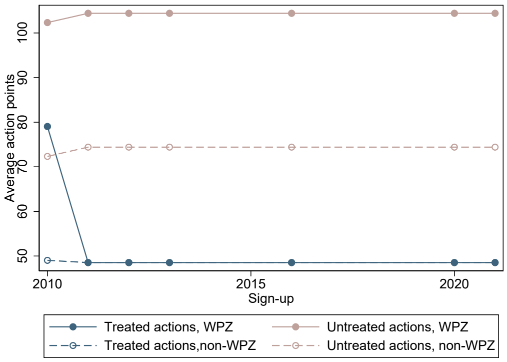

(d) Observable predictors



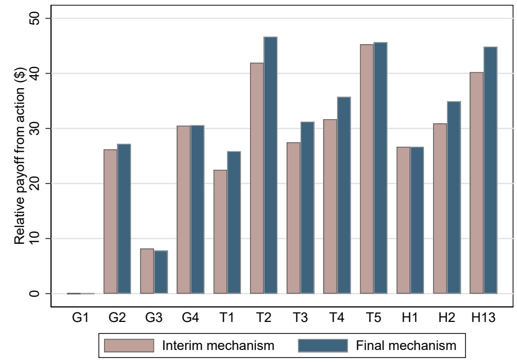

*Notes*: Figures present visual representations of coefficient estimates of versions of Equation (15). All regressions control for characteristics that are incorporated in the scoring rule. Additionality is measured as the share of fields offered into the CRP mechanism that are cropped post auction, conditional on rejection. Estimates are restricted to auction 2016, in which 82% of bidders are rejected. Additionality is measured in 2017-2020. Sub-figure (a) correlates the dollar bid component (per acre, year year) with additionality, conditional on only characteristics included in the scoring rule. Sub-figure (b) adds interaction terms of prior land use (quartiles of prior cropped interacted with re-enrolling CRP status) and deciles of estimated soil productivity. Sub-figure (c) investigates additionality by contract features, relative to a base contract feature of introduced grasses, again controlling for scoring rule characteristics). Sub-figure (c) does not include controls for the dollar bid amount. Sub-figure (d) excludes all endogenous bid characteristics and examines relative additionality, residualized of score characteristics, by deciles of the estimated soil productivity distribution. Standard errors clustered at the bidder level.

Figure 7: Sources of variation in the relative returns to actions

(a) Wildlife Priority Zone Variation



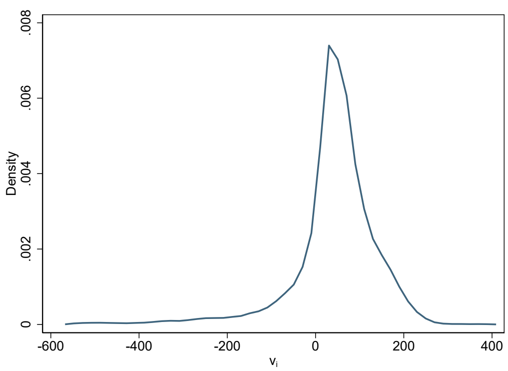

(b) Mid-Mechanism Policy Change



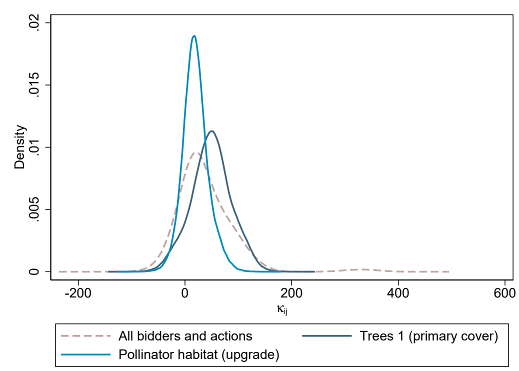

*Notes*: Figure presents sources of policy variation in the scoring rule that yield variation in returns to actions. Sub-figure (a) plots average action points award for a set of "treated" actions, actions for which after the 2011 sign-up WPZ bidders no longer got WPZ points, and "untreated" actions, whose points remained the same, and the same average action points for non-WPZ bidders. Sub-figure (a) plots the average rental rate that would be received for a given target score among bidders under the interim mechanism before the introduction of Climate Smart Practice Incentives, and in the final mechanism after their introduction, for each of the twelve primary covers. G indicates grasses, T indicates trees, H indicates habitat actions.

Figure 8: Estimated cost distributions

(a) Base participation cost $v_i$

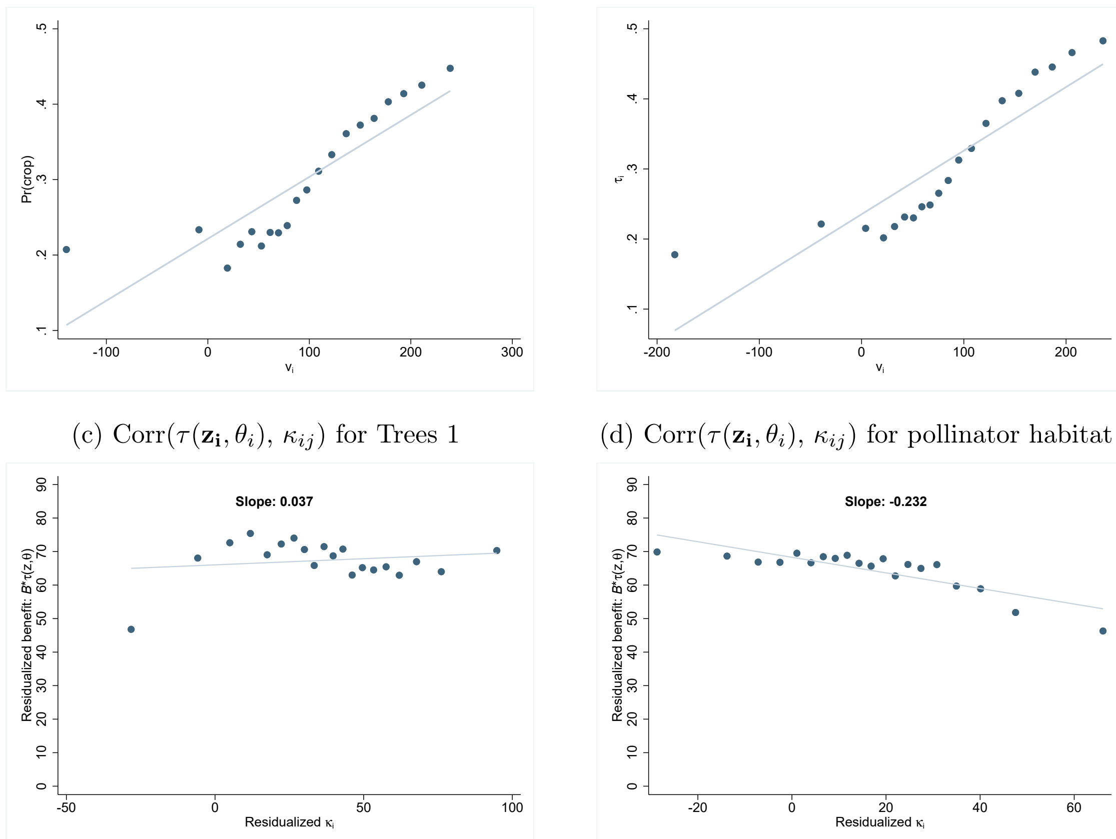



(b) Top-up action costs $\kappa_{ij}$




*Notes*: Figures present estimated kernel density plots of estimates of $v_i$ (a) and $\kappa_{ij}$ (b) and for all auctions in our sample. Sub-figure (a) excludes estimates of $v_i$ below the 1st and above the 99th percentile. Sub-figure (b) plots a density of the $\kappa_{ij}$ across bidders, actions, and sign-ups, and the dispersion of within-action costs for two sample actions. All costs are reported in dollars per acre per year, inflated to 2022 USD.

Figure 9: Relationship between costs and potential outcomes




(a) Correlation between $Y_{i0} = 0$ and $v_i$ for $S_i < \underline{S}$

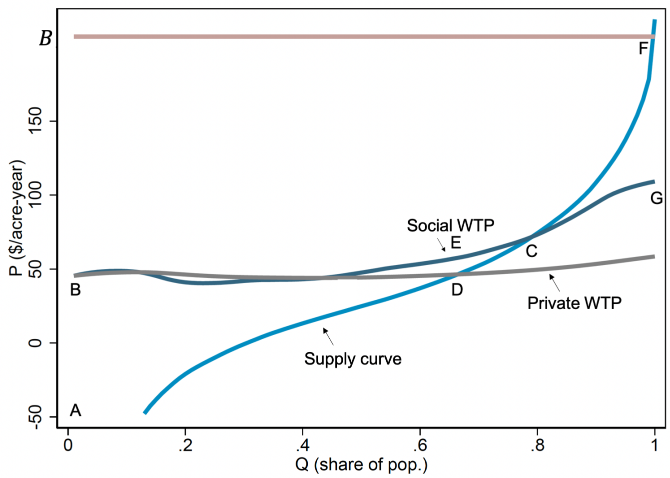
(b) Correlation between $\tau(\mathbf{z_i}, \theta_i)$ and $v_i$

(c) Corr($\tau(\mathbf{z_i}, \theta_i)$, $\kappa_{ij}$) for Trees 1

(d) Corr($\tau(\mathbf{z_i}, \theta_i)$, $\kappa_{ij}$) for pollinator habitat

*Notes*: Sub-figure (a) present binned scatterplots of the probability that offered fields were cropped ($Y_{i0} = 0$) against simulations of $v_i$, for losing bidders among auctions where we observe the geolocation of offered fields (2013 and 2016). Sub-figure (b) plots a binned scatterplot of estimates of $\tau(\mathbf{z_i}, \theta_i)$ against simulations of $v_i$. Figures excludes estimates of $v_i$ below the 1st and above the 99th percentile. Sub-figures (c) and (d) present binned scatter plots of the expected social benefit of land retirement $B \cdot \tau(\mathbf{z}_i, \theta_i)$ against the landowner's cost of undertaking the action $\kappa_{ij}$, controlling and retirement cost $v_i$. The slope of the line reported. Costs and benefits are reported in dollars per acre per year, inflated to 2022 USD.

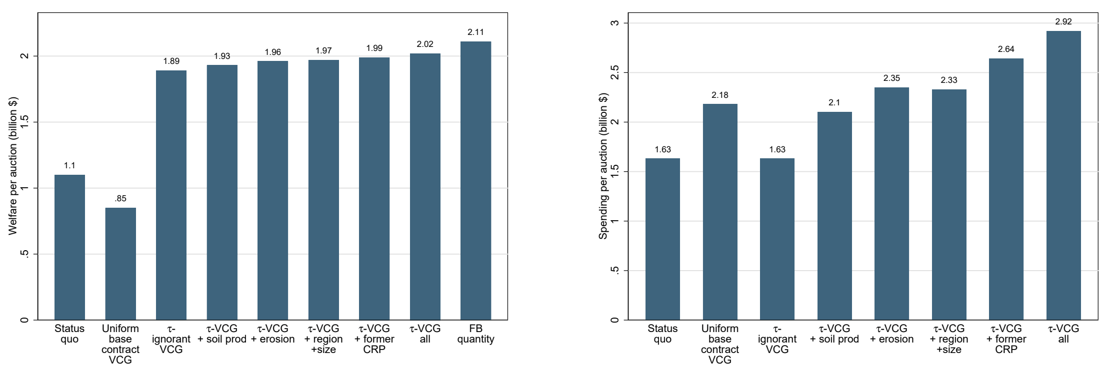
Figure 10: Empirical supply and WTP curves




*Notes*: Figure presents empirical counterparts of the curves in Figure 1a. The curves are residualized on the component of the score $\mathbf{z^t}$, as these attributes are already priced. Benefits are monetized based on our baseline estimates of the valuation of the CRP. Costs are determined as the minimum cost across any action, in order to avoid relying too heavily on a given normalization.

Figure 11: Outcomes under alternative auctions

(a) Surplus (b) Spending




*Notes*: Figure presents counterfactual surplus (environmental benefits net of costs) and payouts under counterfactual auction regimes. Status quo estimates the welfare gains and spending per auction according to the status quo auction design. Subsequent regimes enroll the same quantity of land (i.e. according to the acreage limits given by Congress in the Farm Bill) from the population of bidders, except the final column which shows the welfare/spending from enrolling the welfare-maximizing quantity. The characteristics under each of the $\tau-$VCG auctions describes what characteristics are allowed to influence $\tau(\mathbf{z}, \theta)$ in the mechanism. See Section 8.3 for detailed descriptions of each regime. Results are inflated to 2022 USD.

Table 1: Summary statistics

| | All agricultural land | | All CRP bidders | | CRP bid fields | |
|---|---|---|---|---|---|---|
| | CDL | Admin | CDL | Admin | CDL | Admin |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A. Land use outcomes. Share:** | | | | | | |
| Cropped | 0.302 | 0.282 | 0.209 | 0.213 | 0.151 | 0.183 |
| | (0.374) | (0.396) | (0.289) | (0.297) | (0.287) | (0.380) |
| Corn | 0.110 | 0.108 | 0.073 | 0.076 | 0.051 | 0.057 |
| | (0.244) | (0.265) | (0.175) | (0.186) | (0.170) | (0.226) |
| Soybean | 0.105 | 0.097 | 0.061 | 0.072 | 0.045 | 0.071 |
| | (0.237) | (0.251) | (0.156) | (0.179) | (0.164) | (0.251) |
| Fallow | 0.017 | 0.007 | 0.031 | 0.013 | 0.037 | 0.025 |
| | (0.086) | (0.065) | (0.106) | (0.079) | (0.140) | (0.150) |
| Natural vegetation or grassland | 0.546 | | 0.695 | | 0.736 | |
| | (0.373) | | (0.311) | | (0.334) | |
| **Panel B. Tract characteristics** | | | | | | |
| Size (acres) | 160.7 | | 250.6 | | | |
| | (2690.7) | | (506.5) | | | |
| Soil productivity ($/acre) | 92.4 | | 86.9 | | | |
| | (63.2) | | (58.5) | | | |
| Environmental sensitivity (EBI points) | 53.5 | | 86.5 | | | |
| | (29.8) | | (33.7) | | | |
| **Panel C. Bid characteristics** | | | | | | |
| Rental rate | | | 83.0 | | | |
| | | | (56.4) | | | |
| Acres bid | | | 84.1 | | | |
| | | | (136.3) | | | |
| Share re-enrolling | | | 0.70 | | | |
| | | | (0.46) | | | |
| Action = establish grasses | | | 0.638 | | | |
| | | | (0.481) | | | |
| Action = establish trees | | | 0.111 | | | |
| | | | (0.315) | | | |
| Action = establish habitat | | | 0.201 | | | |
| | | | (0.401) | | | |
| Accept and enroll | | | 0.800 | | | |
| | | | (0.400) | | | |
| N bidders / signup | | | 36,763 | | | |
| N | 7,890,426 | | 257,340 | | | |

*Notes*: Table presents summary statistics of all agricultural tracts, bidding agricultural tracts, and bid fields (a tract is a collection of fields with a common owner-operator). All land use outcomes are reported for the year prior to bidding, among bidders, with years re-weighted in the "All agricultural land" columns to match the distribution of bidder-years. All agricultural land includes both eligible non-bidders and ineligible land. Land use categories follow Lark et al. (2017). Crop outcomes exclude alfalfa and hay. Soil productivity is calculated by NASS and is reported in dollars per acre. Environmental sensitivity (EBI points) are the points given for exogenous characteristics of land in the scoring rule, which can be calculated for all tracts based on their geolocation. Grasses, trees, and habitat action indicators are aggregated over the menu of possible actions within those broad categories.

Table 2: RD evidence: coefficient estimates

| | CDL | Admin |
|---|---|---|
| | (1) | (2) |
| **Panel A: Main outcome: share of tract cropped** | | |
| Pre-sign-up (placebo) | 0.014 | 0.009 |
| | (0.007) | (0.006) |
| Post-period (pooled sign-ups) | -0.075 | -0.091 |
| | (0.007) | (0.006) |
| Post-period (full contract duration: 2010-2020) | -0.109 | |
| | (0.020) | |
| $\tau = 1$ benchmark | -0.405 | |
| Additionality share (full contract duration estimate / $\tau = 1$ benchmark) | 0.27 | |
| **Panel B: Other outcomes** | | |
| Corn | -0.015 | -0.023 |
| | (0.003) | (0.003) |
| Soybean | -0.018 | -0.026 |
| | (0.003) | (0.003) |
| Fallow | -0.008 | -0.011 |
| | (0.002) | (0.001) |
| Natural vegetation or grassland | 0.091 | |
| | (0.007) | |
| **Panel C: Spillovers to non-offered fields** | | |
| Share of non-offered fields cropped | -0.002 | -0.011 |
| | (0.011) | (0.009) |
| N bidders | 258,286 | 258,286 |
| N bidder-years | 3,099,432 | 1,808,002 |

*Notes*: Table presents coefficient estimates from Equation (14), estimated with land use outcomes measured in both the CDL (column 1) and the administrative data (column 2). The full-contract duration focuses only on the 2009 sign-up, in which we have a long enough post period to measure outcomes over the full contract duration, others pool all sign-ups for which we have post-period data: signups 39 (2009), 41 (2011), 43 (2012), 45 (2013), and 49 (2016). Natural vegetation or grassland is only observed in satellite imagery, as only cropped outcomes are reported to the USDA in the Form 578 data. Panel C estimates the effect of winning the auction and enrolling into the CRP on fields on winning tracts but were not directly enrolled. We restrict this analysis to the 2013 and 2016 sign-ups due to data limitations. All results are based on a specification using a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Imbens and Kalyanaraman, 2012; Calonico et al., 2014). Standard errors are clustered at the tract level.

Table 3: The menu of actions: prices and market shares

| | $\overline{t^{-1}(S, \mathbf{a}, \mathbf{z_i^t})}$ | Market share | $\overline{t^{-1}(S, \mathbf{a}, \mathbf{z_i^t})}$ | Market share | $\overline{t^{-1}(S, \mathbf{a}, \mathbf{z_i^t})}$ | Market share |
|---|---|---|---|---|---|---|
| | No upgrade | | + wildlife flood plot | | + pollinator habitat | |
| Grasses 1 | 28.63 | 0.140 | 35.21 | 0.015 | 52.91 | 0.007 |
| Grasses 2 | 74.30 | 0.104 | 77.86 | 0.022 | 86.00 | 0.019 |
| Grasses 3 | 43.64 | 0.067 | 49.37 | 0.005 | 64.68 | 0.009 |
| Grasses 4 | 81.00 | 0.201 | 83.59 | 0.023 | 90.34 | 0.056 |
| Trees 1 | 65.13 | 0.039 | 69.44 | 0.003 | 79.54 | 0.000 |
| Trees 2 | 94.73 | 0.020 | 96.45 | 0.003 | 101.47 | 0.001 |
| Trees 3 | 73.29 | 0.012 | 76.52 | 0.001 | 85.06 | 0.000 |
| Trees 4 | 79.54 | 0.002 | 82.40 | 0.000 | 89.65 | 0.000 |
| Trees 5 | 98.14 | 0.029 | 99.83 | 0.003 | 104.71 | 0.002 |
| Habitat 1 | 75.29 | 0.032 | 78.72 | 0.006 | 86.60 | 0.001 |
| Habitat 2 | 81.73 | 0.039 | 84.25 | 0.007 | 90.84 | 0.014 |
| Habitat 3 | 93.07 | 0.077 | 94.82 | 0.009 | 99.91 | 0.025 |

*Notes*: Table presents the menu of all 36 possible actions, split into 12 primary covers and three possible upgrade options. Table reports average "prices", or the rental rate per acre per year that a bidder could request to undertake a given action to reach the threshold score, and the market share of these actions pooled across the sign-ups in our sample.

Table 4: Summarized action cost ($\kappa_{ij}$) parameter estimates

| | All | Former CRP | Productive land | Large tracts |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\sigma$ | 11.16 | | | |
| | (0.10) | | | |
| Average costs: | | | | |
| Tree primary covers (rel. to grasses) | 58.36 | 54.70 | 43.01 | 73.00 |
| Habitat primary covers (rel. to grasses) | 7.02 | 9.06 | 7.00 | 6.70 |
| Wildlife food plot upgrade | 23.78 | 24.17 | 10.56 | 23.24 |
| Pollinator habitat upgrade | 19.76 | 22.36 | 14.95 | 86.88 |

*Notes*: Table presents our estimates of the dispersion in idiosyncratic action shocks, $\sigma$, and average costs across aggregate primary cover categories (relative to grasses) and upgrade categories (relative to no-upgrade), across all bidders and split by characteristics. Productive land indicates land that has an above-median soil productivity. Large tracts are above-median size bidders. All costs are reported in dollars per acre per year, inflated to 2022 USD.

Table 5: Parameter estimates: $\tau(\mathbf{z}, \theta)$

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $v$ | 0.00010 | 0.00014 | 0.00024 | 0.00014 |
| | (0.00005) | (0.00005) | (0.00005) | (0.00004) |
| Soil productivity | 0.001 | | | |
| | (0.000) | | | |
| Former CRP | -0.236 | -0.243 | -0.236 | -0.156 |
| | (0.007) | (0.006) | (0.006) | (0.006) |
| Size Q2 | 0.009 | 0.011 | 0.022 | 0.002 |
| | (0.009) | (0.008) | (0.008) | (0.007) |
| Size Q3 | 0.006 | 0.009 | 0.020 | -0.009 |
| | (0.009) | (0.009) | (0.009) | (0.007) |
| Size Q4 | -0.033 | -0.027 | -0.010 | -0.052 |
| | (0.010) | (0.010) | (0.010) | (0.008) |
| Prior crop Q2 | | | | 0.048 |
| | | | | (0.008) |
| Prior crop Q3 | | | | 0.158 |
| | | | | (0.010) |
| Prior crop Q4 | | | | 0.318 |
| | | | | (0.014) |
| Prior nat. veg. Q2 | | | | -0.041 |
| | | | | (0.010) |
| Prior nat. veg. Q3 | | | | -0.053 |
| | | | | (0.012) |
| Prior nat. veg. Q4 | | | | -0.040 |
| | | | | (0.014) |
| Region FEs | ✓ | ✓ | ✓ | ✓ |
| Soil productivity FEs | | ✓ | ✓ | ✓ |
| Controls for $\mathbf{z_i^{t1}}$ | | | ✓ | ✓ |

*Notes*: Table presents estimates of $\tau(\mathbf{z}, \theta)$ from a joint model of selection and cropping outcomes, estimated via maximum likelihood (with an "reduced-form" normal selection equation). Our selection equation incorporates all determinants of equilibrium choices of $S_i$: our estimates of $v_i$, observable determinants of $\kappa_{ij}$, and all bidder characteristics incorporated in the scoring rule, $\mathbf{z_i^t}$. The model is estimated at the field level on 10 simulated copies of each bidder, with standard errors clustered at the bidder level. Soil productivity fixed effects include deciles of estimated soil productivity. Controls for $\mathbf{z_i^{t1}}$ include deciles of wind erosion and water erosion, points for ground water and surface water quality estimates, and indicators for whether a bidder is in a water quality zone. Estimates are based on the 2016 auction. $Y_{i0}$ is measured as the share of offered fields that is not cropped. $Y_{i1}$ is assumed to be 1.

Table 6: Welfare under alternative pricing and market structures, base contract

| | First best: set $p_{ij}$ | Miscalibrated pricing (assume $\tau = 1$) | | Accounting for $\tau$ | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Uniform $p$ | Set $p(\mathbf{z^t})$ | Uniform $p$ | Set $p(\mathbf{z^t})$ | Add $\hat{\tau}(\mathbf{z})$ to incentive linearly | | |
| | | | | | | Include all $\mathbf{z}$ | Excl. prior land use | Excl. prior CRP |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Panel A. Govt. buyer,** $\lambda = 0$ | | | | | | | | |
| Welfare | 55.20 | 39.15 | 39.17 | 43.71 | 44.75 | 54.95 | 51.03 | 47.94 |
| Price | -6.96 | | | 75.18 | 63.47 | 64.69 | 62.56 | 61.93 |
| Share contracting | 0.48 | 1.00 | 1.00 | 0.79 | 0.70 | 0.63 | 0.67 | 0.72 |
| **Panel B. Govt. buyer,** $\lambda = 0.15$ | | | | | | | | |
| Welfare | 52.80 | 24.91 | 26.13 | 39.19 | 40.06 | 48.67 | 45.37 | 42.70 |
| Price | -12.53 | 127.36 | 110.60 | 34.56 | 37.51 | 42.83 | 44.05 | 42.37 |
| Share contracting | 0.47 | 0.93 | 0.94 | 0.56 | 0.54 | 0.55 | 0.56 | 0.58 |
| **Panel C. Offset market equilibrium** | | | | | | | | |
| Welfare | 55.20 | | | 42.46 | 43.02 | 54.81 | 50.89 | 47.85 |
| Price | -6.96 | | | 38.00 | 45.64 | 80.71 | 71.33 | 61.69 |
| Share contracting | 0.48 | | | 0.59 | 0.63 | 0.61 | 0.65 | 0.69 |

*Notes*: Table presents counterfactual welfare, prices and quantities. Under equilibrium outcomes, consumers form expectations based on an observed single-dimensional score incorporating characteristics $\mathbf{z^t}$. We exclude prices for the miscalibrated pricing in columns (2) and (3) of panel A because all potential participants enroll. We exclude columns (2) and (3) in panel C because our offset market equilibrium imposes rational expectations, and so these $\tau = 1$ benchmarks are undefined. Exclude prior land use and exclude prior CRP denote dropping those characteristics from our projection of $\tau(\mathbf{z}, \theta)$ onto $\hat{\tau}(\mathbf{z})$. When prices are not uniform, price represents the average price contracted. Values are inflated to 2022 USD.

Table 7: Menu design versus differentiated incentives to separate types

| | Base contract only (optimal uniform $p$) | Optimal uniform base price + $B^j$ | Optimal action-differentiated prices | Optimal $p_j(\mathbf{z^t})$ | Optimal $p_j(\mathbf{z})$, adding $\hat{\tau}(\mathbf{z})$ to incentive linearly |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Welfare | 39.19 | 83.05 | 83.15 | 84.64 | 88.67 |
| Δ Welfare from prev.. col. | | 43.86 | 0.10 | 1.49 | 4.04 |
| Price | 34.56 | 69.51 | 72.92 | 83.05 | 82.72 |
| Share contracting | 0.56 | 0.81 | 0.82 | 0.85 | 0.80 |

*Notes*: Table presents counterfactual welfare, prices and quantities under our richer contracting space with 36 possible contracts. Column (2) prices contracts only according to their productive value. Column (3) finds optimal prices. Columns (4) and (5) further condition incentives on observable characteristics. We impose a cost of funds $\lambda = 0.15$. Prices are average prices paid. Values are inflated to 2022 USD.

# A Theoretical Framework: Details and Proofs

**Proof of Proposition 1** *Part 1.* Considering only the base contract and $\lambda = 0$, Equation 8 simplifies to

$$\max_{p_{\mathbf{z}}} \int^{p_{\mathbf{z}}} (B \cdot \tau(\mathbf{z}, v) - v) \cdot f(v|\mathbf{z}) \tag{22}$$

for each vector of observable characteristics $\mathbf{z}$ with $f(v|\mathbf{z}) = dF(v|\mathbf{z})$. The F.O.C. defining the optimum sets $B \cdot \tau(\mathbf{z}, p_{\mathbf{z}}) - p_{\mathbf{z}} = 0$.

*Part* 2. Considering only the base contract, but now with $\lambda > 0$, the regulator solves:

$$\max_{p_{\mathbf{z}}} \int^{p_{\mathbf{z}}} (B \cdot \tau(\mathbf{z}, v) - v) \cdot f(v|\mathbf{z}) - \lambda p_{\mathbf{z}} F(p_{\mathbf{z}}|\mathbf{z}) \tag{23}$$

with First Order Condition:

$$(B \cdot \tau(\mathbf{z}, p_{\mathbf{z}}) - p_{\mathbf{z}}) \cdot f(p_{\mathbf{z}}|\mathbf{z}) = \lambda (p_{\mathbf{z}} f(p_{\mathbf{z}}|\mathbf{z}) + F(p_{\mathbf{z}}|\mathbf{z})) \tag{24}$$

dividing by $f(p_{\mathbf{z}}|\mathbf{z})$ and re-arranging, we obtain:

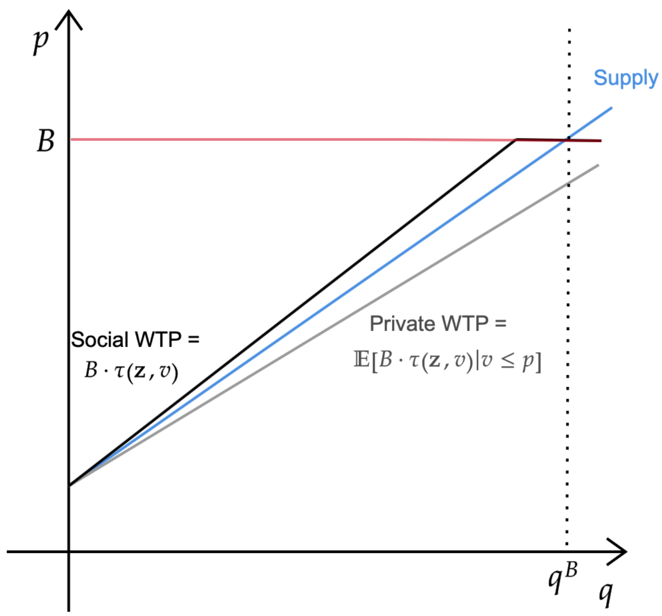
$$p_{\mathbf{z}} = B \cdot \tau(\mathbf{z}, p_{\mathbf{z}}) \cdot \frac{1}{\lambda \left(1 + \frac{1}{\epsilon(\mathbf{z}, p_z^*)}\right) + 1} \tag{25}$$

where $\epsilon(\mathbf{z}, p_z^*)$ is the price elasticity of supply for participants with characteristics $\mathbf{z}$, or $\frac{f(p_{\mathbf{z}}|\mathbf{z}) \cdot p_{\mathbf{z}}}{F(p_{\mathbf{z}}|\mathbf{z})}$.

**Proof of Proposition 2** Because price-taking buyers know the distribution of $\tau(\mathbf{z}, \theta)$ but not each individual $\theta_i$, each buyer takes expectations over all participants in the market and obtains value from a contract with a supplier with characteristics $\mathbf{z}$ to conduct action $j$ equal to $\mathbb{E}[B \cdot \tau(\mathbf{z}, \theta) + B^j | D^j(\mathbf{p}_{\mathbf{z}}; \mathbf{z}, \theta) = 1]$. A competitive equilibrium is defined by a free-entry condition on the *buyer side* for each contract for action $j$ among participants with characteristics $\mathbf{z}$ following Azevedo and Gottlieb (2017). Suppose $p_z^j > \mathbb{E}[B \cdot \tau(\mathbf{z}, \theta) + B^j | D^j(\mathbf{p}_{\mathbf{z}}; \mathbf{z}, \theta) = 1]$. Buyers then obtain negative payoffs, $\mathbb{E}[B \cdot \tau(\mathbf{z}, \theta) + B^j | D^j(\mathbf{p}_{\mathbf{z}}; \mathbf{z}, \theta) = 1] - p_z^j < 0$, and $p_z^j > \mathbb{E}[B \cdot \tau(\mathbf{z}, \theta) + B^j | D^j(\mathbf{p}_{\mathbf{z}}; \mathbf{z}, \theta) = 1]$ cannot be an equilibrium. If $p_z^j < \mathbb{E}[B \cdot \tau(\mathbf{z}, \theta) + B^j | D^j(\mathbf{p}_{\mathbf{z}}; \mathbf{z}, \theta) = 1]$, buyers make positive profits, and thus enter the market and purchase contracts until $p_z^j = \mathbb{E}[B \cdot \tau(\mathbf{z}, \theta) + B^j | D^j(\mathbf{p_z}; \mathbf{z}, \theta) = 1]$. Welfare losses follow directly from both Azevedo and Gottlieb (2017) and the simple set-up in Figure 1a .

**Illustrative example: unravelling** Figure A.1 demonstrates cost and social WTP curves such that the entire market consists of Pareto-improving trades that do not occur because the expected value of each contract lies below the cost of contracting. This is a demonstration of a classic "lemons" market (Akerlof, 1970) where offset markets to fail to realize any amount of the substantial gains from trade.

Figure A.1: Unravelling

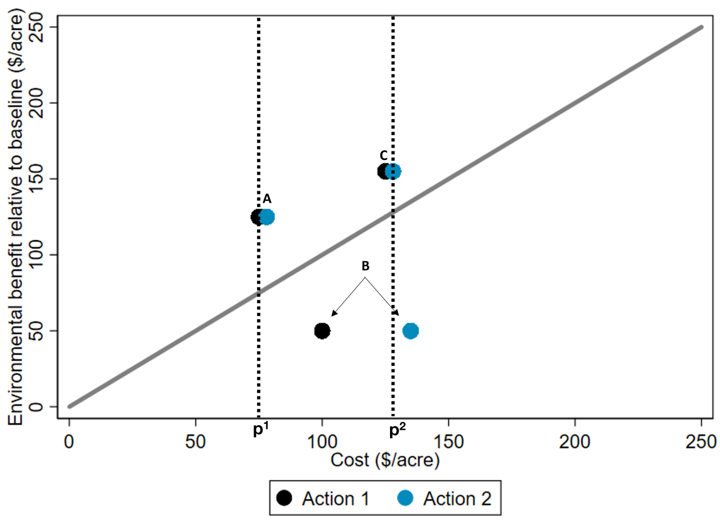



*Notes:* Figure illustrates sources of welfare loss due to private information among suppliers of environmental services. We consider the simple setting of a single base contract of retiring land at cost $v$. Figure 1a plots the supply curve, and social WTP and private (offset market) WTP curves under a uniform price for a specific WTP and supply curve that cause the market to completely unravel.

**Illustrative example: screening contracts** Figure A.2 presents an illustrative example of the possible screening value of top-up actions. Participants' costs are displayed on the x-axis, and participants' value (WTP) are displayed on the y-axis. A, B, and C are each potential participants. Under Action 1, even though it is socially efficient to enroll C, the optimal uniform price enrolls only A to screen out B. Consider adding an additional action (Action 2), e.g. restoring wetlands, that increases the costs of A and C slightly, and B, the low type in this simple example, substantially. Now, the regulator can set the price of

Action 2 to enroll both A and C, and keep the price of Action 1 at its initial level, enrolling no one. Adding the additional action improves welfare, because it relaxed B's incentive compatibility constraint, even though this action had no productive value at all. In our empirical application, higher-quality actions may have both productive and screening value.

Figure A.2: Screening contract illustration




*Notes:* Figure illustrates the screening gains of introducing an additional contract. A, B, and C are potential participants. Action 1 is the status quo base action, and Action 2 is the bundle of a base action and an introduced top-up action. All potential participants above the 45 degree line are efficient to enroll, all potential participants whose costs are below the vertical dashed lines do enroll.

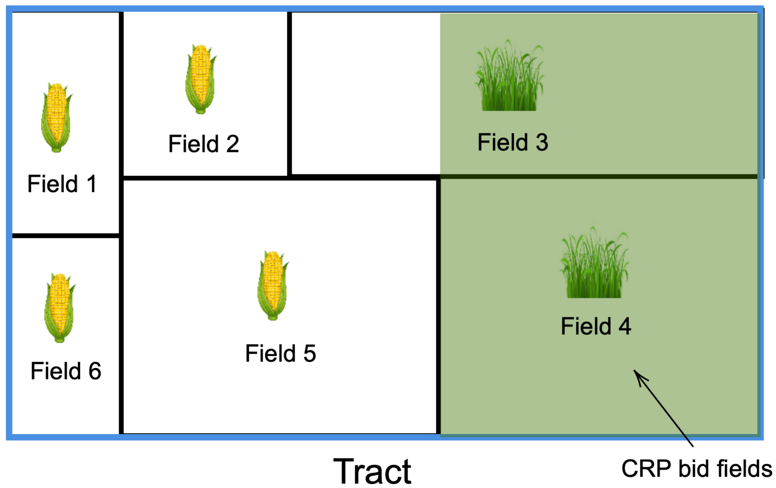
# B Data Details: Measuring Land Use and Constructing our Linked Dataset

In this section, we provide more detail about agricultural units of observation, our land-use datasets and measurement of outcomes, and our linkage procedure to match bids with a panel of land use outcomes.

**Agricultural units: tracts and fields** All agricultural land is the US is divided into fields, or Common Land Units, by the USDA. A field is defined as the smallest unit of land that has: (1) a permanent, contiguous boundary, (2) a common land cover and land management, (3) a common owner.[38] There are 37,480,917 fields in the US (as of 2016), with an average size of 33.82 acres. Each field, by definition, has a single land use.

[38]See https://www.fsa.usda.gov/Assets/USDA-FSA-Public/usdafiles/APFO/support-documents/pdfs/clu_infosheet_2017_Final.pdf for more details.

Figure B.1: Example: tract, fields, and bid fields

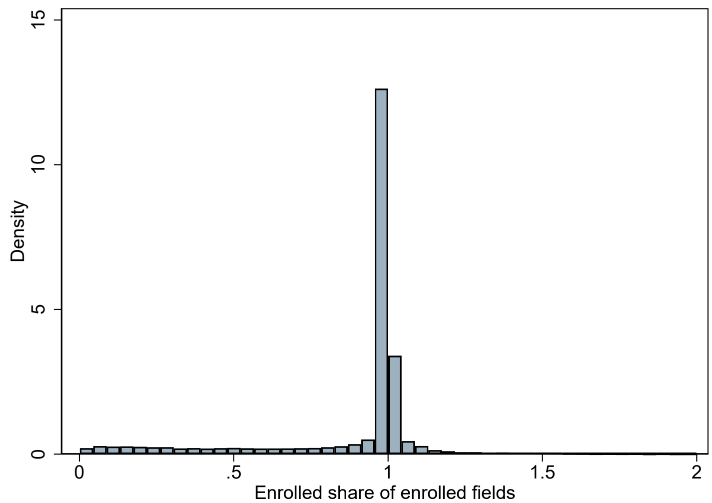



*Notes:* Figure explains the various geographic units in our dataset. The blue outline is a single tract: this is the unit of firm / bidder in our analysis. This tract contains six fields, these are administrative delineations of a tract, each with a single land use. The green shaded area represents an example area bid into the CRP. This could follow field boundaries (as for field 4) or cut into fields (as for field 3).

A tract is a collection of fields under one common ownership that is operated as a farm or part of a farm (a tract is a firm in our setting). The average tract includes 4.75 fields. Each tract can submit at most one bid into a CRP auction. This bid can include any subset of a tract's fields. A bid is not constrained to bid only entire fields; in principle, a bidder can bid any subset of their land, regardless of field delineations. In practice, a large share of bids follow field boundaries, as illustrated by Figure B.2. Figure B.1 provides an illustrative example.

Our dataset includes an identifier and the geolocation of each of the bidding tracts, and their subset fields, for all sign-ups. We only observe the exactly identities of the bid fields in 2013 and 2016.

Figure B.2: Share of offered fields enrolled




*Notes:* Figure shows a histogram of the share of enrolled fields that are offered into the CRP (the shaded green area as a share of the total area of fields 3 and 4 in Figure B.1). The mass point at one indicates that the vast majority of bidders offer the entire field.

**Remote sensing data (CDL)** Our first source of land use data is the Cropland Data Layer (CDL) from 2009 to 2020. The CDL is derived from annual satellite imagery at a 30m by 30m resolution (approximately one quarter acre) for the entire contiguous US. The dataset classifies each pixel into over 50 crop categories and over 20 non-crop categories. The CDL is produced by the National Agricultural Statistics Service (NASS), and trained on administrative data submitted to the USDA for crop insurance purposes (Form 578, discussed in more detail below). The CDL has been used in prior economics research studying cropping and land use (Scott, 2013; Hagerty, 2022).

Our primary analysis aggregates these categories into super-classes of crop versus non-crop, following (Lark et al., 2017). Note that our crop classification excludes alfalfa / hay and fallow / idle cropland. The super-class accuracy of the CDL is very high with $>$ 99% producer's (classified as cropped when truly cropped) and $>$ 98% user's (truly cropped when classified as cropped) accuracy. Despite this high super-class accuracy, remote sensing classifications are subject to measurement error in classification (Alix-Garcia and Millimet, 2022; Torchiana et al., 2022), particularly when analyzing land use transitions, that we take seriously. In order to improve accuracy, some states in some years use prior years' CDL as an input into the training algorithm, providing a further source of bias stemming from the classification algorithm.

We merge the CDL to a shapefile of all agricultural fields in the US, which we can then aggregate to tracts / bidders using USDA identifiers. Though field, and even tract, boundaries can change over time, we can capture these changes flexibly by merging the CDL data to a constant geographic outline of a bidder over time, time-stamped at the point of bidding. Our primary outcome of interest is the crop versus non-crop classification. We construct this both at the field level with a binary indicator taking the value one if crop is the most common land use on the field, and the tract level, where we calculate land use outcomes as (1) the share of pixels that fall into the crop super-class, and (2) a weighted average of field-level cropping outcomes. These two measures are very similar.

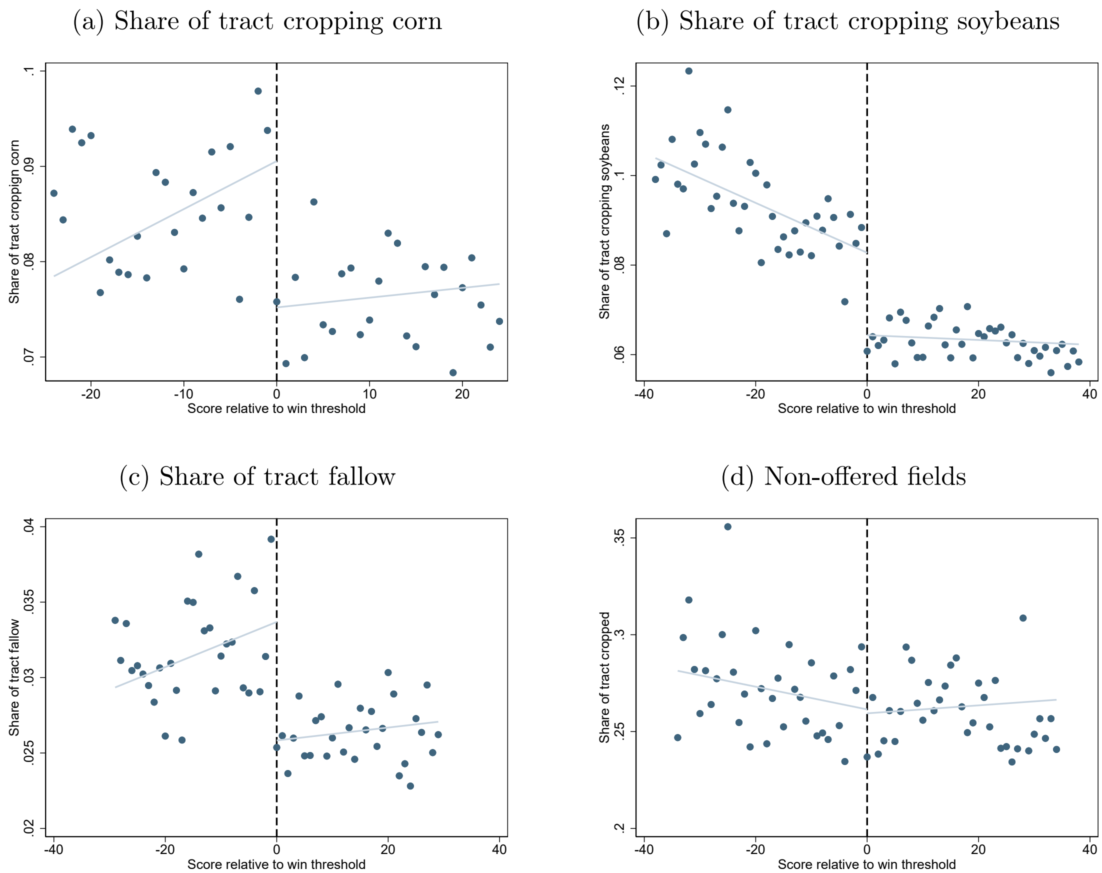
**Form 578 Administrative Data** Our second source of data is new to economics research and is the ground truth administrative data that the CDL is trained on. These are annual field-level reports of total acreage cropped in each (detailed) crop category and enrollment in various USDA programs, including the CRP. Though these are self-reported by farms, crop insurance payouts are dependent on these reports, so farmers are incentivized to report cropped amounts accurately (though not program enrollment). Unlike the CDL, which has coverage over the entire US, field-level data is only submitted if there is an incentive to do so, i.e. if it is cropped (and covered by crop insurance). We assume that all non-reporting fields are not cropped, a limitation relative to the CDL.

We merge 578 administrative data to bidders based on field and tract identifiers. One challenge is that field and tract identifiers can change over time. We account for this by constructing a panel that tracks changes in field identifiers and field delineations over time using their precise geographical locations.

**NAIP Imagery** Our final dataset is derived from the National Agriculture Imagery Program (NAIP). The NAIP is administered through the Forest Service Agency (FSA) of the USDA, and collects 1m resolution images of all agricultural land during growing season. We obtain NAIP images for the exact contours of enrolled fields (the highlighted green area in Figure B.1) to assess compliance with CRP rules by eye using ultra-high resolution imagery and without the challenges of classification bias in the derived data products. We discuss this process in more detail in Appendix F.

# C Supplemental RD Figures and Tables

Figure C.1: Additional RD Plots: CDL




(a) Share of tract cropping corn

(b) Share of tract cropping soybeans

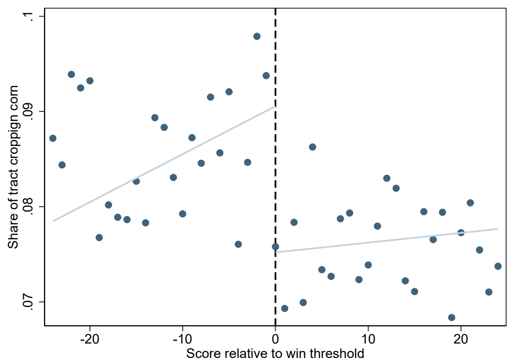
(c) Share of tract fallow

(d) Non-offered fields

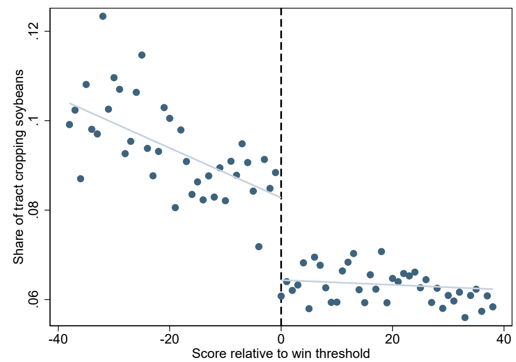
*Notes*: Figure presents regression discontinuity plots with a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Calonico et al., 2014) pooling all sign-ups and estimated on post-auction years (Equation 14 for $r > 0$). Land-use outcomes are derived from the Cropland Data Layer (CDL). Positive numbers in the RD figures correspond to winning and enrolling into the CRP.

Figure C.2: Additional RD Plots: Form 578 Admin Data

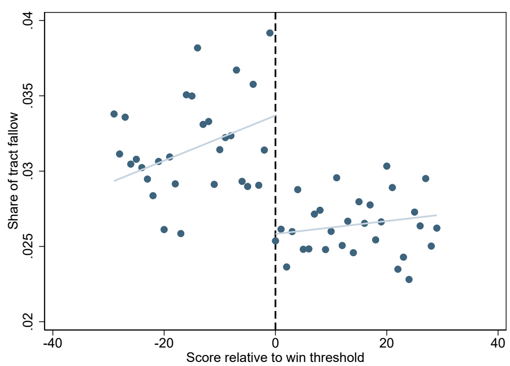
(a) Share of tract cropping corn



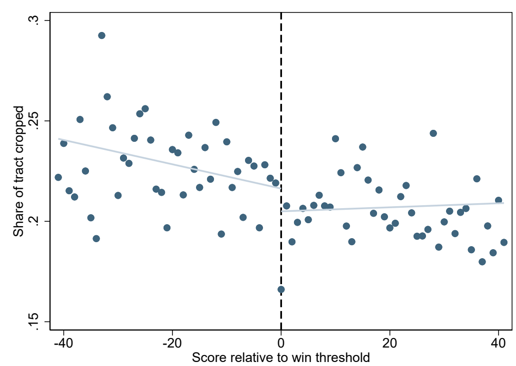

(b) Share of tract cropping soybeans



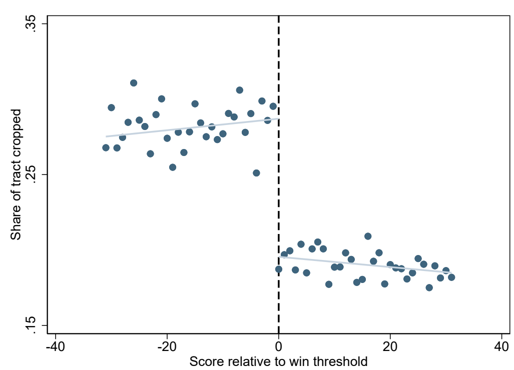

(c) Share of tract fallow




(d) Non-offered fields

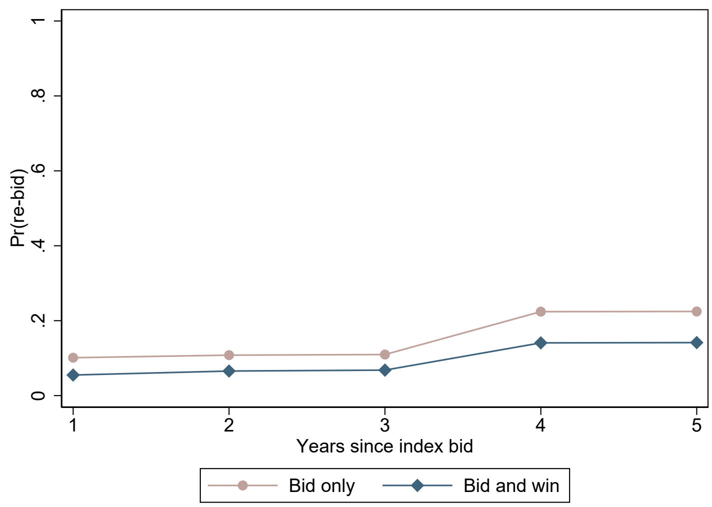



(e) Share of tract cropping




*Notes*: Figure presents regression discontinuity plots with a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Calonico et al., 2014) pooling all sign-ups and estimated on post-auction years (Equation 14 for $r > 0$). Land-use outcomes are derived from the Form 578 administrative data. Positive numbers in the RD figures correspond to winning and enrolling into the CRP.

Figure C.3: Rebidding hazard




*Notes*: Figure plots the share of losers who have rebid at least once in the years following an index sign-up, split by all bidders (beige) and successful bidders (blue). By five years out, fewer than 20% of losing bidders have ever successfully rebid.

Table C.1: RD estimates: split by location of threshold rent of base action

| | CDL | Admin |
|---|---|---|
| | (1) | (2) |
| Quartile 1 price (lowest) | -0.039 | -0.054 |
| | (0.013) | (0.013) |
| Quartile 2 price | -0.059 | -0.068 |
| | (0.012) | (0.012) |
| Quartile 3 price | -0.031 | -0.042 |
| | (0.012) | (0.013) |
| Quartile 4 price (highest) | -0.075 | -0.098 |
| | (0.015) | (0.015) |

*Notes*: Table presents pooled RD coefficients (Equation 14 for $r > 0$) split by the rental rate required for the base contract to achieve the threshold rule. This uses both variation across sign-ups and variation within sign-ups across bidders: bidders with land that is more environmentally sensitive can bid bid a lower rate to obtain a given threshold than those whose lands are given fewer points for environmental sensitivity. Standard errors clustered at the tract level. Outcome variable = share cropped, measured in the CDL.

Table C.2: RD evidence: coefficient estimates, $>5$ acre offers

| | CDL | Admin |
|---|---|---|
| | (1) | (2) |
| **Panel A: Main outcome: share of tract cropped** | | |
| Pre-sign-up (placebo) | 0.016 | 0.014 |
| | (0.007) | (0.006) |
| Post-period (pooled sign-ups) | -0.076 | -0.095 |
| | (0.007) | (0.006) |
| Post-period (full contract duration: 2010-2020) | -0.117 | |
| | (0.020) | |
| $\tau = 1$ benchmark | -0.436 | |
| **Panel B: Other outcomes** | | |
| Corn | -0.016 | -0.023 |
| | (0.003) | (0.003) |
| Soybean | -0.021 | -0.027 |
| | (0.003) | (0.003) |
| Fallow | -0.009 | -0.011 |
| | (0.002) | (0.001) |
| Natural vegetation or grassland | 0.097 | |
| | (0.007) | |
| **Panel C: Spillovers to non-offered fields** | | |
| Share of non-offered fields cropped | -0.002 | -0.011 |
| | (0.011) | (0.009) |
| N bidders | 236,593 | 236,593 |
| N bidder-years | 2,839,116 | 1,656,151 |

*Notes:* Table presents coefficient estimates from Equation (14), estimated with land use outcomes measured in both the CDL (column 1) and the administrative data (column 2). The full-contract duration focuses only on the 2009 sign-up, in which we have a long enough post period to measure outcomes over the full contract duration, others pool all sign-ups for which we have post-period data: signups 39 (2009), 41 (2011), 43 (2012), 45 (2013), and 49 (2016). Natural vegetation or grassland is only observed in satellite imagery, as only cropped outcomes are reported to the USDA in the Form 578 data. Panel C estimates the effect of winning the auction and enrolling into the CRP on fields on winning tracts but were not directly enrolled. We restrict this analysis to the 2013 and 2016 sign-ups due to data limitations. All results are based on a specification using a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Calonico et al., 2014). Standard errors are clustered at the tract level. Restricted to the 92% of bidders offering more than 5 acres into the CRP.

# D Scoring Rule Details: Recreating $t\left(\mathbf{b}_i, \mathbf{z_i^t}\right)$

In this section, we provide more details about $t\left(\mathbf{b_i}, \mathbf{z_i^t}\right)$. Note that the $t\left(\mathbf{b}_i, \mathbf{z_i^t}\right)$ includes two arguments: the bid $\mathbf{b}_i = (r_i, \mathbf{a_i})$ and exogenous characteristics $\mathbf{z_i^t}$.

**Exogenous characteristics** The characteristics $\mathbf{z_i^t}$ that influence the scoring rule include:

- **Whether a bidder is in a Wildlife Priority Zone (WPZ)**, defined high priority wildlife geographic areas. 30 points.

- **Whether a bidder is in a Water Quality Zone (WQZ)**, areas with high value to improving ground or surface water quality. 30 points.
- **Groundwater quality**: an evaluation of the predominant soils, potential leaching of pesticides and nutrients into groundwater, and the impact to people who rely on groundwater as a primary source of drinking water. Continuous score: 0 to 25 points.
- **Surface water quality**: an evaluation of the amount of sediment (and associated nutrients) that may be delivered into streams and other water courses. Continuous score: 0 to 45 points.
- **Erosion potential**: Continuous score of 0 to 100 points depending on the Erodibility Index.
- **Air quality**: an evaluation of the air quality improvements by reducing airborne dust and particular caused by wind erosion from cropland. Continuous score of 0 to 30 points depending on wind speed, wind direction, and the duration of wind events and soil erodibility.
- **Whether a bidder is in an Air Quality Zone (AQZ)**. 5 points.

The characteristics $\mathbf{z_i^t}$ are exogenous in the sense that they depend on a bidders location and not the actions they choose to provide. We consider the parcel of land that a bidder offers into the CRP as fixed. These characteristics, and the points that each bidder is able to obtain based on their location alone, are known for every field in the US.

**Conservation actions** To model bidders' choices over actions and rental rates, we also need to construct the menu of actions available to each bidder and the points that any action-bid combination achieves. The challenge is that the data only records the points assigned for the chosen action, not the menu of possible actions (exogenous points are common across actions, so are recorded for every bidder). We must reconstruct this menu. We do so using the EBI Fact Sheets published for each sign-up.[39] These Fact Sheets are published in order to help bidders make informed decisions about their bids.

Actions can be grouped into two categories: a primary cover, described in Table D.1, which covers the total area offered into the CRP, and an (optional) additional upgrade action,

[39]See https://www.fsa.usda.gov/Assets/USDA-FSA-Public/usdafiles/FactSheets/2020/crp-56th-ebi-fact-sheet-12-31-2020.pdf for more details.

described in Table D.2, which can be offered in addition to the primary cover on a smaller area.

Table D.1: Action choices in detail: primary covers

| Short name | Description |
|---|---|
| Grasses 1 | Permanent introduced grasses and legumes (CP1): Existing stand of one to three species or planting new stand of two to three species of an introduced grass species |
| Grasses 2 | Permanent introduced grasses and legumes (CP1): Existing stand or planted mixture (minimum of four species) of at least 3 introduced grasses and at least one forb or legume species best suited for wildlife in the area. |
| Grasses 3 | Permanent native grasses and legumes (CP2): Existing stand (minimum of one to three species) or planting mixed stand (minimum of three species) of at least two native grass species at least one forb or legume species beneficial to wildlife. |
| Grasses 4 | Permanent native grasses and legumes (CP2): Existing stand or planting mixed stand (minimum of five species) of at least 3 native grasses and at least one shrub, forb, or legume species best suited for wildlife in the area. |
| Trees 1 | Tree planting (softwoods) (CP3): Southern pines, northern conifers, or western pines – solid stand of pines/conifers/softwoods (existing, according to state developed standards, or planted at more than 550 (southern pines), 850 (northern conifers), or 650 (western pines) trees per acre). |
| Trees 2 | Tree planting (softwoods) (CP3): Southern pines, northern conifers, or western pines – pines/confiers/softwoods existing or planted at a rate of 500-550 (southern pines), 750-850 (northern conifers), or 550-650 (western pines) per acre depending on the site index (state-developed standards) with 10-20% openings managed to a CP4D wildlife cover. |
| Trees 3 | Hardwood tree planting (CP3A): Existing or planting solid stand of nonmast producing hardwood species. |
| Trees 4 | Hardwood tree planting (CP3A): Existing or planting solid stand of single hard mast producing species. |
| Trees 5 | Hardwood tree planting (CP3A): Existing or planting mixed stand (three or more species) or hardwood best suited for wildlife in the area or existing or planting stand of longleaf pine or atlantic white cedar – planted at rates appropriate for the site index. |
| Habitat 1 | Permanent wildlife habitat, noneasement (CP4D): Existing stand or planting mixed stand (minimum of four species) of either grasses, trees, shrubs, forbs, or legumes planted in mixes, blocks, or strips best suited for various wildlife species in the area. A wildlife conservation plan must be developed with the participant. |
| Habitat 2 | Permanent wildlife habitat, noneasement (CP4D): Existing stand or planting mixed stand (minimum of five species) or either predominantly native species including grasses, forbs, legumes, shrubs, or trees planted in mixes, blocks, or strips best suited to providing wildlife habitat. Only native grasses are authorized. A wildlife conservation plan must be developed with the participant. |
| Habitat 3 | Rare and declining habitat restoration (CP25): Existing stand or seeding or planting will be best suited for wildlife in the area. Plant species selections will be based upon Ecological Site Description data. |

*Notes:* Table describes the menu of primary cover actions.

Table D.2: Action choices in detail: upgrades

| Short name | Description |
|---|---|
| No upgrade | Primary cover only |
| Wildlife food plot | Wildlife food plots are small plantings in a larger area |
| Pollinator habitat | Existing stand or planting (minimum of .5 acres) of a diverse mix of multiple species suited for pollinators |

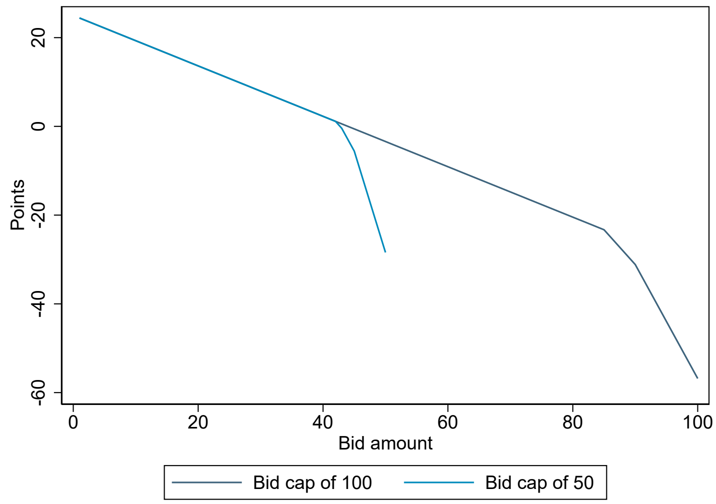
*Notes:* Table describes the menu of upgrade actions.

We obtain the points associated with each of the actions in Tables D.1 and D.2 from the EBI Fact Sheets. The point values assigned to the different actions can vary across bidders based on whether or not a bidder is in a Wildlife Priority Zone (WPZ).

**Bid amount** The final element of the scoring rule is the treatment of $r_i$. Unlike in the quasi-linear environment of Asker and Cantillon (2008), the scoring rule is non-linear in $r_i$ for two reasons. First, the existence of bid caps make some choices infeasible if $r_i > \overline{r}_i$, where $\overline{r}_i$ denotes the $i$ specific bid cap. These bid caps are determined based on the productivity of soils and are known for all tracts in the US. Second, the score introduces non-linearities based on the amount a bidder bids before the bid cap with kinks at 10% and 15% below the bid cap (see Figure D.1 for a demonstration).[40]

[40]Encouragingly, we observe mass points at these 10% and 15% kink points, suggesting that bidders are making sophisticated bid choices.

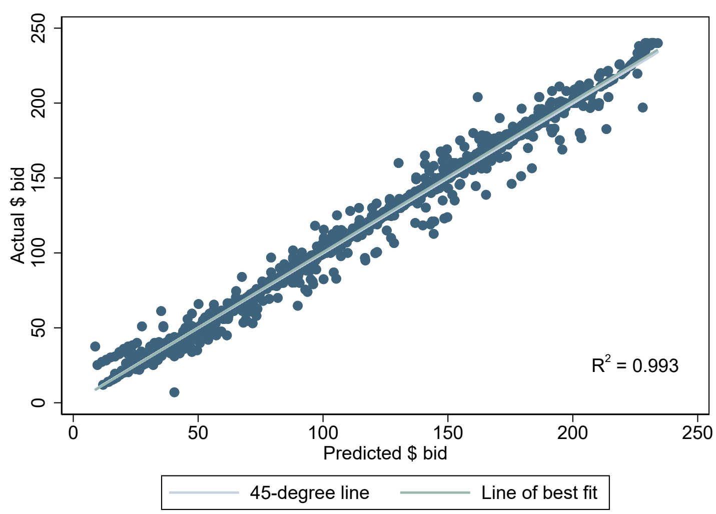
Figure D.1: Demonstrating the non-linear scoring rule




*Notes*: Figure shows an example of the non-linearity in the conversion of bid amount (per acre, per year) to points for two example bidders (one with $\bar{r}_i = 50$ and one with $\bar{r}_i = 100$).

**Testing** $t\left(\mathbf{b}_i, \mathbf{z}_\mathbf{i}^\mathbf{t}\right)$ We incorporate all of these complexities to construct the entire function, $t\left(\mathbf{b}_i, \mathbf{z}_\mathbf{i}^\mathbf{t}\right)$. Appendix Figure D.2 demonstrates that our reconstruction performs extremely well: at observed actions, our predictions of the required bid to achieve the true score predicts the observed bid with an $R^2$ of over 0.99.

Figure D.2: Relationship between predicted and actual bid at observed scores and actions

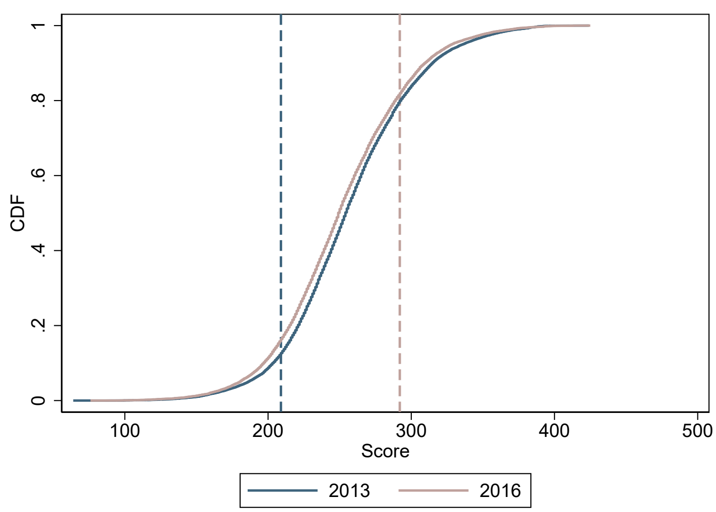



*Notes*: Figure presents a scatter plot of actual bids against predicted bids, given observed actions and scores, based on our construction of $t\left(\mathbf{b}_i, \mathbf{z}_\mathbf{i}^\mathbf{t}\right)$.

# E Additional Details: Bidding Model and Estimation

**Quantity uncertainty** Figure E.1 provides additional support for the assumption (based on institutional features) of uncertainty in quantity cleared (acreage accepted into the program). The 2013 and 2016 auctions had very different quantity thresholds, and thus very different threshold scores — denoted by the dashed lines in blue and beige — but the CDFs of bidder scores lie essentially on top of each other. If anything, the scores are slightly higher in 2013. If bidders knew about the differences in quantity ex-ante, they would bid more aggressively in 2016 in response to a more stringent quantity limit.

Figure E.1: CDF of scores and thresholds across across sign-ups 2013 and 2016




*Notes*: Figure presents ex-post win thresholds and ex-ante bid distributions for the 2013 and 2016 auctions.

**Simulation details** Our resampling procedure to obtain win probabilities follows Hortaçsu and McAdams (2010). Specifically, we:

1. Fit a Beta distribution[41] to the observed distribution of acreage thresholds across auctions. For this, we use additional historic data on auctions starting in 1999. This provides us with 12 auctions.

2. Fit a Beta distribution to the observed distribution of number of opposing bidders across auctions. For this, we again use additional historic data on auctions starting in 1999. This provides us with 12 auctions.

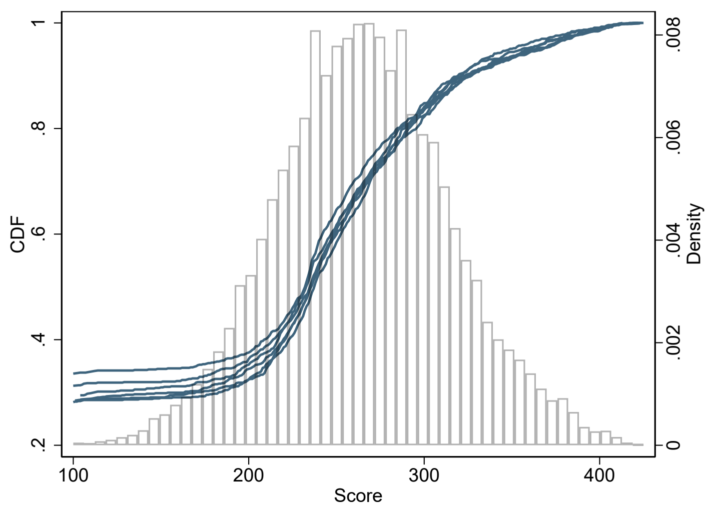
[41]We fit a Beta distribution instead of a log normal distribution to avoid using an unbounded distribution.

3. Draw an acreage threshold from the distribution fit in (1) and the number of opposing bidders, $N$, in (2). Then, for each auction $s$, sample with replacement $N$ bidders from the empirical distribution of bidders in that auction. Given the joint distribution of scores and acreage amounts among the $N$ resampled bidders, and the drawn acreage threshold, find the winning score threshold $S$.

4. Repeat step (3) to obtain an auction specific probability of winning at any given score $G_s(S)$.

Figure E.2 plots the output of our simulation procedure across all auctions in our sample with a histogram of the score distribution.

Figure E.2: CDF of $G_s(S)$ across sign-ups




*Notes*: Figure presents CDFs of the simulated distribution of win probabilities at a given score across auctions. The histogram presents the histogram of scores pooled across auctions.

**Model Fit** Table E.1 assesses the fit of our model by comparing our estimates of the relative costs of grasses, trees, habitat aggregate actions to administrative data collected by the USDA on the costs of those actions. While there is no reason that our revealed preference measures, which could capture many costs or benefits not included in accounting / receipts data, should align perfectly with the accounting measures, it is encouraging for the fit of our model that these comparisons do broadly align, in terms of both rank and approximate magnitude.

Table E.1: Comparison between estimated and administrative cost estimates

| | Estimates (1) | Median admin cost (2) | Average admin cost (3) |
|---|---|---|---|
| Tree primary covers (rel. to grasses) | 58.36 | 26.46 | 73.15 |
| Habitat primary covers (rel. to grasses) | 7.02 | 2.67 | 3.30 |

*Notes*: Table presents average revealed preference estimates of costs of aggregate primary cover categories, relative to grasses (column 1), compared to administrative data collected on the costs of these actions by the USDA (columns 2 and 3).

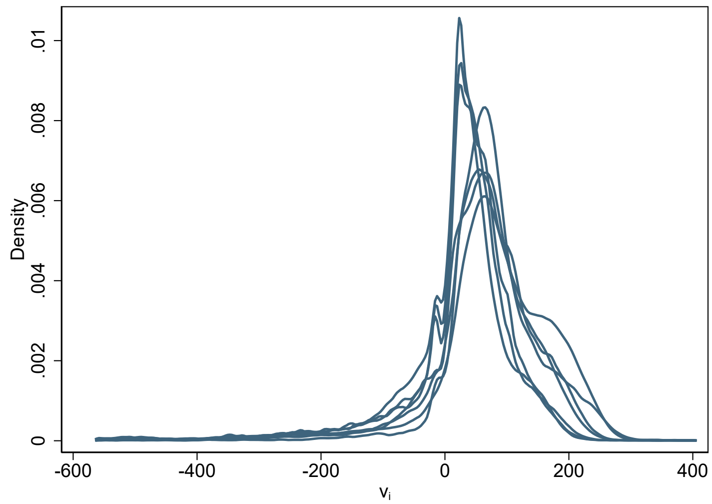
**Additional results** The exhibits below present additional results on the estimated parameters.

Table E.2: Detailed $\kappa_{ij}$ estimates

| | | | By region | | | | |
|---|---|---|---|---|---|---|---|
| | No het. | Main spec | West | Plains | Midwest | South | Atlantic |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Primary cover** | | | | | | | |
| Grasses 1 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Grasses 2 | -9.097 | -0.170 | 4.540 | 6.117 | -16.341 | 32.510 | -5.042 |
| Grasses 3 | 1.868 | 4.278 | 4.816 | -5.711 | 9.256 | 19.851 | 13.935 |
| Grasses 4 | -24.799 | -16.620 | -7.899 | -30.422 | -17.570 | 24.612 | -7.834 |
| Trees 1 | 15.616 | 48.796 | 66.856 | 70.552 | 37.332 | -10.213 | 13.079 |
| Trees 2 | 11.733 | 47.238 | 57.142 | 73.459 | 33.169 | -2.689 | 9.726 |
| Trees 3 | 27.324 | 51.290 | 89.481 | 68.359 | 30.164 | 7.507 | 20.131 |
| Trees 4 | 47.365 | 102.987 | 307.766 | 89.432 | 40.368 | 38.832 | 51.528 |
| Trees 5 | -0.998 | 25.872 | 82.431 | 31.084 | 1.957 | -0.478 | 5.985 |
| Habitat 1 | 8.384 | 10.619 | 22.519 | 1.213 | 8.404 | 30.547 | 19.042 |
| Habitat 2 | -4.365 | 1.072 | 10.153 | -12.722 | 2.727 | 30.147 | 10.472 |
| Habitat 3 | -13.762 | -0.030 | 29.804 | -25.318 | -7.289 | 77.878 | 6.190 |
| **Upgrades** | | | | | | | |
| Wildlife food plot | 24.162 | 23.780 | 42.373 | 26.746 | 11.320 | 25.428 | 20.725 |
| Pollinator habitat | 19.291 | 19.764 | 22.980 | 12.793 | 16.771 | 57.772 | 19.361 |

*Notes*: Table presents average revealed preference estimates of costs of each of the primary and upgrade actions.

Figure E.3: Distribution of $v_i$ by auction




*Notes*: Figure presents estimated distributions of $v_i$ by auction.

# F Additional Details: Estimating $\tau(\mathbf{z}, \theta)$ and Monetizing Benefits

## F.1 Validating compliance

While our RD result provides unbiased estimates of the marginal treatment effect at the score threshold, regardless of compliance, to estimate the entire $\tau(\mathbf{z}, \theta)$ function we need to assess compliance in the status quo regime. Under perfect compliance, we face only a one-sided missing data problem: we do not see $Y_{i0}$ if $D_i = 1$, but we know that $Y_{i1} = 1$ even if $D_i = 0$. In this section, we describe how we assess the status quo compliance regime.

Figure F.1: Sample Images

(a) Enrolled field

(b) Cropped field

*Notes:* Example images for classification. For reasons of compliance, neither of these are actual images of CRP enrolled fields.

To assess compliance, we hired and trained two MIT undergraduates to classify ultra high resolution aerial photographs (NAIP images) of fields at 1m resolution (see Figure F.1 for examples). We focus on the 2016 auction and images taken between 2017 and 2021. Before asking the undergraduates to classify any images, we provided them with a test set of hundreds of images of cropped and uncropped fields across the United States to familiarize themselves with the distinctive visual pattern of cropped fields (see Figure F.1b). After training, we provided each of these undergraduates with over 1,000 images of CRP enrolled fields and hundreds of placebo cropped fields as attention checks. The undergraduate reviewers were blind to whether the images were of CRP enrolled fields or placebo cropped fields. Each of the two reviewers were provided with the same images.

Table F.1 presents results for the classification exercise. We focused on the 83% of CRP images that the reviewers agreed upon for our assessment of compliance, to minimize the potential for classification error. We find only 5% of fields to be out of compliance in all post-period years. Once we drop the two "transition" years from 2017-2018, we find even lower rates of non-compliance, and reject rates of non-compliance above 3%. We attribute the difference between columns (1) and (2) to be driven by the fact that fields appear different when they are transitioning out of cropland, e.g. rows from row cropping may still be visible as new vegetation grows in. While not reported, rates of cropping are substantially higher, at approximately 40%, on placebo cropped fields. This indicates that the undergraduates were in fact paying attention and making meaningful classifications. We note, however, that this number is far below 100%. This is because we instructed our undergraduates to be conservative in their assessment of non-compliance, operating under the (reasonable) null hypothesis that the program is in fact enforced.

Table F.1: Validation of compliance: $Y_i(1) = 0 \ \forall i$

| | All post-period years | Drop first two years |
|---|---|---|
| | (1) | (2) |
| Share of enrolled fields classified as cropped | 0.054 | 0.024 |
| | (0.008) | (0.0085) |
| Upper bound of 95% CI | 0.070 | 0.034 |
| N fields classified (with agreement) | 925 | 842 |
| Rate of agreement across reviewers | 0.824 | 0.863 |

*Notes:* Table presents results from an exercise classifying aerial photographs of enrolled fields as cropped or non-cropped among two reviewers, who also reviewed images of non-CRP fields and were blind to the distinction. Classification focuses on the 2016 sign-up. Column (1) includes photographs from 2017-2021. Column (2) includes only photographs from 2019-2021. Crop classifications are based on only fields in which the two reviewers agree (which occurred for 82-86% of fields). Fields more likely to be flagged as non-compliant (based on remote sensing data) were over-sampled, to be as conservative as possible.

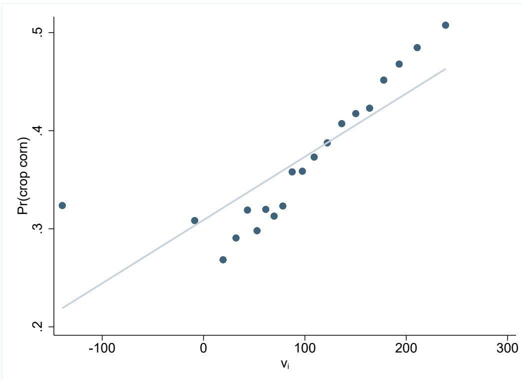
**Why classify photographs by eye?** We briefly note why we conducted this involved exercise to classify compliance by eye using ultra-high resolution photographs instead of the derived remote sensing product (the CDL). We do so for three reasons. First, these photographs are much higher resolution (1 m vs. 30m pixels), allowing a higher degree of accuracy for a sensitive question (is this program being enforced?). Second, conducting tests by eye allows for more flexibility in the face of measurement error than the derived product, e.g. by only focusing on cases where our reviewers agree. And third, and most importantly, the fact that the CDL uses lagged CDLs in its classifier makes it impossible to distinguish non-compliance from classification error.

**Compliance on top-up actions** We note that this exercise only focuses on compliance on the base action, land retirement, not any of the top-up actions, which we cannot observe. We thus use this assessment of compliance to make an inference about the overall compliance regime across all actions.

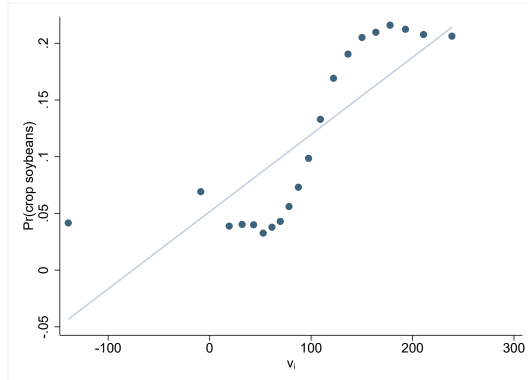
## F.2 Additional Figures: Estimating $\tau(\mathbf{z}, \theta)$

Figure F.2: More correlations between counterfactual land use and $v_i$

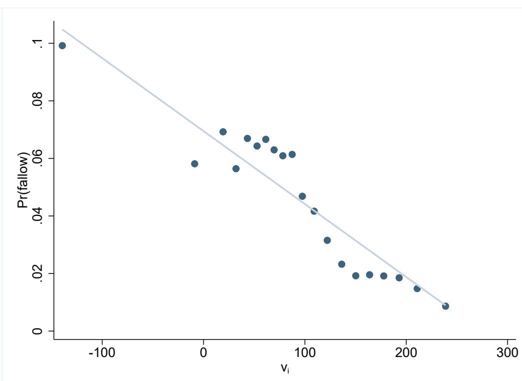
(a) Cropped corn



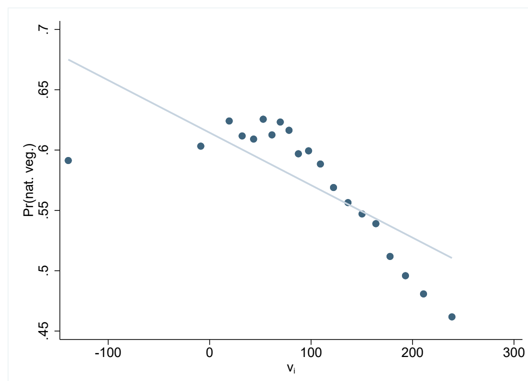

(b) Cropped soybeans




(c) Fallow




(d) Natural vegetation



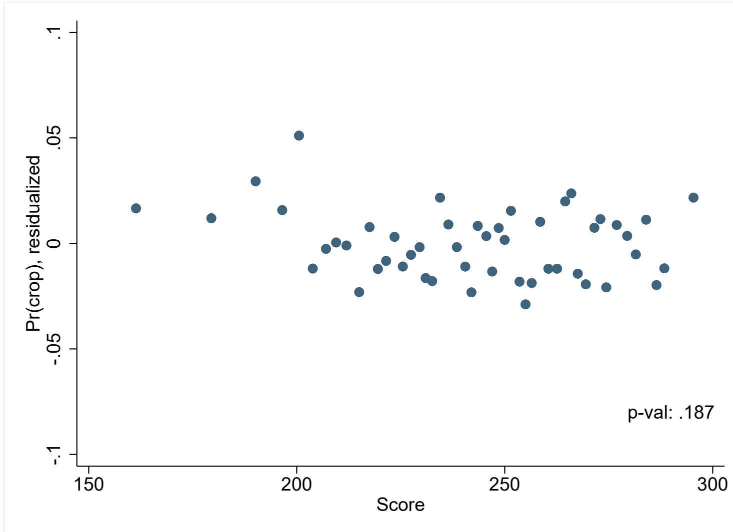

*Notes*: Figures present binned scatterplots of land use outcomes against simulations of $v_i$, for losing bidders among auctions where we observe the geolocation of offered fields (2013 and 2016). Figures excludes estimates of $v_i$ below the 1st and above the 99th percentile.

Table F.2: Parameter estimates: $\tau(\mathbf{z}, \theta)$, robustness to alternative outcome measures

| | Baseline, share of offered fields cropped, CDL | | Indicator: offered fields cropped, CDL | | Indicator: offered fields cropped, Admin data | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $v$ | 0.00024 | 0.00014 | 0.00026 | 0.00016 | 0.00014 | 0.00009 |
| | (0.00005) | (0.00004) | (0.00006) | (0.00005) | (0.00006) | (0.00006) |
| Soil productivity | | | | | | |
| Former CRP | -0.236 | -0.156 | -0.283 | -0.203 | -0.238 | -0.196 |
| | (0.006) | (0.006) | (0.008) | (0.007) | (0.008) | (0.008) |
| Size Q2 | 0.022 | 0.002 | 0.020 | -0.000 | 0.039 | 0.028 |
| | (0.008) | (0.007) | (0.010) | (0.009) | (0.011) | (0.010) |
| Size Q3 | 0.020 | -0.009 | 0.018 | -0.011 | 0.030 | 0.013 |
| | (0.009) | (0.007) | (0.010) | (0.009) | (0.011) | (0.011) |
| Size Q4 | -0.010 | -0.052 | -0.017 | -0.060 | 0.001 | -0.023 |
| | (0.010) | (0.008) | (0.011) | (0.010) | (0.012) | (0.012) |
| Prior crop Q2 | | 0.048 | | 0.040 | | 0.033 |
| | | (0.008) | | (0.010) | | (0.011) |
| Prior crop Q3 | | 0.158 | | 0.152 | | 0.109 |
| | | (0.010) | | (0.012) | | (0.014) |
| Prior crop Q4 | | 0.318 | | 0.322 | | 0.209 |
| | | (0.014) | | (0.017) | | (0.018) |
| Prior nat. veg. Q2 | | -0.041 | | -0.027 | | -0.002 |
| | | (0.010) | | (0.012) | | (0.013) |
| Prior nat. veg. Q3 | | -0.053 | | -0.045 | | 0.011 |
| | | (0.012) | | (0.015) | | (0.016) |
| Prior nat. veg. Q4 | | -0.040 | | -0.029 | | 0.014 |
| | | (0.014) | | (0.016) | | (0.018) |
| Region FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Soil productivity FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Controls for $\mathbf{z_i^{t1}}$ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

*Notes:* Table presents estimates of $\tau(\mathbf{z}, \theta)$ from a joint model of selection and cropping outcomes, estimated via maximum likelihood (with an "reduced-form" normal selection equation, not a fully specified model of bidding). Our selection equation incorporates all determinants of equilibrium choices of $S_i$: our estimates of $v_i$, observable determinants of $\kappa_{ij}$, and all bidder characteristics incorporated in the scoring rule, $\mathbf{z_i^t}$. The model is estimated at the field level on 10 simulated copies of each bidder, with standard errors clustered at the bidder level. Soil productivity fixed effects include deciles of estimated soil productivity. Controls for $\mathbf{z_i^{t1}}$ include deciles of wind erosion and water erosion, points for ground water and surface water quality estimates, and indicators for whether a bidder is in a water quality zone. Estimates are based on the 2016 auction. $Y_{i0}$ is measured as the share of the area of offered fields that is not cropped in the CDL in columns 1 and 2, whether over half of offered fields are not cropped in the CDL (columns 3 and 4) and in the Form 578 data (column 5 and 6). $Y_{i1}$ is assumed to be 1.

Figure F.3: Residualized relationship between score and potential outcomes




*Notes*: Figure presents the relationship between a binary indictor for cropping, residualized of $\left(\mathbf{z_i^{t1}}, \mathbf{z_i^{-t}}, v\right)$ and the score. The remaining variation is derived from $z_i^{t2}$ and the i.i.d. shocks $\epsilon_{ij}$. Figure also plots the p-value of of the coefficient on the score in a joint regression of cropping outcomes on the score and $\left(\mathbf{z_i^{t1}}, \mathbf{z_i^{-t}}, v\right)$. Estimated among losing bidders in the 2016 sign-up only.

## F.3 Valuing benefits $B_{\mathbf{z}}^j$

Recall that WTP for a contract with $i$ to do action $j$ is $B_z \cdot \tau(\mathbf{z}_i, \theta_i) + B_z^j$. Our primary object of interest in estimation is $\tau(\mathbf{z}_i, \theta_i)$, but to evaluate welfare we must scale it by the value of land retirement, $B_z$ and we must value the additional top-up actions $B_z^j$. In this section, we describe how we determine the values $B_z$ and $B_z^j$.

First, we assume that the weights in the scoring rule reflect the relative weight that the planner places on $B_z$ and $B_z^j$, assuming $\tau(\mathbf{z}_i, \theta_i) = 1$.[42] Specifically, we note that scoring rule is separable in actions and bid amount:

$$t\left(\mathbf{b}_i, \mathbf{z_i^t}\right) = \underbrace{t^a\left(\mathbf{a}_i, \mathbf{z_i^t}\right)}_{\text{action points (incl. base action)}} + \underbrace{t^r\left(r_i\right)}_{\text{non-linear function of rental rate}} \tag{26}$$

and we assume that

$$t^a\left(\mathbf{a^j}_i, \mathbf{z_i^t}\right) \cdot \Upsilon = \left(B_z + B_z^j\right) \tag{27}$$

[42]The assumption that $\tau(\mathbf{z}_i, \theta_i) = 1$ for all $i$ rules out the possibility that the regulator is strategically manipulating the scoring rule to screen types. There is no evidence to support this (Ribaudo et al., 2001). Indeed, together with contemporaneous work in Rosenberg et al. (2022), there has been essentially no research or policy attention paid to counterfactual land use among CRP enrollees.

for some scaling factor $\Upsilon$ that scales points into dollars.[43] The remaining piece of information required is therefore an estimate of $\Upsilon$.

This formulation assumes that the weights in the CRP auction reflect the social value of land retirement across $\mathbf{z_i}$ and actions $B^j_{\mathbf{z}}$. This would be violated if, for example, the scoring rule in part reflects political considerations (Ribaudo et al., 2001). We choose to take this approach, versus calibrating $B_z + B^j_z$ from an external integrated assessments model,[44] to focus on asymmetric information about $\tau(\mathbf{z}_i, \theta_i)$ as the primary friction.

We determine $\Upsilon$ based on estimates of the value of the CRP from the literature. Specifically, for any estimate of the dollar value of the CRP, we know

$$\frac{\hat{\Upsilon}}{\sum \mathbb{1}\left\{S_i \geq \bar{S}\right\}} \sum_{i|S_i \geq \bar{S}} t^a\left(\mathbf{a^j}_i, \mathbf{z_i^t}\right) \cdot D^j = \hat{\Omega} \tag{28}$$

for any estimate of the value of the CRP, $\hat{\Omega}$. So we can use Equation 28 to obtain an estimate for $\hat{\Upsilon}$. We note that this formulation requires that the estimates must also assume that $\tau(\mathbf{z}_i, \theta_i) = 1$. This is reasonable as all of the studies that we consider estimate the value of CRP land retirement and actions, relative to a counterfactual of cropping.

We use four values of $\hat{\Omega}$ from the literature. Our baseline estimates take the average across these four.

1. Our first estimate sums the recreational,[45] public works,[46] and air quality benefits[47] from Feather et al. (1999) and adds estimates of the value of greenhouse gas reductions from sequestered CO2 (over the 10-year contract) and reduced fuel and fertilizer use (permanent) monetized at \$43 per metric ton. This leads to an overall estimated value of the CRP of \$98.34 per acre, per year.

2. Our second estimate takes the global valuation of the CRP from Hansen (2007), which is equal to \$255.70, per acre, per year.

3. Our third and fourth estimate take a conservative and generous value of the non-GHG CRP benefits from Johnson et al. (2016) and adds estimates of the value of greenhouse

[43] We use this formulation instead of interpreting the level and shape of $t\left(\mathbf{b}_i, \mathbf{z_i^t}\right)$ as WTP because it is not clear that the level of points reflects a meaningful decision. Taking willingness to pay by extrapolating $t\left(\mathbf{b}_i, \mathbf{z_i^t}\right)$ to zero seems too far out of sample. Moreover, it is not clear that the non-linearities introduced in $t^r\left(r_i\right)$ have anything to do with government valuation.

[44] See `https://naturalcapitalproject.stanford.edu/software/invest` for one such example.

[45] Includes sport-fishing, small-game hunting, noncompetitive viewing, and waterfowl hunting.

[46] Includes cost savings associated with reduced maintenance of roadside ditches, navigation channels, water treatment facilities, municipal water uses, flood damage, and water storage.

[47] Includes reduced health risks and cleaning costs associated with blowing dust.

gas reductions from sequestered CO2 (over the 10-year contract) and reduced fuel and fertilizer use (permanent) monetized at \$43 per metric ton. This leads to estimates of \$367.96 and \$456.04, per acre, per year.

The description above highlights the difficulties of monetizing the value of the all of the environmental benefits of the CRP. We emphasize that our focus is not on obtaining estimates of $B_z + B_z^j$. We use these simply to scale our primary object of interest, $\tau(\mathbf{z}_i, \theta_i) = 1$, and to quantify the productive value of top-up actions.