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

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Abstract

Market mechanisms aim to deliver environmental services at low cost. However, this objective is undermined by participants whose conservation actions are not marginal to the incentive — or "additional" — as the lowest cost providers of environmental services may not be the highest social value. We investigate this potential market failure in the world's largest auction mechanism for ecosystem services, the Conservation Reserve Program, with a dataset linking bids in the program's scoring auction to satellite-derived land use. We use a regression discontinuity design to show that three of four marginal winners of the auction are not additional. Moreover, we find that the heterogeneity in counterfactual land use introduces adverse selection in the market. We then develop and estimate a joint model of multi-dimensional bidding and land use to quantify the implications of this market failure for the performance of environmental procurement mechanisms and competitive offset markets. We design alternative auctions with scoring rules that incorporate the expected impact of the auction on bidders' land use. These auctions increase efficiency by using bids and observed characteristics to select participants based on both costs and expected additionality.

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1 Introduction

Land-use change contributes 13% of global greenhouse gas emissions (Friedlingstein et al., 2022) and leads to biodiversity loss, water pollution, and erosion (Dirzo et al., 2014; Vörösmarty et al., 2010; Borrelli et al., 2017). While environmental markets can, in theory, reduce environmental degradation at low cost (Samuelson, 1954; Anderson and Libecap, 2014; Teytelboym, 2019), many believe that existing mechanisms have failed to meet this potential (Anderson, 2012; Filewod, 2017; Maron et al., 2016; West et al., 2020; Jones and Lewis, 2023). A leading explanation for this failure is the possibility of inframarginality: some participants may have engaged in the incentivized action even absent an incentive. The notion of "additionality," defined as the likelihood that an action is marginal to an incentive, is a central challenge to the design and success of many environmental markets (Engel et al., 2008; West et al., 2023).

Does the challenge of additionality drive markets to failure, undermining environmental incentive policies and offset markets?[1] Or can markets be designed to achieve low-cost climate change mitigation? We explore these questions by analyzing the challenge of additionality as a market failure due to asymmetric information. Social welfare in markets for environmental conservation depends on both a landowner's unobserved additionality and her private cost of complying with the market requirements. Market mechanisms, however, screen only on the latter. If asymmetric information prevents incentives from reflecting heterogeneity in landowner additionality, market mechanisms may not achieve allocative efficiency and in the extreme, may fail (Akerlof, 1970). In this paper, we use this perspective to analyze, test, and quantify this potential failure and to examine remedies in alternative market designs.

We conduct our analysis in the context of the United States Department of Agriculture's (USDA) Conservation Reserve Program (CRP), one of the oldest and largest Payments for Ecosystem Services (PES) mechanisms in the world.[2] The CRP incentivizes agricultural land retirement and conservation actions via procurement auctions of conservation contracts. CRP contracts pay landowners \$1.6-\$1.8 billion per year to take cropland out of production and to plant grass mixes, plant or maintain trees, or establish habitats for a duration of ten

[1]In offset markets, private buyers purchase contracts that "offset" environmental degradation acre-for-acre or ton-for-ton. Offset markets exist in 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 (e.g. compliance offsets in California's cap-and-trade program), between countries to provide flexibility in meeting international emissions commitments (the Clean Development Mechanism and REDD+), and due to the large volume of voluntary net-zero commitments among firms (McKinsey Sustainability, 2021, 2022). See Salzman et al. (2018) for an overview of Payments for Ecosystems Services, specifically.

[2]Over its history, the CRP is the largest PES mechanism in the world. Within a given year, the CRP is second to China's Sloping Land Conversion Program.

years. Combining administrative data and high-resolution satellite imagery, we construct a dataset that links landowners' multi-dimensional bids in the CRP scoring auction to their land use, which we use to measure additionality. The CRP auction provides a rich empirical setting for each step of our analysis: assessing the extent of additionality, testing for asymmetric information, and quantifying their implications for social welfare under current and alternative market designs. Moreover, the insights from this setting are broadly applicable: CRP contracts are structured similarly to other PES programs, to contracts traded in global offset markets, and to private competitive agricultural offset markets in the US.[3]

We first analyze the market failure introduced by additionality with a stylized framework that builds on the graphical analysis in Einav et al. (2010). Landowners differ in two dimensions. The first is their cost of contracting, which includes the forgone option value of cropping and the hassle costs of complying with program requirements. The second is their conservation behavior without the contract, which determines their additionality. The social value of contracting depends on a landowner's cost and additionality, but her choices depend only on her cost and the market incentive. This difference can lead to allocative inefficiency. When a landowner's cost of contracting is positively correlated with her additionality — for example, landowners who expect to conserve regardless of the program have lower opportunity costs of contracting — there will be adverse selection in the market. In procurement, adverse selection can limit the implementability of efficient allocations and undermine the performance of standard mechanisms (Manelli and Vincent, 1995). In competitive offset markets, adverse selection can limit trade because buyers consider the expected additionality of all market participants, not only those contracting at the margin. These challenges can be remedied if markets are designed to close the gap between socially-optimal choices and the choices made in the market.

The stylized framework provides guidance for empirical analysis. Social welfare under current and counterfactual market designs depends on the distribution of landowner contracting costs and the population expectation of additionality at each value of costs. Contracting costs and additionality may be correlated due to landowners' expectations of low payoffs from cropping land. However, landowners may have only limited information about future payoffs to cropping over the contract's duration and incur hassle costs that may be arbitrarily correlated with additionality (Jack and Jayachandran, 2019). The extent of additionality, the existence of adverse selection in the market, and together, their quantitative implications for the performance and design of markets for environmental services are empirical questions.

We begin by examining the extent of additionality in our setting. Credible estimates of

[3]See Kinzig et al. (2011), Engel et al. (2008), and Stubbs et al. (2021), respectively.

additionality, particularly in large-scale mature markets, are scarce as they require knowledge of an unobserved counterfactual. We use the discontinuity in contracting around the winning bid in the procurement auction to evaluate additionality at the margin of contract awards. We find that, as incentivized by the CRP, landowners substitute away from agriculture to natural vegetation and grasslands upon contracting. However, only one quarter of landowners are additional, which we calculate by comparing the regression discontinuity treatment effect to the magnitude of land contracting at the margin. In other words, three quarters of landowners would have conserved without a CRP contract. However, the status quo auction implicitly assumes all landowners are additional in the design of its scoring rule (Claassen et al., 2018).

To test for adverse selection in the market, we correlate heterogeneity in additionality with heterogeneity in the costs of contracting reflected in landowner bids. We make two assumptions — perfect compliance and no spillovers, both of which we test and validate — to obtain a landowner-specific measure of additionality for all rejected bidders (82% in the most restrictive auction). We examine the relationship between landowner-specific additionality and bids following classic tests for asymmetric information in insurance markets (Chiappori and Salanie, 2000) and auctions (Hendricks and Porter, 1988). We document substantial heterogeneity in additionality and a positive correlation between additionality and bids, indicating the presence of adverse selection in the market. The positive correlation persists even conditional on a rich set of observed characteristics. This analysis also highlights opportunities for improvements to market design: heterogeneity in additionality is predicted by landowners' choice of contract in the mechanism and by the observed characteristic of soil productivity.

These facts demonstrate that both additionality and asymmetric information are relevant to the function of this market; to quantify their welfare implications and evaluate the performance of counterfactual market designs, we develop and estimate a joint model of bidding and additionality. First, we infer costs of contracting from revealed preferences in optimal bidding. Then, we estimate landowner additionality, including how it varies with costs, by matching the moments of land use presented in the first half of the paper.

In the CRP auction, landowners submit multi-dimensional bids on a menu of heterogeneous contracts, which are ranked by a scoring rule. This provides a rich environment for market design, as scores across the menu of contracts and observed asymmetry terms are tools to increase social welfare. In the first part of the model, we extend the multi-dimensional bidding models of Asker and Cantillon (2008) and Che (1993) to a setting with a discrete contract choice and a non-linear scoring rule. In the second part, we model additionality with a conditional expectation function that relates land use to both observed characteristics and unobserved landowner costs. This conditional expectation function is the component of the model that captures the possibility of inefficient or adverse selection.

We estimate the model in three steps. The first two steps adapt standard procedures for the empirical analysis of auctions (Guerre et al., 2000; Hortaçsu, 2000; Hortaçsu and McAdams, 2010; Agarwal et al., 2023). First, we estimate bidder beliefs via simulation. Second, we estimate bidder costs via revealed preferences in optimal bidding. Because of the discrete choice in the bidding problem, we rely on variation in the scoring rule for identification. In the final step, we estimate additionality, including how it varies with unobserved landowner costs, by matching the levels of additionality and the correlation between additionality, landowner characteristics, and optimal bids observed in our linked land use and bid data. We use our estimates of additionality to calculate the social benefits of contracting based on valuations of environmental services from the CRP literature and the USDA's revealed preferences across landowners and contracts implied by the scoring rule.

Using these estimates, we first examine whether the existence of a market for conservation increases social welfare. When some landowners in the market are not additional, this is theoretically ambiguous; we investigate it empirically in a simple uniform market for the base contract. We find substantial social welfare gains under the socially-optimal uniform price ($14.66 per acre-year) and in a stylized competitive offset market ($14.11 per acre-year). The difference between these two market structures (-4%) reflects the trade-limiting effects (-15%) of adverse selection in competitive markets. Despite landowners who are not additional and the adverse selection this introduces, we find that the market does not fail.

We then evaluate the performance of the status quo auction mechanism. We estimate that the status quo mechanism leads to social welfare gains of $126 million per auction, relative to no market. However, it implements only 15% of the social welfare gains of an efficient allocation. This allocation determines contract awards based on both landowners' costs and expected social benefits, which depend on additionality.

Implementing the efficient allocation with an incentive compatible auction may not be possible (Myerson, 1981). Because they are less additional, lower cost landowners are not always higher social value. Our estimates imply that the allocation rule for this efficient benchmark need not be monotone in bidder cost.

We instead propose and evaluate alternative auctions with scoring rules that trade off bidders' costs against both their conservation actions' heterogeneous social benefits *and* their expected additionality. This differs from the status quo scoring rule, which does not consider the latter. Alternative scoring rules adjust asymmetry across bidder observables and scores across the menu of contracts based on predictions of additionality. Instead of restricting participation in the market through eligibility requirements, our approach re-designs the auction to *impact conservation,* acknowledging that some landowners in the market may not be additional.

Simple modifications to the auction's scoring rule close the gap between the status quo and efficient allocation by 41%, increasing social welfare by $284 million per auction. All gains are due to changes that incorporate landowner additionality. A large share are from setting the socially-optimal uniform adjustment to the scoring rule. Further gains accrue from using the rule to differentiate among heterogeneously additional landowners. By contrast, switching from the status quo (inefficient) auction to an (if all landowners were additional, efficient) Vickrey-Clarke-Groves mechanism that remains naive to additionality reduces social welfare.

We conclude with the implications of supply-side adverse selection for competitive offset market design.[4] Competitive markets introduce distinct considerations: a differentiated market may or may not be more efficient than a uniform one. Differentiation based on available covariates would increase social welfare in a stylized competitive offset market for the base contract by 15%, reducing both inefficient selection and inefficiently-limited trade due to adverse selection. Next, we consider which contracts could be traded. Markets for tree planting and maintenance unravel, while social welfare losses from adverse selection in other markets, including grasses planting and habitat creation, are limited to at most 3%.

Together, our results highlight that although additionality and the adverse selection that it introduces are relevant in practice, and in theory, can cause markets to fail, voluntary environmental markets can deliver on their promise of low-cost conservation. However, successful market design must consider not only the heterogeneity in private costs that determine choices, but also the implications of these choices for additionality and social welfare in the market.

Related Literature Our primary contribution is to develop an empirical framework to evaluate social welfare under current and counterfactual market designs in the presence of the additionality market failure. We also provide credible estimates of the extent of additionality and evidence of adverse selection in a large-scale, mature market for ecosystem services. Our regression discontinuity estimates of additionality contribute to a literature estimating treatment effects of payments for ecosystem services (Jack, 2013; Alix-Garcia et al., 2015; Jayachandran et al., 2017; West et al., 2020; Rosenberg et al., 2022) and inframarginality in offset markets (Calel et al., 2021). Our framework builds on theoretical analyses of asymmet-

[4]The Growing Climate Solutions Act of 2021 includes provisions for the USDA to serve as a regulator of agricultural offset markets.

ric information (van Benthem and Kerr, 2013; Mason and Plantinga, 2013; Li et al., 2022; Haupt et al., 2023) and empirical tests for selection (Montero, 1999; Jack, 2013; Jack and Jayachandran, 2019) in environmental incentive programs and offset markets.

Though our context is additionality in conservation incentives, our framework relates broadly to the design of environmental incentive programs and other voluntary regulation (Allcott and Greenstone, 2012; Borenstein, 2012; Allcott and Greenstone, 2017; Einav et al., 2022; Ito et al., 2023) and complements work studying other sources of inefficiency in markets for environmental conservation (Harstad, 2016; Harstad and Mideksa, 2017; Aronoff and Rafey, 2023). Beyond environmental markets, our approach to auction design relates to a literature evaluating market designs based on treatment effects, not only revealed preferences (e.g. Agarwal et al. (2020)).

We contribute to a literature studying quality concerns in procurement auctions (Manelli and Vincent, 1995; Decarolis, 2014; Carril et al., 2022; Lopomo et al., 2023), where we provide an empirical framework to evaluate alternative auction designs in the presence of adverse selection on bidder quality (additionality in our setting). This empirical framework draws on a large literature studying selection in insurance markets (Akerlof, 1970; Chiappori and Salanie, 2000; Einav et al., 2010; Bundorf et al., 2012; Marone and Sabety, 2022).

Methodologically, our model and estimation strategy use techniques from a rich literature advancing the empirical analysis of auctions (Guerre et al., 2000; Hortaçsu, 2000; Hortaçsu and McAdams, 2010; Jofre-Bonet and Pesendorfer, 2003; Agarwal et al., 2023). We draw on and extend existing work on scoring and other multi-dimensional auctions (Che, 1993; Asker and Cantillon, 2008, 2010; Lewis and Bajari, 2011; Sant'Anna, 2017; Hanazono et al., 2020; Kong et al., 2022; Allen et al., 2023; Bolotnyy and Vasserman, 2023) to incorporate discrete bidding, a non-linear scoring rule, and a correlation between additionality and bidder costs.

2 Theoretical Framework

We present a framework to analyze additionality in markets for environmental services.

2.1 Model

There exists a continuum of landowners, indexed by i, each making a decision to contract, $x_i \in \{0, 1\}$, to obtain a transfer, p. In Section 5, we adapt this framework to a finite number of landowners bidding for contracts in an auction.

The contract involves a promise to provide an environmental service ($a_i = 1$) versus not ($a_i = 0$). In our setting, $a_i = 1$ denotes agricultural land retirement (conservation) and $a_i = 0$ denotes cropping. The action $a_i = 1$ generates social benefits from positive environmental externalities. The buyer of the contract — either a regulator or a private buyer in an offset market — values the social benefits from $a_i = 1$ at $B > 0$.

Define a_{i1} as landowner i's action when $x_i = 1$ and a_{i0} as her action when $x_i = 0$. We assume perfect compliance, so $a_{i1} = 1$. Because B is generated whenever i chooses $a_i = 1$, regardless of contract choice x_i, the benefit of contracting with i is only the *incremental value* $B \cdot (1 - a_{i0})$. a_{i0} is unobserved whenever $x_i = 1$ and is therefore non-contractible.

Landowner Types Each landowner i is characterized by a type $\theta_i = (c_i, a_{i0})$ distributed according to the cumulative distribution function $F(\theta)$. c_i is a landowner's cost of contracting, defined as the minimum transfer p required for a landowner to accept the contract $x_i = 1$. a_{i0} is, as defined above, the action a landowner would have taken in the absence of the contract.[5] We do not restrict the joint distribution of c_i and a_{i0}. Landowners may have a low c_i because they have unprofitable land that they ultimately do not crop ($a_{i0} = 1$). But landowners may also have only limited foresight about the option value of cropping, and contracting in realistic settings involves activities beyond choosing not to crop that impose hassle costs that enter c_i (Jack and Jayachandran, 2019).[6] It is therefore ambiguous whether and how c_i and a_{i0} are related.

It will be useful to define the conditional expectation function:

$$\tau(c) = \mathbb{E}\left[1 - a_{i0} \,|\, c = c_i\right]. \tag{1}$$

This function describes the expected additionality, or the expected impact of contracting on a_i, among all landowners with the same cost of contracting.

Social versus Landowner Incentives The social surplus of contracting with landowner i is:

$$SS_i = B \cdot (1 - a_{i0}) - c_i. \tag{2}$$

[5] We define landowners by the action a_{i0}, but landowners could alternatively be defined by the cost of a_{i0}. Results that apply to a hidden information model also apply to a hidden action model (Milgrom, 1987).

[6] These include complying with mandates to purchase specific seed mixes whose costs to obtain differ across regions, effort costs to comply with specific configurations of grass planting, tree planting, or habitat establishment required in the contract, paperwork burdens to process payments, audits to manage compliance, and any taste or distaste for participating in an environmental market.

Gains from trade occur when the incremental value of environmental services due to contracting is higher than a landowner's cost of contracting.

Landowners choose $x_i = 1$ if $p \geq c_i$. Let

$$x_i^*(p) = \mathbb{1}\{p - c_i \geq 0\} \tag{3}$$

be landowner i's choice to contract at price p. Equations (2) and (3) show that landowner i transacts based only on p and her contracting cost c_i, but social surplus depends also on $1 - a_{i0}$, or her additionality. p will therefore not necessarily incentivize the highest social surplus landowners to contract.

Efficient Prices and Allocations The socially-optimal uniform price solves:[7]

$$\max_p \int (B \cdot \tau(c) - c)\, x^*(p; c)\, f_C(c)\, dc, \tag{4}$$

where the density f_C is the marginal of $F(\theta)$ on contracting costs, c_i, and $x^*(p; c) = \mathbb{1}\{p - c \geq 0\}$. The solution to this problem is equivalent to one where a quantity is chosen and an allocation is implemented with a Vickrey auction.

Equation (4) shows that f_C and $\tau(c)$ are sufficient statistics for social welfare and landowner choices when p is the only instrument available to allocate landowners to contracts. More generally, f_C and $\tau(c)$ are sufficient statistics for social welfare for any incentive compatible mechanism.[8] Contracting with landowner i will therefore be efficient if and only if:

$$B \cdot \tau(c_i) - c_i \geq 0. \tag{5}$$

Our interest in this stylized framework is in when p will implement this allocation, which we will refer to as the efficient allocation.

2.2 Graphical Analysis

We analyze the efficiency of allocations in the market graphically, plotting markets with different $F(\theta)$ in Figures 1a and 1b. Each figure plots two curves: one based on f_C and

[7] A uniform price is motivated by the absence of observables. This could be because they have already been conditioned on, where equation (4) defines the pricing problem in a sub-population.

[8] See Lopomo et al. (2023) for more details and a proof. See also Einav et al. (2010) on the use of similar sufficient statistics for the analysis of adverse selection in competitive insurance markets

one based on $\tau(c)$. The first curve is the inverse distribution function of contracting costs, $F_C^{-1}(q)$, or the *marginal cost curve* (MC), where the horizontal axis q is the share of the population ranked by contracting costs. The second curve is the value of contracting at each quantile of the distribution of contracting costs, $B \cdot \tau$, or the *contract value curve*.[9] The contract value curve lies weakly below B reflecting the possibility that $a_{i0} = 1$ for some landowners.

Each panel in Figure 1 displays an upwards-sloping contract value curve ($\tau'(c) > 0$). This captures the possibility that landowners' expectations about future payoffs to cropping may influence both c_i and a_{i0}; landowners who expect to conserve may face a low cost of accepting a contract requiring conservation. In other words, there may be adverse selection in the market.[10] Modeling adverse selection with an upwards-sloping contract value curve builds on the widely-used graphical analysis of adverse selection in insurance markets developed in Einav et al. (2010). We emphasize, however, that Figure 1 is for illustration: $\tau(c)$ — including whether it is upwards-sloping — and $F_C^{-1}(q)$ are to be estimated.

The vertical distance between the contract value and marginal cost curves equals $B \cdot \tau(c) - c$, or the average social surplus of contracting with all landowners with costs equal to c. From equation (5), it is efficient to contract only in regions where the contract value curve lies above the marginal cost curve.

In Figure 1a, the efficient allocation can be implemented by setting the socially-optimal p^* at the intersection of the contract value and marginal cost curves, leading to social welfare gains in triangle CDE. Implementing this allocation requires knowledge of both f_C and $\tau(c)$: the distribution of contracting costs and heterogeneous impacts of contracting along this distribution. Mispricing can result in inefficient contracting and social welfare losses. If counterfactual actions are ignored, a common practice, setting $p = B$ leads to social welfare losses in triangle EFG.

In Figure 1b, the efficient allocation cannot be implemented. In the distribution of landowner types illustrated in Figure 1b, the contract value curve lies below the marginal cost curve at low contracting costs (low q). This represents landowners that have low but positive costs of contracting — due to some option value of cropping and/or hassle costs — but a high likelihood of conserving without the contract. In this market, a regulator cannot implement the efficient allocation (triangle EFG), as any incentive that is attractive for landowners in triangle EFG is also attractive for landowners in CDE for whom $B \cdot \tau(c_i) < c_i$. In the

[9]This plots $B \cdot \tau\left(F_C^{-1}(q)\right)$.

[10]Some may argue that using the term "adverse selection" abuses terminology. This is an example of "selection on moral hazard" defined in Einav et al. (2013), which also includes a discussion on terminology.

example market in Figure 1b, the constrained efficient allocation is to contract with no one despite regions of social welfare gains because triangle CDE is larger than triangle EFG.

The difference between equations (2) and (3) causes the inefficiency in Figure 1b. The regulator can only affect allocations based on landowner costs, c_i, and the incentive p, but social surplus depends also on the impact of contracting, or a_{i0}. In contrast to standard markets, the relationship between social surplus and landowner costs may not be not monotonically decreasing. Because the vertical distance between the contract value and marginal cost curves (social surplus) crosses zero from below in Figure 1b, no mechanism can implement the efficient allocation (triangle EFG) as it would require an allocation rule that is not monotonically decreasing in landowner costs (see Myerson (1981); Lopomo et al. (2023)).

If contracts are traded in competitive markets, which we term offset markets,[11] adverse selection can also prevent the competitive equilibrium price from implementing an efficient allocation, even when it is implementable with the price that solves equation (4) (Akerlof, 1970). Price-taking buyers in the market take expectations over the additionality of *all* market participants, not only those contracting at the margin. We define a competitive market price p^c by the equilibrium condition: $p^c = \mathbb{E}\left[B \cdot \tau\left(c_i\right) \mid c_i \leq p^c\right]$.[12] Figure 1c adds the curve defined by $\mathbb{E}\left[B \cdot \tau\left(c_i\right) \mid c_i \leq p\right]$ to the population of landowners presented in Figure 1a.[13] Its intersection with the marginal cost curve defines the competitive market equilibrium, which differs from the socially-optimal price. In the presence of adverse selection, trade in competitive (offset) markets will be limited and efficient contracting, with social welfare gains represented in triangle EFG, will not occur.

Empirical Questions Figure 1 illustrates that the welfare implications of additionality depend on f_C and $\tau\left(c\right)$. The goal of our empirical analysis is therefore to estimate f_C and $\tau\left(c\right)$. But this stylized model was limited in its tools. Our empirical analysis will include a richer set of contracts and observable characteristics. We will then investigate both the possibility of social welfare losses when market incentives do not implement the efficient allocation and social welfare gains from alternative market designs.

[11] We will refer to competitive markets with price-taking buyers as offset markets, though we model buyers as valuing all of the social benefits of the conservation action B, not only an emissions offset.

[12] We focus on the social welfare losses from supply-side adverse selection. We abstract away from the possibility that buyer valuations may diverge from B, that buyers may not know the distribution $F(\theta)$, or that buyers may not value additionality.

[13] This curve is defined as $\int_0^q B \cdot \tau\left(F_C^{-1}\left(\tilde{q}\right)\right) d\tilde{q}$.

3 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 between \$1.6 and \$1.8 billion per year to retire erodible and other environmentally sensitive cropland and adopt additional conservation actions for a contract duration of 10 years. The CRP is one of the largest and most mature PES schemes in the world. It is also a major source of expenditures on environmental policy in the United States; the CRP is one of several conservation programs at the USDA with a combined budget of \$8 billion.[14] Moreover, the structure of the CRP and its incentivized activities are similar to other government financed PES schemes,[15] to offset contracts traded in voluntary markets,[16] and most specifically, to a burgeoning private agricultural offset market in the US. There is substantial policy interest in growing this market. The Growing Climate Solutions Act of 2021 includes provisions for the creation of a USDA-regulated agricultural offset market, in which CRP-style contracts would be sold to private buyers.[17]

Unlike the uniform pricing problem in Section 2, the USDA awards CRP contracts via a complex auction mechanism. This adds richness to both the strategic and contracting environment that we will leverage empirically. Under the CRP's General Enrollment mechanism, eligible landowners bid for heterogeneous contracts in a discriminatory, asymmetric, scoring auction.[18] Contracts are differentiated by conservation actions that "top up" the base action of land retirement. These actions include planting specific grass mixes, planting or maintaining trees, and establishing or restoring pollinator or rare habitats.

Bids are scored according to a known scoring rule that awards bidders points for the environmental sensitivity of their land, their chosen contract (described above), and their bid rental rate, a payment per acre per year. Characteristics of the land that determine points

[14] By comparison, the Superfund program and Weatherization Assistance Programs have annual budgets of \$1.1 billion, and the total Environmental Protection Agency (EPA) budget is \$12 billion. See the USDA FY 2023 Budget Summary, FY 2023 EPA Budget in Brief, and NASCP Weatherization Assistance Program Funding Report for FY 2019 for more details.

[15] See Kinzig et al. (2011) and Salzman et al. (2018) for overviews.

[16] Over 50% of contracts traded in voluntary offset markets are related to land use and management. See the Voluntary Registry Offsets Database at the Berkeley Carbon Trading Project for more details.

[17] See S. 1251 and H.R. 2820 for more details.

[18] In addition to the General Enrollment mechanism, there is a posted-price Continuous Enrollment mechanism for targeted land. Historically, 75% of CRP acreage has been contracted via the General Enrollment mechanism (Hellerstein, 2017).

for environmental sensitivity include erodibility, importance for habitats, potential for water and air pollution, and carbon sequestration potential. Bid rental rates are subject to a bid cap based on the average land rental rate in the county and soil productivity estimates. Appendix A describes the auction mechanism and scoring rule in more detail.

The aggregate acreage to be awarded contracts is determined by Congress in the Farm Bill, which in turn determines the threshold score for contract awards. All bidders with scores above the threshold score are awarded a contract.[19] Given uncertainty in both the aggregate acreage and their opposing bidders, bidders face uncertainty over the threshold score at the time of bidding. Bids are prepared with the assistance of staff at Farm Services Agency county offices, who help landowners trade-off different contracts and bid rental rates.

Auctions 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 auction or are re-enrolling CRP land.[20] This eligibility requirement is designed to limit participation to additional landowners. Landowners 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.[21]

Research quantifying the value of the CRP has documented improvements in wildlife habitats, erosion control, water quality, and carbon sequestration from cropland retirement (Feather et al., 1999; Hansen, 2007; FAPRI-MU, 2007; Allen and Vandever, 2012; Johnson et al., 2016; Hellerstein, 2017). However, these analyses are typically conducted using models that ignore counterfactual land use. Perhaps motivated by eligibility requirements designed to restrict to additional landowners, the scoring rule is constructed under the assumption that land would crop in the absence of the program (Claassen et al., 2018). Because the primary environmental gains from the CRP accrue from land retirement, relative to cropping, the possibility that some landowners conserve absent the CRP ($a_{i0} = 1$) presents the additionality concern.

3.2 Data

Our dataset links bids to a panel of landowners' land use to measure additionality.

[19]There is an additional constraint that no more than 25% of a county's total acreage can be in a CRP contract. This constraint essentially never binds.

[20]The fact that eligibility is determined in a window five years preceding bidding is designed to eliminate any perverse incentives to crop land to in order to become eligible or maintain eligibility for the CRP. Activities in the 1-5 years preceding bidding have no impact on CRP eligibility.

[21]The USDA has occasionally allowed for voluntary contract extensions or automatic re-enrollment. No such initiatives were implemented during our main period of study.

Data on Bids We obtain data on all components of the bid, including the bid rental rate, the bid contract, and the characteristics of landowners that impact the score. Our data cover all seven auctions that occurred from 2009 to 2021. We also obtain data on all CRP contracts.

Each landowner is defined by a collection of fields, or Common Land Units, the smallest agricultural unit with a common land use. CRP contracts typically cover only a subset of a landowner's total fields. Our data include the geolocation of all bidding landowners for all auctions as well as identifiers for the specific fields offered into the mechanism ("bid fields") for one auction (in 2016).

Data on Land Use We link bidders, and for the purpose 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 use both remote sensing and administrative datasets due to their complementary strengths.

Our primary dataset is the Cropland Data Layer (CDL), a remote-sensing product from the National Agricultural Statistics Service (NASS). This dataset provides land cover classifications at 30m by 30m resolution (roughly a quarter acre) from 2009-2020. The binary indicator of crop versus non-crop — our primary outcome of interest — is rarely misclassified (Lark et al., 2021).[22] However, 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).

Our second dataset is field-level administrative data on land use that agricultural landowners report to the USDA in "Form 578" for 2013-2019. These data are accurate and comprehensive for cropped land because crop insurance payouts are dependent on these reports, but have two limitations. Landowners are only incentivized to report Form 578 if fields are insured by crop insurance, and landowners with CRP contracts are mechanically classified as non-cropped.

Our final land-use dataset is a collection of high-resolution satellite imagery (1m) of contracted land collected under the National Agriculture Imagery Program (NAIP) from 2017-2021. We use these images to observe and confirm compliance with CRP rules.

While accurate to assess agricultural land retirement — the main incentivized activity of the CRP — these datasets cannot measure the different "top-up" actions that differentiate

[22] The superclass accuracy of cropland in the Cropland Data Layer has user (probability that a classification of crop is true crop) and producer (probability that true crop is classified as crop) accuracy of over 95% from 2008-2016 (Lark et al., 2021)

the heterogeneous contracts in the mechanism (e.g. specific species). Our main estimates of additionality will focus on the measure that we can observe and the principal goal of the program: the binary outcome of retiring versus cropping land.

Appendix B provides more details about agricultural land units, the construction of our dataset, and the use of aerial photographs to confirm compliance with CRP rules.

Summary Statistics Table 1 presents summary statistics. Columns (1)-(2) summarize all agricultural landowners in the US, including CRP-eligible and ineligible landowners. Columns (3)-(4) summarize all land among bidders in our sample and columns (5)-(6) summarize bid fields.

Panel A presents land use outcomes in the year prior to bidding. Approximately 21% of bidders' land is cropped (18-21% on bid fields) versus 28-30% nationwide. The majority of the remainder is in natural vegetation and grassland. Corn and soybean cultivation account for two-thirds of all cropping. The remote sensing and administrative data generally align, but do not match exactly.

Bidders have lower USDA-constructed estimates of soil productivity (Panel B), are larger, and are more environmentally sensitive as measured by the scoring rule than the average agricultural landowner. These differences, along with the differences in land use in Panel A, are likely driven in part by eligibility requirements that columns (1) and (2) are not conditioning on.

The average bidder offers 84.1 acres into the CRP mechanism (33% of a bidder's land) for a rental rate per acre per year of $83. Two-thirds of bidders bid on a contract that includes a grassland-planting action, 21% choose a wildlife habitat action, and 12% choose a tree-planting action. 70% of bidders are re-contracting after their initial 10-year contract expired.[23] 81% of bidders are awarded contracts across the auctions in our sample. The average auction includes 36,763 bidders.

4 Evidence: Additionality and Asymmetric Information

In this section, we estimate the extent of additionality in the CRP and test for heterogeneity in and asymmetric information about additionality.

[23] Re-contracting bidders are treated identically to new bidders by the scoring rule.

4.1 Regression Discontinuity Estimates of Additionality

Estimates of additionality are important inputs into the evaluation and design of markets for environmental services but require a credible empirical strategy. We exploit the sharp discontinuity in CRP contract awards at the winning score threshold to evaluate the treatment effect of a CRP contract in a regression discontinuity (RD) design.

Empirical Strategy Our RD specification pools all auctions in the sample, normalizes each landowner's score relative to her auction's win threshold, and evaluates how land use outcomes differ over time around this threshold.

Our main specification estimates, for landowner (or bidder) i, in auction g, and year t:

$$y_{igt} = \beta_{r(i,t)} \cdot \mathbb{1}\{S_{ig} \geq \underline{S_g}\} + f_{r(i,t)}(S_{ig} - \underline{S_g}) + \nu_{igt}, \tag{6}$$

where S_{ig} is landowner i's score in auction g, $\underline{S_g}$ is the winning score threshold in auction g, $r(i,t) = t - t_{g(i)}$ normalizes the time dimension relative to the year of each auction ($t_{g(i)}$), and $f_{r(i,t)}(S_{ig} - \underline{S_g})$ are relative-year-specific local-linear regressions in the MSE-optimal bandwidth (Calonico et al., 2014) allowed to differ for positive and negative values of $S_{ig} - \underline{S_g}$. $\beta_{r(i,t)}$ estimates time-varying RD coefficients around the year of the auction. We also estimate the following pooled specification:

$$y_{igt} = \beta \cdot \mathbb{1}\{S_{ig} \geq \underline{S_g}\} + f(S_{ig} - \underline{S_g}) + \nu_{igt}. \tag{7}$$

Restricted to $r(i,t) \leq 0$, equation (7) provides a test of validity. Restricted to $r(i,t) > 0$, β provides an estimate of the treatment effect at the margin of contract awards pooled over auctions and post-auction years.

We estimate equations (6) and (7) at the landowner level to accommodate the possibility of spillovers across bid and non-bid fields. We cluster standard errors at the landowner level.

Validity The RD design is valid under the assumption that bidders possess information about the winning score threshold's distribution, but not its exact ex-post realization. Testing this assumption translates to standard smoothness and manipulation tests for RD analyses (McCrary, 2008); if bidders knew the threshold score, they would optimally bid just above it. Figure 2a presents a histogram of the score distribution normalized relative to the threshold score, $S_{ig} - \underline{S_g}$, or the running variable of the RD. Bidders with positive values are awarded contracts and bidders with negative values are not. Figure 2a confirms the lack of bunching at the winning score threshold. Figure 2b also shows no differential cropping at the discontinuity before the auction, plotting (binned) raw data and estimates of equation (7) for $r(i,t) \leq 0$.

Interpretation of equations (6) and (7) also requires an estimate of the magnitude of the first stage. Figure 2c plots the share of bidders with a CRP contract after the auction around the award threshold (equation (7) for $r(i,t) > 0$) and demonstrates a first stage close to one. We will therefore interpret the RD coefficients from equations (6) and (7) as the impact of a CRP contract.

Results Figure 3 presents raw data and estimates of equation (7) for $r(i,t) > 0$. As the CRP's primary goal is to incentivize agricultural land retirement, our outcome of interest in Figure 3a is the share of each bidder's land that is cropped, which we measure in the remote sensing data. Figure 3a demonstrates that CRP contracts impact land use at the margin of contract awards. Landowners above the score threshold, who are awarded a contract, crop eight percentage points less land than the marginal landowners who are not awarded contracts. This land is instead put into natural vegetation and grassland (trees, shrubs, wetlands and grasses), as incentivized by the CRP (Figure 3b). Because we present estimates at the bidder level, cropping is not zero for winners who typically only contract on a subset of their land.

To analyze the time path of effects and estimate the extent of additionality, Figure 4 presents coefficient estimates of $\beta_{r(i,t)}$ from equation (6) and compares them to a 100% additional ($a_{i0} = 0$ for all i) benchmark. We estimate equation (6) using both the remote sensing data (used in Figures 2b and 3) and the administrative data to ensure that results are consistent across the two datasets. The 100% additional ($\tau = 1$) benchmark in Figure 4 is calculated as the share of marginal bidders' land in a CRP contract. If contracting induced all bidders to change land use, treatment effects would equal the $\tau = 1$ line on Figure 4. Dashed lines represent pooled post-period estimates (equation (7)) in each dataset.

Figure 4 presents four facts. First, consistent with the pre-period placebo test in Figure 2b, coefficient estimates are zero before the auction. Because the estimates in Figure 4 are relative-year-specific RD coefficients, pre-period effects are identified in levels. Second, post-period effect sizes and time-trends are similar in both datasets, confirming that results are not driven by either non-classical measurement error in the remote sensing data or misreporting in the administrative data. Third, while treatment effects grow in the first two years as land transitions, effects are constant over the ten year contract period. Opportunities to rebid, which would cause treatment effects to decrease over time, do not drive down average treatment effects.[24]

Finally, the main result in Figure 4 is that over the 10-year contract, the magnitude of the treatment effect of a CRP contract on land use is substantially smaller than the $\tau = 1$, or 100% additional, benchmark. Figure 4 demonstrates that approximately one in four bidders is additional. Conversely, three of four bidders conserve even absent a CRP contract. Figure 4 provides evidence on the relevance of additionality in the CRP.

Table 2 summarizes results from Figures 2, 3, and 4, presenting estimates for the pooled specification (equation (7)) in both datasets. The main results in Table 2 quantify the additionality estimates from Figure 4: depending on the specification and data, we estimate rates of additionality at the margin of contract awards between 21% and 31%, with a mean and median effect size of 26%. Panel B presents estimates on other land use outcomes.[25]

Discussion Estimates of additionality at the margin provide information about the contract value ($B \cdot \tau$) curve in Figure 1. First, it lies below B, as many landowners are not additional. The results in Figure 4 also highlight the need to estimate, rather than assume, the $\tau(c)$ function. If alternatively, costs and additionality could be summarized by a single index, in which bidders with positive costs are additional and bidders with costs equal to zero are not, then at the margin additionality should be either zero or one. Estimates of additionality at the margin reject both of these hypotheses.[26] This will motivate our modeling and estimation approach: neither estimates of costs nor additionality alone are sufficient to estimate social welfare under current or counterfactual market designs.

Mechanisms We argue that the estimates in Figure 4 are driven by heterogeneous land use absent the contract (a_{i0}) specifically on the land bid into the mechanism. Panel C of Table 2 (and Appendix Figure C.1) documents the absence of any spillovers onto non-bid fields. This could occur either via a leakage mechanism, by which landowners reduce cropping on bid

[24] We observe limited rebidding. Appendix Figure C.4 plots the hazard rate of rebidding following a failed initial bid. Even five years following the initial bid, only approximately 20% of losers have rebid and fewer than 15% have won (despite multiple opportunities). This is consistent with the magnitude of the first stage in Figure 2c and the institutions of the setting. The CRP is so mature that the General Enrollment mechanism is shrinking over time; acreage contracted in later auctions is lower than acreage contracted in earlier auctions over our time period of analysis.

[25] Appendix Figures C.1, C.2, and C.3 present corresponding RD figures. Appendix Table C.2 replicates Table 2 restricting to bids of more than five acres, following Lark et al. (2017).

[26] This interpretation is slightly complicated by bidder asymmetry, contract choices, and the pooling of auctions with different thresholds. Appendix Table C.1 presents RD estimates split by the location of the win threshold parameterized by the amount a bidder would need to bid for the base contract to achieve $\underline{S_g}$ and finds that $0 < \tau < 1$ across groups.

fields but increase it on other fields, or if there are complementarities to cropping multiple fields. We observe no evidence in support of either of these hypotheses.

In theory, both conservation without a CRP contract and cropping with a CRP contract (non-compliance) could contribute to the result in Figure 4. We assess the CRP's compliance regime by inspecting high resolution aerial photographs of over 1,000 contracted fields.[27] As described in more detail in Appendix B, we find no evidence of non-compliance.

Beyond the RD Together, these two results — no spillovers and compliance — provide a basis for empirical analysis beyond the RD. Among rejected bidders, we observe each bidder's a_{i0} on bid fields. With knowledge that $a_{i1} = 1$, we therefore observe $1 - a_{i0}$ for each landowner that loses the auction. In other words, we simplify to a "selective labels" problem (Lakkaraju et al., 2017; Chan et al., 2022; Arnold et al., 2022).

4.2 Testing for Asymmetric Information

Empirical Strategy We use observations of landowner additionality ($1 - a_{i0}$) and bids to conduct a test for asymmetric information in the spirit of Chiappori and Salanie (2000) and Hendricks and Porter (1988). We estimate the following regression specification:

$$1 - a_{i0} = \beta \cdot \mathbf{b}_i + \pi \cdot \mathbf{z}_i + h\left(\mathbf{z}_i^s\right) + \nu_i, \tag{8}$$

where $1 - a_{i0}$ is measured as the share of landowner i's bid fields that are cropped, observed only for landowners without a contract award (those rejected by the auction), $\mathbf{b}_i$ represents characteristics of i's bid, $h\left(\mathbf{z}_i^s\right)$ are controls for characteristics that enter the scoring rule, and $\mathbf{z}_i$ are other landowner characteristics. Every specification of equation (8) includes controls for the scoring rule, which impacts the strategic environment facing bidders. These include estimates of groundwater quality, surface water quality, wind and water erosion (deciles), air quality impacts, and whether a bidder is in a Wildlife Priority Zone or Air Quality Zone. We restrict to the one auction where we observe the delineations of bid fields (the 2016 auction); this is required to construct $1 - a_{i0}$. This auction is also the most restrictive auction in our sample: $1 - a_{i0}$ is observed for 82% of bidders. We will address the complication that equation (8) is estimated in the selected sample of rejected bidders in Section 5.

Following the logic of Chiappori and Salanie (2000) and Hendricks and Porter (1988), a positive correlation between bids and $1 - a_{i0}$ is indicative of asymmetric information about

[27]We use aerial photographs because any measurement error in the remote sensing classifications will mechanically bias toward finding non-compliance.

additionality. In the context of the stylized model in Section 2, a positive correlation implies an upwards-sloping contract value curve, or adverse selection in the market.

Results We first document evidence of adverse selection in the market. Figure 5a presents a binned scatterplot of the correlation between additionality and the bid per acre-year (the bid rental rate), residualized of $h(\mathbf{z}_i^s)$. Figure 5a demonstrates substantial heterogeneity in additionality and a systematic positive relationship between higher bids — reflecting higher costs of contracting — and additionality. The interpretation of Figure 5a is intuitive: bidders with low costs of contracting have low costs in part because of private information that they would be likely to conserve even without a CRP contract. Figure 5b shows that bids remain correlated with additionality, capturing residual private information, conditional on other observables including prior land use interacted with estimates of the soil productivity of the bidders' land

Next, we show that choices of contracts in the mechanism are systematically correlated with additionality. Figure 5c replaces $\mathbf{b}_i$ with a vector of chosen contract indicators — the submitted bid on the menu of contracts — and documents substantial adverse selection (low additionality) on tree-related contracts, relative to the base category of introduced grasses. Figure 5c highlights that contract choices reveal information about additionality and that alternative menus of contracts may lead to different outcomes in the market.

Finally, we present evidence that observable characteristics are predictive of additionality. Figure 5d plots additionality by decile of landowner predicted soil productivity, conditional on $h(\mathbf{z}_i^s)$ 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. This characteristic is an ideal predictor of additionality in theory, and Figure 5d demonstrates that it is predictive of additionality in practice. This result highlights the potential to differentiate incentives using this characteristic, which is not currently incorporated in the scoring rule.

Discussion The analysis in Sections 4.1 and 4.2 provide evidence on the extent of additionality, the presence of asymmetric information in the market, and the availability of tools to differentiate landowners by their additionality. However, the welfare and market design implications of these facts require a quantitative economic framework. In the next section, we develop an empirical approach to obtain the sufficient statistics for welfare presented in Section 2. Relative to that stylized set-up, our empirical model will incorporate heterogeneity across contracts and observable characteristics to capture a richer empirical setting for analysis and market design.

5 Empirical Model of Bidding and Additionality

We develop a joint model of bidding and additionality. We use this model to estimate (i) the distribution of landowner costs of contracting over a menu of contracts and (ii) additionality as a function of landowner costs and observable characteristics. Together with estimates of the social benefits of CRP actions, which we take from the literature, the model facilitates analysis of social welfare under current and counterfactual market designs.

Landowners are characterized by a vector of private costs and bid on discrete contracts, differentiated by heterogeneous conservation actions, in response to a non-linear scoring rule. Landowners also differ in their additionality, which we model with a conditional expectation function that depends on both observable characteristics and bidders' vector of costs. Our empirical strategy first uses the optimality of bidding in the auction to estimate bidders' costs by revealed preferences and then estimates expected additionality as a function of costs and landowner characteristics by matching moments of the observed joint distribution of land use, landowner characteristics, and optimal bids (presented in Section 4).

5.1 Model

Landowners There are N landowners, indexed by i, and J contracts, indexed by j. Each landowner is characterized by (i) her costs (c_i, κ_i) for $\kappa_i = \{\kappa_{ij}\}$, and (ii) her action a_{i0} absent the CRP. Extending the model in Section 2, re-define $F(\theta)$ as the cumulative distribution function of landowner types $\theta_i = ((c_i, \kappa_i), a_{i0})$ and $F_{c,\kappa}$ as the marginal on (c_i, κ_i).

The vector (c_i, κ_i) defines landowner i's costs of contracting. A landowner's cost of contract j is $c_i + \kappa_{ij}$, where c_i is the base cost of contracting, common across contracts, and κ_{ij} is the top-up cost associated with contract j. We assume (c_i, κ_i) are drawn independently across landowners conditional on observables $\mathbf{z}_i$.

It will again be useful to define the function:

$$\tau(\mathbf{z}_i, c_i, \kappa_i) = \mathbb{E}\left[1 - a_{i0} \,|\, \mathbf{z}_i, c_i, \kappa_i\right], \tag{9}$$

or the expected difference in conservation with a CRP contract versus without a CRP contract given observable characteristics $\mathbf{z}_i$ and landowner costs (c_i, κ_i).

Auction Landowners (bidders) submit a two-part bid $\mathbf{b}_i = (r_i, \mathbf{x}_i)$. $\mathbf{x}_i$ is a contract vector, with $x_{ij} = 1$ if the j-th contract is chosen and $x_{ij} = 0$ otherwise. Landowners choose a single contract so $\sum_j x_{ij} = 1$. If landowner i wins the auction, $\mathbf{b}_i$ describes the terms of her CRP contract: she performs the action defined in $\mathbf{x}_i$ and receives a payment of r_i dollars per acre-year. Each bid $\mathbf{b}_i$ is converted into a score according to a known scoring rule $s\left(\mathbf{b}_i, \mathbf{z}_i^s\right)$. All landowners above a winning threshold score $\underline{S}$ are awarded a contract.

Landowner i forms beliefs about the probability of winning the auction with a score S given uncertainty over her competitors and the acreage limit of the auction.[28] We assume that landowner i does not observe the number or characteristics of her competitors, and all landowners form the same beliefs about the distribution of the threshold score $\underline{S}$.[29] Define $G(S) = \Pr\left\{S \geq \underline{S}\right\}$.

Optimal Bidding Each landowner i solves:

$$\mathbf{b}_i^* = \underset{(r,\mathbf{x})}{\operatorname{argmax}} \left\{ \underbrace{(r - c_i - \mathbf{x} \cdot \kappa_i)}_{\text{Payoff to } i \text{ conditional on bid } (r,\mathbf{x})} \times \underbrace{G\left(s\left((r,\mathbf{x}), \mathbf{z}_i^s\right)\right)}_{\text{Probability of } i \text{ winning with bid } (r,\mathbf{x})} \right\}, \tag{10}$$

where a landowner chooses her bid $\mathbf{b}_i = (r_i, \mathbf{x}_i)$ to maximizes her payoff conditional on winning, multiplied by the probability of winning with that bid, given her costs (c_i, κ_i).

Additionality In the contract period, landowners make land use decisions. If awarded a contract, $a_{i1} = 1$. If not, landowners choose a_{i0}, which is not contractible. At the time of bidding, equation (9) is the population expectation of $1 - a_{i0}$ for landowners with observable characteristics $\mathbf{z}_i$ and contracting costs (c_i, κ_i). We estimate the function $\tau\left(\mathbf{z}_i, c_i, \kappa_i\right)$, instead of modeling the choice of a_{i0}, because $\tau\left(\mathbf{z}_i, c_i, \kappa_i\right)$ and $F_{c,\kappa}$ are sufficient statistics for social welfare under current and alternative market designs (see Section 2).

Remarks Landowners compete on both r and $\mathbf{x}$ in equation (10). This captures the importance of competition on contracts in reality and allows for counterfactuals that redesign the menu or incentives across contracts in the scoring rule.[30] Although landowners

[28] The acreage limit is determined by Congress in the Farm Bill. Appendix Figure D.1 documents evidence consistent with quantity uncertainty.

[29] This is motivated by the fact that bidding is decentralized among thousands of bidders across the US.

[30] The EBI Factsheets provided to landowners state: "The single most important producer decision involves determining which cover practice to apply to the acres offered. Planting or establishing the highest scoring cover mixture is the best way to improve the chances of offer acceptance."

are competing on multiple dimensions, whether the landowner wins against her competitors depends only on the choice of score. The bidding problem can be solved as an "inner problem" of a single-agent discrete choice and an "outer problem" of a one-dimensional game, building on Asker and Cantillon (2008) and Che (1993). Each score induces a menu of payoffs from winning the auction for each contract for each bidder (illustrated in Appendix Table A.3). The resulting discrete choice problem is the bidder's "inner problem." Then, the choice of the optimal score, given the optimally chosen contract, defines the bidder's "outer problem."

The bidding problem in equation (10) incorporates two important simplifications. First, bidding is costless and there is no selection into bidding.[31] Second, the bidding problem in equation (10) is static. The CRP is so mature that the quantity procured in the auction is in decline. This limits the option value to rebid, and is reflected in the fact that the vast majority of bidders do not re-bid upon losing (see Appendix Figure C.4). However, in a dynamic framework, the cost parameters estimated from equation (10) 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). Counterfactuals that do not condition on prior actions and hold the sequence of future auctions fixed will not be biased by the static formulation of equation (10).

Although the mechanism is more complex, the market failure is the same as in Section 2. Landowner choices and allocations depend only on the scoring rule $s(\mathbf{b}_i, \mathbf{z}_i^s)$ and costs of contracting (c_i, κ_i), but the efficient allocation depends also on $\tau(\mathbf{z}_i, c_i, \kappa_i)$.

5.2 Identification and Estimation

Identification Because observed bids are discrete, we cannot invert them using bidders' first order conditions to point identify costs as in Guerre et al. (2000). We instead obtain inequalities from the observed $\mathbf{b}_i^* = (r_i, \mathbf{x}_i)$ revealed preferred from optimal bidding in equation (10) that define identified sets containing the true values of (c_i, κ_i) (Agarwal et al., 2023). Instruments in the scoring rule $s((r, \mathbf{x}), \mathbf{z}_i^s)$, which vary the relative payoffs across contracts $\mathbf{x}$ but are conditionally independent of costs, narrow the bounds on the identified sets. Variation in $s((r, \mathbf{x}), \mathbf{z}_i^s)$ traces out the distribution of (c_i, κ_i) conditional on observable characteristics $\mathbf{z}_i$, $F_{c,\kappa\,|\,\mathbf{z}}$. Appendix Figure D.2 provides a graphical explanation; Agarwal et al. (2023) provides a proof.

For identification of $\tau(\mathbf{z}_i, c_i, \kappa_i)$, suppose bidders truthfully report (c_i, κ_i) to the mechanism,

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

but no bidders are awarded contracts. $F(\theta)$ is point identified from observing the joint distribution of (c_i, κ_i) in bids and a_{i0} in the land use data. Our setting differs from this ideal: (i) the discrete choice in equation (10) results in only identified sets for (c_i, κ_i) from observed bids, and (ii) a_{i0} is not observed for the 18% of bidders who win the auction and are awarded a contract. Identification of the function $\tau(\mathbf{z}_i, c_i, \kappa_i)$ uses the observed joint distribution of $1 - a_{i0}$, characteristics $\mathbf{z}_i$, and optimal bids $\mathbf{b}_i^* = (r_i, \mathbf{x}_i)$ and instruments that shift $s((r, \mathbf{x}), \mathbf{z}_i^s)$. $\tau(\mathbf{z}_i, c_i, \kappa_i)$ is the conditional expectation function that rationalizes this joint distribution. With full support, instruments in the scoring rule that shift payoffs across contracts and the probability of winning replicate the "ideal experiment" described above.

We use three sources of variation in the scoring rule as instruments. Two shift relative payoffs across contracts (illustrated in Figure D.3). One shifts only the level of the score. We assume that all three sources of variation are conditionally independent of (c_i, κ_i) and a_{i0}. The first source of variation is a mid-mechanism policy change: after bids were initially collected in 2021, Climate Smart Practice Incentives — additional payments dependent on contracts' carbon sequestration potential — were announced and bids were recollected under the new scoring rule. We obtained the bids submitted in both the interim and final mechanisms, which provides variation in the relative payoffs across contracts for the same bidders and same contract period.[32] The second source of variation comes from the fact that bidders in Wildlife Priority Zones (WPZs) face different payoffs across contracts both cross-sectionally and over time. The third source of variation is similar, whether a bidder is in an Air Quality Zone (AQZ), but shifts only the level of the score. The use of these instruments are justified by the fact that WPZ and AQZ status are based on state priorities and the sensitivity of wildlife or the importance of air quality, not characteristics of landowners or their land.

Parameterization Although with sufficient variation in the scoring rule, the model is non-parametrically identified, to take it to the data, we parameterize $F_{c,\kappa\,|\,\mathbf{z}}$ and $\tau(\mathbf{z}_i, c_i, \kappa_i)$. Landowners make a discrete choice across contracts with heterogeneous features, so we parameterize (c_i, κ_i) with a characteristics model:

$$c_i \sim N\left(c(\mathbf{z}_i), \sigma_c^2(\mathbf{z}_i)\right) \quad \kappa_{ij} = p_j(\mathbf{z}_i) + u_j(\mathbf{z}_i) + \epsilon_{ij} \quad \epsilon_{ij} \overset{iid}{\sim} N\left(0, \sigma_\kappa^2(\mathbf{z}_i)\right). \tag{11}$$

c_i and κ_{ij} are drawn from independent normal distributions with means and variances that depend on observable characteristics, $\mathbf{z}_i$. κ_{ij} costs are differentiated by contract features, p_j and u_j. p_j defines mean costs for a vector of primary covers, which vary by the left-most

[32] We can use this policy experiment to directly test that landowners are competing on contracts; 8% of landowners change their contract choice under the new scoring rule.

four categories in Figure 5c, relative to the base category of introduced grasses (normalized to zero). u_j is a vector of upgrade covers, which varies by the right-most two categories in Figure 5c plus the no-upgrade option, normalized to zero. The parameterization in equation (11) parsimoniously captures differences across contracts.[33]

We also parameterize

$$\tau(\mathbf{z}_i, c_i, \kappa_i) = \pi \cdot \mathbf{z}_i + \beta \cdot c_i + \alpha \cdot \kappa_i. \tag{12}$$

This specification allows $\tau(\mathbf{z}_i, c_i, \kappa_i)$ to depend on observable characteristics, $\mathbf{z}_i$, and unobserved bidder costs (c_i, κ_i), where we align the dimension of α with the primary and upgrade parameterization of κ_{ij}, i.e. we impose that $\alpha_j = \alpha_{j'}$ if $p_j = p_{j'}$ and $u_j = u_{j'}$.

Estimation Estimation proceeds in three steps and closely follows the identification argument. In the first step, we estimate landowner beliefs $G(S)$ via simulation. In the second step, we estimate the parameters of $F_{c,\kappa\,|\,\mathbf{z}}$ via revealed preferences in observed optimal bids (equation (10)). In the third step, we estimate $\tau(\mathbf{z}_i, c_i, \kappa_i)$ using the Step 2 estimates of $F_{c,\kappa\,|\,\mathbf{z}}$ and optimal bidding in equation (10) to simulate and match land-use moments of the joint distribution of $1 - a_{i0}$, $\mathbf{b}_i^* = (r_i, \mathbf{x}_i)$, and $\mathbf{z}_i$. Steps 1 and 2 are a common approach to the empirical analysis of auctions (Guerre et al., 2000; Hortaçsu and McAdams, 2010; Agarwal et al., 2023) and Steps 2 and 3 are a common approach to the empirical analysis of selection markets (Bundorf et al., 2012; Tebaldi, 2022). Appendix D provides additional details.

Step 1: Simulate $G(S)$ First, we estimate $G(S)$ by simulation following Hortaçsu (2000); Hortaçsu and McAdams (2010). We fit Beta distributions to the number of bidders and acreage limits across auctions. We supplement our primary dataset with additional historic data on acreage limits and the numbers of bidders for all auctions from 2000 to 2021 to fit these distributions. Then, we simulate the numbers of bidders and the acreage thresholds and re-sample from the observed joint distribution of the scores and acreages of bidders within each auction.

Step 2: Estimate Costs The next step estimates $F_{c,\kappa\,|\,\mathbf{z}}$ using the parameterization in (11) and the optimality of observed bids from equation (10). We classify bidders into 32

[33] Landowners face a discrete choice over each of the primary and upgrade covers, but primary and upgrade covers can be combined. There are 36 total possible contracts, reflecting finer categorizations of primary covers beyond the five dimensions in p_j (twelve total) that each can be combined with an upgrade option. See Appendix A for more details.

categories of observable types $\mathbf{z}_i$ that parameterize $F_{c,\kappa\,|\,\mathbf{z}}$ based on interactions of quartiles of soil productivity, prior CRP status, and prior land use status.

We estimate the parameters of $F_{c,\kappa\,|\,\mathbf{z}}$ via Maximum Simulated Likelihood (MSL). This estimator maximizes the likelihood of each bidder's observed score-contract combination. Estimation poses a computational challenge because the combined discrete-continuous bidding problem makes choice sets extremely large without allowing for an inversion. We address this challenge in two ways. First, we coarsen the bid space used to construct each bidder's likelihood contribution, maintaining the full dimensionality of the problem when solving equation (10).[34] Second, we use a change of variables and importance sampling (following Ackerberg (2009)) to reduce the computational burden associated with searching over a high dimensional bid space for each simulation draw.

Step 3: Estimate Additionality The third step estimates the parameters in equation (12), (π, β, α), via the Method of Simulated Moments (MSM). This estimator searches for the parameters (π, β, α) that rationalize moments of the joint distribution of $1-a_{i0}$, $\mathbf{b}_i^* = (r_i, \mathbf{x}_i)$, and $\mathbf{z}_i$ observed in the data (key moments are illustrated in Figures 5). Specifically, we simulate $\left(c_i^k, \kappa_i^k\right)$ from $F_{c,\kappa\,|\,\mathbf{z}}$ estimated in Step 2, solve for the optimal $\mathbf{b}_i^{*k}$ (equation (10)) for each simulation draw k, and search for the parameters (π, β, α) that match: (i) additionality at the winning score threshold, (ii) additionality among all rejected bidders and by observable characteristics, (iii) the covariance between additionality and chosen scores, and (iv) the additionality among all landowners choosing a given contract.

We measure additionality as $1 - a_{i0}$ among rejected bidders in the remote sensing land use data, as in Section 4.2. All moments condition on optimal bids that are below the score threshold. This feature of the estimator accounts for the sample selection in Figure 5. The observables $\mathbf{z}_i$ in $\tau\left(\mathbf{z}_i, c_i, \kappa_i\right)$ are the 32 observable bidder types that parameterize $F_{c,\kappa\,|\,\mathbf{z}}$ and the remaining components of the scoring rule.

5.3 Parameter Estimates

Costs Figures 6a and 6b plot the estimated distributions of c_i and κ_{ij}.[35] A large share of landowners have low values of c_i, below \$50 per acre, per year with a tail of bidders with higher c_i. Top-up costs κ_{ij} are mostly positive; most contracts are more costly than the normalized category of introduced grasses. Table 3 summarizes mean costs across contract

[34] We coarsen the observed continuous choice of score into deciles of the score distribution and the choice of contract into seven categories corresponding to the seven dimensions of p_j and u_j. See Appendix D.

[35] Appendix Table D.1 presents parameter estimates for select cells of $\mathbf{z}_i$ and standard errors.

features and highlights observable heterogeneity along landowner soil productivity. Relative costs across contracts are generally intuitive. Higher soil productivity bidders have higher costs for primary covers, but lower costs for upgrade covers.

Because costs are estimated using only revealed preferences in bids, Figure 6c examines whether estimated costs correlate with land use. Figure 6c presents a binned scatterplot of $1 - a_{i0}$ against mean base costs c_i among rejected bidders. Figure 6c documents that landowners with higher mean base costs are more additional. This both validates the revealed preference estimates and indicates the presence of adverse selection in the market mediated by observables.

Appendix D examines model fit and compares estimated top-up costs to some limited administrative data on costs submitted to the USDA. Our fit is reasonable and model-implied costs are similar in rank and in magnitude to the administrative data.

Additionality Table 4 presents select parameter estimates in $\tau(\mathbf{z}_i, c_i, \kappa_i)$ that describe how additionality varies with (c_i, κ_i). The remaining parameters estimate how additionality varies across observable characteristics.

Each column of Table 4 presents a different specification of $\tau(\mathbf{z}_i, c_i, \kappa_i)$. Columns (1) and (2) restrict to a correlation between additionality and c_i and impose that $\alpha = 0$. Column (1) includes observable characteristics from the scoring rule and column (2) adds observable characteristics that parameterize $F_{c,\kappa\,|\,\mathbf{z}}$ (interactions of soil productivity and prior land use). Consistent with the positive correlation between bids and additionality in Figures 5a and 5b, the positive coefficients in columns (1) and (2) of Table 4 indicate that landowner additionality is systematically correlated with costs, conditional on observable characteristics. The magnitude of the coefficients presented in Table 4 imply that a one standard deviation increase in c_i is associated with an eight percentage point increase in additionality. The coefficient estimates in Table 4 reflect the adverse selection presented in Figures 5a and 5b.

Columns (3) and (4) allow additionality to also depend on κ_i. Column (3) only allows tree-related action costs to impact additionality. The coefficient on tree-related κ_{ij} is positive and large, while the coefficient on c_i is reduced, but still positive. Column (4) allows additionality to vary with κ_i more flexibly, and the residual correlation between costs and additionality loads onto κ_i. The largest coefficient remains on tree-related contracts.

The model-implied estimate of additionality at the RD margin is between 22-23%, within our range of estimates of 21%-31%. This is expected, as our estimation strategy matches land use moments directly.

5.4 From Additionality to Contract Value

To calculate social welfare, we require estimates of the social benefits of contracted actions, $B_j(\mathbf{z}_i^s)$. We now index $B_j(\mathbf{z}_i^s)$ by j to account for heterogeneous social benefits across contracts and allow $B_j(\mathbf{z}_i^s)$ to depend on observable characteristics in the scoring rule $\mathbf{z}_i^s$ that capture heterogeneity in the environmental sensitivity of landowners. We take average estimates of the value of CRP actions from literature that quantifies the benefits from habitat restoration and reductions in erosion, water and air pollution, and greenhouse gas emissions from the CRP (Johnson et al., 2016; Feather et al., 1999; Hansen, 2007). We take relative valuations across landowners with characteristics $\mathbf{z}_i^s$ and across contracts j from the scoring rule. We therefore consider social welfare under valuations $B_j(\mathbf{z}_i^s)$ revealed preferred by the USDA. See Appendix E for more details.

One remaining detail concerns the fact that additionality is one-dimensional (land-retirement), but the menu of contracts is multi-dimensional. This is due to fundamental data limitations, the substantial simplification that focusing on only this one dimension affords, and the fact that the primary incentivized activity of the CRP is land retirement. Our baseline specification follows Section 2 and calculates contract value as $B_j(\mathbf{z}_i^s)\cdot\tau(\mathbf{z}_i, c_i, \kappa_i)$.[36]

6 Social Welfare and Alternative Market Designs

With estimates of the costs (c_i, κ_i) and expected social benefits $B_j(\mathbf{z}_i^s)\cdot\tau(\mathbf{z}_i, c_i, \kappa_i)$ of contracting, we turn to analyzing the social welfare and market design consequences of additionality. Define the expected social surplus of contracting with landowner i for contract j as:

$$B_j(\mathbf{z}_i^s)\cdot\tau(\mathbf{z}_i, c_i, \kappa_i) - c_i - \kappa_{ij}. \tag{13}$$

Equation (13) is based on $\tau(\mathbf{z}_i, c_i, \kappa_i)$ not the ex-post realization $1-a_{i0}$. Because current and counterfactual mechanisms screen only on $(\mathbf{z}_i, c_i, \kappa_i)$, using equation (13) for comparisons of social welfare under current and alternative market designs is without further loss.[37]

We first examine allocative efficiency and pricing in the context of our graphical framework with a uniform price and a single contract. In these analyses, we collapse heterogeneity to one dimension of cost for a single contract and the expected additionality at each point in

[36] In Appendix F, we present results under an alternative assumption where additionality only affects the base contract. This assumes a valuation of contracts equal to $B_0(\mathbf{z}_i^s)\cdot\tau(\mathbf{z}_i, c_i, \kappa_i) + B^j(\mathbf{z}_i^s)$, where $B_0(\mathbf{z}_i^s)$ is the value of the base action and $B^j(\mathbf{z}_i^s)$ is the incremental value of the top-up action.

[37] We will not compute a full information benchmark based on $((c_i, \kappa_i), a_{i0})$.

this one-dimensional cost distribution (as in Section 2). We then build on the graphical analysis — incorporating heterogeneity across landowners and contracts — to investigate the performance and design of current and counterfactual auctions and competitive markets for conservation (offset markets).

6.1 Graphical Analysis

Base Contract Figure 7 presents the empirical analogue of Figure 1, graphing the marginal cost (MC), contract value ($B \cdot \tau$), and average contract value curves for the base contract. We simulate the minimum cost to landowners of fulfilling the base contract to construct the MC curve. Then, we calculate the average $B_0\left(\mathbf{z}_i^s\right) \cdot \tau\left(\mathbf{z}_i, c_i, \kappa_i\right)$, where $B_0\left(\mathbf{z}_i^s\right)$ denotes the social benefit of the base action, at each quantile of this cost distribution to obtain the contract value curve. The two facts from Section 4 are reflected in Figure 7. The contract value curve lies below B, representing landowners who are not additional (Section 4.1), and is upwards-sloping, representing adverse selection (Section 4.2). Figure 7 offers three conclusions about the welfare implications of these two facts in the context of our stylized framework.

First, the contract value curve crosses the marginal cost curve from above: the empirical market described by Figure 7 is similar to Figure 1a, not Figure 1b. The socially-optimal uniform price implements the one-dimensional efficient allocation defined by equation (5) with social surplus equal to the vertical distance between the contract value and marginal cost curves. This leads to social welfare gains of \$14.66 per acre-year in region CDG. Figure 7 demonstrates that the potential market failure introduced by additionality does not lead the market to completely fail.

Second, Figure 7 illustrates inefficient contracting when prices are set at B (the average $B_0\left(\mathbf{z}_i^s\right)$ across landowners), ignoring counterfactual land use. Pricing at B leads to social welfare losses of \$11.79 per acre-year in triangle GHI, 80% of the gains realized in triangle CDG. These social welfare losses underscore the importance of quantitative analysis of the joint distribution of the costs of contracting and additionality to set socially-optimal incentives to implement efficient allocations.

Third, Figure 7 illustrates the trade-limiting effects of adverse selection in competitive (offset) markets with price-taking buyers. We isolate the effect of supply-side adverse selection by assuming buyers in competitive markets possess the same full-information preferences as the USDA, but take expectations over the additionality of all market participants. This demand curve is illustrated with the gray average contract value curve in Figure 7. Adverse selection would limit trade in a competitive market to the equilibrium quantity $q^c = 0.58$, a 15% reduction from the socially optimal quantity $q^* = 0.68$. Triangle EFG represents social welfare gains from contracting that are not realized in competitive markets. The magnitude of triangle EFG is 4% of the (one-dimensional) efficient allocation, triangle CDG. Though the adverse selection introduced by additionality exists in the market, limits trade, and reduces social welfare, it does not unravel the market.

Overall, Figure 7 presents a relatively optimistic view of markets for environmental services, which contrasts with arguments that establishing these markets is a futile endeavor (Anderson, 2012). Figure 7 also illustrates why. Perhaps surprisingly, the contract value curve is flat for landowners with low contracting costs.

Heterogeneity Figure 8 uses the estimated heterogeneity to examine differences in the graphical analysis across observable characteristics and contracts. This heterogeneity will serve as a basis for counterfactual market designs.

Figures 8a and 8b replicate Figure 7 in sub-populations split by estimated soil productivity. Both contract value and marginal cost curves differ in the lowest versus high quintile of the soil productivity distribution, implying different socially-optimal prices.

Figure 8c examines heterogeneity across contracts. We focus on tree contracts due to the evidence of substantial adverse selection in Table 4 and the prevalence of tree-related PES programs and offset contracts. Figure 8c calculates the marginal cost curve as the minimum cost required to fulfill any tree-related contract and plots the average $B_j(\mathbf{z}_i^s) \cdot \tau(\mathbf{z}_i, c_i, \kappa_i)$ at each quantile of this distribution. The exercise requires substantial out-of-sample extrapolation, but it illustrates how alternative landowner type distributions across important classes of contracts in our setting can generate different conclusions.

In Figure 8c, the contract value curve crosses the marginal cost curve from below, leading to social welfare losses at low q. The socially-optimal uniform price cannot implement the one-dimensional efficient allocation (DE) defined in equation (5). This is because, as in Figure 1b, the ordering of landowners by social surplus (the vertical distance between the contract value and marginal cost curves) differs from the ordering of landowners by contracting costs (the construction of the x-axis, q). Because they are less additional, the lowest cost landowners are not the highest social value.

Figure 8c also illustrates that supply-side adverse selection would cause a competitive (offset) market for tree contracts to unravel.

6.2 Alternative Auctions

The standard auction design problem focuses on cost-minimizing procurement auctions, but the objective of payments for ecosystem services mechanisms is to *impact outcomes* (conservation) at lowest cost. Many other incentive-based public policies face similar objectives. However, standard mechanisms focused on cost-minimization, which consider reports of (c_i, κ_i) but not the effect of contracting on conservation $\tau(\mathbf{z}_i, c_i, \kappa_i)$, may not advance this goal.

We simulate bidding and additionality under status quo and counterfactual auctions to investigate this possibility and the performance of alternative designs. Figure 9 and Table 5 present results. Figure 9 plots social welfare under each allocation:

$$\sum_i \sum_j \left(B_j\left(\mathbf{z}_i^s\right) \cdot \tau\left(\mathbf{z}_i, c_i, \kappa_i\right) - c_i - \kappa_{ij}\right) \cdot x_{ij}. \tag{14}$$

Table 5 tabulates the bars in Figure 9 and reports additional details: USDA spending, landowner surplus, the value of environmental benefits $\sum_i \sum_j B_j\left(\mathbf{z}_i^s\right) \cdot \tau\left(\mathbf{z}_i, c_i, \kappa_i\right) \cdot x_{ij}$, average additionality, and the share of bidders allocated a contract. Each bar of Figure 9 corresponds to the same numbered column in Table 5.

The Status Quo Auction versus an Efficient Benchmark Because social welfare depends on additionality but the design of the status quo auction does not, the social value of the CRP is ambiguous. We document social welfare gains of \$126 million per auction in the status quo (bar (1) of Figure 9). This is calculated by simulating optimal bidding in the mechanism with the estimated distribution of (c_i, κ_i) and beliefs $G(S)$.

However, social welfare under the status quo auction is only 15% of an efficient benchmark. This efficient benchmark is defined as the allocation that uses all observables $\mathbf{z}_i$ and the full vector of costs (c_i, κ_i) to maximize social welfare (equation (14)) subject to two constraints. First, each landowner must obtain at most one contract $\sum_j x_{ij} \leq 1$. Second, no more landowners are allocated contracts than in the status quo. Because many landowners are not additional, the efficient allocation involves contracting with fewer landowners than the status quo and the quantity constraint does not bind (column (2) of Table 5).

This efficient allocation may not be implementable in an incentive compatible auction if social surplus and allocations are not monotone in bidder costs (Myerson, 1981). This complication is relevant because of adverse selection; once the mechanism's impact on conservation (additionality) is considered, the lowest cost landowners may not be the highest social value. This issue is illustrated in principle in Figure 1b and based on our estimates in Figure 8c.

Alternative Auctions: Vickrey Auctions with Scoring The status quo auction underperforms the efficient allocation in part because it does not consider additionality in its design. Implementing the efficient allocation may be impossible, but changes in design to incorporate additionality may close the gap.

In practice, a common approach to additionality is to define eligibility requirements that determine who and what is allowed to trade.[38] Emphasis is placed on identifying additional participants who are then allowed to participate in the market.

We consider a more flexible approach that treats landowners asymmetrically by their expected additionality. Contracting with a low expected additionality landowner could be justified at sufficiently low cost. Conversely, landowners who are likely to be additional may still counterfactually conserve with some probability. This approach accommodates a minimum standard — incentives could be zero for some participants or some conservation actions — but it also allows incentives to differ across landowner observables and contracts in the market. We implement this approach in counterfactual scoring auctions that construct scoring rules based on predictions of $B_j\left(\mathbf{z}_i^s\right) \cdot \tau\left(\mathbf{z}_i, c_i, \kappa_i\right)$. These auctions build directly on the status quo, which uses a scoring rule based on $B_j\left(\mathbf{z}_i^s\right)$.

Define a *contract value scoring rule* $s_j\left(\mathbf{z}_i\right)$ to parameterize the (score-implied) expected social benefit of contracting with a bidder with characteristics $\mathbf{z}_i$ for contract j. We focus on linear rules based on (a simplified version of) the functional form of the status quo scoring rule,[39]

$$s_j\left(\mathbf{z}_i\right) = \omega_{\mathbf{z}} \cdot \mathbf{z}_i + \omega_j, \tag{15}$$

where $\omega_{\mathbf{z}}$ parameterizes scores across observables $\mathbf{z}_i$ (asymmetry terms) and ω_j parameterizes scores across contracts j.

We implement allocations defined by the status quo and alternative scoring rules with a Vickrey-Clarke-Groves (VCG) mechanism.[40] We term these auctions "Vickrey auctions with

[38] For examples, see the Clean Development Mechanism Methodology Booklet, the REDD+ eligibility requirements, and the Verified Carbon Standard.

[39] We simplify the status quo scoring rule by eliminating heterogeneity across contracts based on WPZ status and non-linearities in the scoring rule. See Appendix A for more details.

[40] A VCG mechanism is a generalization of a second price auction. Many of the well-known undesirable properties of VCG mechanisms do not apply in our setting because bidders have substitutes preferences (see Ausubel and Milgrom (2005)).

scoring," which maximize a definition of social welfare implied by the scoring rule $s_j(\mathbf{z}_i)$:

$$\sum_i \sum_j \left(s_j(\mathbf{z}_i) - c_i - \kappa_{ij}\right) \cdot x_{ij}. \tag{16}$$

Bidders are treated asymmetrically by $s_j(\mathbf{z}_i)$ not $\tau(\mathbf{z}_i, c_i, \kappa_i)$: compare equations (14) and (16). In Vickrey auctions with scoring, bidders truthfully report their vector of (c_i, κ_i), then are ranked by $\max_j s_j(\mathbf{z}_i) - c_i - \kappa_{ij}$.[41] The highest scoring bidders subject to the auction's quantity threshold are allocated the contract $\arg\max_j s_j(\mathbf{z}_i) - c_i - \kappa_{ij}$.[42] Unlike in Asker and Cantillon (2008) and Che (1993), the scoring rule may not capture all heterogeneity in $\tau(\mathbf{z}_i, c_i, \kappa_i)$. $s_j(\mathbf{z}_i)$ depends only on observable characteristics. Moreover, some characteristics may not be used to avoid introducing perverse incentives to game the scoring rule (e.g. prior land use).

Vickrey auctions with scoring have three advantages. First, they focus attention on the design of the scoring rule because they implement an allocation that maximizes scoring-rule-implied social welfare (equation (16)). Second, allocations are not computationally demanding to calculate. Finally, they are simple: the market designer needs only to compute $s_j(\mathbf{z}_i)$.[43]

Social Welfare Under Status Quo and Alternative Scoring Rules Bars (3)-(6) of Figure 9 adjust the scoring rule $s_j(\mathbf{z}_i)$, holding the number of awarded contracts fixed at the status quo quantity. Each bar evaluates the allocation implemented by the auction with equation (14). Additional details are reported in the corresponding columns of Table 5.

Bar (3) maintains the status quo scoring rule, $s_j(\mathbf{z}_i) = B_j(\mathbf{z}_i^s)$, but changes the auction mechanism to VCG. This counterfactual isolates the impact of a scoring rule that is naive to additionality (bar (2) versus bar (3)) and provides a basis for further comparisons that change only the rule $s_j(\mathbf{z}_i)$ but hold constant the VCG auction mechanism. If all landowners were additional, the scoring rule defined by $s_j(\mathbf{z}_i) = B_j(\mathbf{z}_i^s)$ would implement the efficient allocation and dominate the status quo. Instead, it slightly *underperforms* it. Correcting

[41] The term $\max_j s_j(\mathbf{z}_i) - c_i - \kappa_{ij}$ is a bidder's pseudo-type in the terminology of Asker and Cantillon (2008). It is the maximum level of scoring-rule-implied social surplus that bidder i can generate.

[42] The VCG incentive payment that implements this allocation is:

$$\sum_j s_j(\mathbf{z}_i) \cdot x_{ij}^* + \sum_{i' \neq i} \sum_{j'} \left(s_{j'}(\mathbf{z}_{i'}) - c_{i'} - \kappa_{i'j'}\right) \cdot x_{i'j'}^* - \sum_{i' \neq i} \sum_{j'} \left(s_{j'}(\mathbf{z}_{i'}) - c_{i'} - \kappa_{i'j'}\right) \cdot x_{i'j'}^{-i},$$

where $\{x_{ij}^*\}$ denotes the allocation that maximizes $\sum_{i'} \sum_{j'} \left(s_{j'}(\mathbf{z}_{i'}) - c_{i'} - \kappa_{i'j'}\right)$ given all reports of $(c_{i'}, \kappa_{i'j'})$ in the population and $\{x_{i'j'}^{-i}\}$ denotes the allocation that solves $\max_x \sum_{i' \neq i} \sum_{j'} \left(s_{j'}(\mathbf{z}_{i'}) - c_{i'} - \kappa_{i'j'}\right) \cdot x_{i'j'}^{-i}$.

[43] This is in contrast to alternatives that could incorporate randomization, as in Lopomo et al. (2023).

inefficient design features of the status quo auction, e.g. bid caps, does not increase social welfare when the scoring rule does not incorporate additionality. The comparison of bar (3) to bars (1) and (2) illustrates that the poor performance of the status quo, relative to the efficient allocation, is because $\tau(\mathbf{z}_i, c_i, \kappa_i)$ is not incorporated into the mechanism.

Bars (4)-(6) in Figure 9 adjust the scoring rule $s_j(\mathbf{z}_i)$ defined in equation (15) based on predictions of additionality. First, we adjust the scoring of the menu of contracts, ω_j. In bar (4), ω_j is calculated to maximize equation (14), holding $\omega_{\mathbf{z}}$ constant at the status quo rule.[44] This change to the scoring rule doubles the social welfare gains of the auction relative to the status quo ($128 million per auction). Relative to the status quo rule, re-weighting ω_j accounts for both heterogeneity in $\tau(\mathbf{z}_i, c_i, \kappa_i)$ as a function of κ_i — for example, a landowner's choice of a tree-related contract reveals that her conservation is unlikely to be additional — and the fact that the full social benefits across actions is not realized when conservation would have counterfactually occurred.

Next, we adjust the bidder asymmetry terms across observables, $\omega_{\mathbf{z}}$, in equation (15). Displayed in bars (5) and (6) in Figure 9, this change leads to a further $46 million of social welfare gains per auction (37% of the status quo). Bar (5) first re-weights the existing characteristics in the scoring rule, $\mathbf{z}_i^s$. In the status quo, asymmetry is based only on environmental sensitivity; re-weighting $\omega_{\mathbf{z}}$ across $\mathbf{z}_i^s$ based also on additionality contributes two-thirds of the social welfare gains from adjusting the bidder asymmetry terms. The final adjustment (bar (6)) adds an additional characteristic to the rule: an "additionality factor" $\hat{\tau}(\mathbf{z}_i)$. This builds on the scoring rule's design, which adds together many "factors" to construct a composite score of bidder characteristics.[45] We calculate $\hat{\tau}(\mathbf{z}_i)$ by projecting $\tau(\mathbf{z}_i, c_i, \kappa_i)$ on immutable characteristics of landowners already collected by the USDA, but not all incorporated in the status quo scoring rule: deciles of soil productivity and wind and water erosion. Then, we calculate the social-welfare maximizing score using both $\mathbf{z}_i^s$ and $\hat{\tau}(\mathbf{z}_i)$ as asymmetry terms in equation (15). The simple change of adding this single "additionality factor" to the scoring rule increases social welfare by a further 12% of the status quo.

Figure 9 illustrates that simple changes to the scoring rule can lead to significant social welfare gains. In contrast to standard cost-minimizing procurement auctions, these auctions are designed to *impact conservation* at lowest cost. A scoring rule that incorporates landowners' expected additionality balances the objectives of allocating contracts to both low cost and high social benefit, additional landowners.

[44] We solve for the ω_j that maximize equation (14) given simulations of landowner (c_i, κ_i), estimates of $\tau(\mathbf{z}_i, c_i, \kappa_i)$, calibrations of $B_j(\mathbf{z}_i^s)$, and the allocation rule, holding $\omega_{\mathbf{z}}$ fixed at the status quo scoring rule.

[45] For more details on these factors, see an example EBI Factsheet here.

Social Welfare Under Alternative Market Sizes Beyond the allocation rule, additionality also impacts the socially-optimal size of the market. This also contributes to the gap between bars (1) and (2) but was ignored in the prior counterfactuals, which held the number of contract awards constant at the status quo.

Because many landowners are not additional, the status quo quantity procured is higher than is socially-optimal. Bar (7) in Figure 9 keeps the scoring rule $s_j(\mathbf{z}_i)$ of bar (6) but awards contracts only to landowners with $\max_j s_j(\mathbf{z}_i) - c_i - \kappa_{ij} \geq 0$. This reduction in market size increases social welfare by a further \$110 million dollars per auction.

Together, simple adjustments to both the size of the market and the scoring rule based on predicted additionality closes the gap between the status quo (bar (1)) and the efficient allocation (bar (2)) by 41% (an increase of \$284 million per auction).[46] Each component of the mechanism — adjusted incentives across contracts, across characteristics, and the overall size of the market — is a quantitatively important contribution to this improvement.

Mechanisms: Additionality in the Scoring Rule The alternative auctions in Figure 9 outperform the status quo by adjusting the scoring rule to reflect the social benefit of contracting, which depends on additionality. This occurs via two channels.

First, the status quo scoring rule $B_j(\mathbf{z}_i^s)$ over-weights asymmetry across characteristics $\mathbf{z}_i^s$ and contracts j. The heterogeneous social benefits of conservation $B_j(\mathbf{z}_i^s)$ are not fully realized when conservation would have counterfactually occurred. An auction that treats bidders and contracts asymmetrically by $B_j(\mathbf{z}_i^s)$ may not implement an efficient allocation. This relates to the social welfare losses from pricing at B illustrated in Figure 7.

Second, as highlighted in Figure 8, bidders may be systematically heterogeneous in their additionality, which can be exploited in the scoring rule. Adjusting the scoring rule based on heterogeneity in additionality — using observable characteristics and choices of contracts — more closely aligns the allocation implemented by the auction with the socially-optimal allocation that considers heterogeneity in both additionality and costs.

Figure 10 explores these two mechanisms. Figure 10 holds quantity constant and plots social welfare under the status quo auction (bar (1)), a Vickrey auction with a scoring rule $s_j(\mathbf{z}_i) = \theta \cdot B_j(\mathbf{z}_i^s)$ for the (single) multiplier θ chosen to maximize equation (14) (bar (2)), and a Vickrey auction with a scoring rule that adjusts ω_j and $\omega_{\mathbf{z}}$ to maximize equation (14) (bar (3), which replicates the auction in bar (6) in Figure 9). Bar (2) examines the social welfare

[46]Further differences between bar (7) and bar (2) reflect (i) $\mathbf{z}_i$ that are not incorporated into the scoring rule to avoid perverse incentives to game the rule, (ii) private landowner costs in $\tau(\mathbf{z}_i, c_i, \kappa_i)$, and (iii) the functional form of equation (15) relative to $B_j(\mathbf{z}_i^s) \cdot \tau(\mathbf{z}_i, c_i, \kappa_i)$.

gains achieved with only a uniform instrument to adjust the scoring rule for additionality. Bar (3) further adjusts ω_j and $\omega_{\mathbf{z}}$ to reflect heterogeneously additional landowners.

Figure 10 demonstrates that adjusting the scoring rule based on heterogeneity in additionality yields substantial social welfare gains of \$23 million per auction (bar (3)), but that a uniform adjustment for additionality (bar (2)) achieves a large share of the gains relative to the status quo. An auction that incorporates asymmetry in the social benefits of actions must also reflect the additionality of landowners in its design (see bar (2)). Moreover, further adjusting asymmetry based on heterogeneity in additionality yields further social welfare gains, equivalent to 18% of the status quo (see bar (3)).

USDA Spending Beyond social welfare, the budgetary implications of alternative auctions may be relevant in practice. Among implementable auctions we consider, the auction with the greatest social welfare gains also reduces USDA spending relative to the status quo (column (7) of Table 5). This occurs because the status quo auction contracts with too many landowners. Reducing the size of the market, and therefore total USDA spending, increases social welfare. Appendix F also evaluates social welfare with a cost of public funds, motivated by the need to finance expenditures with distortionary taxation. Social welfare with a cost of public funds is negative under the status quo, but becomes positive and substantial under alternative designs.

However, Table 5 also demonstrates that in all auctions, government spending exceeds the value of environmental services procured, $\sum_i \sum_j B_j \left(\mathbf{z}_i^s\right) \cdot \tau \left(\mathbf{z}_i, c_i, \kappa_i\right) \cdot x_{ij}$. This is due to the presence of adverse selection in the market: the marginal landowner has a higher value of $\tau \left(\mathbf{z}_i, c_i, \kappa_i\right)$ than the inframarginal landowner.

6.3 Offset Market Design

We conclude with the implications of supply-side adverse selection for the performance and design of competitive (offset) markets for environmental services. We continue to isolate the effect of supply-side adverse selection. We assume that buyers have the same full-information preferences as the USDA and form expectations over the value of any contract given the equilibrium price(s). We ask two questions motivated by the analysis in Section 6.1. First, should offset markets be differentiated? And second, which markets risk unravelling?

The effect of differentiation on social welfare in competitive markets is ambiguous (Einav and Finkelstein, 2011). We analyze this market design choice empirically in Figure 11a, restricting analysis to the base contract. Figure 11a plots the percent reduction in quantities traded and social welfare in a competitive market, relative to with socially-optimal prices, under uniform and differentiated markets. In the uniform market, there is only a single socially-optimal price and market-clearing condition. In the differentiated market, we project $B_0\left(\mathbf{z}_i^s\right)\cdot\tau\left(\mathbf{z}_i, c_i, \kappa_i\right)$ onto immutable observable characteristics ($\mathbf{z}_i^s$, soil productivity, and erosion) and then segment the market into deciles of predicted contract value. This "certification scheme" is similar in structure to existing rating schemes in environmental markets.[47] Figure 11a also presents social welfare per acre-year under each of these offset market designs.

Differentiation reduces social welfare losses from adverse selection in competitive markets from 5% to less than 1% and increases social welfare by 15% overall via more efficient trades in the market. The gains from differentiation are high even in the ex-ante ambiguous competitive market setting, supporting on-going efforts to collect detailed information to predict additionality in environmental markets.[48]

Next, we investigate which contracts can be successfully traded in competitive markets, motivated by Figures 7 and 8c. We consider uniform markets for grass-, tree-, and habitat-related contracts. Figure 11b plots the reduction in social welfare relative to the socially optimal uniform price in each of these three hypothetical markets. Tree-related contracts unravel, but social welfare losses for the remaining contracts are limited to at most 3%.

Figure 11 presents a relatively optimistic view of offset markets and actionable insights for market design. We offer three ideas about features of our setting that contribute to this conclusion. First, the eligibility requirements for the CRP are stringent enough that there is some probability that landowners are additional even at the bottom of the contracting cost distribution. Second, hassle costs and long-term contracts mute the extent of adverse selection, which limits unravelling. Finally, agricultural decisions are simple to predict, offering covariates to differentiate landowners and increase social welfare.

7 Conclusion

Additionality is a central challenge to environmental market design. It undermines the appeal of market-based mechanisms if incentives attract the least additional landowners.

This paper combines data and theory to document this potential market failure, quantify its implications for social welfare, and evaluate alternative market designs in the largest auction mechanism for ecosystem services in the world. Linking satellite data to auction bids, we

[47]See, for example, Carlyx Global, BeZero Ratings, and Sylvera.
[48]See, for example, Google, Microsoft, and the platform NCX.

use a regression discontinuity design to demonstrate that only one quarter of landowners are additional. Moreover, heterogeneity in counterfactual land use introduces adverse selection in the market. To quantify the implications of these facts and test possible remedies, we develop and estimate a joint model of multi-dimensional bidding and land use that incorporates adverse selection on additionality.

With socially-optimal incentives, the market can deliver social welfare gains, but the lowest cost providers of environmental services are not always the highest social value. Re-designing the auction's scoring rule to incorporate predicted additionality substantially outperforms the status quo, and a simple differentiation scheme also increases social welfare in competitive offset markets.

A common market design solution to the issue of additionality is to define eligibility requirements that restrict who and what can trade; in this paper, we propose a more flexible approach. Because many markets will inevitably attract landowners who are with some probability not additional, allocation mechanisms should consider this dimension of heterogeneity in their design. We show how auctions can be used to cost-effectively *impact conservation,* selecting participants based on both expected additionality and costs, despite the existence of many landowners in the market that are not additional. Segmenting offset markets yields social welfare gains via similar mechanisms.

Our analysis focused only on the supply-side market failure of additionality. Investigating other features of offset markets, including demand, the incentives of platforms and certifiers that facilitate trade, and both of their interactions with supply-side additionality and adverse selection are interesting and impactful avenues for future research.

More broadly, our results highlight that successful market design depends not only on market participants' private costs, but also on whether their behavior in the market advances a socially desirable outcome. Developing empirical approaches to apply this idea to the design of other markets and policy objectives is a rich and exciting area for research.

References

Ackerberg, Daniel A., "A new use of importance sampling to reduce computational burden in simulation estimation," *QME*, December 2009, *7* (4), 343–376.

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

_ , Pearl Li, and Paulo Somaini, "Identification using Revealed Preferences in Linearly Separable Models," October 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 Non-classical Measurement Error in Satellite Data on Deforestation," *Journal of the Association of Environmental and Resource Economists*, December 2022.

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, "Is There an Energy Efficiency Gap?," *Journal of Economic Perspectives*, February 2012, *26* (1), 3–28.

_ and _ , "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.

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

Arnold, David, Will Dobbie, and Peter Hull, "Measuring Racial Discrimination in Bail Decisions," *American Economic Review*, September 2022, *112* (9), 2992–3038.

Aronoff, Daniel and Will Rafey, "Conservation priorities and environmental offsets: Markets for Florida Wetlands," July 2023.

Asker, John and Estelle Cantillon, "Properties of scoring auctions," *The RAND Journal of Economics*, 2008, *39* (1), 69–85.

_ **and** _ , "Procurement when price and quality matter," *The RAND Journal of Economics*, 2010, *41* (1), 1–34.

Ausubel, Lawrence M. and Paul Milgrom, "The Lovely but Lonely Vickrey Auction," in Peter Cramton, Yoav Shoham, and Richard Steinberg, eds., *Combinatorial Auctions*, The MIT Press, December 2005, p. 0.

Bolotnyy, Valentin and Shoshana Vasserman, "Scaling Auctions as Insurance: A Case Study in Infrastructure Procurement," *Econometrica*, 2023, *91* (4), 1205–1259.

Borenstein, Severin, "The Private and Public Economics of Renewable Electricity Generation," *Journal of Economic Perspectives*, February 2012, *26* (1), 67–92.

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.

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.

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

Chan, David C., Matthew Gentzkow, and Chuan Yu, "Selection with Variation in Diagnostic Skill: Evidence from Radiologists," *The Quarterly Journal of Economics*, May 2022, *137* (2), 729–783.

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

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

Claassen, Roger, Eric N. Duquette, and David J. Smith, "Additionality in U.S. Agricultural Conservation Programs," *Land Economics*, February 2018, *94* (1), 19–35.

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.

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.

_ , _ , Stephen P. Ryan, Paul Schrimpf, and Mark R. Cullen, "Selection on Moral Hazard in Health Insurance," *American Economic Review*, 2013, *103* (1), 178–219.

_ , _ , Yunan Ji, and Neale Mahoney, "Voluntary Regulation: Evidence from Medicare Payment Reform*," *The Quarterly Journal of Economics*, February 2022, *137* (1), 565–618.

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

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.

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

Friedlingstein, Pierre, Michael O'Sullivan, Matthew W. Jones, Robbie M. Andrew, Luke Gregor, Judith Hauck, Corinne Le Quéré, Ingrid T. Luijkx, Are Olsen, Glen P. Peters, Wouter Peters, Julia Pongratz, Clemens Schwingshackl, Stephen Sitch, Josep G. Canadell, Philippe Ciais, Robert B. Jackson, Simone R. Alin, Ramdane Alkama, Almut Arneth, Vivek K. Arora, Nicholas R. Bates, Meike Becker, Nicolas Bellouin, Henry C. Bittig, Laurent Bopp, Frédéric Chevallier, Louise P. Chini, Margot Cronin, Wiley Evans, Stefanie Falk, Richard A. Feely, Thomas Gasser, Marion Gehlen, Thanos Gkritzalis, Lucas Gloege, Giacomo Grassi, Nicolas Gruber, Özgür Gürses, Ian Harris, Matthew Hefner, Richard A. Houghton, George C. Hurtt, Yosuke Iida, Tatiana Ilyina, Atul K. Jain, Annika Jersild, Koji Kadono, Etsushi Kato, Daniel Kennedy, Kees Klein Goldewijk, Jürgen Knauer, Jan Ivar Korsbakken, Peter Landschützer, Nathalie Lefèvre, Keith Lindsay, Junjie Liu, Zhu Liu, Gregg Marland, Nicolas Mayot, Matthew J. McGrath, Nicolas Metzl, Natalie M. Monacci, David R. Munro, Shin-Ichiro Nakaoka, Yosuke Niwa, Kevin O'Brien, Tsuneo Ono, Paul I. Palmer, Naiqing Pan, Denis Pierrot, Katie Pocock, Benjamin Poulter, Laure Resplandy, Eddy Robertson, Christian Rödenbeck, Carmen Rodriguez, Thais M. Rosan, Jörg Schwinger, Roland Séférian, Jamie D. Shutler, Ingunn Skjelvan, Tobias Steinhoff, Qing Sun, Adrienne J. Sutton, Colm Sweeney, Shintaro Takao, Toste Tanhua, Pieter P. Tans, Xiangjun Tian, Hanqin Tian, Bronte Tilbrook, Hiroyuki Tsujino, Francesco Tubiello, Guido R. van der Werf, Anthony P. Walker, Rik Wanninkhof, Chris Whitehead, Anna Willstrand Wranne, Rebecca Wright, Wenping Yuan, Chao Yue, Xu Yue, Sönke Zaehle, Jiye Zeng, and Bo Zheng, "Global Carbon Budget 2022," *Earth System Science Data*, November 2022, *14* (11), 4811–4900.

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.

Hanazono, Makoto, Yohsuke Hirose, Jun Nakabayashi, and Masanori Tsuruoka, "Theory, Identification, and Estimation for Scoring Auctions," August 2020.

Hansen, LeRoy, "Conservation Reserve Program: Environmental Benefits Update," *Agricultural and Resource Economics Review*, October 2007, *36* (2), 267–280.

Harstad, Bård, "The market for conservation and other hostages," *Journal of Economic Theory*, November 2016, *166*, 124–151.

_ **and Torben K. Mideksa**, "Conservation Contracts and Political Regimes," *The Review of Economic Studies*, October 2017, *84* (4), 1708–1734.

Haupt, Andreas, Nicole Immorlica, and Brendan Lucier, "Voluntary Carbon Market Design," August 2023.

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

Hendricks, Kenneth and Robert Porter, "An Empirical Study of an Auction with Asymmetric Information," *American Economic Review*, 1988, *78* (5), 865–83.

Hortaçsu, Ali, "Mechanism Choice and Strategic Bidding in Divisible Good Auctions: An Empirical Analysis Of the Turkish Treasury Auction Market," November 2000.

_ **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.

Ito, Koichiro, Takanori Ida, and Makoto Tanaka, "Selection on Welfare Gains: Experimental Evidence from Electricity Plan Choice," *American Economic Review*, November 2023, *113* (11), 2937–2973.

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.

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.

Jofre-Bonet, Mireia and Martin Pesendorfer, "Estimation of a Dynamic Auction Game," *Econometrica*, 2003, *71* (5), 1443–1489.

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.

Jones, Julia P. G. and Simon L. Lewis, "Forest carbon offsets are failing," *Science*, August 2023, *381* (6660), 830–831.

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.

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

Lakkaraju, Himabindu, Jon Kleinberg, Jure Leskovec, Jens Ludwig, and Sendhil Mullainathan, "The Selective Labels Problem: Evaluating Algorithmic Predictions in the Presence of Unobservables," *KDD: proceedings. International Conference on Knowledge Discovery & Data Mining*, August 2017, *2017*, 275–284.

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.

_ , 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.

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

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

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.

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.

Marone, Victoria R. and Adrienne Sabety, "When Should There Be Vertical Choice in Health Insurance Markets?," *American Economic Review*, January 2022, *112* (1), 304–342.

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.

McCrary, Justin, "Manipulation of the running variable in the regression discontinuity design: A density test," *Journal of Econometrics*, February 2008, *142* (2), 698–714.

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.

Milgrom, Paul, "Adverse Selection Without Hidden Information," June 1987.

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.

Myerson, Roger B., "Optimal Auction Design," *Mathematics of Operations Research*, 1981, *6* (1), 58–73.

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.

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

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.

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

Sant'Anna, Marcelo Castello Branco, "Empirical analysis of scoring auctions for oil and gas leases," October 2017.

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 November 2021.

Tebaldi, Pietro, "Estimating Equilibrium in Health Insurance Exchanges: Price Competition and Subsidy Design under the ACA," March 2022.

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.

Train, Kenneth E., *Discrete Choice Methods with Simulation*, 2nd edition ed., Cambridge ; New York: Cambridge University Press, June 2009.

van Benthem, Arthur and Suzi Kerr, "Scale and transfers in international emissions offset programs," *Journal of Public Economics*, November 2013, *107*, 31–46.

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.

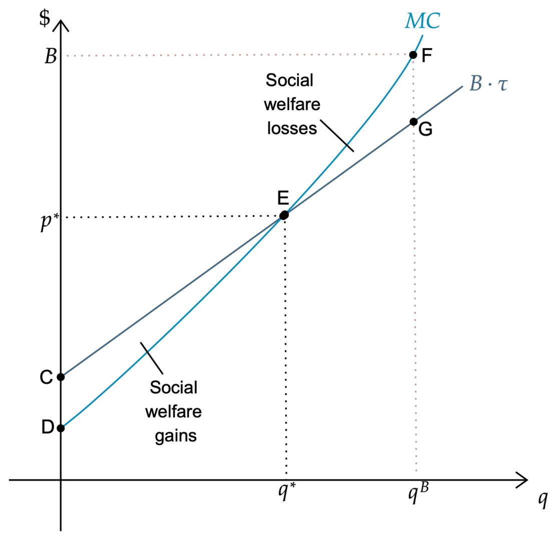
West, Thales A. P., Jan Börner, Erin O. Sills, and Andreas Kontoleon, "Overstated carbon emission reductions from voluntary REDD+ projects in the Brazilian Amazon," *Proceedings of the National Academy of Sciences*, September 2020, *117* (39), 24188–24194.

_ , Sven Wunder, Erin O. Sills, Jan Börner, Sami W. Rifai, Alexandra N. Neidermeier, Gabriel P. Frey, and Andreas Kontoleon, "Action needed to make carbon offsets from forest conservation work for climate change mitigation," *Science*, August 2023, *381* (6660), 873–877.

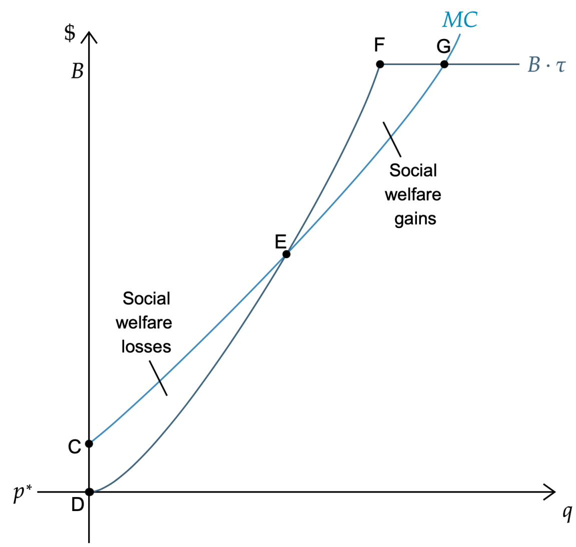
Figures and Tables

Figure 1: Graphical Analysis

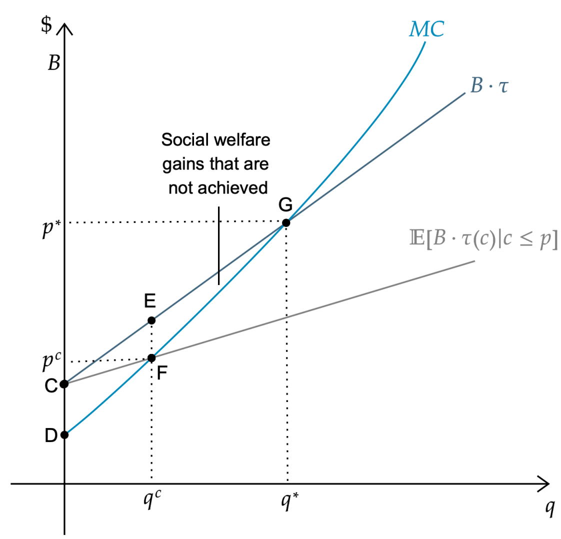
(a) Efficient allocation can be implemented



(b) Efficient allocation cannot be implemented



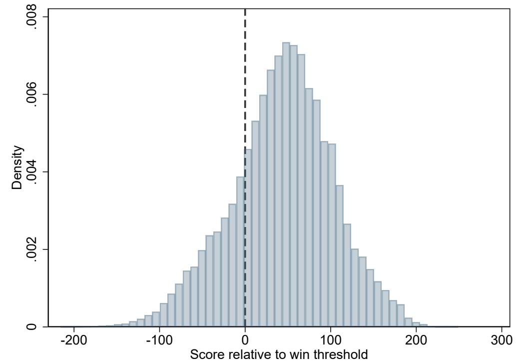
(c) Inefficiency in competitive markets



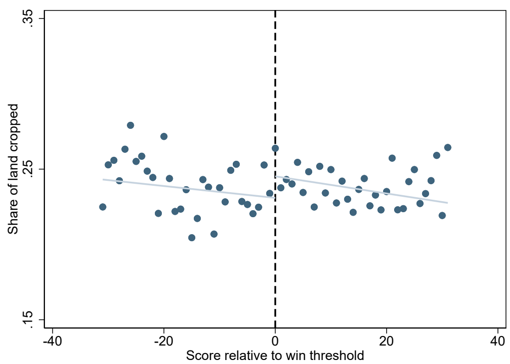
Notes: Figure describes markets characterized by marginal cost ($MC = F_C^{-1}(q)$) and contract value ($B \cdot \tau$) curves. The horizontal axis is the share of the population ordered by costs of contracting c_i. B denotes the social benefits of $a_{i1} = 1$. $B \cdot \tau$ denotes the incremental social benefits of contracting (contract value), relative to no contract, at each quantile of landowner costs of contracting. The vertical distance between the $B \cdot \tau$ and MC curves represents the social surplus from contracting. Upwards-sloping $B \cdot \tau$ curves illustrate markets with adverse selection. Panel (a) documents a population distribution in which the efficient allocation (defined in equation (5)) can be implemented with the socially optimal uniform price p^* and panel (b) documents a population distribution in which it cannot. Panel (a) also demonstrates the social welfare losses from mis-pricing (at B) (triangle EFG). Panel (c) includes a curve defining the average contract value of all landowners selecting into the market at any given price p, $\mathbb{E}[B \cdot \tau(c) \mid c \leq p]$. This defines the value of a contract to a price-taking buyer in a stylized competitive (offset) market. The intersection of the MC and average contract value curves define a competitive market equilibrium price p^c. In panel (c), adverse selection limits trade in competitive markets with social welfare gains in triangle EFG that are not achieved.

Figure 2: Regression Discontinuity Validity and First Stage

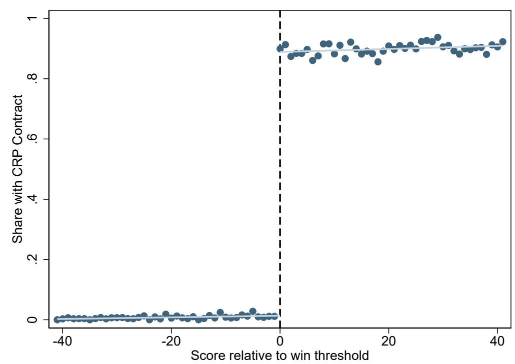
(a) Histogram of running variable



(b) Placebo: pre-auction



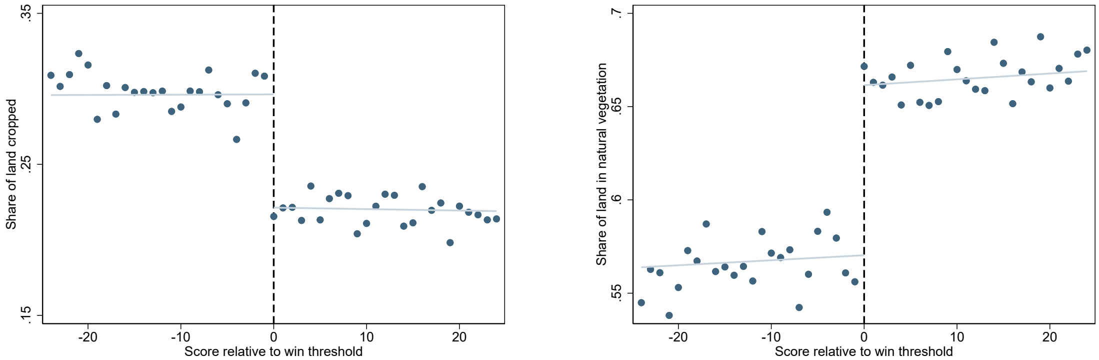
(c) First stage: contracting



Notes: Panel (a) presents a histogram of bidders' scores in the auction relative to that auction's win threshold, $S_{ig} - \underline{S_g}$, pooled across auctions. This is the running variable for the regression discontinuity design: bidders above zero win the auction. Panels (b) and (c) present raw data and estimates from equation (7). Panel (b) is estimated for $r(i,t) \leq 0$ (pre-auction), and panel (c) is estimated for $r(i,t) > 0$ (post-auction). The outcome in panel (b) is the share of the bidder's land that is cropped, measured in the remote sensing data. The outcome in panel (c) is an indicator for a bidder obtaining a CRP contract. Positive numbers on the x-axis correspond to winning scores, negative numbers correspond to losing scores. In panel (a), each observation is a bidder, in panels (b) and (c), each observation is a bidder-year.

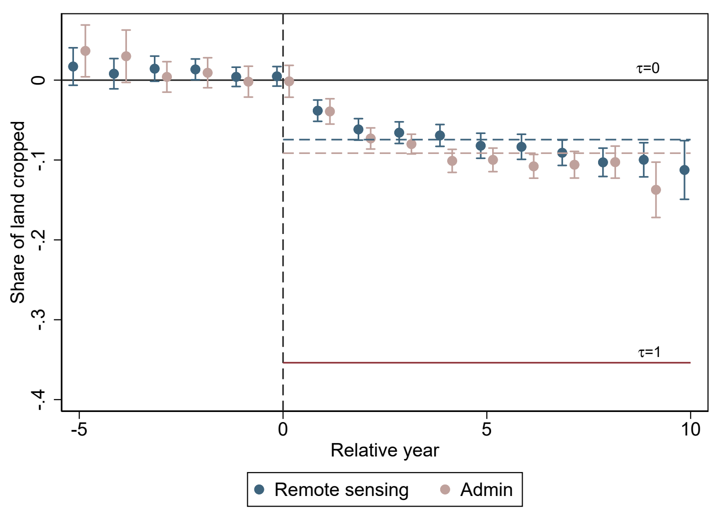
Figure 3: The Effect of a CRP Contract on Land Use

(a) Share of land cropped (b) Share of land in natural vegetation



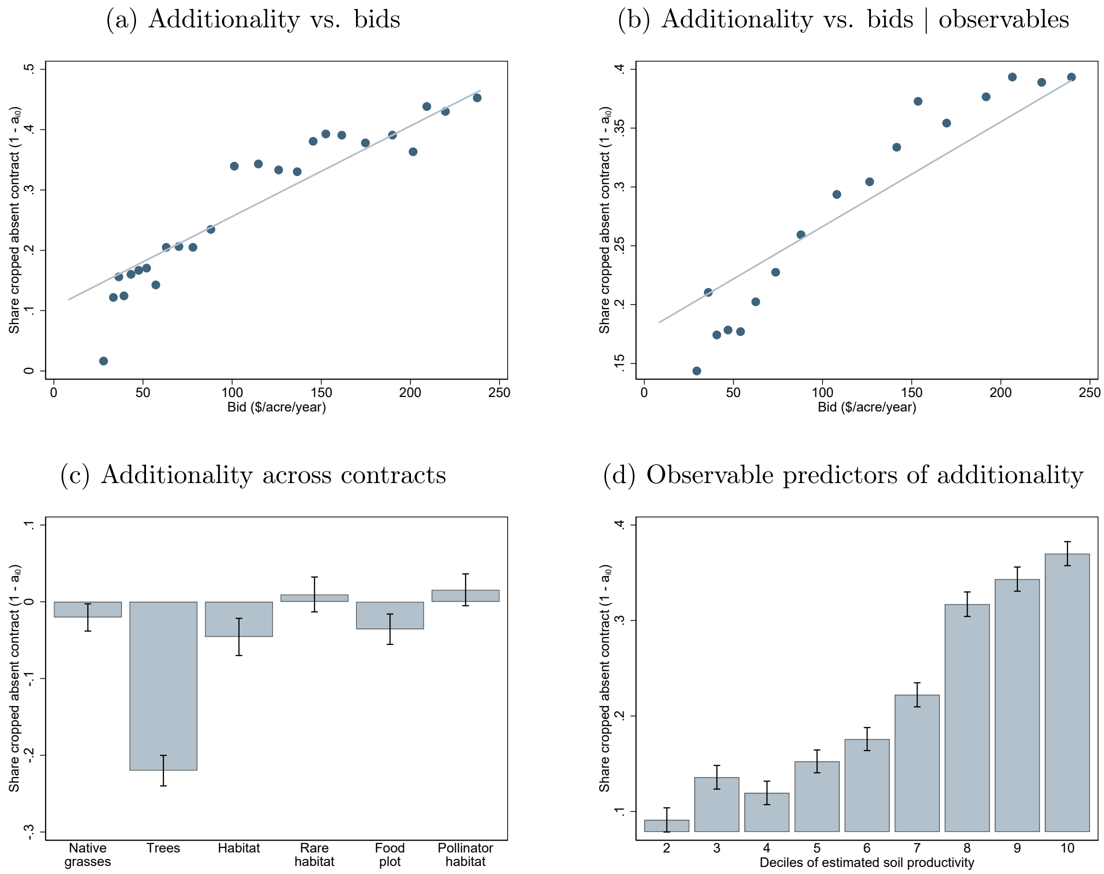
Notes: Panels (a) and (b) present raw data and estimates from equation (7) for $r(i,t) > 0$ (post-auction). Outcomes are the share of the bidder's land that is cropped (a) and the share of the bidder's land that is in natural vegetation (trees, grassland, shrubs, and wetlands) (b), both measured in the remote sensing data. The running variable is the difference between each bidder's score and the threshold score. Positive numbers on the x-axis correspond to winning scores, negative numbers correspond to losing scores. Each observation is a bidder-year. Appendix Figure C.3 provides corresponding figures with outcomes measured in the administrative data. Corresponding coefficient estimates and standard errors presented in Table 2.

Figure 4: Regression Discontinuity Estimates of Additionality



Notes: Figure plots coefficient estimates from equation (6). The outcome is the share of each bidder's land that is cropped, measured with both remote sensing and administrative datasets. The x-axis is the year relative to the year of each bidder's auction: $r(i,t) = t - t_{g(i)}$. Positive years correspond to post-auction years. Each point is a regression discontinuity coefficient. Dashed lines indicate the pooled post-auction treatment effects (equation (7) estimated for $r(i,t) > 0$). The black line at 0 ($\tau = 0$) and red line at -.35 ($\tau = 1$) indicate the implied effect size if $a_{i0} = 1\ \forall i$ and $a_{i0} = 0\ \forall i$, respectively. $\tau = 1$ represents a benchmark where all landowners are additional. This is calculated as the share of land contracting in the MSE-optimal bandwidth (Calonico et al., 2014) used to estimate the RD. Each observation is a bidder-year. Standard errors are clustered at the bidder level. Ten years is the full duration of a CRP contract. Corresponding coefficient estimates and standard errors presented in Table 2.

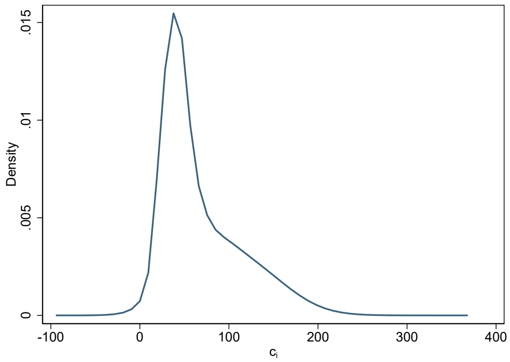
Figure 5: Testing for Asymmetric Information



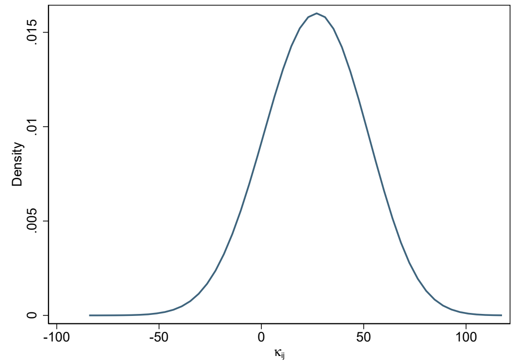
Notes: Figures present visual representations of estimates of equation (8). All regressions control for landowner characteristics in the scoring rule: whether a bidder is in a wildlife priority zone, estimates of groundwater quality, estimates of surface water quality, estimates of wind and water erosion (deciles), air quality impacts, and whether or not a bidder is in an air quality zone. The outcome variable in all panels is a landowner-specific measure of additionality $(1 - a_{i0})$. This is calculated as the share of all fields bid into the CRP mechanism that are cropped post auction for rejected landowners. The sample is restricted to the 2016 auction, in which 82% of bidders are rejected and the delineations of bid fields are observed. Cropping on bid fields is measured in 2017-2020 in the remote sensing data (see Figure C.5 for corresponding figures using the administrative data). Panel (a) is a binned scatterplot correlating the dollar bid (per acre, per year) with additionality, conditional on characteristics included in the scoring rule. Panel (b) adds controls for interaction terms of prior land use (quartiles of share of land cropped prior to bidding and re-enrolling CRP status) and deciles of estimated soil productivity. Panel (c) plots relative additionality by the chosen contract in the bid, relative to an omitted category of introduced grasses. Panel (d) plots relative additionality by deciles of estimated soil productivity. Standard errors clustered at the bidder level.

Figure 6: Estimated Landowner Cost Distribution

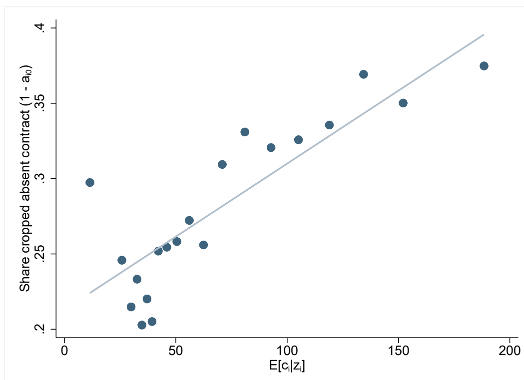
(a) Base cost c_i



(b) Top-up costs κ_{ij}

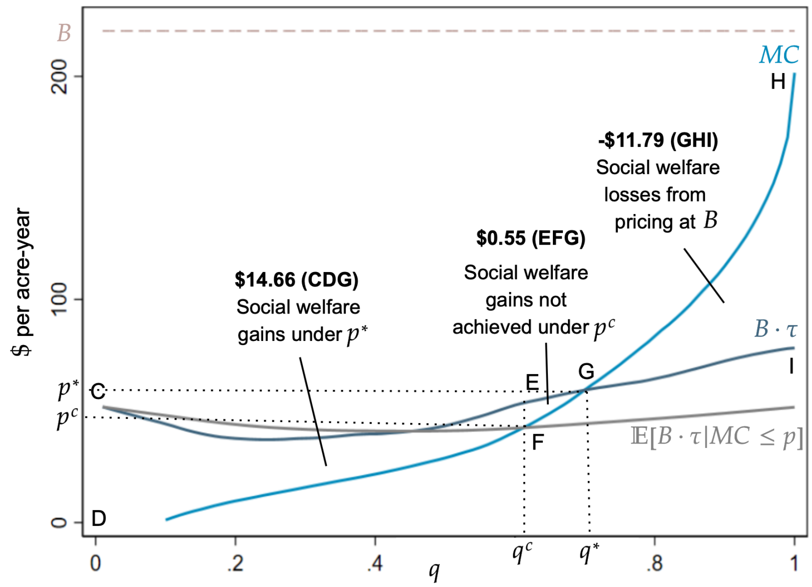


(c) Land use vs. revealed preference cost estimates



Notes: Panels (a) and (b) present kernel density plots of estimates of the base cost c_i (a) and top-up cost κ_{ij} (b) of contracting. Panels (a) and (b) pool bidders across auctions. Costs are estimated using revealed preferences in optimal bidding (equation (10)). See Section 5.2 for estimation details. Panel (c) correlates expected base costs, c_i, conditional on observable characteristics $\mathbf{z}_i$, with land use outcomes measuring landowner additionality in the remote sensing data. Panel (c) is restricted to the 2016 auction and the 82% of bidders who lose (see Section 4.2 for more details). $\mathbf{z}_i$ includes interactions of soil productivity, prior CRP, and prior land use. Costs are reported in dollars per acre per year.

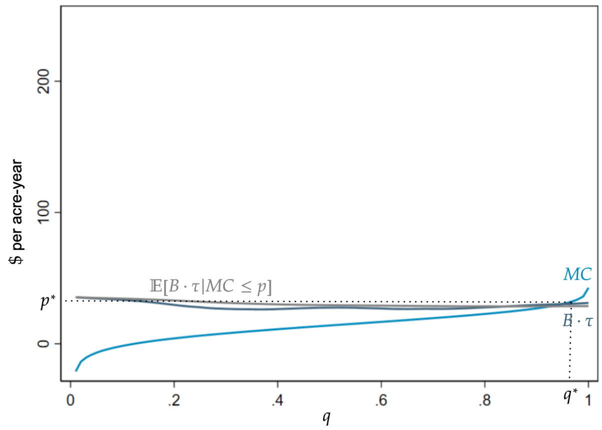
Figure 7: Empirical Graphical Analysis



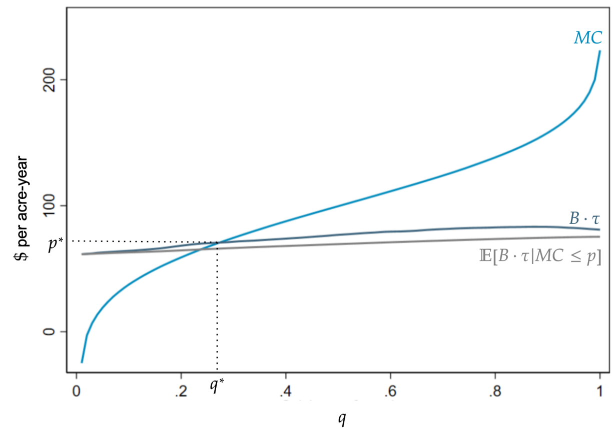
Notes: Figure presents the empirical version of Figure 1 for the base contract. The horizontal axis is the share of the population, ordered by contracting costs. Values are reported in dollars per acre per year. The MC curve is the inverse distribution function of the minimum cost to fulfill the base contract. B denotes the average value of the base contract action, calculated as described in Appendix E. $B \cdot \tau$ denotes the incremental value of contracting, relative to no contract, averaged at each quantile of the population distribution of the base costs of contracting. The vertical distance between the $B \cdot \tau$ and MC curves represents the social surplus from contracting at each quantile of the population distribution of contracting costs. The upwards-sloping $B \cdot \tau$ curve illustrates the presence of adverse selection in the market. The intersection of the MC and $B \cdot \tau$ curve denotes the socially-optimal uniform price, p^*. Triangle CDG represents social welfare gains under the socially-optimal price. The triangle GHI represents social welfare losses from mispricing at B. The average contract value curve calculates the average $B \cdot \tau$ of all landowners selecting into the market at any given price p, $\mathbb{E}[B \cdot \tau | MC \leq p]$. This defines the value of a contract to a price-taking buyer in a stylized competitive (offset) market. The intersection of the MC and average contract value curves define a competitive market equilibrium price p^c. Adverse selection limits trade in competitive markets leading to social welfare gains that are not realized (triangle EFG).

Figure 8: Empirical Graphical Analysis: Heterogeneity Across Observables and Contracts

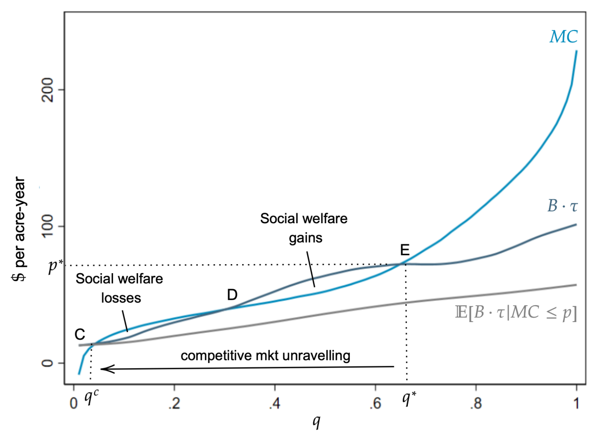
(a) Lowest quintile soil productivity



(b) Highest quintile soil productivity

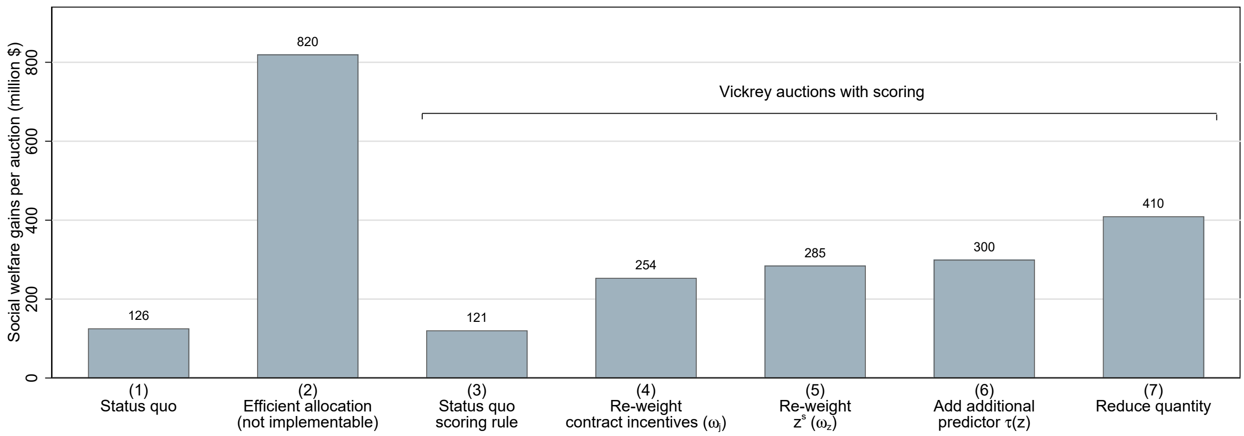


(c) Tree planting and maintenance contracts



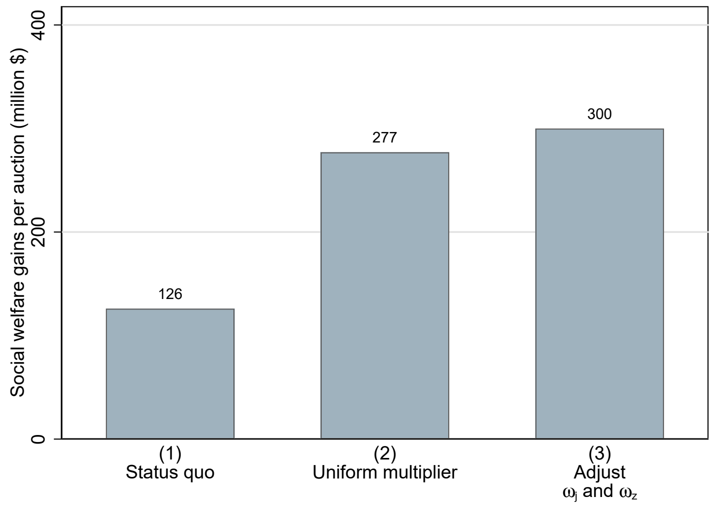
Notes: Figures presents empirical version of Figure 1. Panels (a) and (b) calculate the MC curve as the inverse distribution function of the minimum cost to fulfill the base contract, split by whether landowners are in the lowest or highest quintile of soil productivity. In panel (c), the MC curve is calculated as the inverse distribution function of the minimum cost to fulfill a tree planting and maintenance contract. The horizontal axis is the share of the population, ordered by contracting costs for the base contract in each sub-population ((a) and (b)) and for tree planting and maintenance contracts (c). $B \cdot \tau$ denotes the incremental value of contracting, relative to no contract, averaged at each quantile of contracting costs for the base contract in each sub-population ((a) and (b)) and for tree planting and maintenance contracts (c). The vertical distance between the $B \cdot \tau$ and MC curves represents the social surplus from contracting at each quantile of contracting costs. p^* denotes the socially-optimal price, set at the intersection of the $B \cdot \tau$ and MC curves. The average contract value curve (gray) calculates the average $B \cdot \tau$ of all landowners selecting into the market at any given price p, $\mathbb{E}[B \cdot \tau | MC \leq p]$. This defines the value of a contract to a price-taking buyer in a stylized competitive (offset) market. In panel (c), the efficient allocation defined in equation (5) cannot be implemented. The stylized competitive market also unravels.

Figure 9: Social Welfare Under Alternative Auctions



Notes: Figure presents estimates of the social welfare gains (defined in equation (14)) under status quo and alternative auctions. Results reported in million dollars per auction. All auctions impose that each landowner obtains at most one contract and that total contracts awarded cannot exceed the status quo. Bar (1) simulates the status quo. Bar (2) calculates the social welfare gains under an efficient allocation that allocates contracts using all $\mathbf{z}_i$ and (c_i, κ_i) to maximize equation (14). Due to adverse selection, this allocation may not be implementable. Bars (3)-(7) calculate social welfare under alternative Vickrey auctions with scoring (see Section 6.2 for more details). Bars (3)-(6) hold quantity (the number of landowners allocated contracts) constant at the status quo and change the scoring rule $s_j(\mathbf{z}_i)$ defined in equation (15). Bar (3) uses the existing scoring rule $s_j(\mathbf{z}_i) = B_j(\mathbf{z}_i^s)$. Bar (4) uses a scoring rule with the social-surplus maximizing incentives across contracts (ω_j). Bar (5) uses a scoring rule with the social-surplus maximizing asymmetry across bidders using characteristics already in the scoring rule $(\mathbf{z}_i^s)$. Bar (6) adds an additional characteristic to the scoring rule, a prediction of $\tau(\mathbf{z}_i, c_i, \kappa_i)$ based on immutable characteristics of landowners already collected by the USDA (deciles of soil productivity and wind and water erosion). Bar (7) uses the same scoring rule as bar (6) but reduces the number of contracts allocated to landowners: only landowners with positive scoring-rule-implied social surplus $\max_j s_j(\mathbf{z}_i) - c_i - \kappa_{ij} \geq 0$ are awarded contracts. See each bar's corresponding column in Table 5 for more details.

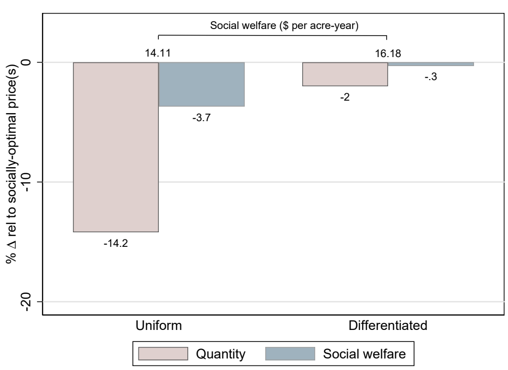
Figure 10: Mechanisms: Uniform vs. Heterogeneous Scoring Rule Adjustments



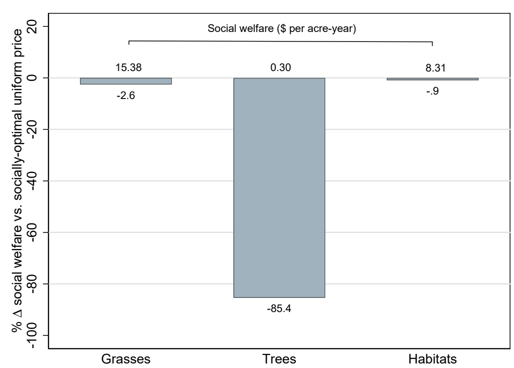
Notes: Figure presents estimates of the social welfare gains (defined in equation (14)) under status quo and alternative auctions. Results reported in million dollars per auction. All auctions impose that each landowner obtains at most one contract. All auctions hold constant the total number of landowners awarded contracts at the status quo. Bar (1) simulates the status quo. Bars (2) and (3) simulate Vickrey auctions with scoring (see Section 6.2 for more details). Bar (2) uses a scoring rule $s_j\left(\mathbf{z}_i^s\right) = \theta \cdot B_j\left(\mathbf{z}_i^s\right)$ for a uniform multiplier θ that maximizes equation (14). Bar (3) corresponds to Bar (6) in Figure 9: it uses the social welfare maximizing $\omega_j$and $\omega_{\mathbf{z}}$ using all characteristics in the rule and a prediction of $\tau\left(\mathbf{z}_i, c_i, \kappa_i\right)$ based on immutable characteristics of landowners already collected by the USDA (deciles of soil productivity and wind and water erosion).

Figure 11: Offset Market Design

(a) Uniform vs. differentiated market



(b) By contract type



Notes: Figures describe social welfare and quantities traded under a stylized competitive offset equilibrium versus under socially-optimal prices. The competitive market equilibrium is calculated under the assumption that buyers have the same full-information preferences as the USDA and form expectations over the value of any contract given the equilibrium price(s). Panel (a) restricts to the base contract and reports quantities traded and social welfare under a competitive market equilibrium relative to socially-optimal prices in a uniform and a differentiated market. In the uniform market, there is only a single socially-optimal price and market-clearing condition. In the differentiated market, the market is segmented into deciles of predicted contract value (based on $\mathbf{z}_i^s$, soil productivity, and erosion). Panel (b) plots the percent reduction in social welfare under a stylized competitive market equilibrium relative to socially-optimal prices under three different hypothetical markets, each with only one contract traded at a uniform price. The numbers above the bars in panels (a) and (b) tabulate total social welfare (per acre-year) in each competitive market.

Table 1: Summary Statistics

	All agricultural land		Bidders		Bid fields	
	Remote sensing	Admin	Remote sensing	Admin	Remote sensing	Admin
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Land use						
Share cropped	0.30	0.28	0.21	0.21	0.21	0.18
Share corn	0.11	0.11	0.07	0.08	0.07	0.06
Share soybean	0.11	0.10	0.06	0.07	0.07	0.07
Share fallow	0.02	0.01	0.03	0.01	0.05	0.03
Share nat. veg. or grassland	0.55		0.70		0.65	
Panel B. Land characteristics						
Size (acres)	160.7		250.6			
	(2690.7)		(506.5)			
Soil productivity ($/acre)	92.4		86.9			
	(63.2)		(58.5)			
Enviro sensitivity (points)	53.5		86.5			
	(29.8)		(33.7)			
Panel C. Bid characteristics						
Rental rate ($/acre/year)			83.0			
			(56.4)			
Acres bid			84.1			
			(136.3)			
Share re-contracting			0.70			
Contract action = grasses			0.67			
Contract action = trees			0.12			
Contract action = habitat			0.21			
Share contracting			0.81			
N bidders / auction			36,763			
N	7,890,426		258,286		61,703	

Notes: Table presents summary statistics of all agricultural landowners (columns (1)-(2)), bidding landowners (columns (3)-(4)), and bid fields (columns (5)-(6)), defined as the delineated land area entered into the mechanism to be awarded a CRP contract (observed only for bidders in the 2016 auction). Standard deviations in parenthesis. Panel A reports land use outcomes in the remote sensing (CDL) and admin (Form 578) data. All land use outcomes are reported for the year prior to bidding among bidders. Years in columns (1)-(2) are re-weighted to match the distribution of bidder-years. Columns (1) and (2) 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 points are the points given for characteristics of land in the scoring rule. Rental rate is reported in dollars per acre per year and is the dollar component of the bid in the auction. Acres bid is the total acreage entered into the auction to be awarded a CRP contract. Grasses, trees, and habitat contract indicators are aggregated over the menu of possible contracts.

Table 2: Regression Discontinuity Coefficient Estimates

	Remote sensing (1)	Admin (2)
Panel A: Main outcome: share of land cropped		
Pre-auction (placebo)	0.014	0.009
	(0.007)	(0.006)
Post-auction (pooled sign-ups)	-0.075	-0.091
	(0.007)	(0.006)
Implied additionality	21%	26%
Post-auction (full contract duration: 2010-2020)	-0.109	
	(0.020)	
Implied additionality	31%	
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-bid fields		
Share of non-bid fields cropped	-0.001	-0.000
	(0.015)	(0.015)
N bidders	258,286	258,286
N bidder-years	3,099,432	1,808,002

Notes: Table presents coefficient estimates from equation (7) with land use outcomes measured in the remotely sensed (column (1)) and administrative (column (2)) data. All results use a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Calonico et al., 2014). The full-contract duration specification restricts to the 2009 auction, others pool all auctions with post-period data (2009, 2011, 2012, 2013, and 2016). The pooled post-period includes an average of 7-8 post-auction years. Natural vegetation or grassland is only observed in remotely sensed data. Calculations of implied additionality divide the treatment effect estimates by the amount of land contracting among winning bidders in the MSE-optimal bandwidth. Panel C estimates the effect of a CRP contract on non-bid, and therefore non-contracting, fields to test for spillovers. This analysis is restricted to the 2016 auction. Standard errors are clustered at the bidder level.

Table 3: Mean Landowner Costs of Contracting

	All	Landowners with above median soil productivity
	(1)	(2)
Base cost (c_i)	67.49	87.05
Top-up cost (κ_{ij})		
Introduced grasses (normalized)	0.	0.
Native grasses	0.11	3.38
Trees	24.41	26.65
Habitat	14.87	17.49
Rare habitat	15.33	17.98
Wildlife food plot	18.58	15.32
Pollinator habitat	18.03	17.54

Notes: Table presents estimated mean landowner costs of contracting for the base cost c_i and top-up cost κ_{ij} reported in dollars per acre per year. The cost of each contract j is defined as $c_i + \kappa_{ij}$. Costs are estimated using revealed preferences in optimal bidding (equation (10)). See Section 5.2 for estimation details. Column (1) presents mean costs for all bidders across all auctions, and column (2) restricts to landowners with above median soil productivity. See Appendix Table D.2 for a comparison to administrative data.

Table 4: Additionality as a Function of Landowner Costs

	Estimates of $\tau(\mathbf{z}_i, c_i, \kappa_i)$			
	(1)	(2)	(3)	(4)
β: coefficient on base cost (c_i)	0.0018	0.0020	0.0007	-0.0002
	(0.0002)	(0.0002)	(0.0003)	(0.0004)
α: coefficient on top-up cost (κ_{ij})				
Trees			0.0035	0.0046
			(0.0002)	(0.0005)
Native grasses				-0.0011
				(0.0006)
Habitat				-0.0004
				(0.0005)
Rare habitat				0.0027
				(0.0007)
Wildlife food plot				0.0031
				(0.0006)
Pollinator habitat				0.0010
				(0.0005)
Includes $\mathbf{z}_i^s$	✓	✓	✓	✓
Includes prior land use and soil prod. $\mathbf{z}_i$		✓	✓	✓

Notes: Table presents select coefficient estimates of $\tau(\mathbf{z}_i, c_i, \kappa_i)$ (equation (12)). Coefficients measure how additionality varies with a $1 per acre, per year change in costs. Positive coefficients indicate a positive correlation between costs of contracting and additionality, or adverse selection in the market. Parameter estimates obtained via the Method of Simulated Moments estimator described in Section 5.2. This estimator matches moments of land use in the remote sensing data (for losing bidders in the 2016 auction) and bids given simulated (c_i, κ_i) and optimal bidding in equation (10). All specifications include flexible controls for the components of the scoring rule excluding landowners' Wildlife Priority Zone and Air Quality Zone status. Columns (2)-(4) control for the 32 cells of soil productivity, prior CRP status, and prior cropping status that parameterize bidder costs. Standard errors are calculated using 100 bootstrap draws and do not (yet) account for variance in the Step 2 estimates.

Table 5: Outcomes Under Alternative Auctions

	Status quo	Efficient allocation	Vickrey auctions with scoring				
			Status quo rule	Re-weight contracts (ω_j)	Re-weight $\mathbf{z}_i^s$ ($\omega_{\mathbf{z}}$)	Add $\hat{\tau}(\mathbf{z}_i)$ (incl. $\mathbf{z}_i$ not in status quo rule)	Reduce quantity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Welfare and spending (million \$ per auction):							
Social welfare	126	820	121	254	285	300	410
USDA spending	1,323		2,033	1,760	1,703	1,724	936
Landowner surplus	546		906	1,176	1,127	1,147	580
Environmental value	902	1,239	1,130	838	861	876	766
Panel B. Other outcomes							
Additionality $\mid$ contract	0.206	0.424	0.199	0.200	0.209	0.213	0.215
Share awarded contract	0.81	0.55	0.81	0.81	0.81	0.81	0.70

Notes: Table presents results under current and alternative auctions. Panel A tabulates social welfare (equation (14)), USDA spending, landowner surplus, and environmental value $\sum_i \sum_j B_j\left(\mathbf{z}_i^s\right) \cdot \tau\left(\mathbf{z}_i, c_i, \kappa_i\right) \cdot x_{ij}$ in million dollars per auction. Panel B tabulates average additionality of contracting landowners and the share of landowners with a contract. All auctions impose that each landowner obtains at most one contract and that total contracts awarded cannot exceed the status quo. Column (1) simulates the status quo. Column (2) simulates an efficient allocation that allocates contracts using all $\mathbf{z}_i$ and (c_i, κ_i) to maximize equation (14). Due to adverse selection, this allocation may not be implementable. Columns (3)-(7) simulate alternative Vickrey auctions with scoring (see Section 6.2 for more details). Columns (3)-(6) hold quantity (the number of landowners allocated contracts) constant at the status quo and change the scoring rule $s_j\left(\mathbf{z}_i\right)$ defined in equation (15). Column (3) uses the existing scoring rule $s_j\left(\mathbf{z}_i\right) = B_j\left(\mathbf{z}_i^s\right)$. Column (4) uses a scoring rule with the social-surplus maximizing incentives across contracts (ω_j). Column (5) uses a scoring rule with the social-surplus maximizing asymmetry across bidders using characteristics already in the scoring rule $(\mathbf{z}_i^s)$. Column (6) adds an additional characteristic to the scoring rule, a prediction of $\tau\left(\mathbf{z}_i, c_i, \kappa_i\right)$ using immutable characteristics of landowners already collected by the USDA but not all included in the status quo scoring rule (deciles of soil productivity and wind and water erosion). Column (7) uses the same scoring rule as column (6) but reduces the number of contracts allocated to landowners: only landowners with positive scoring-rule-implied social surplus $\max_j s_j\left(\mathbf{z}_i\right) - c_i - \kappa_{ij} \geq 0$ are awarded contracts. Each column corresponds to a bar in Figure 9.

A Institutional Appendix: The CRP Mechanism

The scoring rule depends on characteristics of the land, the conservation action defined in the contract, and the dollar component of the bid (the bid rental rate). We describe the details associated with each of these components below. The details of the scoring rule are published each year in EBI Factsheets.[49]

Land characteristics The characteristics 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 particulate 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.

These characteristics depend on a bidder's location and not their bid, i.e. they determine bidder asymmetry in the scoring rule. These characteristics are known for every agricultural field in the US.

[49] See an EBI Factsheet for an example.

Heterogeneous contracts defined by conservation actions Conservation actions can be grouped into two categories: a primary cover, described in Table A.1, which covers the total area offered into the CRP, and an (optional) additional upgrade action, described in Table A.2, which can be offered in addition to the primary cover on a smaller area. In total, there are 36 possible contracts: 12 primary covers interacted with three upgrade cover options (including no upgrade).

Table A.1: Contract Action Choices: 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 A.2: Contract Action Choices: 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 contract options, defined by the actions in Tables A.1 and A.2 from the EBI Fact Sheets. The point values assigned to the different contracts can vary across bidders based on whether or not a bidder is in a Wildlife Priority Zone (WPZ).

Bid rental rate The scoring rule is non-linear in r_i. 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. The scoring rule also includes non-linearities based on the amount a bidder bids below the bid cap with kinks at 10% and 15% below the bid cap.[50] The weight on this component is announced only after bids are collected, but it has remained essentially constant throughout our sample period, so we treat it as known.

An example menu The mechanism implies a menu of payments for each contract at each score. These menus differ by observable characteristics of landowners due to asymmetry in the existing rule. Table A.3 describes an example menu.

[50] We observe bunching at the kink points, suggesting that bidders understand the scoring rule and make sophisticated choices in the mechanism.

Table A.3: Payments (for a Target Score of $\underline{S}$) and Market Shares Across Contracts

	Average payment at threshold score	Market share	Average payment at threshold score	Market share	Average payment at threshold score	Market share
	No upgrade		+ wildlife flood plot		+ pollinator habitat	
Intro Grasses 1	28.63	0.140	35.21	0.015	52.91	0.007
Intro Grasses 2	74.30	0.104	77.86	0.022	86.00	0.019
Native Grasses 1	43.64	0.067	49.37	0.005	64.68	0.009
Native Grasses 2	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
Rare Habitat	93.07	0.077	94.82	0.009	99.91	0.025

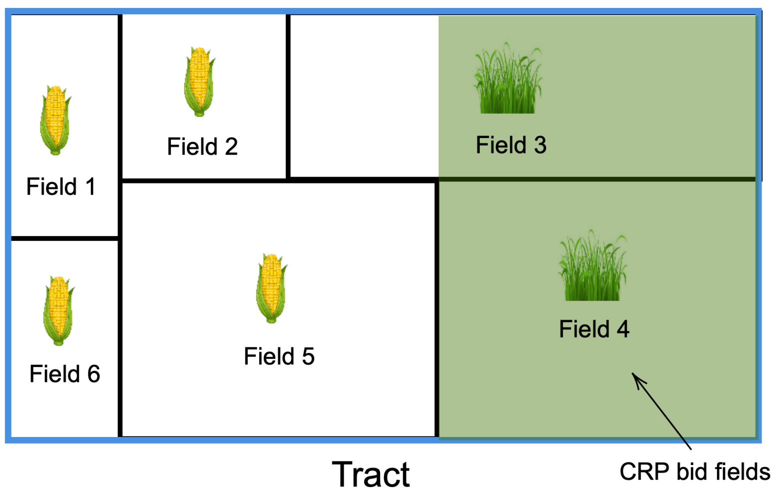
Notes: Table presents the menu of all 36 possible contracts, split into 12 primary covers and three upgrade options. Table reports payments across contracts, calculated as the rental rate per acre per year to reach a given score (held fixed in this table at the threshold score, $\underline{S}$) with a given contract. Payments vary across bidders with heterogeneous $\mathbf{z}_i^s$; this table calculates the averages across all bidders. Table also reports the market shares of each contract, pooled across auctions.

B Data Appendix

Agricultural Units: Tracts and Fields Figure B.1 provides an illustrative example of the various agricultural land units.

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: (i) a permanent, contiguous boundary, (ii) a common land cover and land management, and (iii) a common owner.[51] 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.

Figure B.1: Example: Tract, Fields, and Bid Fields



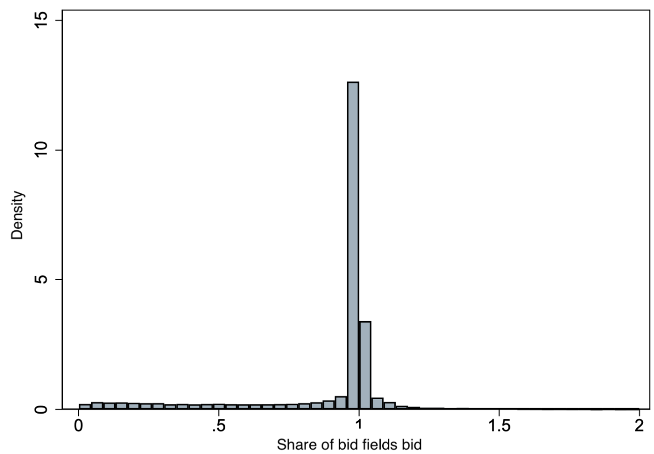
Notes: Figure explains the various geographic units in our dataset. The blue outline is a single tract: this is the unit of landowner (bidder) in our analysis. This tract contains six fields, these are administrative delineations of a tract, each with a single land use. The green shaded area represents 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 landowner, or bidder, 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. In our analyses, we therefore treat bid fields as defining the land offered into the mechanism.

[51] See the Common Land Unit Information Sheet published by the USDA for more details.

Our dataset includes an identifier and the geolocation of each of the bidding tracts, and their subset fields, for all auctions. We only observe the identifiers of the bid fields in 2016.

Figure B.2: Share of Bid Fields Bid into the Mechanism



Notes: Figure shows a histogram of the share of the land of the bid fields that are bid 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 bid 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 is 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 agriculture and land use (Scott, 2013; Hagerty, 2022).[52]

Our primary analysis aggregates CDL classifications into super-classes of crop versus non-crop, following (Lark et al., 2017). Also following Lark et al. (2017), our crop classification excludes alfalfa, hay, fallow, and idle cropland. The super-class accuracy of the CDL is high with $>$ 95% average producer's (classified as cropped when truly cropped) and user's (truly cropped when classified as cropped) accuracy in the years 2008-2016 (Lark et al., 2017). 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. Moreover, in order to improve accuracy,

[52]See https://www.nass.usda.gov/Research_and_Science/Cropland/SARS1a.php for more details and Metadata.

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 landowners (tracts) using USDA identifiers. We merge the CDL data to the geocoded location of the bidder, time-stamped at the point of bidding.

Calculating land use outcomes at the tract level as either the share of pixels that fall into the crop super-class, or a weighted average of field-level (binary) cropping indicators produce similar results. We use the former in our main specifications.

Form 578 Administrative Data Our second source of data (from Form 578) is new to economics research. It is the administrative data submitted to the USDA that the CDL is trained on. The data consist of annual field-level reports of total acreage cropped in detailed crop categories and enrollment in USDA programs. Though Form 578 is self-reported, crop insurance payouts depend on these reports. 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. This is the primary limitation of the administrative data relative to the CDL.

We merge the Form 578 administrative data to bidders based on field and tract identifiers. We construct a panel that tracks changes in field identifiers over time using their geolocation.

NAIP Imagery Our final dataset is derived from the National Agriculture Imagery Program (NAIP) collected via Google Earth Engine. The NAIP is administered through the Forest Service Agency (FSA) of the USDA, and collects 0.6-1m resolution images of all agricultural land during growing season. We obtain NAIP images for enrolled land (the highlighted green area in Figure B.1) to assess compliance with CRP rules. We use high-resolution photographs as classification error in the derived (CDL) data product would mechanically bias toward finding non-compliance.

Figure B.3: Sample Images

(a) Enrolled field

(b) Cropped field

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

Validating Compliance To assess compliance, we hired and trained two MIT undergraduates (the "reviewers") to classify high resolution aerial photographs (NAIP images) of fields at 1m resolution (see Figure B.3 for examples). We focus on the 2016 auction and images taken between 2017 and 2021. Before asking the reviewers to classify any images, we provided them with a test set of hundreds of images of cropped and uncropped fields across the US. The reviewers used this "test set" to familiarize themselves with the visual patterns of cropped fields (see Figure B.3b). We then provided each of the reviewers with over 1,000 images of CRP enrolled fields and hundreds of placebo cropped fields as attention checks. The 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 B.1 presents results for the classification exercise. We restrict to 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; the reviewers were making meaningful classifications. We note, however, that this number is far below 100%. This is because we instructed the reviewers to be conservative in their assessment of non-compliance, operating under the (reasonable) null hypothesis that the program is in fact enforced.

Table B.1: Validation of Compliance: $a_{i1} = 1\ \forall i$

	All post-period years (1)	Drop first two years (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

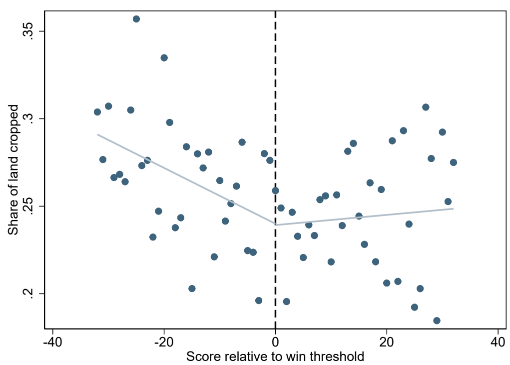
Notes: Table presents results from an exercise classifying aerial photographs of contracted fields as cropped or non-cropped among two reviewers, who also reviewed images of non-CRP fields and were blind to the distinction. Classification focuses on the 2016 auction. Column (1) includes photographs from 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.

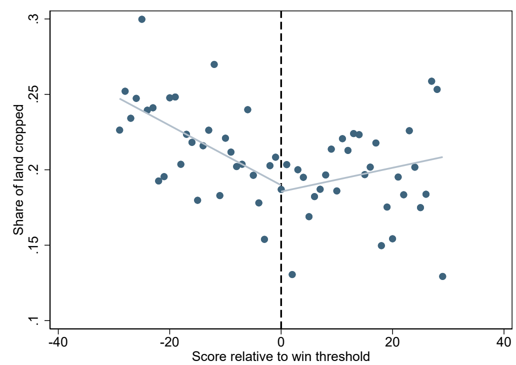
This exercise only studies compliance on the base action, land retirement, not the top-up actions, which we cannot observe. We thus use this assessment of compliance to make an inference about the overall compliance regime across all actions.

C Supplemental Figures and Tables

RD

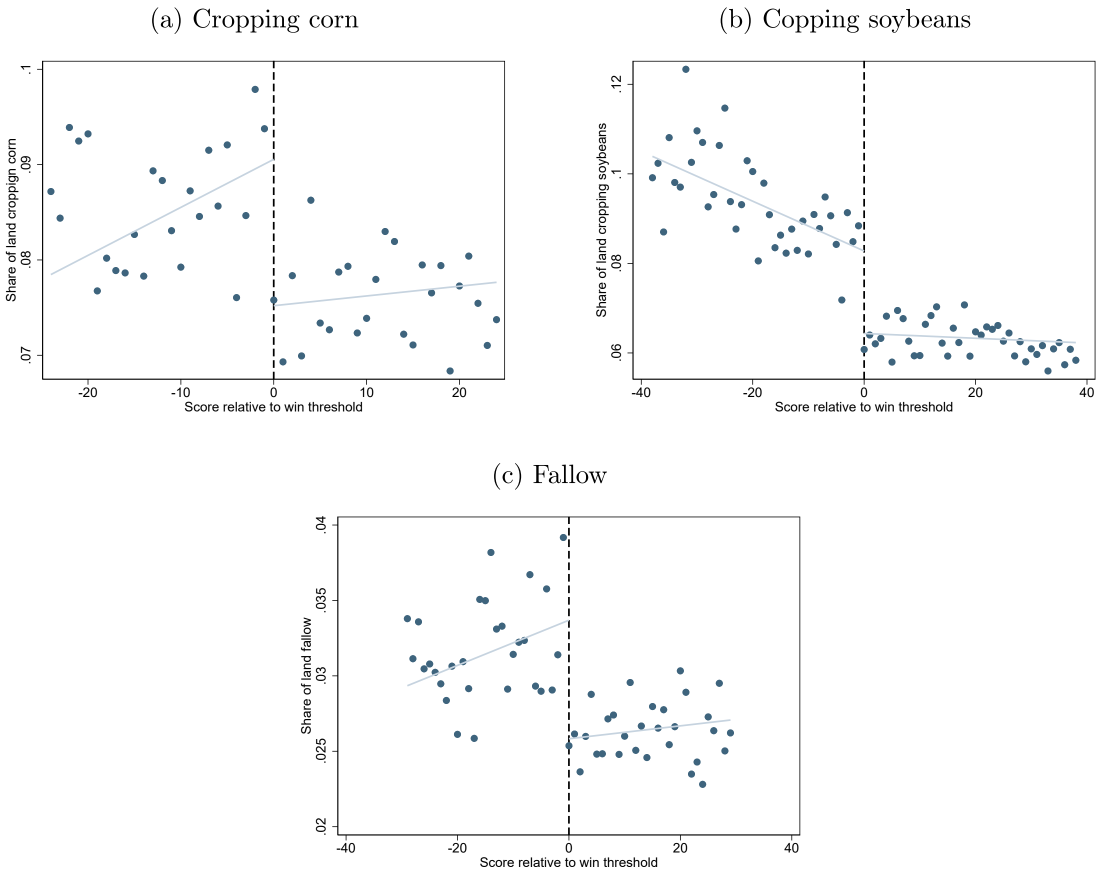
Figure C.1: Spillovers: Cropping Effects on Non-Bid Fields





Notes: Panels (a) and (b) present raw data and estimates from equation (7) for $r(i,t) > 0$ (post-auction). Regression is estimated at the field level, restricting to non-bid fields for bidding landowners. Estimates are restricted to the 2016 auction where delineations of bid and non-bid fields are observed. Land-use outcomes are measured as the share of the bidding land that is cropped using the remote sensing data (a) and administrative data (b). The running variable is the difference between each bidder's score and the threshold score. Positive numbers on the x-axis correspond to winning scores, negative numbers correspond to losing scores. Each observation is a bidder-year. Corresponding coefficient estimates and standard errors presented in Table 2.

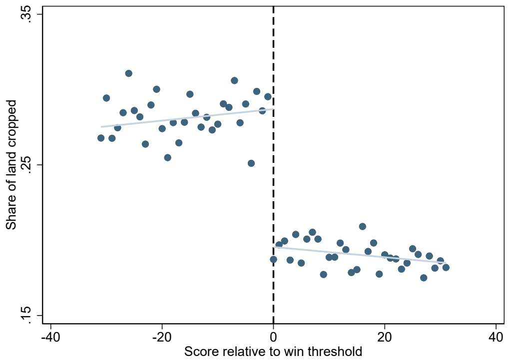
Figure C.2: Additional RD Plots: Remote-Sensing Data



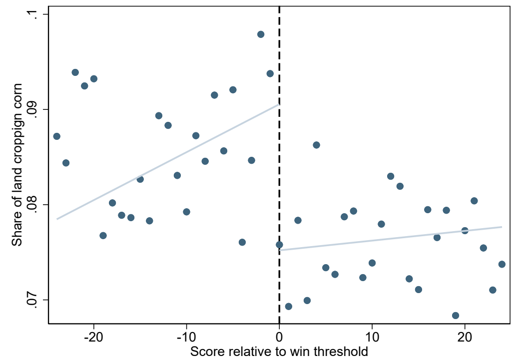
Notes: Figure presents raw data and estimates from equation (7) for $r(i,t) > 0$ (post-auction). Land-use outcomes are measured using crop classifications in the remote sensing data. The running variable is the difference between each bidder's score and the threshold score. Positive numbers on the x-axis correspond to winning scores, negative numbers correspond to losing scores. Each observation is a bidder-year. Corresponding coefficient estimates and standard errors presented in Table 2.

Figure C.3: Additional RD Plots: Admin Data

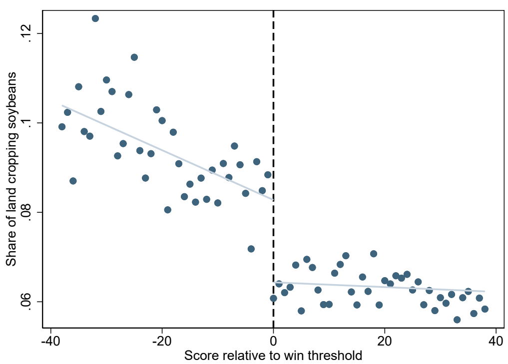
(a) Cropping



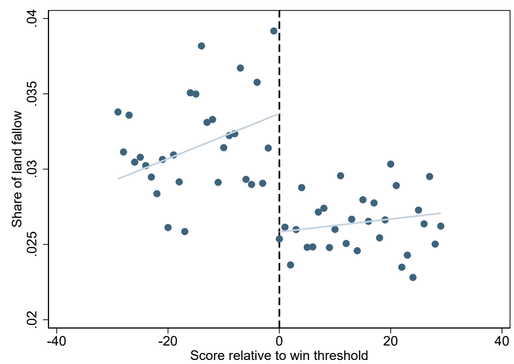
(b) Cropping corn



(c) Cropping soybeans

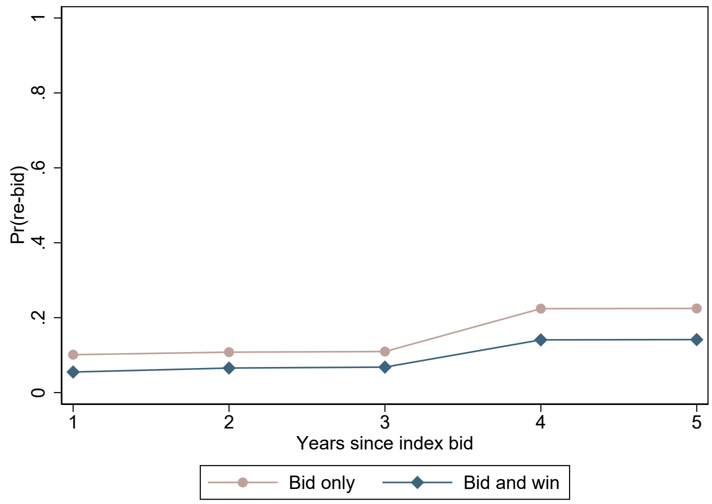


(d) Fallow



Notes: Figure presents raw data and estimates from equation (7) for $r(i,t) > 0$ (post-auction). Land-use outcomes are measured using crop classifications in the Form 578 data reported to the USDA. The running variable is the difference between each bidder's score and the threshold score. Positive numbers on the x-axis correspond to winning scores, negative numbers correspond to losing scores. Each observation is a bidder-year. Corresponding coefficient estimates and standard errors presented in Table 2.

Figure C.4: Rebidding Hazard



Notes: Figure plots the share of losing bidders who have rebid at least once in the years following an index auction, split by all bidders (beige) and successful bidders (blue).

Table C.1: RD Estimates: By Win Threshold of Bid Rental Rate for Base Contract

	Remote-sensing	Admin
	(1)	(2)
Quartile 1 threshold bid (lowest)	-0.039	-0.054
	(0.013)	(0.013)
Quartile 2 threshold bid	-0.059	-0.068
	(0.012)	(0.012)
Quartile 3 threshold bid	-0.031	-0.042
	(0.012)	(0.013)
Quartile 4 threshold bid (highest)	-0.075	-0.098
	(0.015)	(0.015)

Notes: Table presents pooled RD coefficients (Equation (7) for $r(i,t) > 0$ (post-auction) split by the bid rental rate required to achieve the threshold score with the base contract. This parameterizes heterogeneity in the location of the discontinuity across auctions and variation within auctions across bidders (based on $\mathbf{z}_i^s$). The outcome is the share of a bidder's land that is cropped, measured in the remotely sensed data. Standard errors clustered at the tract level.

Table C.2: RD Coefficient Estimates | Bid $\geq$ Five Acres of Land

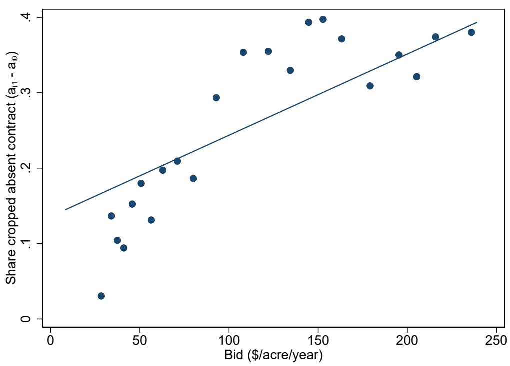
	Remote sensing	Admin
	(1)	(2)
Panel A: Main outcome: share of land cropped		
Pre-sign-up (placebo)	0.016	0.014
	(0.007)	(0.006)
Post-period (pooled sign-ups)	-0.076	-0.095
	(0.007)	(0.006)
Post-period (full contract duration: 2010-2020)	-0.117	
	(0.020)	
Panel B: Other outcomes		
Corn	-0.016	-0.023
	(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	-0.001	-0.000
	(0.015)	(0.015)
N bidders	236,593	236,593
N bidder-years	2,839,116	1,656,151

Notes: Table presents coefficient estimates from equation (7) with land use outcomes measured in the remotely sensed (column (1)) and administrative (column (2)) data, restricted to bidders who bid more then five acres into the mechanism (following Lark et al. (2017)). All results use a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Calonico et al., 2014). The full-contract duration specification restricts to the 2009 auction, others pool all auctions with post-period data (2009, 2011, 2012, 2013, and 2016). The pooled post-period includes an average of 7-8 post-auction years. Natural vegetation or grassland is only observed in remotely sensed data. Calculations of implied additionality divide the treatment effect estimates by the amount of land contracting among winning bidders in the MSE-optimal bandwidth. Panel C estimates the effect of a CRP contract on non-bid, and therefore non-contracting, fields to test for spillovers. This analysis is restricted to the 2016 auction. Standard errors are clustered at the bidder level.

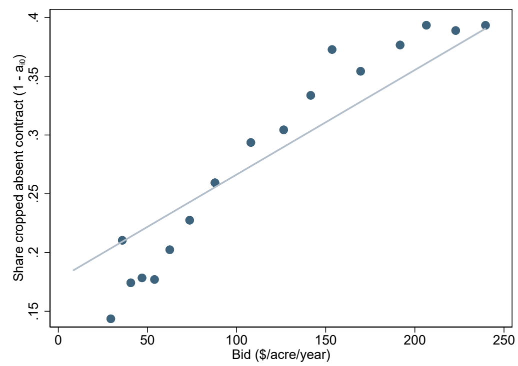
Testing for Asymmetric Information

Figure C.5: Testing for Asymmetric Information, Admin Data

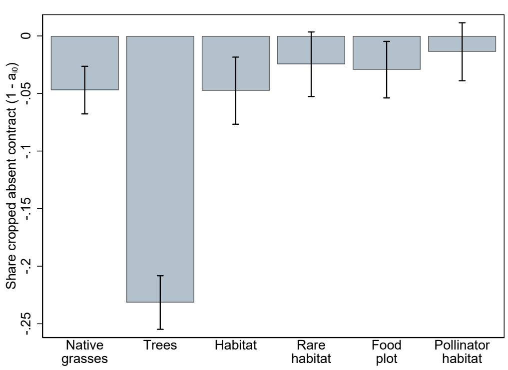
(a) Additionality vs. bids



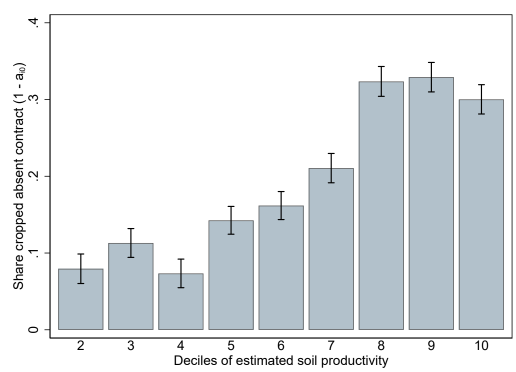
(b) Additionality vs. bids | observables



(c) Additionality across contracts



(d) Observable predictors of additionality



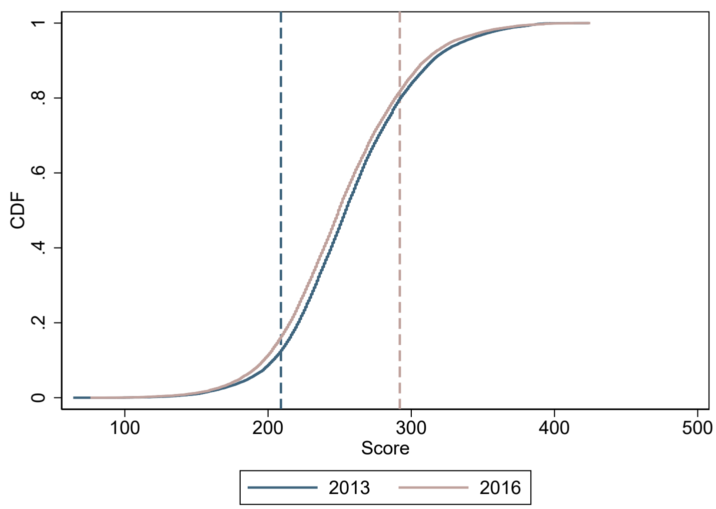
Notes: Figures present visual representations of estimates of equation (8). All regressions control for landowner characteristics in the scoring rule: whether a bidder is in a wildlife priority zone, estimates of groundwater quality, estimates of surface water quality, estimates of wind and water erosion (deciles), air quality impacts, and whether or not a bidder is in a air quality zone. The outcome variable in all panels is a landowner-specific measure of additionality $(1 - a_{i0})$. This is calculated as the share of all fields bid into the CRP mechanism that are cropped post auction for rejected landowners. The sample is restricted to the 2016 auction, in which 82% of bidders are rejected and the delineations of bid fields are observed. Cropping on bid fields is measured in 2017-2020 in the administrative data. Panel (a) is a binned scatterplot correlating the dollar bid (per acre, per year) with additionality, conditional on characteristics included in the scoring rule. Panel (b) adds controls for interaction terms of prior land use (quartiles of share of land cropped prior to bidding and re-enrolling CRP status) and deciles of estimated soil productivity. Panel (c) plots relative additionality by the chosen contract in the bid, relative to an omitted category of introduced grasses. Panel (d) plots relative additionality by deciles of estimated soil productivity. Standard errors clustered at the bidder level.

D Model and Estimation Details

Information

Quantity uncertainty Figure D.1 provides empirical support for the uncertainty in quantity cleared based on the acreage limit of the auction (determined by the Farm Bill). 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 cumulative distribution functions (CDFs) of bidder scores are similar.

Figure D.1: CDF of Scores versus Winning Thresholds: 2013 versus 2016



Notes: Figure presents ex-post win thresholds and cumulative distribution functions (CDFs) of ex-ante score distributions for the 2013 and 2016 auctions.

Identification

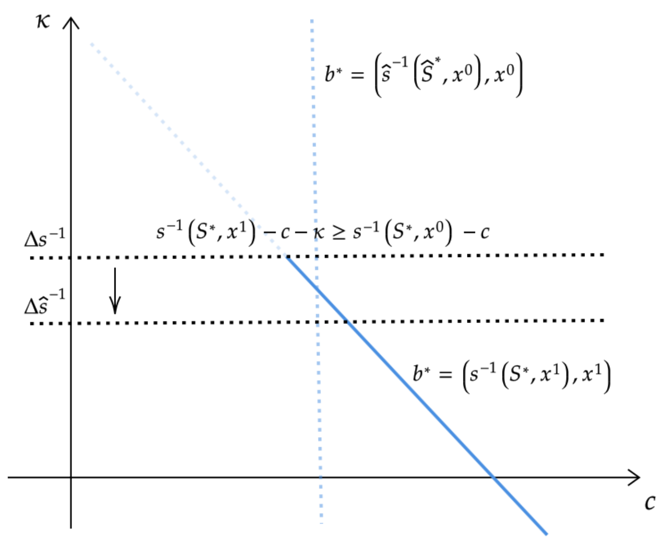
Figure D.2 presents a graphical identification argument in the simple case with only two contract choices (one normalized to have $\kappa = 0$) and a quasi-linear scoring rule. $s^{-1}(S^*, x)$ describes the payment a bidder can receive to achieve score S^* with action x (see Table A.3 for an illustration of this function).

The choice to bid S^* and x^1 under scoring rule s defines the blue line segment containing the true parameters c and κ. S^* can be inverted as in Guerre et al. (2000) to point identify $c + \kappa$ (the line containing the blue line segment in Figure D.2). The observation that x^1 was chosen (not x^0) to reach S^*, given the different payoffs associated with x^0 and x^1 in the scoring rule, bounds the magnitude of κ, defining the line segment. If κ were higher than the horizontal line in Figure D.2, it would have been optimal to reach score S^* with x^0 instead of x^1.

Variation in the scoring rule that shifts the payoffs to x^1 versus x^0, i.e. from s to $\hat{s}$, traces out the density of bidder costs as bidders' optimal choices change in response to the variation in the scoring rule. For example, the vertical dashed line documents a bidder who changes her optimal bid to x^0 with $\hat{S}^*$ under the new rule.

This argument extends to non-linearities in the scoring rule, a larger menu of contracts, and the fact that scores can only be integers. See (Agarwal et al., 2023) for more details.

Figure D.2: Graphical Identification Argument



Notes: Figure presents a graphical identification argument.

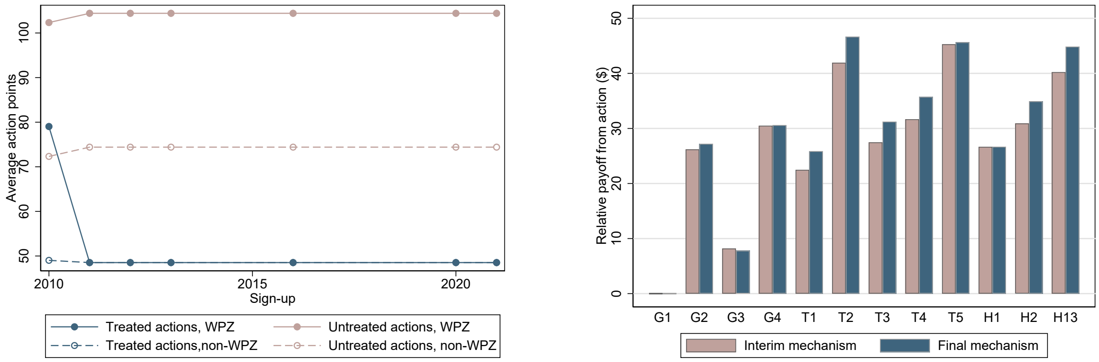
As discussed in the main text, the final component of the model, $\tau\left(\mathbf{z}_i, c_i, \kappa_i\right)$, is identified by also observing a_{i0} jointly with optimal bids (including as they change with the variation from s to $\hat{s}$ described in Figure D.2).

Figure D.2 clarifies the need for variation in the scoring rule to trace out the distribution of c and κ. Figure D.3 describes this variation in our context.

Figure D.3: Sources of Variation in the Scoring Rule

(a) Wildlife Priority Zone Variation

(b) Mid-Mechanism Policy Change

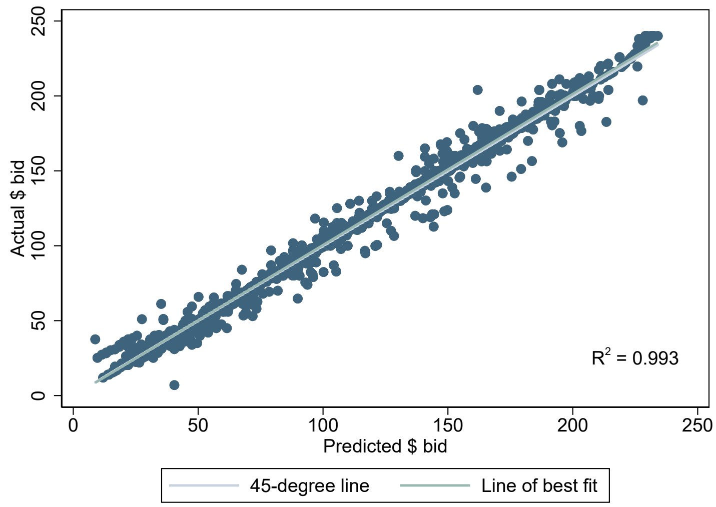


Notes: Figure presents sources of policy variation in the scoring rule that yield variation in payments across contracts differentiated by top-up conservation actions. Panel (a) plots average action points awarded for a set of "treated" actions, actions for which after the 2011 auction WPZ bidders no longer got WPZ points, and "untreated" actions, whose points remained the same, and the same average action points for non-WPZ bidders. Panel (b) plots the average rental rate that would be received for a target score (illustrated using the threshold 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 habitats.

Estimation

Step 0: Constructing the Scoring Rule We only observe scores for chosen bids $\mathbf{b}_i$, so we construct the function $s\left(\mathbf{b}_i, \mathbf{z}_i^s\right)$ from the EBI Factsheets. Figure D.4 confirms that our reconstruction performs well: at observed actions, our scoring-rule-implied required bid rental rate to achieve the score chosen in the data predicts the observed bid rental rate with an R^2 of over 0.99.

Figure D.4: True versus Predicted Bid Rental Rate at Observed Scores and Contracts



Notes: Figure presents a scatter plot of true versus predicted bid rental rates at observed contract and score choices to validate the construction of $s\left(\mathbf{b}_i, \mathbf{z}_i^s\right)$.

Step 1: Obtain Bidder Beliefs via Simulation Our resampling procedure to simulate the probability of winning at any score, $G(S)$ follows Hortaçsu (2000); Hortaçsu and McAdams (2010). Specifically, we:

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

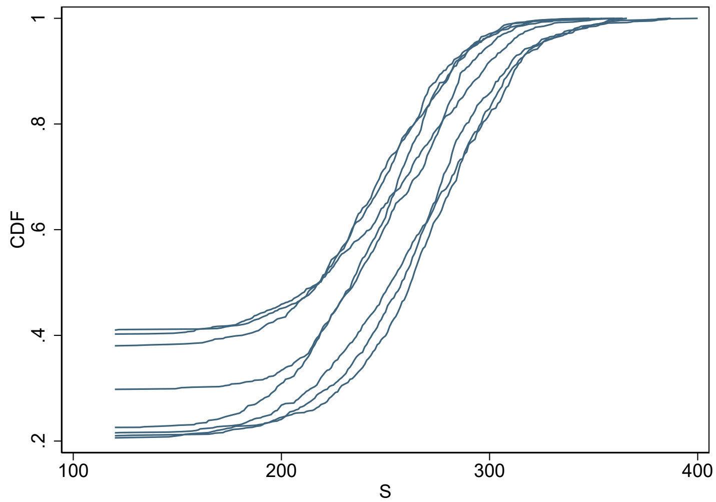
2. Fit a Beta distribution to the observed distribution of number of opposing bidders across auctions. For this step, we again use additional historic data on auctions starting in 1999. This provides us with 12 auctions.

3. Draw an acreage threshold from the distribution fit in Step 1 and the number of opposing bidders, N, in Step 2. Then, for each auction g, 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 $G_g(S)$.

Bidders form expectations about the distribution of competing scores without knowledge of their competitors' identities or characteristics, consistent with the large and decentralized bidding process, so $G_g(S)$ is the same for all bidders. Figure D.5 plots the output of our simulation procedure across all auctions.

Figure D.5: Probability of Winning at Score S



Notes: Figure presents CDFs of the simulated distribution of win probabilities at a given score across auctions.

Step 2: Estimate $F_{c,\kappa\,|\,\mathbf{z}}$ Our estimation procedure is as follows:

1. **Construct a proposal distribution.** We begin by constructing a proposal distribution from which to draw proposal (c_i, κ_i) draws. We obtain our proposal distribution by estimating a simplified version of the model. Bidders choose a score using only their *expectations* of their κ_{ij} draws, then given that score, choose an optimal contract. In this model, estimation of κ_{ij} and c_i can be separated into a discrete choice problem and an inversion. We obtain parameter estimates from this simplified model, then set our proposal distribution to be independent normals with the estimated means and variances of this simplified model (inflating the variance by 25%).

2. **Draw from proposal and solve the bidder's problem.** Following the approach of Ackerberg (2009), we use a change of variables to draw simulations of $\left(c_i^k, \kappa_i^k\right)$ from the proposal distribution and solve the bidder's problem in equation (10) for each bidder and each simulation draw. Bidders can only bid integer scores, so to solve equation (10), we search over all feasible score-contract combinations among integers in the support of observed scores. This change of variables allows us to solve the bidder's problem only $N \times K$ times, once for each bidder and each simulation draw, instead of $N \times K \times R$ times, for each evaluation of the objective function (R times).

3. **Coarsen choice probabilities.** Because the number of possible bids is large (on the order of 10,000 choices), we face the challenge that the probability of simulating each bid observed in the data is low. We address this challenge by coarsening the bidder's solution obtained in Step 2. We coarsen to the cartesian product of (i) deciles of the scoring rule and (ii) the five dimensions of p_j when u_j is the no upgrade option, plus the two upgrade options. Let $\widetilde{\mathbf{b}}_i^* = \left(\tilde{S}_i, \tilde{\mathbf{x}}_i\right)$ denote the optimal coarsened bid observed in the data.

4. **Reweight simulation draws.** We can then construct the importance sampling estimator by re-weighting simulation draws. The likelihood of observing the coarsened choice in the data, $\widetilde{\mathbf{b}}_i^* = \left(\tilde{S}_i, \tilde{\mathbf{x}}_i\right)$, given a parameter guess θ, is:

$$\mathcal{L}_i = \frac{1}{K} \sum \mathbb{1}\left(\widetilde{\mathbf{b}}_i^* = \widetilde{\mathbf{b}}_i^{*k} | \left(c_i^k, \kappa_i^k\right)\right) \frac{p\left(\left(c_i^k, \kappa_i^k\right) | \theta\right)}{g\left(\left(c_i^k, \kappa_i^k\right)\right)}, \tag{17}$$

   where $\widetilde{\mathbf{b}}_i^{*k}$ is the coarsened optimal bid given simulation draw $\left(c_i^k, \kappa_i^k\right)$, the solution to the bidder's problem in equation (10), and the coarsening described in Step 3. Equation (17) then re-weights simulation draws by $\frac{p\left(\left(c_i^k, \kappa_i^k\right)|\theta\right)}{g\left(\left(c_i^k, \kappa_i^k\right)\right)}$, where $p\left(\left(c_i^k, \kappa_i^k\right) | \theta\right)$ is the probability of observing simulation draw $\left(c_i^k, \kappa_i^k\right)$ given parameter guess θ, and $g\left(\left(c_i^k, \kappa_i^k\right)\right)$ the probability of observing $\left(c_i^k, \kappa_i^k\right)$ given the proposal distribution from Step 1.

5. **Find θ to maximize the log likelihood**. We suppressed dependence in (17) on $\mathbf{z}_i$. We estimate θ separately for each of the 32 cells of observable heterogeneity for a sample of 1,000 bidders in each cell in each auction (due to computational constraints on the USDA servers). An auxiliary benefit of the importance sampling approach of Ackerberg (2009) is that it yields a differentiable objective function.

6. **Repeat**. We repeat Steps 2-5 several times, using estimates from the solution to Step 5 as the new proposal distribution. Our final estimates use 10,000 simulation draws to mitigate simulation bias (Train, 2009).

Step 3: Estimate $\tau\left(\mathbf{z}_i, c_i, \kappa_i\right)$ Our final step involves estimating the conditional expectation function $\tau\left(\mathbf{z}_i, c_i, \kappa_i\right) = \mathbb{E}\left[1 - a_{i0} \,|\, \mathbf{z}_i, c_i, \kappa_i\right] = \pi \cdot \mathbf{z}_i + \beta \cdot c_i + \alpha \cdot \kappa_i$. We match model implied moments of additionality to observed moments of additionality, $1 - a_{i0}$, among bidders who lose the auction. We search for $\theta^\tau = (\pi, \beta, \alpha)$ that minimizes $\hat{g}\left(\theta^\tau\right)' A \hat{g}\left(\theta^\tau\right)$ for weight matrix A and $\hat{g}\left(\theta^\tau\right) = \hat{\mathbb{E}}\left[m_i - \frac{1}{K}\sum_k m_i\left(\theta^\tau | c_i^k, \kappa_{\mathbf{i}}^{\mathbf{k}}\right)\right]$, where $\hat{\mathbb{E}}$ denotes the sample expectation, for m_i equal to:

- Additionality at the award threshold: $(1-a_{i0})\cdot\mathbb{1}\left[\underline{S}-b<s\left(\mathbf{b}_i^*,\mathbf{z}_i^s\right)<\underline{S}\right]$ for bandwidth b.

- Additionality by observable characteristics: $(1-a_{i0})\cdot\mathbb{1}\left[s\left(\mathbf{b}_i^*,\mathbf{z}_i^s\right)<\underline{S}\right]\cdot\mathbf{z}_i$.

- Covariance between additionality and chosen scores: $(1-a_{i0})\cdot s\left(\mathbf{b}_i^*,\mathbf{z}_i^s\right)\cdot\mathbb{1}\left[s\left(\mathbf{b}_i^*,\mathbf{z}_i^s\right)<\underline{S}\right]$.

- Additionality within chosen contracts: $(1-a_{i0})\cdot\mathbb{1}\left[x_{ij}=1\right]\cdot\mathbb{1}\left[s\left(\mathbf{b}_i^*,\mathbf{z}_i^s\right)<\underline{S}\right]$.

Our estimation approach follows the following steps:

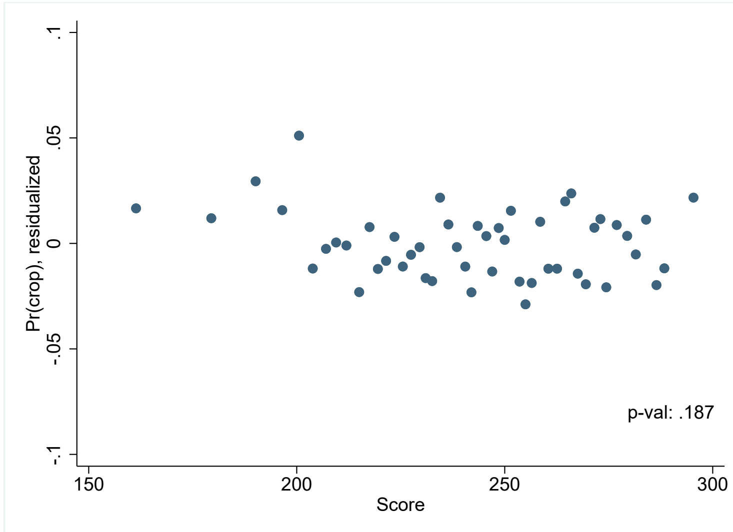
1. Draws simulations $\left(c_i^k,\kappa_i^k\right)$ from $F_{c,\kappa\,|\,\mathbf{z}}$ estimated in Step 2.
2. Calculate optimal bids $\mathbf{b}_i^*$ given $\left(c_i^k,\kappa_i^k\right)$ using equation (10).
3. Calculate $m_i\left(\theta^\tau|c_i^k,\kappa_i^k\right)$ by replacing $1-a_{i0}$ with $\pi\cdot\mathbf{z}_i+\beta\cdot c_i+\alpha\cdot\kappa_i$ and observed bids with simulated optimal bids for each simulation draw k and parameter guess θ^τ.
4. Minimize the objective $\hat{g}\left(\theta^\tau\right)'A\hat{g}\left(\theta^\tau\right)$.

We use the two-step optimal weight matrix for the matrix A.

Because we require an observation of bid fields to calculate $1-a_{i0}$, we estimate $\tau\left(\mathbf{z}_i,c_i,\kappa_i\right)$ using only the auction where we observe bid fields (2016). Our primary estimates use the remote-sensing data from 2017-2020 to measure $1-a_{i0}$. We assume that the relationships estimated in $\tau\left(\mathbf{z}_i,c_i,\kappa_i\right)$ in this auction can be extrapolated to the other auctions in our sample, and that $\tau\left(\mathbf{z}_i,c_i,\kappa_i\right)$ can be estimated in only the three years following the auction. This may seem unappealing given the transition period in Figure 4, but we note that $1-a_{i0}$ is calculated among losing bidders, not those transitioning into land retirement.

As discussed in the main text, we require instruments that shift $s\left(\mathbf{b}_i^*,\mathbf{z}_i^s\right)$ but that are conditionally independent of a_{i0}. We use landowners' Wildlife Priority Zone and Air Quality Zone status as instruments. We conduct a test to provide additional support for this assumption. Specifically, we estimate the simplified version of the model described in Step 1 of our Step 2 estimator, in which we can point identify c_i with an inversion. We show in Figure D.6 that cropping outcomes are independent of the score after controlling for c_i and the remaining observables in $\tau\left(\mathbf{z}_i,c_i,\kappa_i\right)$. This suggests that the residual variation in the score is conditionally independent of a_{i0}.

Figure D.6: Residualized Correlation Between Scores and Cropping



Notes: Figure presents the relationship between a binary indictor for cropping, residualized of observable characteristics, a point-identified c_i estimate from an alternative model, and scoring rule characteristics except for Wildlife Priority Zone and Air Quality Zone. Estimated among losing bidders in the 2016 auction only.

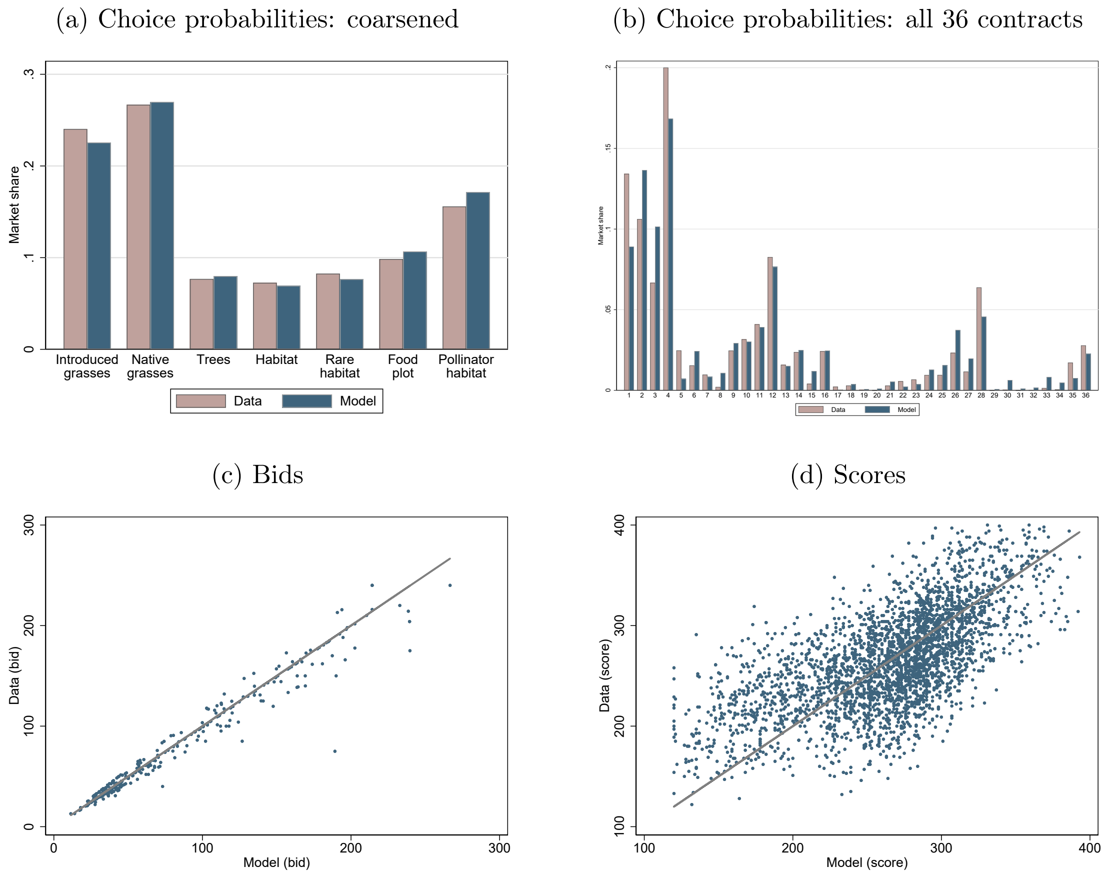
We calculate standard errors via bootstrapping. Our final procedure will bootstrap over the entire estimation procedure to incorporate estimation error in earlier steps. The current standard errors do not incorporate estimation error in (c_i, κ_i).

Table D.1: $F_{c,\kappa\,|\,\mathbf{z}}$ Parameter Estimates (Select $\mathbf{z}_i$)

	Former CRP = 0				Former CRP = 1			
Prior crop	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Soil prod.	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
c_i								
Mean	31.65	37.51	66.35	135.97	36.55	42.90	66.85	126.27
	(0.02)	(0.04)	(0.05)	(0.06)	(0.02)	(0.03)	(0.05)	(0.06)
Log σ_c	1.60	2.77	3.53	3.61	1.16	2.60	3.47	3.89
	(0.004)	(0.002)	(0.001)	(0.001)	(0.004)	(0.002)	(0.001)	(0.001)
κ_{ij}								
Means								
Native grasses	0.70	-4.46	3.96	-0.61	-2.59	-4.76	4.87	2.31
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Trees	28.57	27.53	30.11	34.51	15.85	19.25	23.77	30.67
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Habitat	17.25	12.71	16.82	22.01	13.96	11.76	15.94	12.92
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Rare habitat	17.73	15.63	17.97	10.05	18.30	12.96	22.57	19.60
	(0.04)	(0.04)	(0.03)	(0.03)	(0.05)	(0.04)	(0.04)	(0.03)
Wildlife food plot	23.77	23.07	12.69	14.24	25.66	18.65	14.45	16.24
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Pollinator habitat	16.72	10.81	14.12	18.00	22.04	18.68	18.27	17.40
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Log σ_κ	2.70	2.86	2.81	2.76	2.85	2.84	2.83	2.81
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)

Notes: Table presents presents parameter estimates for 8 cells of $\mathbf{z}_i$. Standard errors calculated using the inverse of the negative Hessian, calculated numerically. Standard errors do not account for simulation error or the estimation error in the first step estimator of $G(S)$.

Figure D.7: Model Fit



Notes: Figures summarize model fit by comparing simulated choices of contracts, bids, and scores to the data.

Table D.2: Comparison Between Estimated and Administrative Cost Estimates

	Estimates	Median admin cost	Average admin cost
	(1)	(2)	(3)
Tree primary covers (rel. to grasses)	24.36	26.46	73.15
Habitat primary covers (rel. to grasses)	15.05	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).

E Valuing Benefits

We assume that the weights in the scoring rule $B_j(\mathbf{z}_i^s)$ reflect the relative social benefits (in dollars) across j and $\mathbf{z}_i^s$, assuming $a_{i0} = 0$ for all i. The mechanism implicitly makes trade-offs in the scoring rule that monetize relative preferences across contracts and characteristics.

Using this logic requires two assumptions. First, we require the assumption that $a_{i0} = 0$ for all i, motivated by Claassen et al. (2018), who write: *Benefit-cost indices are used to rank applications for acceptance in all major USDA conservation programs... Existing indices, however, implicitly assume full additionality.* Second, we require that the weights in the scoring rule are not distorted to reduce expenditures (Che, 1993). There is no evidence to support this behavior (Ribaudo et al., 2001), and moreover, the USDA values transfers to agricultural landowners. We assume that the USDA maximizes social welfare by announcing its preferences in the scoring rule.

However, the USDA revealed-preferred values of $B_j\left(\mathbf{z}_i^s\right)$ may not necessarily align with the true environmental benefits for a variety of reasons, e.g. political concerns (Ribaudo et al., 2001). We choose to take this USDA-revealed-preferred approach, versus calibrating $B_j\left(\mathbf{z}_i^s\right)$ from an external integrated assessments model,[53] to focus on additionality as the primary source of social welfare losses.

To calculate these scoring-rule implied relative valuations, we note that scoring rule is separable in the actions incentivized by the heterogeneous contracts and the bid (\$) rental rate

$$s\left(\mathbf{b}_i, \mathbf{z}_i^s\right) = \underbrace{s_a\left(\mathbf{x}_i, \mathbf{z}_i^s\right)}_{\text{action points}} + \underbrace{s_r\left(r_i\right)}_{\text{bid rental rate points}} \tag{18}$$

and construct a quasi-linear approximation to the scoring rule to obtain relative willingness to pay. The scoring rule departs from quasi-linearity because of kinked incentives in points bidders receive as a percentage of their bidcap. We "quasi-linearize" the scoring rule by taking the average of $s_r'\left(r_i\right)$ in the region without the added percentage points bonus and the region with the percentage point bonus (at the median bidcap value).[54]

Using our "quasi-linearized" approximation to the scoring rule, we know how the USDA trades off higher costs with heterogeneous environmental benefits across contracts j and observable characteristics $\mathbf{z}_i^s$. However, the scoring rule is not directly informative about the level of social benefits. We obtain this using estimates of the value of the CRP from the literature. We assume that all impacts of the CRP accrue only over the contract period.

We use following values of the CRP from the literature. Our baseline estimates take the average across these three studies.

[53]See `https://naturalcapitalproject.stanford.edu/software/invest` for an example.

[54]The fact that different bidders face different scoring rules based on their bidcap does not reflect differential valuation of environmental benefits across bidders.

1. Our first estimate sums the recreational,[55] public works,[56] and air quality benefits[57] from Feather et al. (1999) and adds estimates of the value of greenhouse gas reductions from sequestered CO_2 (over the 10-year contract) and reduced fuel and fertilizer use[58] monetized at $43 per metric ton. This leads to an overall estimated value of the CRP of $98.34 per acre, per year. This is likely to be an under-estimate because biodiversity is only valued insofar as it provides recreational benefits, and this estimate does not include water quality improvements from reduced run-off.

2. Our second estimate takes the valuation of the CRP from Hansen (2007), and adds estimates of the value of greenhouse gas reductions from sequestered CO_2 (over the 10-year contract) and reduced fuel and fertilizer use, which then equals $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 gas reductions from sequestered CO_2 (over the 10-year contract) and reduced fuel and fertilizer use. This leads to estimates of $367.96 and $456.04, per acre, per year. These may be an over-estimate because benefits are estimated in only one geographic area, which may have more environmentally sensitive land.

The description above highlights the difficulties of monetizing the value of the all of the environmental benefits of the CRP, both in terms of quantifying all of the potential environmental benefits. We emphasize that our focus is not on obtaining estimates of $B_j(\mathbf{z}_i^s)$, but rather on $\tau(\mathbf{z}_i, c_i, \kappa_i)$; results can be recalculated for any alternative valuation of $B_j(\mathbf{z}_i^s)$. Quantifying the environmental value of ecosystem services is an important complementary area of research.

F Additional Counterfactuals

Cost of Public Funds Figure E.1 considers the same auctions presented in Figure 9, but evaluates social welfare with a cost of funds $\lambda = 0.15$. Under this framework, 15% of

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

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

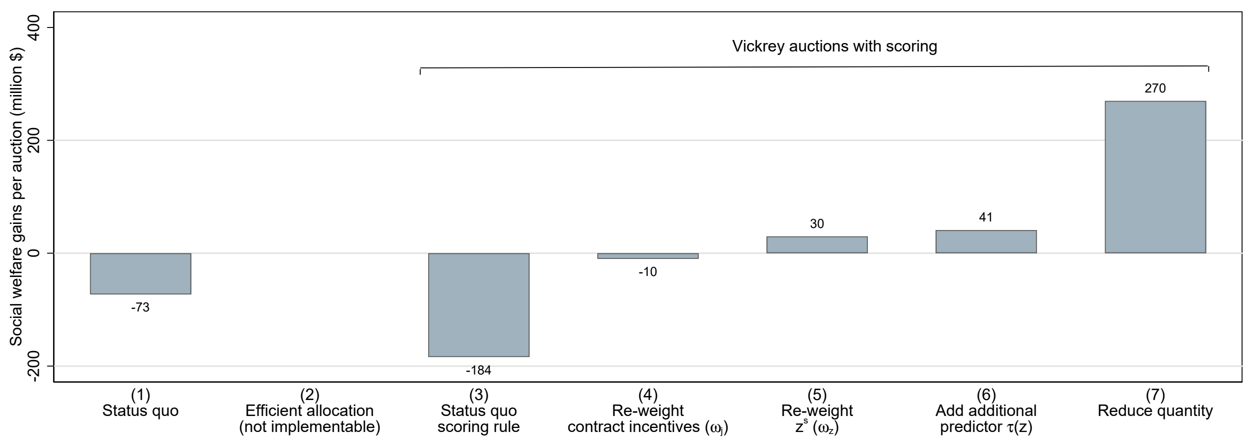
[57] Includes reduced health risks and cleaning costs associated with blowing dust.

[58] See https://www.fsa.usda.gov/Assets/USDA-FSA-Public/usdafiles/EPAS/natural-resouces-analysis/nra-landing-index/2017-files/Environmental_Benefits_of_the_US_CRP_2017_draft.pdf.

all USDA spending is considered deadweight loss, motivated by the social costs of financing expenditures via distortionary taxation. With a cost of funds, the status quo auction reduces social welfare. However, social welfare gains become positive once the auction is designed to consider additionality. In bar (7), social welfare gains are large at \$270 million per auction.

Figure E.1 evaluates auctions using the same scoring rules as in Figure 9. With weights ω_j and $\omega_{\mathbf{z}}$ re-optimized to reduce government spending, social welfare gains would be higher.

Figure E.1: Social Welfare Under Alternative Auctions: Cost of Funds

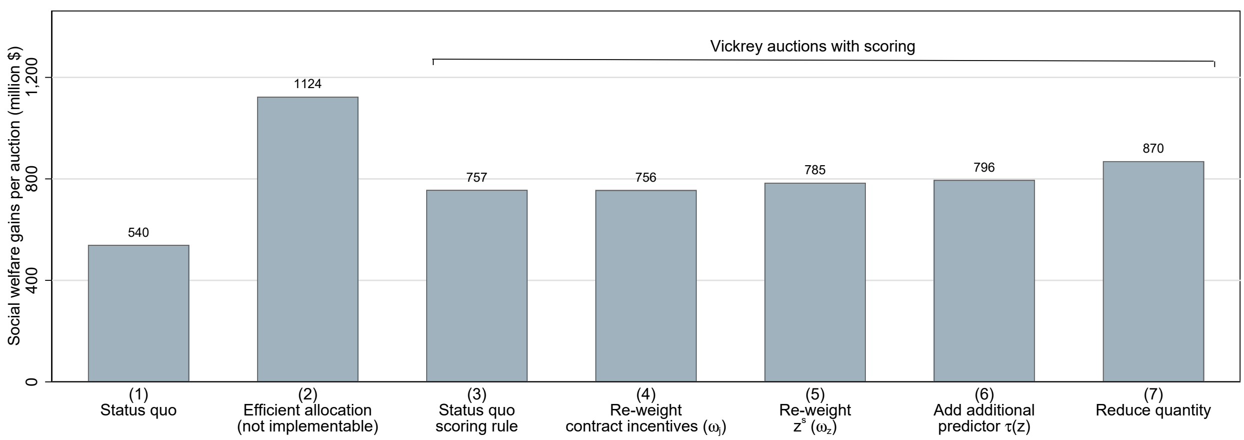


Notes: Figure presents estimates of the social welfare gains (defined in equation (14) with a cost of funds $\lambda = 0.15$) under status quo and alternative auctions. Results reported in million dollars per auction. All auctions impose that each landowner obtains at most one contract and that total contracts awarded cannot exceed the status quo. Bar (1) simulates the status quo. Bar (2) calculates the social welfare gains under an efficient allocation that allocates contracts using all $\mathbf{z}_i$ and (c_i, κ_i) to maximize equation (14). Due to adverse selection, this allocation may not be implementable. Bars (3)-(7) calculate social welfare under alternative Vickrey auctions with scoring (see Section 6.2 for more details). Bars (3)-(6) hold quantity (the number of landowners allocated contracts) constant at the status quo and change the scoring rule $s_j(\mathbf{z}_i)$ defined in equation (15). Bar (3) uses the existing scoring rule $s_j(\mathbf{z}_i) = B_j(\mathbf{z}_i^s)$. Bar (4) uses a scoring rule with the social-surplus maximizing incentives across contracts (ω_j). Bar (5) uses a scoring rule with the social-surplus maximizing asymmetry across bidders using characteristics already in the scoring rule $(\mathbf{z}_i^s)$. Bar (6) adds an additional characteristic to the scoring rule, a prediction of $\tau(\mathbf{z}_i, c_i, \kappa_i)$ based on immutable characteristics of landowners already collected by the USDA (deciles of soil productivity and wind and water erosion). Bar (7) uses the same scoring rule as bar (6) but reduces the number of contracts allocated to landowners: only landowners with positive scoring-rule-implied social surplus $\max_j s_j(\mathbf{z}_i) - c_i - \kappa_{ij} \geq 0$ are awarded contracts. See each bar's corresponding column in Table 5 for more details.

Top-Actions not Affected by Additionality For all analyses beyond those restricted to the base contract, we require an assumption about how additionality impacts the social value derived from the top-up actions that differentiate the contracts in the mechanism. This is due to fundamental data limitations (see Section 3.2). Our primary specification defines the social benefit of contracting as $B_j(\mathbf{z}_i^s) \cdot \tau(\mathbf{z}_i, c_i, \kappa_i)$. In this specification, no social benefits are generated when a landowner is not additional. This could be either because, as with land retirement, top-up actions (or close substitutes) would have occurred even absent a CRP contract. It could also be motivated by an assumption that land retirement and the top-up actions are complements in the USDA's valuation of contracting.

In this section, we consider an alternative assumption in which the incremental actions incentivized by the contracts are always additional. Specifically, we consider an alternative valuation of contracts equal to $B_0\left(\mathbf{z}_i^s\right) \cdot \tau\left(\mathbf{z}_i, c_i, \kappa_i\right) + B^j\left(\mathbf{z}_i^s\right)$, where $B_0\left(\mathbf{z}_i^s\right)$ is the social benefit of the base action and $B^j\left(\mathbf{z}_i^s\right)$ is the incremental social benefit of the top-up action beyond the base action. This could be motivated by a scenario in which contracting impacted the specific species mix, which we assume the USDA values at $B^j\left(\mathbf{z}_i^s\right)$, even if it did not impact land retirement. Under this assumption, over one third of the total social surplus at stake is not impacted by additionality at all. This makes correctly incentivizing the top-up actions — whose relative valuations are derived solely from monetizing the scoring rule — matter substantially to the performance of the mechanism. This is another reason to favor our baseline assumption over this alternative.

Figure E.2: Social Welfare Under Alternative Auctions: Alternative Top-Up Assumption



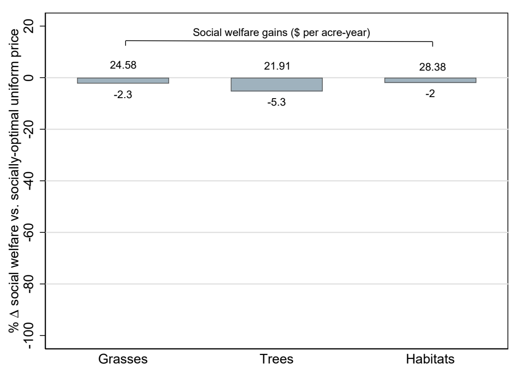
Notes: Figure presents estimates of the social welfare gains (defined in equation (14), but replacing $B_j\left(\mathbf{z}_i^s\right) \cdot \tau\left(\mathbf{z}_i, c_i, \kappa_i\right)$ with $B_0\left(\mathbf{z}_i^s\right) \cdot \tau\left(\mathbf{z}_i, c_i, \kappa_i\right) + B^j\left(\mathbf{z}_i^s\right)$ where $B_0\left(\mathbf{z}_i^s\right)$ is the social benefit of the base action and $B^j\left(\mathbf{z}_i^s\right)$ is the incremental value of the top-up action) under status quo and alternative auctions. Results reported in million dollars per auction. All auctions impose that each landowner obtains at most one contract and that total contracts awarded cannot exceed the status quo. Bar (1) simulates the status quo. Bar (2) calculates the social welfare gains under an efficient allocation that allocates contracts using all $\mathbf{z_i}$ and (c_i, κ_i) to maximize equation (14). Due to adverse selection, this allocation may not be implementable. Bars (3)-(7) calculate social welfare under alternative Vickrey auctions with scoring (see Section 6.2 for more details). Bars (3)-(6) hold quantity (the number of landowners allocated contracts) constant at the status quo and change the scoring rule $s_j\left(\mathbf{z}_i\right)$ defined in equation (15). Bar (3) uses the existing scoring rule $s_j\left(\mathbf{z}_i\right) = B_j\left(\mathbf{z}_i^s\right)$. Bar (4) uses a scoring rule with the social-surplus maximizing incentives across contracts (ω_j). Bar (5) uses a scoring rule with the social-surplus maximizing asymmetry across bidders using characteristics already in the scoring rule $\left(\mathbf{z}_i^s\right)$. Bar (6) adds an additional characteristic to the scoring rule, a prediction of $\tau\left(\mathbf{z}_i, c_i, \kappa_i\right)$ based on immutable characteristics of landowners already collected by the USDA (deciles of soil productivity and wind and water erosion). Bar (7) uses the same scoring rule as bar (6) but reduces the number of contracts allocated to landowners: only landowners with positive scoring-rule-implied social surplus $\max_j s_j\left(\mathbf{z}_i\right) - c_i - \kappa_{ij} \geq 0$ are awarded contracts.

Figure E.2 re-creates Figure 9 under this alternative assumption. Social welfare under the status quo is higher, but the status quo still achieves less than half of the social welfare gains under the efficient allocation. The biggest difference between Figures 9 and E.2 is the large social welfare gains from the switch to the VCG mechanism, holding the scoring rule constant (bar (3)). This is because the Vickrey auction with scoring using the status quo rule now efficiently incentivizes choices across contracts. Because the top-up actions represent a large share of social welfare gains at stake in the mechanism, incentivizing them efficiently is important for the auction's performance.

Adjusting the mechanism for heterogeneity in additionality is still quantitatively important: moving from bar (3) to bar (6) increases social welfare by 7% of the status quo, or 15% of the gains of the improvement between bar (1) and bar (6). Also as in our baseline estimates, quantity procured is higher than is socially optimal. Reducing quantity to reflect the many landowners who are not additional increases social welfare by a further 13% of the status quo social welfare gains.

We emphasize that the exercise of Figure E.2 is not to document that results are quantitatively the same under this alternative assumption versus our baseline assumption. The assumptions are very different, so naturally lead to some different quantitative implications. Instead, we highlight that the insights from our baseline assumption are quantitatively relevant even when a large share of the surplus at stake in the mechanism ($B^j(\mathbf{z}_i^s)$) is not impacted by additionality.

Figure E.3: Alternative Assumption: Offset Market Design Across Contracts



Notes: Figure plots the percent reduction in social welfare under a stylized competitive market equilibrium relative to socially-optimal prices under three different hypothetical markets, each with only one contract traded at a uniform price. The numbers above the bars in panels (a) and (b) tabulate total social welfare (per acre-year) in each competitive market. The competitive market equilibrium is calculated under the assumption that buyers have the same full-information preferences as the USDA and form expectations over the value of any contract given the equilibrium price(s). In this figure, we assume that $B_0(\mathbf{z}_i^s) \cdot \tau(\mathbf{z}_i, c_i, \kappa_i) + B^j(\mathbf{z}_i^s)$, where $B_0(\mathbf{z}_i^s)$ is the social benefit of the base action and $B^j(\mathbf{z}_i^s)$ is the incremental value of the top-up action, instead of our baseline assumption of $B_j(\mathbf{z}_i^s) \cdot \tau(\mathbf{z}_i, c_i, \kappa_i)$.

We also examine how this alternative assumption impacts our analysis of competitive offset market design. Most of the analysis in the main text is focused on the base contract (e.g. Figures 7 and 11a), so is unaffected by our assumptions about top-up actions. However, our analysis in Figure 11b is affected. Figure E.3 re-creates Figure 11b under this section's alternative assumption about top-up actions. Figure E.3 documents social welfare losses from adverse selection, but markets for tree planting and maintenance contracts no longer unravel. This occurs because the social value from $B^j(\mathbf{z}_i^s)$ is generated regardless of additionality, propping up the market. While we think that our baseline assumption likely holds, this exercise is informative of an alternative lever for market design. Offset markets can bundle additional benefits (often termed "co-benefits") into the contract that are unaffected by additionality. These benefits not only provide additional social value, but can also prevent market unravelling due to adverse selection.