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, targeting incentives to participants whose conservation actions are marginal to the program, referred to as "additional" participants, is complicated by asymmetric information. We investigate this market design challenge in the world's largest auction mechanism for ecosystem services, the Conservation Reserve Program, with a dataset linking auction bids and 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 bidding and land use to quantify the implications of this market failure for the performance and design of environmental procurement mechanisms and competitive offset markets. Both status quo and standard cost-minimizing mechanisms underperform implementable alternatives that treat landowners asymmetrically by the incentive's expected impact on conservation. Because they are less additional, the lowest cost providers of environmental services are not always the highest social value.

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1 Introduction

Land-use change contributes 9% of global greenhouse gas emissions (Le Quéré et al., 2015) 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 largely failed to meet this potential (Anderson, 2012; Filewod, 2017; Maron et al., 2016). A leading rationale 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., 2020).

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?[2] 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 market incentives from reflecting heterogeneity in landowner additionality, market mechanisms may not achieve allocative efficiency and in the extreme, can fail completely (Akerlof, 1970; Manelli and Vincent, 1995). 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.[3] The CRP incentivizes agricultural land retirement and conservation activities via procurement auctions of conservation contracts.

[1] In offset markets, private buyers purchase contracts that "offset" any environmental degradation acre-for-acre, ton-for-ton, or dollar-for-dollar. Markets for offsets have emerged across a range of settings, due to direct implementation from regulators (wetlands and air pollution), to allow for gains from trade between regulated and unregulated industries (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 exploding volume of voluntary net-zero commitments among firms (McKinsey Sustainability, 2021, 2022). See Salzman et al. (2018) for an overview of the scale and growth of Payments for Ecosystems Services.

[2] See Griscom et al. (2017) for a discussion of the benefits of land stewardship to address climate change and other environmental harms.

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

These contracts pay landowners nearly $2 billion per year to take cropland out of production and plant grass mixes, trees, or establish habitats for a duration of ten years. Combining administrative data and high-resolution satellite imagery, we construct a dataset that links landowners' bids to their eventual 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 welfare under current and alternative market designs. Moreover, the insights gained from this setting are broadly applicable: CRP contracts are structured similarly to other PES programs,[4] to contracts traded in global offset markets (Engel et al., 2008), and to private competitive agricultural offset markets in the US (Stubbs et al., 2021).

We first develop a stylized welfare framework that builds on the widely-used graphical analysis in Einav et al. (2010). Landowners differ in both their cost of contracting and their conservation absent a CRP contract. The social value of contracting depends on each landowner's additionality — the impact of the incentive on her conservation — but her choices depend only on her costs and the market incentive. Markets designed to impact conservation are complicated by this divergence, which can lead to allocative inefficiency and, when a landowner's cost of contracting is low because she expects to conserve in the absence of a CRP contract, adverse selection.[5] In procurement, adverse selection can limit the implementability of efficient allocations and undermine the performance of standard mechanisms (Myerson, 1981; Manelli and Vincent, 1995; Lopomo et al., 2023). In competitive offset markets, adverse selection can limit trade when buyers of contracts take expectations over the additionality of *all* market participants, not only those contracting at the margin (Akerlof, 1970). These challenges can be remedied if markets are designed — via differentiated incentives or the design of the menu of contracts — to close the gap between socially-optimal choices and the choices made in the market.

Our stylized framework also provides guidance for empirical analysis. Social welfare under current and counterfactual market designs depends on the distribution of contracting costs and the relationship between costs and additionality. Contracting costs and additionality may be linked by expectations of low payoffs from cropping land. However, landowners may have only limited foresight over long-term (10-year) contracts and must pay additional hassle costs in realistic settings (Jack and Jayachandran, 2019). The extent of additionality, the existence of adverse selection in the market, and together, their quantitative implications

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

[5] Following Milgrom (1987), we use the terminology adverse selection without requiring that it is formally modeled as a landowner's hidden *information*, i.e. her information about her future costs of conserving (versus her conservation action). See Einav et al. (2013) for a discussion.

for the performance and design of markets for environmental conservation are empirical questions.

We begin by examining the extent of additionality. Credible estimates of 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 acceptance. Landowners substitute away from agriculture to natural vegetation and grasslands upon contracting, as incentivized by the CRP. However, only one quarter of landowners are additional, which we calculate by comparing our estimated regression discontinuity treatment effect to the magnitude of land contracting at the margin. In other words, three quarters of landowners would have conserved in the absence of the incentive. Additionality concerns are quantitatively important in this setting but are not incorporated into the design of the status quo mechanism (Claassen et al., 2018).

To test for asymmetric information about additionality, we relate heterogeneity in additionality to 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 our most restrictive auction). We examine the relationship between landowner-specific additionality and landowner-specific 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 relationship between additionality and bids, indicating the presence of adverse selection in the market. This relationship is in part mediated by landowners' choice of contract — the auction mechanism is multi-dimensional and involves a choice among a menu of contracts — and in part by observable characteristics such as soil productivity estimates. These patterns present opportunities for improvements to market design, but bids remains predictive of additionality — capturing residual private information — even conditional on a rich set of observable characteristics.

To quantify the welfare implications of these facts 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 optimal bidding, then, we estimate additionality by matching the patterns of land use in the first half of the paper. In the CRP auction, landowners submit multi-dimensional bids across heterogeneous contracts, which are ranked by a scoring rule. This provides a rich environment for market design, as both the menu of contracts and observable predictors can be 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 discrete contract features and a non-linear scoring rule. In the second part, we model additionality and the potential for adverse selection with a conditional expectation function that relates land use to both observed characteristics and unobserved landowner costs. This conditional expectation is the model primitive that captures heterogeneity in the social benefits of contracting across landowners and the possibility of inefficient or adverse selection.

We estimate our model in three steps. The first two steps adapt standard procedures in 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 and its dependence on unobserved landowner costs by matching the levels of additionality and the relationship between additionality, observable 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 implied by the scoring rule.

We first examine allocative efficiency and pricing in the context of our simple welfare framework with a uniform instrument and a single contract. Although adverse selection limits trade and reduces social welfare, it will not unravel the market for the base contract of land retirement. We find substantial welfare gains under the socially-optimal uniform incentive (\$14.66 per acre-year) and in a stylized competitive offset market (\$14.11 per acre-year). The divergence between these two market structures (-4%) reflects the trade-limiting effects (-15% relative to the efficient quantity) of adverse selection in competitive markets (Akerlof, 1970). This simple analysis illustrates a primary conclusion of our quantitative economic framework: despite (i) landowners who are not additional and (ii) the adverse selection this introduces, we find that the market *can* succeed.

However, our results also highlight challenges to implementation and opportunities for improvements to market design. First, realizing these social welfare gains requires calculating the socially-optimal incentive, which depends on estimates of the population distribution of contracting costs and additionality across this distribution. Mis-pricing that ignores counterfactual conservation can erode almost all (80%) of the social welfare gains of the market. Second, conclusions are heterogeneous across contract types: in tree-planting and maintenance contracts, the (one-dimensional) efficient allocation cannot be implemented with any incentive and the market unravels. Finally, we document heterogeneity in socially-optimal incentives across landowners by estimates of soil productivity, a feature that is not incorporated in the status quo scoring rule.

Motivated by this analysis, we design and evaluate alternative auctions that extend standard cost-minimizing mechanisms to incorporate the auctioned contract's expected impact on conservation (additionality). Our estimates imply that the status quo scoring auction realizes only 15% of the social welfare gains from an efficient benchmark that allocates contracts based on both costs and additionality. However, implementing this allocation with an incentive compatible mechanism is not possible; because they are less additional, lower cost landowners are not always higher social value (Myerson, 1981). We instead design alternative auctions that adjust the scoring rule, setting incentives across contracts and asymmetry across bidders — using immutable characteristics already collected by the USDA — based on predictions of additionality. These simple modifications to the existing scoring rule close the gap between the status quo and efficient allocation by 41%, while switching from the status quo (inefficient) auction mechanism to an (absent the complication of additionality, efficient) Vickrey-Clarke-Groves mechanism that remains naive to additionality slightly widens it.

We conclude with the implications of our estimates of supply-side adverse selection for competitive offset market design.[6] Competitive markets introduce distinct welfare considerations: a differentiated market may or may not be more efficient than a uniform one. We find that contract differentiation based on readily available covariates would increase welfare in a stylized competitive offset market by 15%, reducing both inefficient selection and inefficiently-limited trade due to adverse selection. Next, we consider which contracts could be successfully traded. We find that only markets for tree planting and maintenance unravel, while social welfare losses from adverse selection in other markets — grasses, habitats — are limited to at most 3%, even with uniform pricing.

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 climate change mitigation. 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, social welfare, and the success of the market.

Related Literature Our primary contribution is to develop an empirical framework to evaluate welfare under current and counterfactual environmental market designs that address

[6]This is not merely a hypothetical scenario: the Growing Climate Solutions Act of 2021 included provisions for the creation of a USDA-regulated agricultural offset market, in which CRP-style contracts would be traded in a competitive market.

the issue of additionality. In doing so, we also provide credible estimates of additionality and evidence of adverse selection in a large-scale, mature market. We build on a literature estimating treatment effects of payments for ecosystem services, a line of inquiry motivated by the possibility of participants who not additional (Jack, 2013; Alix-Garcia et al., 2015; Jayachandran et al., 2017; West et al., 2020; Calel et al., 2021; Rosenberg et al., 2022). Our focus on asymmetric information also builds on theoretical analyses of (Bushnell, 2011; 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) in environmental incentive programs and offset markets.

Though our application is about additionality and conservation incentives, our framework relates broadly to the design of other environmental incentive programs (Boomhower and Davis, 2014; Borenstein and Davis, 2016; Allcott and Greenstone, 2017; Ito et al., 2021) and complements work studying other sources of inefficiency in markets for environmental conservation (Aronoff and Rafey, 2022). Beyond environmental markets, our approach to auctions in this paper relates to a literature evaluating counterfactual market designs considering treatment effects, not only revealed-preference measures of participant welfare (Agarwal et al., 2020; Kapor et al., 2022; Barahona et al., 2023).

Our theoretical framework relates to a large literature studying asymmetric information in insurance markets (Akerlof, 1970; Chiappori and Salanie, 2000; Einav et al., 2010; Bundorf et al., 2012; Marone and Sabety, 2022) and a literature on adverse selection in procurement auctions (Manelli and Vincent, 1995; Lopomo et al., 2023; Carril et al., 2022).

Methodologically, our model and estimation strategy draws on 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 extend existing work on scoring and other multi-dimensional[7] auctions (Che, 1993; Asker and Cantillon, 2008, 2010; Hanazono et al., 2020; Kong et al., 2022; Bolotnyy and Vasserman, 2023; Allen et al., 2023) to incorporate discrete bidding, a non-linear scoring rule, and adverse selection captured by a correlation between additionality and bidder costs.

[7]Our model includes multi-dimensional private costs; though not our focus, we therefore also relate to empirical work that has addressed the paucity of theoretical results on multidimensional screening (Rochet and Stole, 2003) with empirical evaluations of alternative auction formats, e.g. Kong et al. (2022).

2 Theoretical Framework

We begin with a simple framework to formalize the welfare effects of additionality in markets for environmental services.

2.1 Model

We consider a population of landowners, indexed by i, each making a decision to contract, $x_i \in \{0, 1\}$, to obtain a transfer, p. 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 and $a_i = 0$ denotes cropping. The action $a_i = 1$ generates social value from positive environmental externalities. The buyer of the contract — either a regulator or a private buyer in an offset market — values the benefits from $a_i = 1$ at $B > 0$.

Contract Value We 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 the social value 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 We assume there exists a continuum of landowners; in Section 5 we adapt our framework to an auction with finitely many bidders. 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 could have taken in the absence of the contract.[8] 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).[9] It is therefore ambiguous whether and how c_i and a_{i0} are related.

[8] We define landowners by their action a_{i0}, but the second dimension of θ_i could alternatively be defined by a landowner's cost of conserving. Any results that apply to a hidden information model (where landowners differ in their costs of conserving) would apply to a hidden action model (where landowners differ in a_{i0}) (Milgrom, 1987).

[9] These include complying with mandates to purchase specific seed mixes, paperwork burdens to process payments, audits to manage compliance, and any taste or distaste for participating in an environmental market.

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:

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

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

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

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 on $1 - a_{i0}$, or her additionality. The incentive p will therefore not necessarily incentivize the highest social surplus landowners to contract.

Efficient Prices and Allocations The socially-optimal uniform price p solves:

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

where the density f_C is the marginal of $F(\theta)$ on contracting costs, c_i. The solution to this problem is equivalent to one where a quantity is chosen and an allocation is implemented with an efficient 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.[10] With a uniform price p, all landowners with the same c_i make the same choices to contract.

[10] See Einav et al. (2010) and Lopomo et al. (2023) for discussions of the use of these sufficient statistics for the welfare analysis of adverse selection in competitive insurance markets and auctions, respectively.

Contracting with landowner i will therefore be efficient[11] if and only if:

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

Our interest in this stylized framework is in when a uniform price 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 by adapting the graphical framework of Einav et al. (2010). Figures 1a and 1b plot two markets defined by different population distributions $F(\theta)$ summarized by f_C and $\tau(c)$. The first curve is the inverse distribution function of contracting costs, $F_C^{-1}(q)$, or the *marginal cost curve* (MC), where 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*.[12] The contract value curve lies weakly below B, the social value of $a_i = 1$, reflecting the possibility that $a_{i0} = 1$ for some landowners who conserve in the absence of the contract. Each panel in Figure 1 displays an upwards-sloping contract value curve ($\tau'(c) > 0$), reflecting the possibility that expectations over a_{i0} may influence c_i, or that landowners who expect to conserve in the absence of the contract may face a low cost of accepting a contract to conserve. This captures the potential for adverse selection in the market,[13] though we emphasize that this is for illustration: the function $\tau(c)$ and $F_C^{-1}(q)$ are to be estimated.

The vertical distance between the contract value and marginal cost curves equals $B \cdot \tau(c_i) - c_i$. Because it is efficient to contract with all landowners for whom the inequality in (5) holds, regions where the contract value curve lies above the marginal cost curve represent social welfare gains, while the opposite represent social welfare losses.

In Figure 1a, the efficient allocation can be implemented by setting 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

[11] With additional instruments to differentiate landowners (observable characteristics, heterogeneous contracts), equation (5) is no longer the relevant efficiency criterion. Allowing for this will be a primary focus of our empirical framework. An alternative interpretation is that all observable characteristics available for pricing have already been conditioned on, and that f_C and $\tau(c)$ describe a given sub-population.

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

[13] Some may claim that using "adverse selection" is a slight abuse of terminology, as selection in the market is based on expectations about an action, a_{i0}. This is an example of "selection on slopes" or "selection on moral hazard" in the terminology of Einav et al. (2013).

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, including in our empirical setting of the CRP (Claassen et al., 2018), setting $p = B$ leads to social welfare losses denoted by triangle EFG.

Figure 1b illustrates a market with a different landowner type distribution in which the efficient allocation *cannot* be implemented. In Figure 1b, the contract value curve lies below the marginal cost curve at the bottom of the distribution, reflecting low additionality at low, but still positive, levels of contracting costs. In this region, landowners with low costs still have *some* positive option value of cropping and/or pay hassle costs, but ultimately have a high likelihood of conserving in the absence of the contract ($a_{i0} = 1$). In this market, a regulator cannot implement the efficient allocation (triangle EFG) with any price, as any price 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 example market in Figure 1b, the 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 choices, which depend on prices and contracting costs, but social surplus depends on the impact of contracting on a_i.[14] Unlike in standard markets, the relationship between social surplus and landowner costs need not be not monotonically decreasing. Because $B \cdot \tau(c_i) - c_i$ — the vertical distance between the contract value and marginal cost curves — crosses zero *from below* in Figure 1b, no mechanism can implement the efficient allocation (triangle EFG) (Myerson, 1981; Manelli and Vincent, 1995; Lopomo et al., 2023).[15]

If contracts are traded in competitive markets — as in offset markets, or more broadly any market for environmental services with price-taking buyers — adverse selection can prevent a competitive equilibrium price from implementing an efficient allocation (Akerlof, 1970). Buyers in the market take expectations over the additionality of *all* market participants, not only those contracting at the margin, and we define a uniform competitive market price p^c by the equilibrium condition: $p^c = \mathbb{E}[B \cdot \tau(c_i) \mid c_i \leq p^c]$.[16] In Figure 1c, we add the curve defined by $\mathbb{E}[B \cdot \tau(c_i) \mid c_i \leq p]$ at each point $p = F_C^{-1}(q)$ to the population of landowners

[14] This is similar to the "backwards-sorting" in insurance markets discussed in Bundorf et al. (2012) and Marone and Sabety (2022).

[15] Despite the fact that social surplus is negative for landowners with low values of contracting costs, satisfying landowners' incentive compatibility constraints requires that these landowners face a weakly higher allocation probability than the landowners with high contracting costs and positive social surplus from contracting.

[16] We thus focus on the potential for supply-side adverse selection as the principal driver of social welfare losses in offset markets. Additional considerations to determine the equilibrium of these markets are necessary

illustrated in Figure 1a.[17] Its intersection with the marginal cost curve defines the competitive market equilibrium, which differs from the socially-optimal price at the intersection of the marginal cost and contract value curves. In the presence of adverse selection, trade in competitive (offset) markets will be limited and regions of efficient contracting, with social welfare gains represented in triangle EFG, will not be realized.

Empirical Questions Figure 1 illustrates that the welfare implications of additionality depend on f_C and $\tau(c)$: these will be our empirical objects of interest. But this stylized model was limited in its tools. Our empirical analysis will include a richer set of contracts and observable characteristics to differentiate landowners by their additionality. We can then investigate not only the possibility of *social welfare losses* when market incentives do not implement the efficient allocation, but the potential for *social welfare gains* from alternative market designs.

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 just under two billion dollars per year to retire highly erodible and other environmentally sensitive cropland and adopt additional conservation activities for a contract duration of 10 years. The CRP is one of the largest and most mature PES schemes in the world, and is a major source of expenditures on environmental policy in the United States.[18] Moreover, the structure of the CRP and its incentivized activities are similar to

if buyer valuations of the contracted action diverge from B or if buyers have only limited information about the distribution of $F(\theta)$. We assume that the only difference between the regulator and private buyers is whether they are solving the problem in equation (4) (the regulator) or choosing to purchase a contract based on whether $\mathbb{E}\left[B \cdot \tau(c_i) \mid c_i \leq p\right] \geq p$ (competitive markets). Investigating demand for contracts in rapidly growing offset markets is outside the scope of this paper but is an exciting avenue for future research.

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

[18] By comparison, the Superfund program and Weatherization Assistance Programs have annual budgets of $1.2 billion and $400 million, respectively. More broadly, more is spent on conservation incentive programs at the USDA ($12 billion, annually) than the entire Environmental Protection Agency (EPA) budget or on all environmental programs at the Department of Energy (both $8-$9 billion).

other government financed PES schemes,[19] to offset contracts traded in voluntary markets,[20] and most specifically, to a burgeoning private agricultural offset market in the US.[21] There is substantial policy interest in growing this market. The Growing Climate Solutions Act of 2021 included provisions for the creation of a USDA-regulated agricultural offset market, in which CRP-style contracts would be traded by private actors.[22]

Unlike the simple pricing mechanism presented 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.[23] 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 level of environmental sensitivity — based on erodibility, importance for habitats, potential for water and air pollution, and carbon sequestration potential — of their land, for the specific contract that they choose, and for a bid rental rate that they would be willing to accept for the contract. Rental rates are subject to a bid cap (the Soil Rental Rate) based on the average land rental rate in the county and soil productivity estimates. Appendix A describes the scoring rule in more detail.

The aggregate acreage enrolled in an auction 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.[24] The uncertain acreage threshold, in combination with with uncertainty over opposing bidders' scores, makes the threshold score ex-ante uncertain to bidders. Bids are prepared with the assistance of staff at Farm Services Agency county offices, who helps landowners understand the win probabilities with different

[19]China's Sloping Land Conversion Program and the U.K.'s Environmental Stewardship Program are notable examples. See Kinzig et al. (2011) and Salzman et al. (2018) for overviews.

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

[21]As of 2021, at least 10 companies had established platforms for the trade of agricultural offset contracts. See Stubbs et al. (2021) for an overview of the market.

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

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

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

contract and rental rate combinations.

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.[25] 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.[26]

Research quantifying the value of the CRP has documented improvements in wildlife habitat, erosion control, water quality, and carbon sequestration from cropland retirement (Allen and Vandever, 2012; Hansen, 2007; Hellerstein, 2017; FAPRI-MU, 2007; Johnson et al., 2016). However, these analyses are typically conducted using models that ignore counterfactual land use. In research, policy, cost-benefit analyses of the CRP, and the construction of the scoring rule, it is assumed that all 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 in the absence of the CRP ($a_{i0} = 1$) presents the additionality concern in this setting.

3.2 Data

The key feature of our dataset is that we link bids to a panel of landowners' land use.

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 eight auctions that occurred from 2009 to 2021. We also obtain data on all CRP contracts.

Each landowner owns a collection of fields, delineated by Common Land Units, defined as the smallest geographic 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).

[25] 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.

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

Data on Land Use We link bidders, and for the purposes of comparison, agricultural non-bidders, to a panel of land use outcomes. The primary land use outcome of interest is whether land is cropped versus retired, as this is the behavior incentivized by the CRP. We use both remote-sensing and administrative datasets to measure this behavior due to their complementary strengths. The remote-sensing product is accurate and available for all fields, but is potentially subject to non-classical measurement error, whereas the administrative data is self-reported for only a subset of fields, but is not subject to the same measurement error.

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, including over 50 crop and 20 non-crop 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).[27] 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), discussed in more detail in Appendix B.

Our second land use dataset is field-level administrative data on land use that all agricultural landowners report to the USDA in "Form 578" for 2013-2019. These data are highly accurate and comprehensive for cropped land because crop insurance payouts are dependent on these reports, but have two limitations. First, landowners with CRP contracts are mechanically coded as non-cropped, forcing us to assume, rather than test, a compliance regime, and second, landowners only report land use if fields are insured by crop insurance.

Our final land-use dataset is an un-processed collection of high-resolution satellite imagery (0.6m to 1m) of contracted land collected under the National Agriculture Imagery Program (NAIP) from 2017-2021. We use these to observe and confirm compliance with CRP rules (see Appendix B for more details).

While highly accurate in assessing agricultural land use and retirement — the main incentivized activity of the CRP — these datasets cannot convincingly differentiate among the different "top-up" actions that differentiate 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 cropping versus retiring land.

[27] The measurement of cropland in the Cropland Data Layer has both 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)

Summary Statistics Table 1 presents summary statistics. Columns (1)-(2) present summary statistics for all agricultural landowners in the US, which includes both CRP-eligible and ineligible landowners. Columns (3)-(4) summarize all land owned by the bidders in our sample and columns (5)-(6) summarize the specific bid fields.

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

CRP-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 in our sample offers 84.1 acres into the CRP mechanism (33% of a bidder's land) for a rental rate per acre per year of $83. Almost two-thirds of bidders bid on a contract that includes a grassland-planting action, 20% choose a wildlife habitat action, and 10% choose a tree-planting action. 70% of bidders are re-enrolling after their initial 10-year contract expired.[29] 80% of bidders are awarded contracts across the auctions in our sample, with the average auction including 36,763 bidders.

4 Evidence on 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.

4.1 Regression Discontinuity Estimates of Additionality

Estimates of additionality are key inputs into the evaluation and design of markets for environmental services, but require a credible empirical strategy to estimate the impact of

[28] In columns (1)-(2), we weight landowner-years to match the distribution of years prior to bidding among bidding landowners (in columns (3)-(4)).

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

the market incentive on conservation. We exploit the sharp discontinuity in CRP contract awards at the winning score threshold, $\underline{S}$, to evaluate the treatment effect of a CRP contract in a regression discontinuity (RD) design.

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

Our main specification takes advantage of the panel nature of our dataset and estimates the following equation, 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 $r(i,t) = t - t_{g(i)}$ normalizes the time dimension to the year relative to each landowner i's auction ($t_{g(i)}$), so $\beta_{r(i,t)}$ describes time-varying RD coefficients around the index auction date. $f_{r(i,t)}(S_{ig} - \underline{S_g})$ are relative-year-specific local-linear regressions in the MSE-optimal bandwidth (Calonico et al., 2014) allowed to differ on either side of the discontinuity. We also estimate and provide corresponding RD figures for the following pooled specification:

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

When estimated when $r(i,t) \leq 0$, equation (7) provides a test of validity, as there should be no discontinuity ($\beta = 0$), and when estimated on $r(i,t) > 0$, β provides an estimate of the pooled treatment effect at the margin of contract awards.

We estimate equations (6) and (7) at the bidder level. This allows for the possibility of spillovers across bid and non-bid fields. We cluster standard errors at the bidder level.

Validity The validity of the RD design hinges on uncertainty in the ex-post location of the winning score threshold. While bidders may possess information ex-ante about the possible realizations of this threshold, which they use to construct their bids, we assume that bidders do not know the threshold's precise ex-post location and optimally bid just above it. Testing this assumption translates to standard smoothness and manipulation tests for RD analyses (McCrary, 2008). 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 threshold. In Figure 2b, we also show a lack of differential land use at the discontinuity before the auction, where we plot the raw data and fit parameters from equation (7) restricted to only $r(i,t) \leq 0$.

The second assumption necessary for interpretation of equations (6) and (7) is that that being above the score threshold is highly predictive of receiving a CRP contract, relative to being below the score threshold, i.e. we require an estimate of the magnitude of the first stage. Figure 2c plots the share of bidders with a CRP contract after the auction around the award threshold, estimating equation (7) for $r(i,t) > 0$, and demonstrates a first stage close to one. Based on Figure 2c, we will interpret the RD coefficients in equations (6) and (7) as reflecting the impact of receiving a CRP contract.

Results Figure 3a presents raw data and fit parameters corresponding to the treatment effect of a CRP contract, estimating equation (7) for $r(i,t) > 0$. As the CRP's primary goal is to incentivize agricultural land retirement, our outcome of interest is the share of each bidder's land that is cropped. The discontinuity in land use outcomes — winning fields crop 8% less of their land — rejects the null hypothesis of no treatment effect of the program ($\tau = 0$) for bidders at the $S_{ig} = \underline{S_g}$ margin. 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 outcomes are not zero for winners, who typically only contract on a subset of their land. These treatment effects reject the most pessimistic views of environmental markets: that no participants' behaviors are marginal to the incentive.

We estimate our main time-varying RD specification in equation (6) and present coefficient estimates in Figure 4. Figure 4 contains estimates 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. We also include on the graph a full additionality ($\tau = 1$) benchmark for bidders at the $S_{ig} = \underline{S_g}$ margin. This is calculated as the share of each marginal bidder's land that enters into a CRP contract. If contracting induced 100% of bidders to change land use — the definition of a full additionality benchmark — we would observe treatment effects equivalent to the $\tau = 1$ line on Figure 4. Dashed lines represent pooled post-period estimates.

Four facts emerge from the estimates presented in Figure 4. First, in line with the pre-period placebo test in Figure 2b, we see no effects at the discontinuity before the auction. Because Figure 4 is a year-by-year RD, pre-period effects are identified in levels and in trends and are zero in both. Second, encouragingly, post-period effect sizes and time-trends are similar using both datasets, confirming that our results are not driven by either non-classical measurement error in the remote sensing data or misreporting in the administrative data. Third, while treatment effects grow in the first couple of years, indicating land in transition, effects are constant over the ten year contract period, reflecting the fact that opportunities to rebid — which would cause treatment effects to decrease over time — are not driving down average treatment effects.[30]

Finally, our main result from 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 $\tau = 1$ full additionality benchmark. Figure 4 demonstrates that approximately one in four bidders is additional. Conversely, three of four bidders conserve even absent the CRP and do not generate any incremental value from land retirement upon contracting. Figure 4 thus provides evidence on the relevance of the additionality challenge in this landmark PES program.

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 acceptance between 21% and 31%, with a mean and median effect size of 26%. We also present estimates on other land use outcomes (Panel B).[31]

Discussion Our estimates of additionality at the margin provide information about the distribution of types $F(\theta)$, summarized by the (example) curves in Figure 1. First, the contract value curve $B \cdot \tau$ lies substantially below B. Second, a more subtle implication of our estimates is the need to accommodate a flexible relationship between contracting costs and additionality to capture the shape of the function $\tau(c)$. If alternatively, contracting costs and additionality could be summarized by a single index, in which bidders with positive values of contracting costs are additional and bidders with contracting costs equal to zero are not, then at the margin, additionality should be either zero or one. Our RD results — which analyze additionality at the margin — reject both of these hypotheses.[32]

[30]We see little evidence of substantial rebidding at all: Appendix Figure C.4 plots the hazard rate of rebidding following a failed initial bid: even five years following the initial bid, after which bidders have had multiple opportunities to rebid, only approximately 20% of losers have rebid and fewer than 15% have won. This is consistent with both the large magnitude of the first stage presented in Figure 2c and the institutions of the setting. The CRP is so mature that if anything, the General Enrollment mechanism is shrinking over time (acreage contracted in the later auctions is substantially lower than acreage contracted in earlier auctions in our sample).

[31]Appendix Figures C.2 and C.3 present additional corresponding RD figures.

[32]This interpretation is slightly complicated by bidder characteristics (asymmetry) and additional action choices that shift the score, and because we pooled sign-ups with different thresholds. In Appendix Table

Mechanisms: Testing Spillovers and Non-Compliance We argue that our estimates are driven by heterogeneous land use absent the contract (a_{i0}) specifically on the land bid into the mechanism. In Panel C of Table 2 (and Appendix Figure C.1), we document the absence of any positive or negative spillovers onto non-bid fields among bidding landowners. This could occur either via a leakage mechanism, by which landowners reduce cropping on bid fields but increase it on other fields, or if there are complementarities to cropping multiple fields. We see no evidence of either of these hypotheses.[33]

In theory, the lack of additionality could be driven by both conservation without a CRP contract ($a_{i0} = 1$, as in our stylized model in Section 2) and cropping with a CRP contract (non-compliance). We assess the CRP's compliance regime by systematically inspecting ultra-high resolution (0.6-1m) aerial photographs of over 1,000 enrolled fields.[34] As described in more detail in Appendix B, we find no evidence of non-compliance.

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

4.2 Testing for Asymmetric Information

In this sub-section, we investigate whether there exists heterogeneity in additionality and asymmetric information about it.

Empirical strategy We observe both a landowner specific measure of $1 - a_{i0}$ and a landowner-specific bid — a function of the costs of contracting — among all rejected bidders. We use these two observations to conduct a test for asymmetric information in the spirit of

C.1, we presents RD estimates split by the location of the threshold — parameterized by the amount a bidder would need to bid for the base contract to achieve $\underline{S}$ — and finds that $0 < \tau < 1$ across groups.

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

[34]We chose to use aerial photographs instead of either the processed satellite imagery or the administrative data because any measurement error in the remote sensing product will mechanically bias toward finding non-compliance and the administrative data will never record non-compliance, as landowners would never report rule-breaking. We hired two MIT undergraduate research assistants to blindly classify high resolution images of both CRP fields and a set of non-CRP (cropped) fields.

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 $1 - a_{i0}$ denotes i's ex-post realization of additionality, measured as the share of i's bid fields that are cropped, observed only for 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 characteristics that may be predictive of additionality. Our main empirical exercise will estimate equation (8), turning on and off various components, but always including controls for the scoring rule, which impacts the strategic environment facing bidders. A positive correlation between bids and $1 - a_{i0}$ is indicative of asymmetric information. We estimate equation (8) in the one auction in which we observe the delineations of the bid fields (the 2016 auction), which is required to construct $1 - a_{i0}$. This auction is also the most restrictive auction in our sample: $1 - a_{i0}$ is unmasked for the vast majority of bidders (82%).[35]

Results Figure 5a presents a binned scatterplot of the correlation between additionality and the dollar amount bid per acre per year, residualized of $h\left(\mathbf{z_i^s}\right)$. Figure 5a demonstrates substantial heterogeneity in additionality and a systematic positive relationship between higher bids — reflective of 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 information that they would be likely to conserve even without a CRP contract. In other words, the results in Figure 5a provide evidence of asymmetric information and adverse selection. Figure 5b takes the analysis one step further and shows that bids remain correlated with additionality even conditional on information that *could be*, but is not currently, incorporated in the mechanism, namely prior land use decisions interacted with estimates of the soil productivity of the bidders' land.

Figure 5c uses the fact that bidders bid on a menu of contracts, each with a different conservation action. Figure 5c tests for heterogeneity in additionality across chosen contract features by replacing $\mathbf{b_i}$ with a vector of contract indicators. The most striking feature of Figure 5c is the strong evidence of adverse selection on tree-related contracts, relative to the base category of introduced grasses. The patterns in Figure 5c highlight that contract

[35] We will address the issue that we are measuring these relationships in the selected sample of rejected bidders with our structural model in Section 5.

choices reveal information about additionality. Figure 5c also illustrates that markets for tree-related contracts may be much more adversely selected than others.

Finally, Figure 5d turns to heterogeneity that can be captured by observable characteristics. Figure 5d plots the relative additionality by decile of predicted soil productivity, conditional on $h\left(\mathbf{z_i^s}\right)$ but excluding any endogenous bid choices from the regression specification. These estimates of soil productivity are collected by the USDA and are designed to approximate the amount that a landowner would be able to earn on a given parcel of land. These characteristics serve as ideal predictors of additionality in theory, and indeed this characteristic is strongly predictive of additionality in practice. Figure 5d highlights the potential to differentiate landowners using this predictive 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, 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 the potential for improvements to market design.

5 Empirical Model of Bidding and Additionality

The goal of our empirical model is to estimate (i) the population distribution of contracting costs across a menu of contracts, and (ii) the conditional expectation of additionality as a function of contracting costs and observable characteristics. Together with estimates of the social value of contracted activities, which we take from the CRP literature, these estimands will allow us to calculate landowner choices, additionality, and welfare under current and alternative market designs.

Our model extends the multi-dimensional bidding models of Asker and Cantillon (2008) and Che (1993). Landowners are characterized by a multi-dimensional private cost 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' multi-dimensional contracting costs. Our empirical strategy first uses the optimality of bidding in the auction to estimate bidders' vector of contracting costs by revealed preferences and then relates additionality to these contracting costs and landowner characteristics by matching the observed relationship between land use, landowner characteristics, and optimal bids in our linked satellite and bid data.

5.1 Model

Landowners We define N landowners, indexed by i, by (i) their cost of each contract indexed by j, $(c_i, \kappa_\mathbf{i})$ for $\kappa_\mathbf{i} = \{\kappa_{ij}\}$, and (ii) their action a_{i0} in the absence of the CRP. As in Section 2, we define $F(\theta)$ as the joint distribution of landowner types, where now $\theta_i = ((c_i, \kappa_\mathbf{i}), a_{i0})$.

The first component, $(c_i, \kappa_\mathbf{i})$, defines landowner i's cost of contracting, where c_i is the base cost of contracting, common across contracts, and κ_{ij} is the top-up cost associated with contract j. A landowner's willingness to accept a given contract is therefore $c_i + \kappa_{ij}$.

We again define the function:

$$\tau(\mathbf{z_i}, c_i, \kappa) = \mathbb{E}\left[1 - a_{i0} \,|\, \mathbf{z_i}, c_i, \kappa_\mathbf{i}\right], \tag{9}$$

or the expected difference in conservation with versus without the contract, as a function of observable characteristics $\mathbf{z}_i$ and bidder costs $(c_i, \kappa_\mathbf{i})$.

Auction Mechanism and Information The auction mechanism takes in 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 make a single discrete choice of contract, so $\sum_j x_{ij} = 1$. If i wins, $\mathbf{b_i}$ 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, $s(\mathbf{b_i}, \mathbf{z_i^s})$, that takes as arguments the bid $\mathbf{b_i}$ and exogenous characteristics $\mathbf{z_i^s}$, where $\mathbf{z_i^s}$ denotes the subset of observable characteristics that are incorporated into the scoring rule. All landowners above a winning threshold score $\underline{S}$ are awarded a contract.

Landowner i forms expectations about her probability of winning the auction with a given score based on realizations of two distributions. The first is over i's competitors, specifically the joint distribution of the scores, acreages, and number of competing bidders. We assume that i does not observe the number or characteristics of her competitors, consistent with the fact that bidding is decentralized and involves thousands of bidders across dozens of states.

The second source of uncertainty is over the magnitude of the acreage limit determined by Congress in the Farm Bill.[36] We assume that landowners do not condition on their own characteristics when forming these expectations, so all landowners face the same probability of winning at a given score S, which we denote by $G(S) = \Pr\{S \geq \underline{S}\}$.

Payoffs and Optimal Bidding Each landowner i solves:

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

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 at that bid, given her costs $(c_i, \kappa_\mathbf{i})$.

Additionality In the contract period following the auction, landowners make land use decisions. If awarded a contract $a_i = 1$. If not, landowners choose a_{i0}, which is not contractible. At the time of bidding, $\tau(\mathbf{z}_i, c_i, \kappa_\mathbf{i})$ captures the population expectation of $1 - a_{i0}$ given observable characteristics $\mathbf{z_i}$ and contracting costs $(c_i, \kappa_\mathbf{i})$. Rather than model a_{i0} directly, we work with the sufficient statistics of the population distribution of contracting costs and the function $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$ as in Section 2. We therefore treat the conditional expectation function $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$ as a primitive of the model to be estimated.[37]

Remarks Landowners are competing on both price and contract features in equation (10). This captures the fact that quality competition is an important component of the bidding environment,[38] and allows for counterfactuals that design the the menu of contracts via incentives in the scoring rule according to landowners' additionality. An important simplification in equation (10) is that although landowners are competing on multiple dimensions, all strategic considerations are channelled through the one-dimensional choice of score. This builds on the insights of Asker and Cantillon (2008) and Che (1993), separating the bidding problem into an "inner problem" of a single-agent discrete choice and an "outer problem" of a one-dimensional game. Each score induces a menu of payoffs from winning the auction

[36] Appendix Figure D.1 provides empirical support for the assumption of quantity uncertainty: the distributions of submitted scores are essentially identical across sign-ups with large ex-post differences in acreage limits.

[37] This is similar to the empirical approach of Bundorf et al. (2012).

[38] From the EBI Factsheets provided to landowners: "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."

for each contract for each bidder.[39] The resulting discrete choice problem is the bidder's "inner problem." Then, the choice of the optimal score — given the (inner) optimally chosen contract — defines the bidder's "outer problem."

We highlight two simplifications. First, we assume bidding is costless; we do not model a bid preparation cost or selection into bidding.[40] Second, we model bidding as static, reflecting the institutional feature that the CRP is so mature that it is actually, if anything, in decline, limiting the option value to rebid, and reflected in the fact that the vast majority of bidders do not re-bid upon losing (see Figure C.4). However, in a dynamic framework, the cost parameters estimated from the formulation in 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). Even in the presence of sequential auctions, counterfactuals that (i) do not condition on dynamic actions, e.g. prior land use, and (ii) hold the design of future auctions fixed will not be biased by our static formulation.

Although the contracting and choice environment is now more complex, the basic market failure introduced by additionality is the same as in the stylized set-up of Section 2. Bidders make choices that depend on the scoring rule $s(\mathbf{b_i}, \mathbf{z_i^s})$ and their costs of contracting, $(c_i, \kappa_\mathbf{i})$. However, the (constrained) efficient allocation of landowners to contracts depends on $\tau(\mathbf{z}_i, c_i, \kappa_\mathbf{i})$.

5.2 Identification and Estimation

Identification Because the CRP auction involves bidding on discrete contracts, we cannot invert bids using bidders' first order conditions to point identify costs as in the approach pioneered by Guerre et al. (2000). We instead obtain inequalities based on optimal bidding and the revealed preferred $\mathbf{b_i^*} = (r_i, \mathbf{x_i})$ contract-bid combinations (the solution to equation (10)) that define identified sets containing the true values of $(c_i, \kappa_\mathbf{i})$ that rationalize the observed bids (Agarwal et al., 2023). We rely on choice shifters that vary the relative returns to contracts to narrow the bounds on these identified sets. In the limit, with sufficient variation in $s(\mathbf{b_i}, \mathbf{z_i^s})$, we can trace out the distribution of $(c_i, \kappa_\mathbf{i})$ conditional on observable characteristics $\mathbf{z_i}$. Appendix Figure D.2 provides a graphical explanation; Agarwal et al. (2023) provides a formal proof.

If the bid space were rich enough to point identify costs with an inversion or — even simpler — if bidders truthfully reported their costs to the mechanism *and* we observed an infinitely

[39] See Appendix Table A.3 for an example of such a menu.

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

restrictive auction, in which bids were collected but all bidders were rejected, $F(\theta)$ would be point identified by inverting bids to obtain costs (or observing them directly) and relating them to a_{i0} measured in the land use data. Our setting differs from this ideal due to both (i) the discrete bid space, which yields only inequalities for $(c_i, \kappa_{\mathbf{i}})$ and (ii) the fact that a_{i0} is masked for the 18% of bidders who are awarded a CRP contract. Identification of the function $\tau(\mathbf{z_i}, c_i, \kappa_{\mathbf{i}})$ uses the fact that we observe the joint distribution of $1 - a_{i0}$, exogenous characteristics $\mathbf{z_i}$, and optimal bids $\mathbf{b_i^*} = (r_i, \mathbf{x_i})$ *and* instruments that shift both the relative returns to contracts and the probability of winning (and being observed in our sample). We estimate a conditional expectation function that rationalizes this joint distribution observed in the data (analyzed in Section 4). With full support, the choice and level shifters in the scoring rule (our instruments) replicate our "ideal experiment." To take our model to the data, however, we impose parametric assumptions on the distribution of $(c_i, \kappa_{\mathbf{i}})$ and the function $\tau(\mathbf{z_i}, c_i, \kappa_{\mathbf{i}})$.

Parameterization Due to the discrete contract choice in the bidder's problem, we parameterize (c_i, κ_i) with a characteristics model:

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

c_i and κ_{ij} are drawn from independent normal distributions with means and variances that are allowed to depend on observable characteristics, $\mathbf{z_i}$. κ_{ij} costs are further 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 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 key differences across contracts.[41]

Finally, we parameterize

$$\tau\left(\mathbf{z_i}, c_i, \kappa_{\mathbf{i}}\right) = \pi \cdot \mathbf{z_i} + \beta \cdot c_i + \alpha \cdot \kappa_{\mathbf{i}}. \tag{12}$$

This specification allows $\tau(\mathbf{z_i}, c_i, \kappa_i)$ to depend on observable characteristics, $\mathbf{z_i}$, and unobserved bidder types, c_i and $\kappa_{\mathbf{i}}$, 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 $u_j = u_{j'}$.

[41] 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 detail.

Estimation Our estimation strategy proceeds in three steps and closely follows the identification argument. In the first step, we estimate landowner beliefs about $G(S)$ via simulation. In the second step, we estimate the distribution of contracting costs $(c_i, \kappa_\mathbf{i})$ via optimal bidding (equation (10)) and revealed preferences from observed bids via Maximum Simulated Likelihood. Then, in the third step, we estimate $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$ using both the estimated distribution of $(c_i, \kappa_\mathbf{i})$ and optimal bidding to match (simulated) land-use moments presented in the first half of the paper. 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 markets with selection, typically applied to insurance markets (Bundorf et al., 2012; Tebaldi, 2022).

Step 1: Simulate $G(S)$ First, we estimate the win probability $G(S)$ by simulation following Hortaçsu (2000); Hortaçsu and McAdams (2010). We fit Beta distributions to the number of bidders and acreage limits observed in our data, where we use additional historic data on acreage thresholds and the numbers of bidders for all auctions from 2000 to 2021. Then, we simulate each auction, drawing the numbers of bidders and the acreage thresholds from our fit distributions, and re-sampling from the observed joint distribution of the scores and acreages of bidders within each auction. From this procedure, we obtain auction-specific estimates of $G(S)$. Appendix D provides more detail.

Step 2: Estimate the Distribution of $(c_i, \kappa_\mathbf{i})$ Our next step estimates the distribution of contracting costs, $(c_i, \kappa_\mathbf{i})$ conditional on observable bidder types $\mathbf{z_i}$ using the optimality of observed bids from equation (10).

We classify bidders into 32 categories of observable types that constitute the observable heterogeneity in $\mathbf{z_i}$ that we use to parameterize $(c_i, \kappa_\mathbf{i})$. These types are based on interactions of quartiles of soil productivity, prior CRP status, and prior land use status. These characteristics are predictive of bidder costs and allow us to flexibly capture observable heterogeneity.

We use two sources of variation in the scoring rule that shift the relative returns to contracts for identification. The first is an unusual 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 returns to contracts for the same bidders and same contract period.[42] We also use the fact that bidders in Wildlife

[42]A useful feature of this unusual policy experiment is that we can directly test that landowners are indeed

Priority Zones face different payoffs for actions, both cross-sectionally and over time. We assume that conditional on $\mathbf{z_i}$, whether or not a bidder is in a WPZ does not impact $(c_i, \kappa_\mathbf{i})$. This is justified by the fact that Wildlife Priority Zones are based on state priorities, not characteristics of landowners or their land. Figure D.3 illustrates these sources of variation.

We estimate the distribution of $(c_i, \kappa_\mathbf{i})$ using a Maximum Simulated Likelihood (MSL) estimator, which maximizes the likelihood of each bidder's observed score-contract combination $(\mathbf{b}_\mathbf{i}^*)$. Estimation poses a computational challenge because the combined discrete-continuous bidding problem makes choice sets extremely large without allowing for an inversion as in Guerre et al. (2000). 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 for the bidder's solution to equation (10).[43] 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 to solve each bidders' problem for each simulation draw. We discuss the details of this estimation procedure in more detail in Appendix D.

Step 3: Estimate Additionality $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$ We estimate the parameters in the function $\tau(\mathbf{z_i}, c_i, \kappa)$, (π, β, α), via the Method of Simulated Moments (MSM), where we search for the parameters (π, β, α) that rationalize the level of additionality, the covariance between additionality and observable characteristics $\mathbf{z_i}$, and the relationship between $(c_i, \kappa_\mathbf{i})$ and additionality reflected in the relationship between chosen bids and $1 - a_{i0}$ in Figures 5b and 5c. Specifically, we draw simulations $\left(c_i^k, \kappa_\mathbf{i}^\mathbf{k}\right)$ from our estimated distribution, solve for the optimal $\mathbf{b}_\mathbf{i}^*$ using equation (10), 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 landowners with a given chosen contract. We match model implied moments of $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$ to observed moments of additionality among rejected bidders, measured as $1 - a_{i0}$ in the remote-sensing land use data, as in Section 4.2.

All of the moments that we match in this final step condition on optimal bids being below the score threshold. This feature of our estimator thus accounts for the fact that the relationships in Figure 5 are estimated in a selected sample. The data generating process that governs

competing on discrete contract features. We observe that the *same landowner* changes her optimal action under the new scoring rule, for the same contract period, 8% of the time.

[43] Specifically, we coarsen the observed continuous choice of score into a discrete choice to locate in 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 for more details.

our sample selection is now *known*: it is based on optimal bidding in equation (10) given the distribution of $(c_i, \kappa_{\mathbf{i}})$ estimated in Step 2 .

We rely on variation in the scoring rule $s\left(\mathbf{b_i}, \mathbf{z_i^s}\right)$ that is conditionally independent of a_{i0}. Specifically, we assume that whether a bidder is in a Wildlife Priority Zone (WPZ) or an Air Quality Zone (AQZ) is unrelated to a_{i0}, as they are determined based on state priorities and the sensitivity of wildlife or the importance of air quality, which, especially conditional on the rich set of observable bidder types, $\mathbf{z_i}$, is plausibly unrelated to land use decisions. We include the 32 bidder types that parameterize $(c_i, \kappa_{\mathbf{i}})$ and the remaining components of the scoring rule as observable predictors $\mathbf{z_i}$. We discuss this third estimation step in more detail in Appendix D.

5.3 Parameter Estimates

Estimates of the $(c_i, \kappa_{\mathbf{i}})$ **Distribution** Figures 6a and 6b plot the estimated distributions of c_i and κ_{ij}.[44] A large share of landowners have low values of c_i, below \$50 per acre, per year with a tail of bidders with higher values of 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 types and highlights observable heterogeneity along landowner soil productivity. Relative costs across contracts are generally intuitive. Landowners with higher soil productivity have different mean values of (c_i, κ_i), but it is not the case that bidders differ on a single dimensional level shift: higher soil productivity bidders have higher costs for primary covers, but lower costs for upgrade covers.

Because the $(c_i, \kappa_{\mathbf{i}})$ distribution was estimated from bidding behavior alone, we can examine whether these revealed preference estimates correlate with land use. Figure 6c examines this relationship, which is mediated by observable characteristics $\mathbf{z_i}$ among rejected bidders. We see strong evidence of a positive relationship — higher c_i landowners have higher additionality, which is an encouraging validation of our revealed preference estimates, and indicative that our model is capturing adverse selection in this market (mediated by observables).

Appendix D summarizes the bidding model fit and compares estimated κ_{ij} to external estimates of contract costs from administrative data submitted to the USDA. Our fit is reasonable, especially given our parsimonious parameterization in (11), and model-implied costs are similar in rank and in magnitude to the administrative data.

[44] Appendix Table D.1 presents parameter estimates for select example cells of $\mathbf{z_i}$ and standard errors.

Estimates of Additionality $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$ In Table 4, we present select parameter estimates in $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$. We focus on describing the relationship between additionality and unobserved bidder types $(c_i, \kappa_\mathbf{i})$. The remaining parameters capture the projection of $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$ onto observable characteristics.

Each column of Table 4 presents a different specification of $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$. In columns (1) and (2), we only allow for a relationship between the base cost c_i and additionality, i.e. we impose that $\alpha = 0$. In column (1), we also include observable characteristics from the scoring rule and in column (2) we add the full set of observable bidder types that parameterized $(c_i, \kappa_\mathbf{i})$, which include estimates of soil productivity and prior land use. Consistent with the residual positive relationship between bids and additionality in Figure 5b, the positive coefficients in columns (1) and (2) of Table 4 indicate landowners possess and act upon residual private information about additionality, even conditional on a rich set of observable characteristics. The magnitude of the coefficient presented in Table 4 implies that a one standard deviation increase in c_i would increase additionality by eight percentage points, or 31% of our baseline additionality estimate of 26%. This result captures asymmetric information about additionality in the context of our model.

Columns (3) and (4) allow additionality to also depend on $\kappa_\mathbf{i}$. Column (3) only allows tree-related action costs to impact additionality, reflecting the strong tree-specific adverse selection in Figure 5c. The coefficient on tree-related κ_{ij} is positive and large, while the coefficient on c_i is reduced, but still positive. When we allow for a more flexible relationship between additionality and $\kappa_\mathbf{i}$ in $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$, the residual relationship between costs and additionality loads onto κ_{ij} with the largest coefficient on tree-related contracts.

Our 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

Armed with estimates of the joint distribution of $(c_i, \kappa_\mathbf{i})$ and $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$, the final outstanding ingredient is the social value 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 values 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 the CRP from literature that quantifies the benefits from habitat restoration and reductions in erosion, water and air pollution, and greenhouse gas emissions from CRP actions (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 (Ribaudo et al., 2001). We therefore consider social welfare under valuations $B_j(\mathbf{z_i^s})$ revealed preferred by the USDA. We emphasize that the valuation of these benefits is not the primary focus of our analysis: our interest is in the welfare and market design implications of additionality (our estimates of $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$) which can be calculated for any valuations $B_j(\mathbf{z_i^s})$.

One remaining detail concerns the fact that our measure of additionality is one-dimensional on only the land-retirement margin, but the set of contracts is multi-dimensional. This is due to fundamental data limitations and the substantial simplification that focusing on only this one dimension affords. Our baseline specification calculates contract value as $B_j(\mathbf{z_i^s}) \cdot \tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$, following our stylized set-up in Section 2, and reflecting the fact that the CRP is a land retirement program.[45] See Appendix E for more details on our process of obtaining estimates of $B_j(\mathbf{z_i^s})$.

6 Welfare and Alternative Market Designs

With estimates of both the costs $(c_i, \kappa_\mathbf{i})$ and expected social benefits $B_j(\mathbf{z_i^s}) \cdot \tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$ of contracting, we turn to analyzing the welfare and market design consequences of additionality. Extending our framework in Section 2, define the expected social surplus of contracting with landowner i for contract j as:

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

This efficiency criterion is based on the conditional expectation function $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$ and not the ex-post realization of the action a_{i0}. Because current and counterfactual mechanisms screen only on $(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$, using equation (13) for comparisons of social welfare under current and alternative market designs is without further loss.[46]

[45]We also present an auxiliary set of results under an alternative assumption, where we assume that additionality only affects the base contract and that the incremental value of the top-up actions across the heterogeneous contracts in unaffected by additionality. Specifically, we also conduct analyses under an alternative valuation of contracts equal to $B^0(\mathbf{z_i^s}) \cdot \tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i}) + B^j(\mathbf{z_i^s})$, 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. This could be if, for example, contracting impacted the specific species mix, which we assume the USDA values at $B^j(\mathbf{z_i^s})$, even if it did not impact land retirement.

[46]See Section 2 for more discussion of this point. The one consequence of using equation (13) as our efficiency criterion is that any full information benchmark is full information about $(c_i, \kappa_\mathbf{i})$ not $((c_i, \kappa_\mathbf{i}), a_{i0})$. This is desirable because we do not know the extent of information about a_{i0} available to landowners at the time of contracting.

We first examine allocative efficiency and pricing in the context of our graphical framework: with a uniform incentive and a single contract. In these analyses, we collapse heterogeneity in our estimated distribution to a single dimension of costs of contracting for a single contract and the expected additionality at each point in this distribution, as in Section 2. We then build on our graphical analysis — incorporating heterogeneity across landowners and contracts — to investigate the performance and design of (i) current and counterfactual auctions and (ii) competitive markets for conservation contracts (e.g. agricultural 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 calculate these curves by drawing from our estimated distribution of costs, calculating the minimum cost to landowners of fulfilling the base contract to obtain the MC curve and then calculating the average $B_j\left(\mathbf{z_i^s}\right) \cdot \tau\left(\mathbf{z_i}, c_i, \kappa_\mathbf{i}\right)$ at each quantile of this distribution to obtain the contract value curve. Our two main facts from Section 4 are reflected in Figure 7. The contract value curve lies below B, reflecting landowners who conserve in the absence of the contract (Section 4.1), and is upwards-sloping, consistent with our evidence of adverse selection (Section 4.2). Figure 7 offers three conclusions about the welfare implications of these two facts in the context of our simple framework.

First, the contract value curve crosses the marginal cost curve "from above:" the empirical market described by Figure 7 appears more like Figure 1a than Figure 1b. The socially-optimal uniform price therefore implements the one-dimensional constrained efficient allocation, based on equation (5), or 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 CDE. In other words, 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 $B_j\left(\mathbf{z_i^s}\right)$ across landowners), ignoring counterfactual land use. Pricing at B leads to social welfare losses of \$11.79 per acre-year in triangle EHI, 80% of the gains realized in triangle CDE. These social welfare losses underscore the importance of quantitative analysis of the joint distribution of the costs of contracting and additionality to implement efficient allocations.

Third, we use Figure 7 to highlight the Akerlof (1970) trade-limiting effects of adverse selection in competitive markets for conservation with price-taking buyers (e.g. offset markets). 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. We illustrate this demand curve with the 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 represent social welfare gains from contracting that are not realized in competitive markets. The magnitude of triangle EFG is 4% of the (constrained) efficient allocation (triangle CDG). Though the adverse selection introduced by additionality (i) exists in the market and (ii) limits trade and reduces social welfare, it does not unravel the opportunity for trade.

Overall, Figure 7 presents a relatively optimistic view of markets for environmental services, which contrasts with arguments that the complications introduced by additionality can make establishing these markets a futile endeavor (Anderson, 2012). Figure 7 also illustrates why: the contract value curve is flat at low levels of contracting costs. Among landowners with low costs of contracting, the option value of cropping is small but non-zero, so some landowners are ultimately additional even at the bottom, where heterogeneity in hassle costs drives choices.

Heterogeneity Across Landowners and Contracts We also use our graphical analysis to examine heterogeneity across observable characteristics and contracts. This heterogeneity will serve as a basis for our counterfactual market designs.

Figures 8a and 8b examine heterogeneity by observable characteristics for the base contract, constructed as in Figure 7. Figures 8a and 8b plot separate curves by whether a landowner is in the lowest versus highest quintile of the soil productivity distribution. Both distributions of contracting costs and expected additionality are different across these two populations implying different socially-optimal prices.

Next, we turn to heterogeneity across contracts, focusing on tree contracts due to (i) our evidence that they are particularly adversely selected, and (ii) the prevalence of tree-related PES payments and offset contracts. Figure 8c re-creates Figure 7 for tree contracts, now calculating the marginal cost curve as the minimum cost required to fulfill any tree-related contract and plotting the average $B_j\left(\mathbf{z_i^s}\right) \cdot \tau\left(\mathbf{z_i}, c_i, \kappa_\mathbf{i}\right)$ at each quantile of this distribution. The exercise requires substantial out-of-sample extrapolation, but it illustrates how alternative type distributions across important classes of contracts can generate different conclusions in our setting.

In Figure 8c, the contract value curve crosses the marginal cost curve “from below,” leading to welfare losses at the bottom of the contracting cost distribution. In Figure 8c, even the socially-optimal uniform price cannot implement the one-dimensional constrained efficient allocation (DE). 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) diverges from the ordering of landowners by contracting costs (ordered on the x-axis). 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-style) market for tree contracts to unravel, even absent any demand-side frictions.

6.2 Alternative Auctions

The standard auction design problem focuses on cost-minimizing procurement auctions. However, the goal of payments for ecosystem services mechanisms — as well many other incentive-based public policies — is to also *impact outcomes* (e.g. conservation), not only to allocate contracts, at lowest cost. Standard mechanisms focused on cost-minimization, which consider reports of $(c_i, \kappa_\mathbf{i})$ but not the effect of contracting on conservation captured by $\tau\left(\mathbf{z_i}, c_i, \kappa_\mathbf{i}\right)$, may not advance this goal.

We investigate this possibility and the performance of alternative designs by simulating outcomes under status quo and counterfactual auctions. Figure 9 and Table 5 present results. Figure 9 plots social welfare

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

Table 5 tabulates the bars in Figure 9 and reports additional details, including total government spending, landowner surplus, the value of environmental benefits $\sum_i \sum_j B_j\left(\mathbf{z_i^s}\right) \cdot \tau\left(\mathbf{z_i}, c_i, \kappa_\mathbf{i}\right) \cdot x_{ij}$, 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 The dependence of social welfare on *impacts* — or $\tau\left(\mathbf{z_i}, c_i, \kappa_\mathbf{i}\right)$ — makes the welfare effects of the CRP ambiguous because the status quo auction does not consider additionality in its design. We document social welfare gains of \$126 million per auction (bar (1) of Figure 9). We calculate this by simulating optimal bidding in the mechanism using our estimated distribution of $(c_i, \kappa_\mathbf{i})$ and beliefs about win probabilities $G(S)$.

However, the status quo auction achieves only 15% of the social welfare gains of an efficient allocation. The efficient allocation uses all observables $\mathbf{z_i}$ and the full vector of costs $(c_i, \kappa_\mathbf{i})$ to maximize social welfare (equation (14)) subject to two constraints: (i) each landowner must obtain at most one contract $\sum_j x_{ij} \leq 1$ and (ii) no more landowners are allocated contracts than the status quo. Because many landowners are not additional, the efficient allocation involves contracting with fewer landowners than the status quo (see column (2) of Table 5) and the quantity constraint does not bind.

This allocation may not be implementable in an incentive compatible auction if social surplus and allocations are not monotone in bidder type (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 always 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 practical changes to market design may close the gap. How should the market be re-designed?

A common approach focuses on eligibility requirements that define who and what is allowed in the market. Emphasis is placed on identifying additional, or marginal, participants or actions. Those who fail to meet this minimum standard are excluded from the market, while all others are allowed to trade.[47]

We consider a more flexible approach that differentiates incentives by 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 counterfactually conserve with some positive probability. Minimum standards are accommodated; incentives could be zero for some participants or some conservation actions.

We implement this approach in counterfactual scoring auctions, where we construct scoring rules based on predictions of $B_j\left(\mathbf{z_i^s}\right) \cdot \tau\left(\mathbf{z_i}, c_i, \kappa_\mathbf{i}\right)$. These auctions are also realistic and simple adjustments to the status quo scoring auction (with a score defined only by $B_j\left(\mathbf{z_i^s}\right)$).

We 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

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

linear contract value scoring rules based on (a simplified version of)[48] the functional form of the status quo scoring rule,

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

where $\omega_{\mathbf{z}}$ governs bidder asymmetry across observables $\mathbf{z_i}$ and ω_j governs the incentives across the menu of contracts.

Our counterfactual auctions implement allocations using the status quo and alternative contract value scoring rules with a Vickrey-Clarke-Groves (VCG) mechanism.[49] We term these auctions "Vickrey auctions with scoring." Vickrey auctions with scoring maximize a definition of social welfare implied by the scoring rule $s_j\left(\mathbf{z_i}\right)$:

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

In Vickrey auctions with scoring, bidders are treated asymmetrically by (some) observable characteristics and by contracts j, but not by $\tau\left(\mathbf{z_i},c_i,\kappa_{\mathbf{i}}\right)$. Bidders truthfully report their vector of $(c_i,\kappa_{\mathbf{i}})$, then are ranked by the score $\max_j s_j\left(\mathbf{z_i}\right)-c_i-\kappa_{ij}$, and the highest scoring bidders subject to the auction's quantity threshold are allocated the contract $\arg\max_j s_j\left(\mathbf{z_i}\right)-c_i-\kappa_{ij}$.[50] Unlike standard analyses of scoring auctions (Che, 1993; Asker and Cantillon, 2008), the scoring rule does not capture all heterogeneity in $\tau\left(\mathbf{z_i},c_i,\kappa_{\mathbf{i}}\right)$, which depends on unobservables $(c_i,\kappa_{\mathbf{i}})$ and some characteristics $\mathbf{z_i}$ that cannot be used in the rule (e.g. prior land use that would introduce incentives to game the rule). We evaluate the allocation implemented by the auction using the definition of social welfare in equation (14).

Vickrey auctions with scoring have three advantages. First, they focus attention on the design of the scoring rule. Second, they are computationally simple to calculate. The alternative — keeping the auction format the same as the status quo and computing equilibria in alternative asymmetric, multi-dimensional, discriminatory auctions — would be much more demanding.

[48] We simplify the current scoring rule by (i) eliminating heterogeneity in the value of different contracts by wildlife priority zone, and (ii) eliminating non-linearities (kink-points) in the scoring rule which arise from the fact that bidders are allocated additional points based on their bid relative to their bid cap with kinked incentives.

[49] Many of the well-known undesirable properties of Vickrey-Clarke-Groves mechanisms do not apply in our setting because bidders have substitutes preferences (Ausubel and Milgrom, 2005).

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

$$s_j\left(\mathbf{z_i}\right)+\sum_{i'\neq i}\sum_{j'}\left(s_{j'}\left(\mathbf{z_{i'}}\right)-c_{i'}-\kappa_{i'j'}\right)\cdot x^*_{i'j'}\left(\left(c,\kappa\right)_{i,-i}\right)-\sum_{i'\neq i}\sum_{j'}\left(s_{j'}\left(\mathbf{z_i}\right)-c_{i'}-\kappa_{i'j'}\right)\cdot x^*_{i'j'}\left(\left(c,\kappa\right)_{-i}\right),$$

where $x^*_{ij}\left(\left(c,\kappa\right)_{i,-i}\right)$ denotes the allocation that maximizes $\sum_{i'}\sum_{j'}\left(s_{j'}\left(\mathbf{z_{i'}}\right)-c_{i'}-\kappa_{i'j'}\right)$ given all reports of (c_i,κ_{ij}) and $x^*_{ij}\left(\left(c,\kappa\right)_{-i}\right)$ denotes the allocation that maximizes it without i.

Finally, the market designer needs only to compute $s_j(\mathbf{z_i})$.

Social Welfare Under Current and Alternative Scoring Rules Bars (3) through (6) in Figure 9 adjust the scoring rule $(s_j(\mathbf{z_i}))$ keeping the number of awarded contracts fixed at the status quo quantity. Additional details about the allocation and spending are reported in the corresponding columns (3)-(6) of Table 5.

The third bar in Figure 9 uses the status quo scoring rule, $s_j(\mathbf{z_i}) = B_j(\mathbf{z_i^s})$, but changes the auction mechanism to VCG. Recall that this scoring rule is naive to additionality (Claassen et al., 2018). If all landowners were additional, this auction would implement the efficient allocation and dominate the status quo. Instead, it slightly *underperforms* it. While other design features of the status quo, including bid caps or inefficient incentives across contracts, could lead to social welfare losses, correcting them does increase social welfare. 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 $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$ is not incorporated into the design of the mechanism.

The final three bars in Figure 9 adjust the scoring rule based on predictions of additionality. Bar (4) uses a scoring rule (equation (15)) with incentives across contracts (ω_j) calculated to maximize equation (14).[51] This doubles the social welfare gains under status quo with an increase of $128 million. Adjusting incentives across contracts (ω_j) accounts for both heterogeneity in $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$ as a function of $\kappa_\mathbf{i}$, e.g. a landowner's choice of a tree-related contract reveals that her conservation is unlikely to be impacted by the contract, and the fact that the full social value across actions is not realized when conservation would have counterfactually occurred.

Bars (5) and (6) in Figure 9 similarly adjust the bidder asymmetry terms across observables $(\omega_\mathbf{z})$ in equation (15), leading to an additional $46 million of welfare gains, or 37% of the status quo. Bar (5) re-weights existing characteristics governing bidder asymmetry in the scoring rule $(\mathbf{z_i^s})$, which in the status quo are based on environmental sensitivity but not additionality. Bar (6) adds an additional characteristic to the scoring rule, a projection of $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$ on immutable characteristics of landowners already collected by the USDA: deciles of soil productivity and wind and water erosion. Adding this predictor to the scoring rule increases social welfare by 12% of the social welfare gains of the status quo. However, two-thirds of the gains from adjusting bidder asymmetry are captured by only re-weighting

[51] We solve for the ω_j that maximize social surplus defined in equation (13) given our simulations of landowner $(c_{i,}, \kappa_\mathbf{i})$, our estimates of $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$ and calibrations of $B_j(\mathbf{z_i^s})$, and our allocation rule, which ranks landowners and awards contracts by $\max_j s_j(\mathbf{z}_i) - c_i - \kappa_{ij}$, holding $\omega_\mathbf{z}$ fixed at the status quo scoring rule.

characteristics in the scoring rule. We emphasize that these are light-touch changes to the design of the scoring rule. We (i) do not incorporate all of the observables in $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$, as lagged land use or CRP enrollment may introduce perverse incentives for gaming, and (ii) even when we add additional characteristics to the rule, we add only one.

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 adjust asymmetry across bidders and incentives across contracts to *impact conservation* at lowest cost.

Social Welfare Under Alternative Market Sizes Beyond the allocation rule, the extent of additionality also impacts the socially-optimal size of the market. This was ignored in the auctions displayed in bars (3)-(6), 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, adjusting both the size of the market and the scoring rule based on predictions of additionality closes the gap between the status quo and the efficient allocation by 41%, an increase of \$284 million per auction.[52] Each component of the mechanism — adjusted incentives across contracts, asymmetry across bidders, and the overall size of the market — is a quantitatively important contribution to this improvement.

Budgetary Implications Adjusting both the quantity and the scoring rule by predictions of additionality outperforms implementable alternatives while also reducing spending relative to the status quo (column (7) of Table 5). This occurs because reducing the size of the market, and therefore total spending, increases social welfare.

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

[52]Further differences between bar (7) and bar (2) reflect a combination of (i) $\mathbf{z}_i$'s that are predictive of additionality but are not incorporated into the scoring rule to avoid perverse dynamic incentives (e.g. lagged land use), (ii further predictive content of private landowner costs in $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$ in that could be used to allocate contracts, (iii) binding monotonicity constraints, and (iv) the functional form of our scoring rule relative to $B_j(\mathbf{z_i^s}) \cdot \tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$.

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.[53] We continue to 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). Our analysis answers two questions motivated by the graphical 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 10a, focusing for simplicity on only the base contract. Figure 10a plots the percent reduction in quantities traded and social welfare in a competitive market, relative to with socially-optimal prices, under uniform and differentiated pricing regimes. Under the uniform market, there is only a single socially-optimal price and a single market-clearing condition. Under the differentiated market, we project the base contract value 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 rating schemes in voluntary environmental markets.[54] We also include on Figure 10a the welfare per acre-year under each of these offset market designs.

We find that differentiation reduces the extent of welfare losses from adverse selection in competitive markets from 5% to less than 1% and increases welfare by 15% overall via more efficient trades in the market. The gains from differentiated incentives are thus high even in the ex-ante ambiguous competitive market setting, supporting on-going efforts to collect and price upon detailed information to predict additionality in voluntary environmental markets.[55]

Our second question concerns which contracts can and cannot be successfully traded in competitive markets. Our analysis builds directly on the comparison between Figures 7 and 8c. Figure 10b considers hypothetical single-contract markets, and plots the reductions in quantities traded and social welfare — relative to the socially optimal uniform price — across markets defined by the three broad categories of contracts in our setting: grasses, trees, and habitats. Only tree-related contracts unravel; welfare losses for the remaining contracts are

[53] We refer to these counterfactual competitive markets as "offset markets," but note that conservation activities in both this and real-world contexts provide value beyond a one-for-one emissions offset.

[54] See, for example, Carlyx Global, BeZero Ratings, and Sylvera.

[55] Many of the largest private procurers of clean energy, such as Google and Microsoft, have outlined methodologies to calculate the "additionality" of the energy project. Other firms are developing products to "estimate additionality" for conservation offsets, e.g. NCX.

limited to at most 3%.

Figure 10 presents (i) a relatively optimistic view of the proposed USDA-regulated competitive agricultural offset market, and (ii) actionable insights for market design, though both admittedly abstract away from demand-side frictions that may compound our counteract supply-side adverse selection. What features of our setting drive these results? First, the eligibility requirements for the CRP are stringent enough — a requirement of historically working farmland — that there is some probability of additionality even at the bottom of the contracting cost distribution. Second, the requirement of specific contracting activities, which introduces hassle costs, and the possibility that landowners may have only limited information about future actions mute the extent of adverse selection which limits unravelling. Finally, agricultural decisions are relatively easy to understand and predict, offering readily available covariates to increase social welfare.

7 Conclusion

Additionality is a central challenge to many areas of environmental market design. Asymmetric information can complicate the basic appeal of market-based mechanisms if market incentives attract only the least additional landowners. This paper combines rich new data and economic theory to test for this potential failure, quantify its implications for social welfare, and evaluate alternative market designs in the largest auction mechanism for ecosystem services in the world.

We first document evidence that highlights the potential for inefficiency and the relevance of additionality for market design. Linking satellite data to auction bids, we use a regression discontinuity design to demonstrate that only one quarter of landowners are additional. Moreover, we show that the heterogeneity in additionality among landowners generates adverse selection in the market. We then develop and estimate a joint model of multi-dimensional bidding and additionality with adverse selection to quantify the implications of these facts and propose and test possible remedies.

We find that with socially-optimal incentives, the market can deliver social welfare gains. However, the lowest cost providers of environmental services are not always the highest social value. This feature complicates market design, undermining the performance of standard procurement mechanisms and limiting trade in a stylized competitive market. Re-designing the auction's scoring rule, by setting incentives across contracts and asymmetry across bidders based on predictions of additionality, more than doubles the social welfare gains of the status quo auction. Similar simple differentiation schemes — using only immutable characteristics that the USDA already collects — also improves welfare in competitive offset markets.

Our analysis focused exclusively on the effects of supply-side asymmetric information. Investigating additional features of rapidly expanding — but often apparently dysfunctional — voluntary environmental markets is an important next step. Understanding offset demand, the incentives of platforms and certifiers that facilitate trade, and both of their interactions with supply-side 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. Applying this idea to the design of other environmental markets is a rich and exciting area for research.

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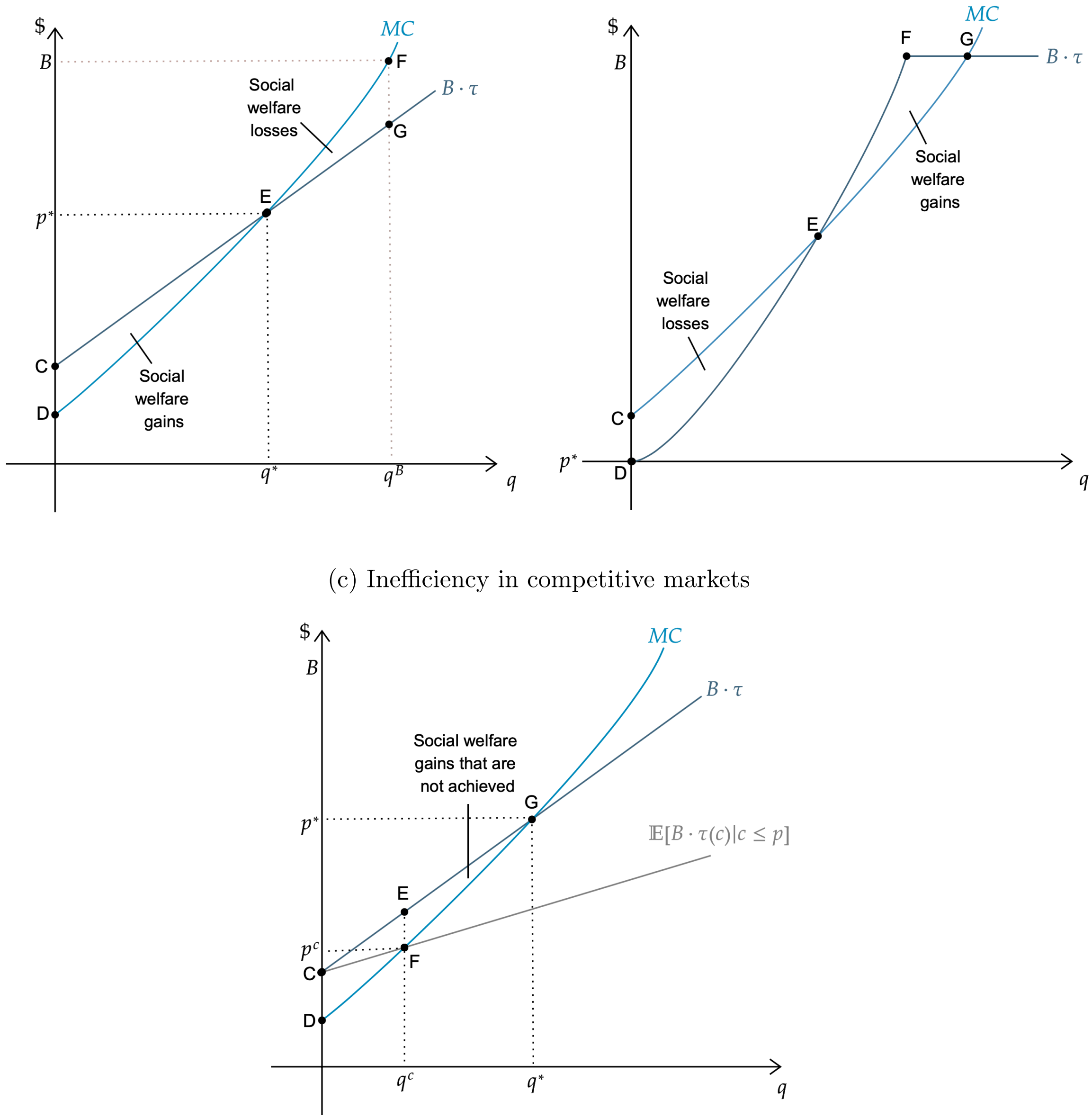
Figures and Tables

Figure 1: Graphical analysis

(a) Efficient allocation can be implemented (b) Efficient allocation cannot be implemented

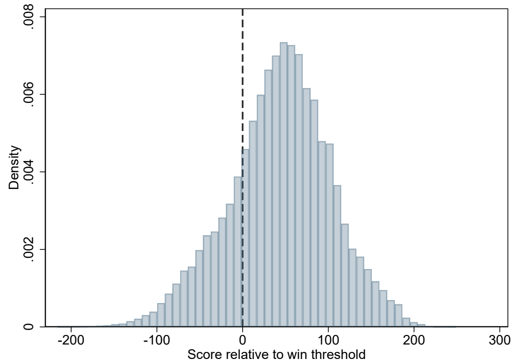


(c) Inefficiency in competitive markets

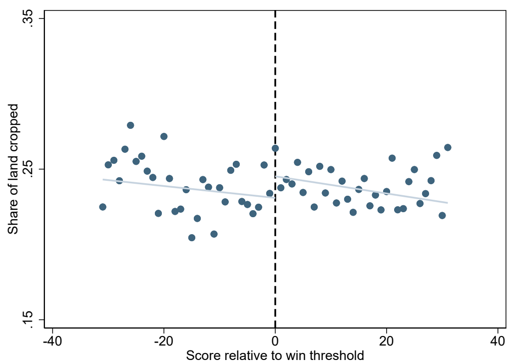
Notes: Figures describe markets as characterized by marginal cost ($MC = F_C^{-1}(q)$) and contract value $B \cdot \tau$ curves. B denotes the value of the environmental service $a_i = 1$, whereas $B \cdot \tau$ denotes the incremental value of contracting, relative to no contract. The vertical distance between the $B \cdot \tau$ and the MC curves represent social welfare gains from contracting. Panel (a) documents a population distribution in which the efficient allocation, in which all landowners with $B \cdot \tau(c_i) \geq c_i$ contract, can be implemented with 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). Panel (c) adds a curve defining the average contract value of all landowners selecting into the market at any given price p, $\mathbb{E}\left[B \cdot \tau(c) \mid c \leq p\right]$, which defines the value of a contract to a buyer in a stylized competitive (offset) market. The intersection of the MC and average contract value curves define a competitive market equilibrium. The upwards-sloping $B \cdot \tau$ curve, indicative of adverse selection, limits trade in competitive markets and leads to social welfare losses (triangle EFG), relative to the efficient allocation (CDG).

Figure 2: RD validity and first stage

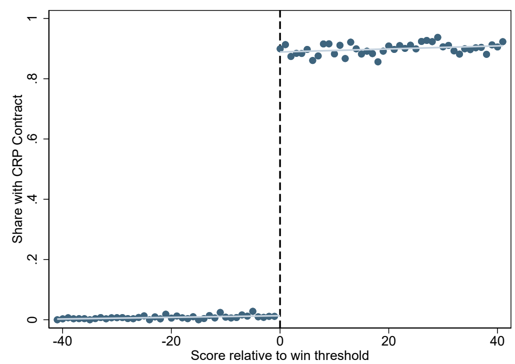
(a) Histogram of running variable



(b) Placebo: pre-auction



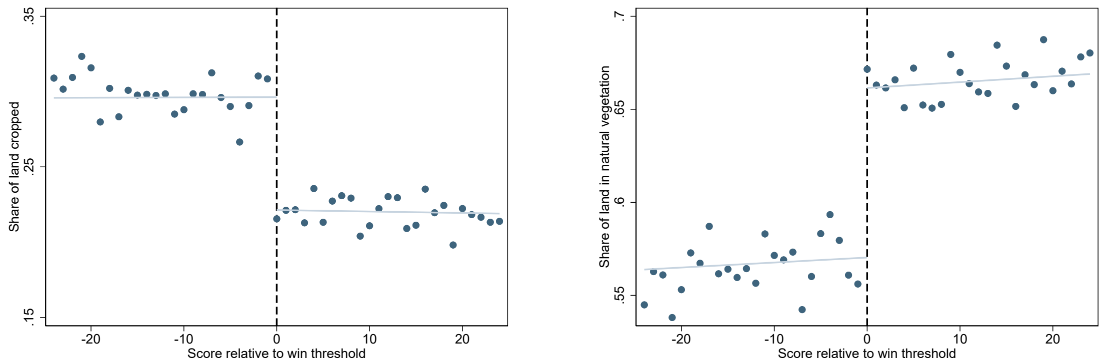
(c) First stage: contracting



Notes: Panel (a) presents a histogram of bidders' scores relative to the win threshold (the running variable for the RD analysis, $S_{ig} - \underline{S_g}$), pooled across auctions. Bidders above zero win. Panels (b) and (c) present raw data and estimated parameters from equation (7) with a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Calonico et al., 2014). Panel (b) is estimated for only $r(i,t) \leq 0$ (pre-auction), and panel (c) is estimated for only $r(i,t) > 0$ (post-auction). Panel (b) presents a placebo RD plot examining land-use outcomes, measured as the share of the bidder's land that is cropped in the remote sensing data, in all years before the auction. Panel (c) plots the share of bidders that obtain a CRP contract. Positive numbers on the x-axis correspond to winning scores, negative numbers correspond to losing scores. Each observation is a bidder.

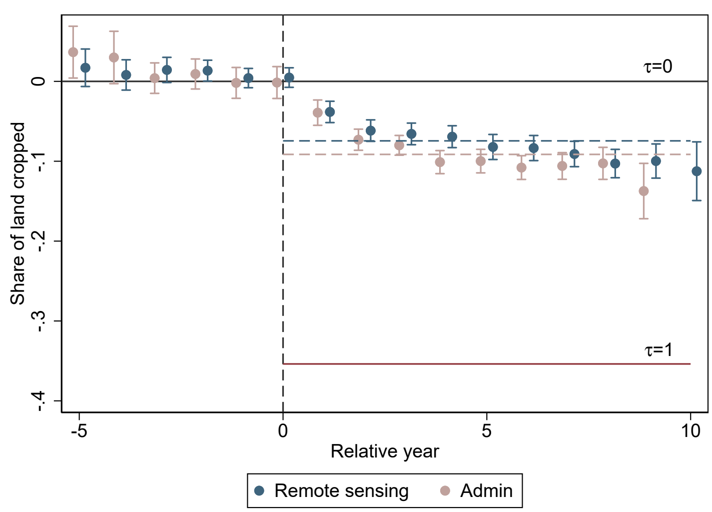
Figure 3: The effect of a CRP contract on land use

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



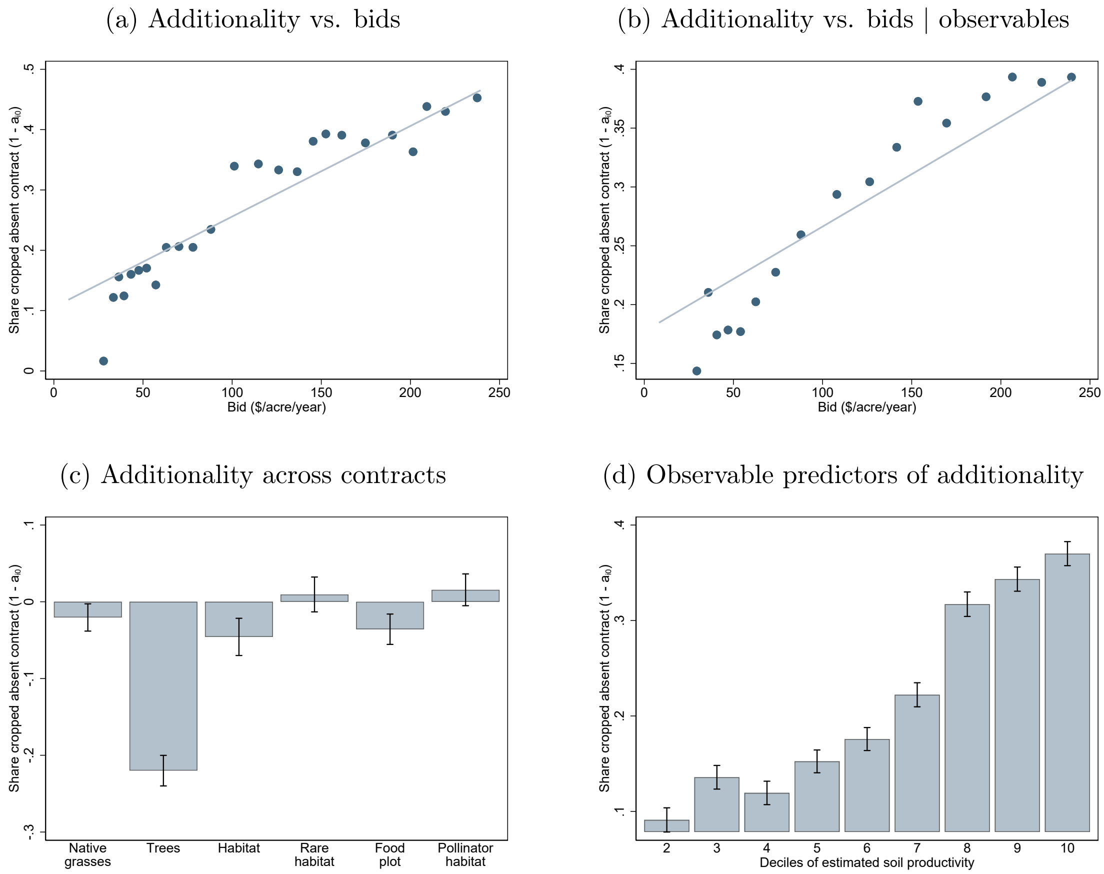
Notes: Panels (a) and (b) present raw data and estimated parameters from equation (7) with a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Calonico et al., 2014) for $r(i,t) > 0$ (post-auction). Land-use outcomes are measured as the share of the the bidder's land that is cropped (a) and the share of the bidder's land that is in natural vegetation (trees, grassland, shrubs, and wetland) (b), both measured using 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. 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), using a local linear specification in the MSE-optimal bandwidth (Calonico et al., 2014) allowed to differ on either side of the discontinuity. 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 index year of each bidder's auction: $r(i,t) = t - t_{g(i)}$. Positive years correspond to post-auction years. Each point represents a RD regression coefficient, estimated at the bidder level. Dashed lines indicate the pooled treatment effects (equation (7) estimated for $r(i,t) > 0$). The black line at 0 and red line at -.35 indicate the effect sizes if no one changed behavior, and if everyone with a contract changed behavior, respectively. $\tau = 1$ represents the "full additionality" benchmark, which is calculated as the share of land contracting in the MSE-optimal bandwidth. Standard errors are clustered at the bidder level. Each observation is a bidder. Ten years is the full contract duration of a CRP contract. Corresponding coefficient estimates and standard errors presented in Table 2.

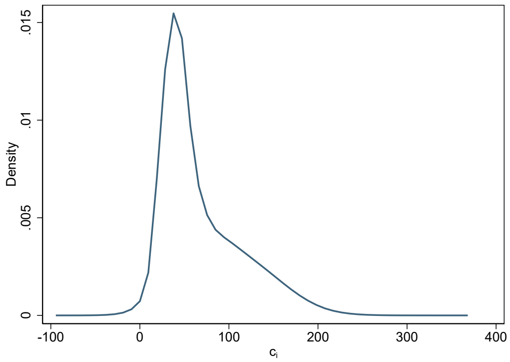
Figure 5: Testing for asymmetric information



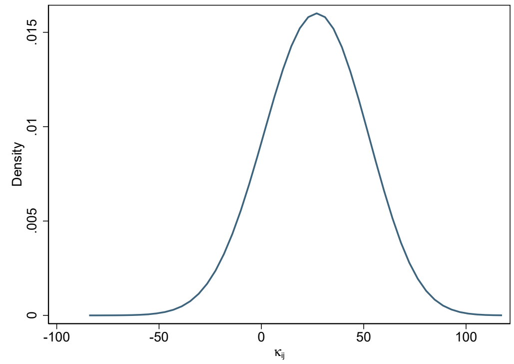
Notes: Figures present visual representations of coefficient estimates of various specifications of equation (8). A positive relationship between bids, or specific contract features, and additionality indicates adverse selection. All regressions control for characteristics that are incorporated in the scoring rule: whether a bidder is in a wildlife priority zone, estimates of groundwater quality, estimates of surface water quality, estimates of win and water erosion (deciles), air quality impacts, and whether or not a bidder is in a air quality zone. Additionality is measured as the share of fields offered into the CRP mechanism that are cropped post auction, conditional on rejection. Estimates are restricted to the auction in 2016, in which 82% of bidders are rejected and the delineations of bid fields are observed. Additionality is measured in 2017-2020 in the remote sensing data (see Figure C.5 for similar results in the administrative data). Panel (a) correlates the dollar bid component (per acre, year year) with additionality, conditional on only characteristics included in the scoring rule. Panel (b) adds interaction terms of prior land use (quartiles of prior cropped interacted with re-enrolling CRP status) and deciles of estimated soil productivity. Panel (c) investigates relative additionality by contract features, relative to a base contract feature of introduced grasses. Panel (d) examines relative additionality by deciles of the estimated soil productivity distribution. Standard errors clustered at the bidder level.

Figure 6: Estimated landowner cost distributions

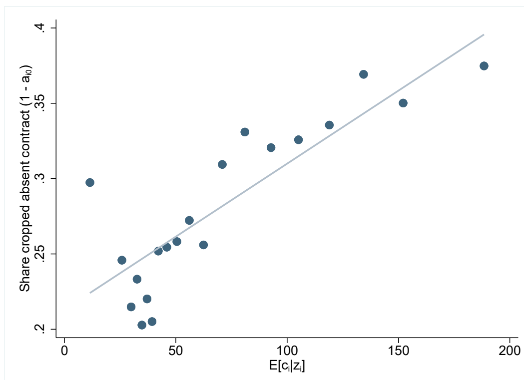
(a) Base cost c_i



(b) Top-up costs κ_{ij}

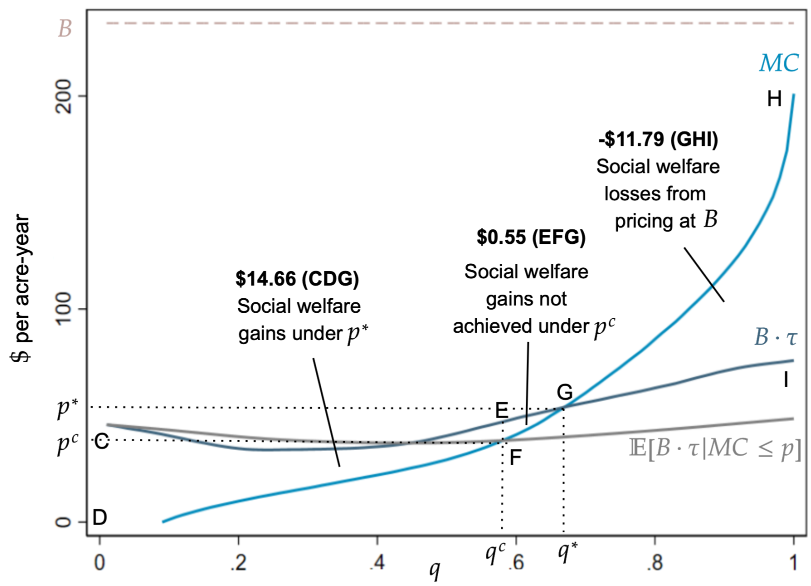


(c) Land use versus revealed preference costs



Notes: Figures present kernel density plots of estimates of the base cost c_i (a) and top-up cost κ_{ij} (b) for all auctions in our sample. These costs are estimated using revealed preferences from optimal bidding behavior. See the discussion in Section 5.2 for estimation details. Panel (c) correlates expected base costs, c_i, based on observable characteristics $\mathbf{z_i}$, with land use outcomes (share cropped) measured on bid fields. This analysis is restricted to the 2016 auction where we observe bid fields, which allows us to measure additionality directly, and is restricted to the 82% of bidders who are rejected (for whom additionality is observed). $\mathbf{z_i}$ includes interactions of soil productivity, prior CRP, and prior land use. All costs are reported in dollars per acre per year. Land use outcomes in panel (c) are measured using the remote sensing data.

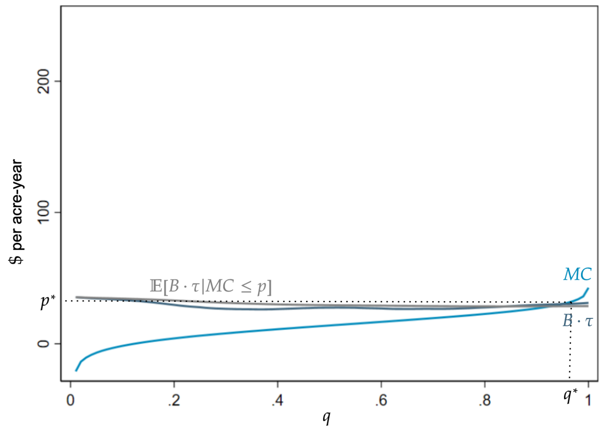
Figure 7: Empirical graphical analysis



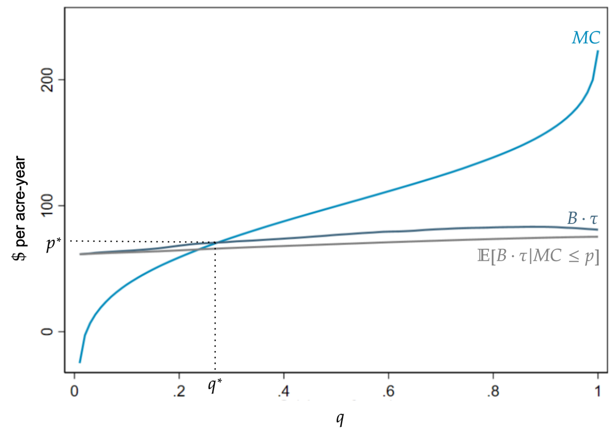
Notes: Figure presents empirical counterparts of the curves in Figure 1 for the base contract. Dollar values are reported in dollars per acre per year. MC is calculated as the minimum cost to fulfill the base contract. B denotes the average value of the base contract action, calculated as described in Appendix E, whereas $B \cdot \tau$ 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 the MC curves represent social welfare gains (or losses) from contracting. 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 area GHI represents social welfare losses from mis-pricing at B. The gray average contract value curve calculates the average $B \cdot \tau$ of all landowners selecting into the market at any given price p, which defines the value of a contract to a buyer in a stylized competitive (offset) market. The intersection of the MC and average contract value curves define a competitive market equilibrium. The upwards-sloping $B \cdot \tau$ curve, indicative of adverse selection, limits trade in competitive markets and leads to social welfare gains that are not realized in a stylized competitive market (triangle EFG).

Figure 8: Graphical analysis: heterogeneity across contracts and observables

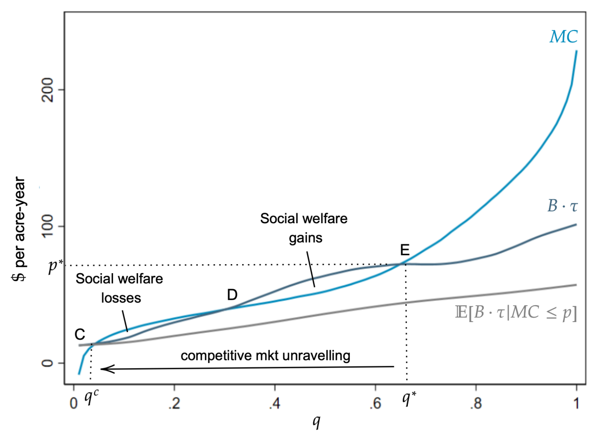
(a) Lowest quintile soil productivity



(b) Highest quintile soil productivity

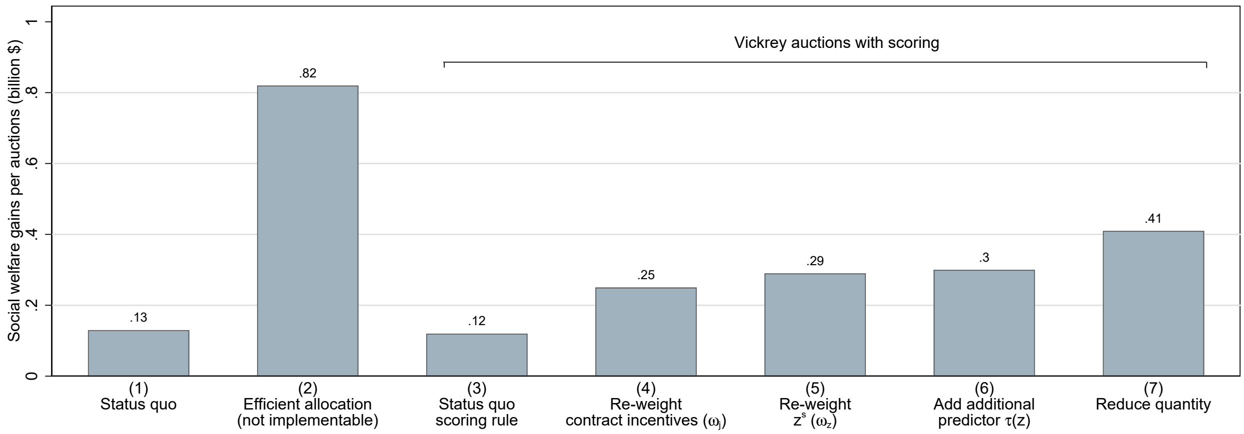


(c) Tree contracts



Notes: Figures presents empirical counterparts of the curves in Figure 1. In panels (a) and (b), we calculate the MC curve as 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), we calculate the MC curve as the minimum cost to fulfill a tree planting and maintenance contract. $B \cdot \tau$ denotes the contract value curve, or the incremental value of contracting, relative to no contract, averaged at each quantile of the sub-population distribution of the base costs of contracting (in panels (a) and (b)) or of a tree-planting and maintenance contract (in panel (c)). The vertical distance between the $B \cdot \tau$ and the MC curves represent social welfare gains (or losses) from contracting. p^* denotes the socially optimal price. The gray average contract value curve calculates the average $B \cdot \tau$ of all landowners selecting into the market at any given price p, which defines the value of a contract to a buyer in a stylized competitive (offset) market. Sub-figure (c) demonstrates a market where the one-dimensional constrained efficient allocation (defined in equation (5)) cannot be implemented, as an incentive that is attractive for the landowners in DE is also attractive for the landowners in CD. The stylized competitive market also unravels.

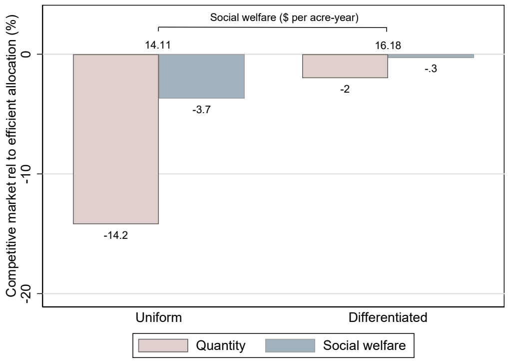
Figure 9: Social welfare under alternative auctions



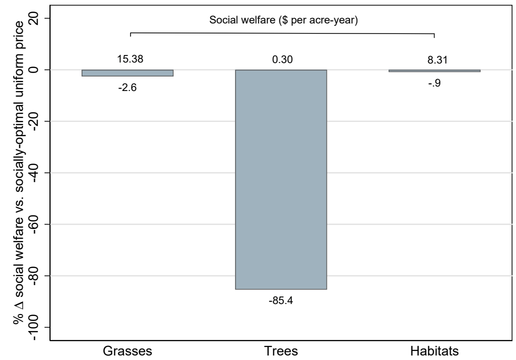
Notes: Figure presents estimates of the social welfare gains under status quo and alternative auctions, calculated (per auction, in billion $) with the efficiency criterion in equation (13). All auctions impose the feasibility constraints that (i) each landowner can obtain at most one contract and (ii) total contracts allocated cannot exceed the status quo. The status quo is simulated using optimal bidding, the estimated distribution of $(c_i, \kappa_\mathbf{i})$ and beliefs about win probabilities $G(S)$. The efficient allocation calculates the social welfare gains under a full information (about $(c_i, \kappa_\mathbf{i})$) benchmark. The remaining auctions implement scoring auctions using a Vickrey-Clarke-Groves (VCG) mechanism with different scoring rules (see Section 6.2 for more details), which we term "Vickrey auctions with scoring." Bars (3)-(6) hold quantity (the number of landowners allocated contracts) constant at status quo levels and change the scoring rule $s_j(\mathbf{z_i})$ defined in equation (15). Bar (3) implements a VCG mechanism with 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. In the status quo, these are based on environmental sensitivity but not additionality (bar (5) adjusts for additionality). Bar (6) adds an additional characteristic to the scoring rule, a projection of $\tau(\mathbf{z_i}, c_i, \kappa_\mathbf{i})$ 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 $\max_j s_j(\mathbf{z_i}) - c_i - \kappa_\mathbf{i} \geq 0$ are awarded contracts. See Table 5 for more details.

Figure 10: Offset market design

(a) Differentiated versus uniform market



(b) By contract type



Notes: Figures describe social welfare and quantities traded under a competitive offset equilibrium versus socially-optimal prices. We focus on supply side adverse selection: the competitive market 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) analyzes the base contract and reports quantities trade and social welfare under a stylized competitive market equilibrium relative to socially-optimal prices under a uniform and a differentiated market. Under the uniform market, there is only a single socially-optimal price and a single market-clearing condition. Under the differentiated market, we project the base contract value onto immutable observable characteristics ($\mathbf{z_i^s}$, soil productivity and erosion) and then segment the market into deciles of predicted contract value. The numbers above the bars tabulate total social welfare (per acre-year) in the competitive market. Panel (b) analyzes social welfare under a stylized competitive market equilibrium relative to socially-optimal prices (the bars) and total social welfare (the levels reported above the bars, reported in dollars per acre-year) under three different hypothetical markets, each with only one type of contract traded with a uniform price.

Table 1: Summary statistics

	All agricultural land		All 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	0.282	0.21	0.21	0.21	0.18
Corn	0.11	0.11	0.07	0.08	0.07	0.06
Soybean	0.11	0.10	0.06	0.07	0.07	0.07
Fallow	0.02	0.01	0.03	0.01	0.05	0.03
Natural vegetation 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)			
Environmental sensitivity	53.5		86.5			
	(29.8)		(33.7)			
Panel C. Bid characteristics						
Rental rate			83.0			
			(56.4)			
Acres bid			84.1			
			(136.3)			
Share re-enrolling			0.70			
			(0.46)			
Contract action = grasses			0.638			
			(0.481)			
Contract action = trees			0.111			
			(0.315)			
Contract action = habitat			0.201			
			(0.401)			
Accept and contract			0.800			
			(0.400)			
N bidders / auction			36,763			
N	7,890,426		257,340		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 one auction). Panel A reports land use outcomes in our two datasets, remote sensing (the CDL) and admin (Form 578). All land use outcomes are reported for the year prior to bidding, among bidders, with years re-weighted in the "All agricultural land" columns to match the distribution of bidder-years. All agricultural land includes both eligible non-bidders and ineligible land. Land use categories follow Lark et al. (2017). Crop outcomes exclude alfalfa and hay. Soil productivity is calculated by NASS and is reported in dollars per acre. Environmental sensitivity (EBI points) are the points given for characteristics of land in the scoring rule, which can be calculated for all landowners based on their geolocation. Grasses, trees, and habitat contract indicators are aggregated over the menu of possible contracts within those broad categories.

Table 2: RD evidence: coefficient estimates

	Remote-sensing (1)	Admin (2)
Panel A: Main outcome: share of tract 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-offered fields		
Share of non-offered 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), estimated with land use outcomes measured in both the remotely sensed data (column 1) and the administrative data (column 2). The full-contract duration focuses only on the 2009 auction, in which we have a long enough post period to measure outcomes over the full contract duration, others pool all auctions for which we have post-period data: auctions in 2009, 2011, 2012, 2013, and 2016. On average the pooled post-period includes 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 at the RD margin. Panel C estimates the effect of a CRP contract on non-bid, and therefore non-contracting, fields to test for spillovers. We restrict this analysis to the 2016 auction due to a requirement of bid field delineations. All results are based on a specification using a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Calonico et al., 2014). Standard errors are clustered at the tract level.

Table 3: Summarized mean landowner costs of contracting

	All (1)	Landowners with above median soil productivity (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 mean landowner costs of contracting, for the base cost c_i and top-up cost κ_{ij} for all auctions in our sample, where the cost of each contract j is defined as $c_i + \kappa_{ij}$. Costs are estimated based on revealed preferences in bidding behavior. See the discussion in Section 5.1 for estimation details. Column (1) presents mean costs for all bidders across all auctions, and column (2) presents estimates for the subset of bidders with observable types $\mathbf{z_i}$ that correspond to above-median population soil productivity. Costs are reported in dollars per acre-year. See Appendix Table D.2 for a comparison with administrative data.

Table 4: Additionality as a function of unobserved landowner costs

	(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 observable bidder cost types		✓	✓	✓

Notes: Table presents select coefficient estimates characterizing the relationship between additionality $\tau(\mathbf{z_i}, c_i, \kappa_i)$ and estimated landowner costs of contracting (equation (12)). Coefficients measure the effect of a $1 per acre, per year change in costs on additionality. Parameter estimates obtained via the Method of Simulated Moments, described in Section 5.1. This estimator relates observed patterns of land use among rejected bidders to bids, given estimated distributions of $(c_i, \kappa_\mathbf{i})$ and optimal bidding in Equation (10). All specifications include flexible controls for the components of the scoring rule except for landowners' Wildlife Priority Zone and Air Quality Zone status, which are excluded instruments. Columns $(2)-(4)$ control for the 32 cells of bidder type determined by soil productivity, prior CRP status, and prior land use status. Estimates are obtained using bid-field-level observations of cropping (for which we observe $1 - a_{i0}$) in the remote sensing data for the 2016 auction. Standard errors are calculated using 100 bootstrap draws. These do not (yet) account for estimation error in the $(c_i, \kappa_\mathbf{i})$ distribution used to simulate optimal bids. Positive coefficients indicate a positive relationship between costs of contracting and additionality, or adverse selection in the market.

Table 5: Outcomes under alternative auctions

	Status quo	Efficient allocation	Vickrey auctions with scoring				
			Existing rule $B_j(\mathbf{z_i})$	Re-weight contracts (ω_j)	Re-weight $\mathbf{z_i^s}$ $(\omega_{\mathbf{z}})$	Add $\tau(\mathbf{z_i})$ (incl. $\mathbf{z_i}$ not in existing rule)	Reduce quantity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Welfare and spending (billion \$ per auction):							
Social welfare	0.126	0.820	0.121	0.254	0.285	0.300	0.410
USDA spending	1.323		2.033	1.760	1.703	1.724	0.936
Landowner surplus	0.546		0.906	1.176	1.127	1.147	0.580
Environmental value	0.902	1.239	1.130	0.838	0.861	0.876	0.766
Panel B. Share:							
Additionality | contract	0.206	0.424	0.199	0.200	0.209	0.213	0.215
Landowners with contract	0.810	0.546	0.810	0.810	0.810	0.810	0.704

Notes: Table presents estimates of social welfare, USDA spending, landowner surplus, and environmental value $\sum_i \sum_j B_j\left(\mathbf{z_i^s}\right) \cdot \tau\left(\mathbf{z_i}, c_i, \kappa_\mathbf{i}\right) \cdot x_{ij}$ under status quo and alternative auctions, calculated (per auction, in billion \$), as well as the average additionality of contracting landowners and the share of landowners with a contract. Social welfare is calculated based on equation (14). All auctions impose the feasibility constraints that (i) each landowner can obtain at most one contract and (ii) total contracts allocated cannot exceed the status quo. Columns (1) and (3)-(6) hold the number of landowners constant at the status quo. The status quo is simulated using optimal bidding, the estimated distribution of $(c_i, \kappa_\mathbf{i})$ and beliefs about win probabilities $G(S)$. The efficient allocation calculates the social welfare gains under a full information (about $(c_i, \kappa_\mathbf{i})$) benchmark. This allocation may not be implementable in an auction, therefore values for USDA spending and landowner surplus are excluded. The remaining auctions implement scoring auctions using a Vickrey-Clarke-Groves (VCG) mechanism with different scoring rules (see Section 6.2 for more details). Columns (3)-(6) hold quantity (the number of landowners allocated contracts) constant at status quo levels and change the scoring rule $s_j(\mathbf{z_i})$ defined in equation (15). Column (3) implements a VCG mechanism with the existing scoring rule $\left(s_j(\mathbf{z_i}) = B_j\left(\mathbf{z_i^s}\right)\right)$. 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. In the status quo, these are based on environmental sensitivity but not additionality (column (5) adjusts for additionality). Column (6) adds an additional characteristic to the scoring rule, a projection of $\tau\left(\mathbf{z_i}, c_i, \kappa_\mathbf{i}\right)$ on immutable characteristics of landowners already collected by the USDA: 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 $\max_j s_j(\mathbf{z_i}) - c_i - \kappa_\mathbf{i} \geq 0$ are awarded contracts. Columns (1)-(7) corresponds to bars (1)-(7) 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 bid amount. We describe the details associated with each of these components below. The details of the scoring rule are published each year in EBI Factsheets.[56]

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.

[56] See `https://www.fsa.usda.gov/Assets/USDA-FSA-Public/usdafiles/FactSheets/2020/crp-56th-ebi-fact-sheet-12-31-2020.pdf` 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: Action choices in detail: primary covers

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

Notes: Table describes the menu of primary cover actions.

Table A.2: Action choices in detail: upgrades

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

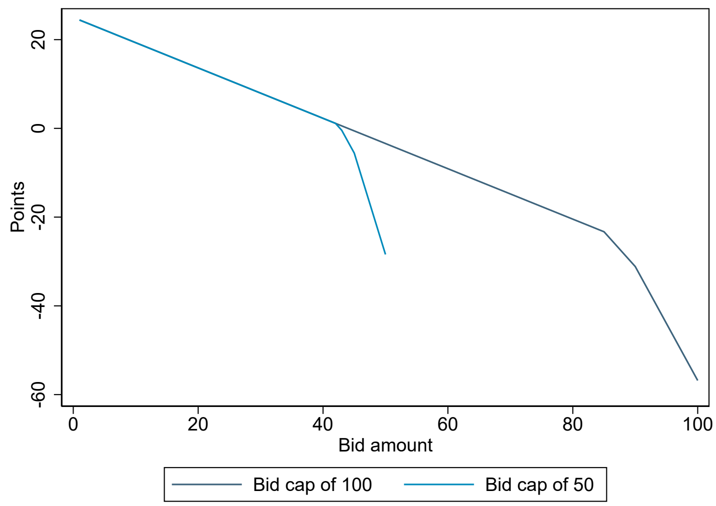
Notes: Table describes the menu of upgrade actions.

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

Bid amount The final element of the scoring rule is the rental rate. Unlike in the quasi-linear environment of Asker and Cantillon (2008), the scoring rule is non-linear in r_i for two reasons. First, the existence of bid caps make some choices infeasible if $r_i > \overline{r}_i$, where $\overline{r}_i$ denotes the i specific bid cap. These bid caps are determined based on the productivity of soils and are known for all tracts in the US. Second, the score introduces non-linearities based on the amount a bidder bids below the bid cap with kinks at 10% and 15% below the bid cap (see Figure A.1 for a demonstration).[57] Technically, 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.

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

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



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

An example menu The mechanism implies a "menu" of payoffs for each action at each score. These menus differ by observable characteristics of landowners. Table A.3 describes on example menu.

Table A.3: Example menu of contracts: prices and market shares

	Average payment at thresh-old score	Market share	Average payment at thresh-old score	Market share	Average payment at thresh-old 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 possible upgrade options. Table reports payments ("prices") across contracts, calculated as the rental rate per acre per year that a bidder could request to choose a contract and reach a given score. Because this varies across scores and across bidders, in this table, we calculate payments at the threshold score and report averages across all bidders. Table also reports the market shares of each contract, pooled across the auctions in our sample.

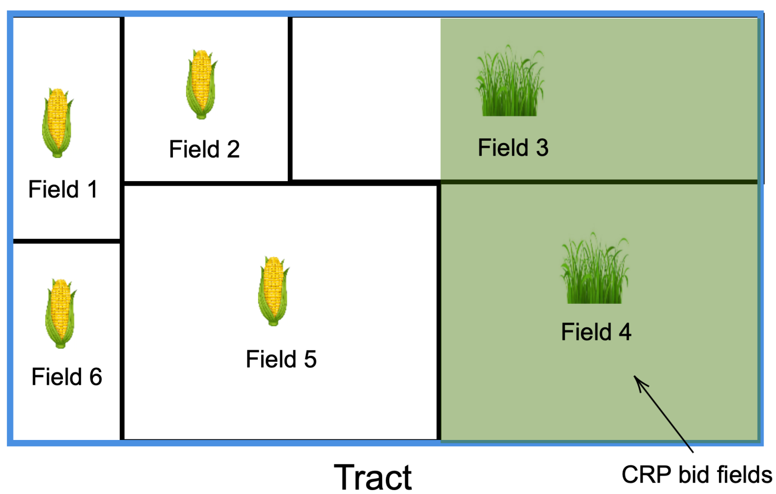
B Data Appendix

Measuring Land Use and Constructing our Linked Dataset

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

Agricultural Units: Tracts and Fields All agricultural land is the US is divided into fields, or Common Land Units, by the USDA. A field is defined as the smallest unit of land that has: (1) a permanent, contiguous boundary, (2) a common land cover and land management, (3) a common owner.[58] 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).

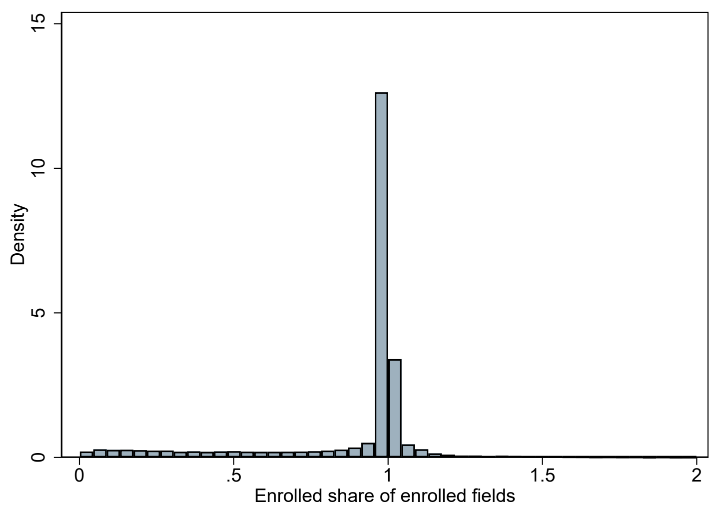
A tract is a collection of fields under one common ownership that is operated as a farm or part of a farm (a tract is a landowner, or bidder, in our setting). The average tract includes 4.75 fields. Each tract can submit at most one bid into a CRP auction. This bid can include

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

any subset of a tract's fields. A bid is not constrained to bid only entire fields; in principle, a bidder can bid any subset of their land, regardless of field delineations. In practice, a large share of bids follow field boundaries, as illustrated by Figure B.2. Figure B.1 provides an illustrative example.

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

Figure B.2: Share of offered fields enrolled



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

Remote Sensing Data (CDL) Our first source of land use data is the Cropland Data Layer (CDL) from 2009 to 2020. The CDL is derived from annual satellite imagery at a 30m by 30m resolution (approximately one quarter acre) for the entire contiguous US. The dataset classifies each pixel into over 50 crop categories and over 20 non-crop categories. The CDL is produced by the National Agricultural Statistics Service (NASS), and 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).

Our primary analysis aggregates these categories 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 and fallow, and idle cropland. The super-class accuracy of the CDL is very high with $>$ 99% producer's (classified as cropped when truly cropped) and $>$ 98% user's (truly cropped when classified as cropped) accuracy in 2016. 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, 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. A challenge to constructing this dataset is that field and boundaries can change over time. We can capture these changes by merging the CDL data to a constant geographic outline of a bidder over time, time-stamped at the point of bidding.

Our primary outcome of interest is the crop versus non-crop classification. 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 is new to economics research and is the ground truth administrative data that the CDL is trained on. These are annual field-level reports of total acreage cropped in a series of detailed crop categories and enrollment in various USDA programs, including the CRP. Though these are self-reported by farms, crop insurance payouts are dependent on these reports, so farmers are incentivized to report cropped amounts accurately (though not program enrollment). Unlike the CDL, which has coverage over the entire US, field-level data is only submitted if there is an incentive to do so, i.e. if it is cropped and covered by crop insurance. We assume that all non-reporting fields are not cropped. 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. Here, the challenge of bid and tract identifiers changing over time is more pronounced. We account for it by constructing a panel that tracks changes in field identifiers and field delineations over time using their precise (and potentially changing) geolocations.

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 the exact contours of enrolled fields (the highlighted green area in Figure B.1) to assess compliance with CRP rules by eye. We do this to side-step the possibility of bias due to classification error in the derived (CDL) data product, which would mechanically bias toward finding non-compliance. We discuss this process in more detail in the next sub-section.

Validating compliance

While our RD result provides an unbiased estimate of the treatment effect of a CRP contract award at the winning score threshold, regardless of compliance, to obtain a landowner-specific measure of additionality $(a_{i1} - a_{i0})$ we need to assess compliance in the status quo regime. Under perfect compliance, we can simplify to a selective labels problem (Lakkaraju et al., 2017; Chan et al., 2022; Arnold et al., 2022).

Figure B.3: Sample Images

(a) Enrolled field

(b) Cropped field

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

To assess compliance, we hired and trained two MIT undergraduates to classify 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 undergraduates to classify any images, we provided them with a test set of hundreds of images of cropped and uncropped fields across the United States to familiarize themselves with the distinctive visual pattern of cropped fields (see Figure B.3b). After training, we provided each of these undergraduates with over 1,000 images of CRP enrolled fields and hundreds of placebo cropped fields as attention checks. The undergraduate reviewers were blind to whether the images were of CRP enrolled fields or placebo cropped fields. Each of the two reviewers were provided with the same images.

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

Table 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.

Why Classify Photographs by Eye? First, these photographs are much higher resolution (1 m vs. 30m pixels) in the CDL, allowing a higher degree of accuracy for a sensitive question (is this program being enforced?). Second, conducting tests by eye allows for more flexibility in the face of measurement error than the derived product, e.g. by only focusing on cases where our reviewers agree. And third, and most importantly, it is impossible to distinguish non-compliance from classification error in the CDL.

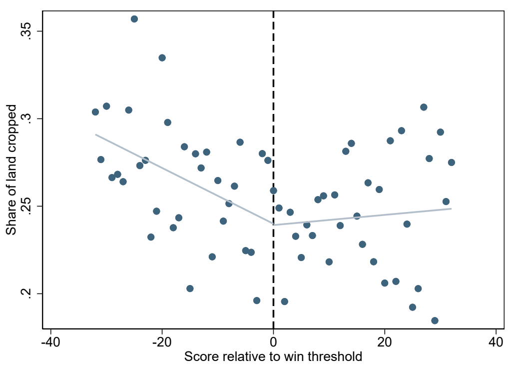
Compliance on Top-up Actions We note that this exercise only focuses on compliance on the base action, land retirement, not any of the top-up actions, which we cannot observe. We thus use this assessment of compliance to make an inference about the overall compliance regime across all actions.

C Supplemental Figures and Tables

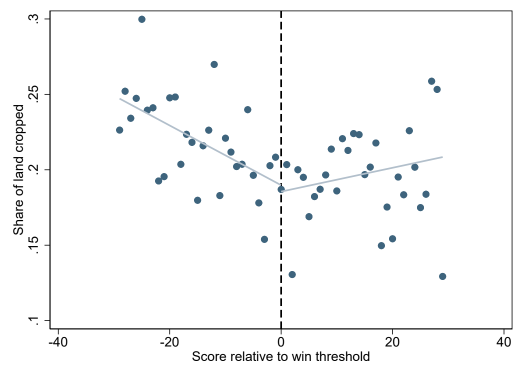
RD

Figure C.1: Spillovers: cropping effects on non-bid fields

(a) Remote sensing

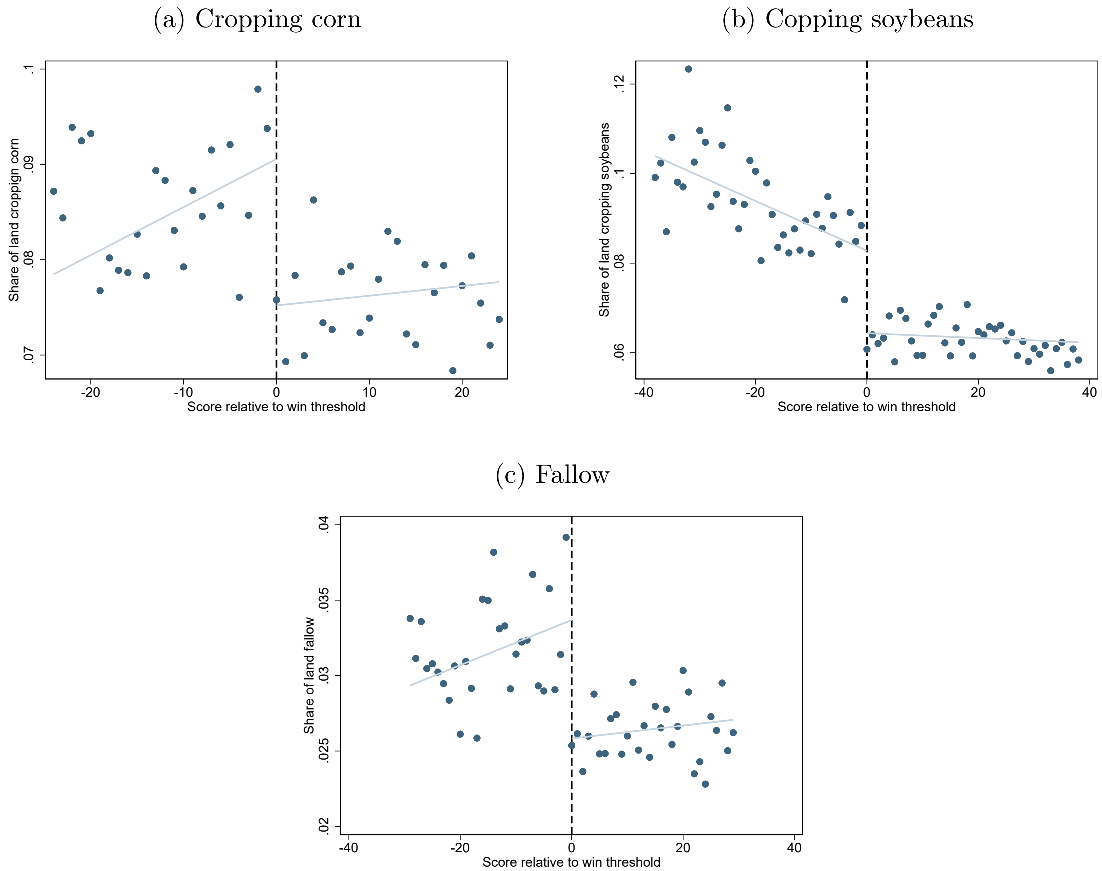


(b) Admin



Notes: Panels (a) and (b) present raw data and estimated parameters from equation (7) with a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Calonico et al., 2014) 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. Corresponding coefficient estimates and standard errors presented in Table 2.

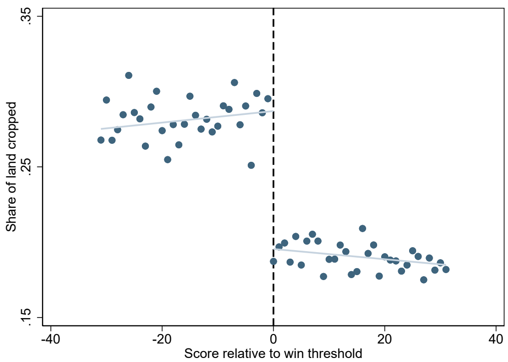
Figure C.2: Additional RD plots: remote-sensing



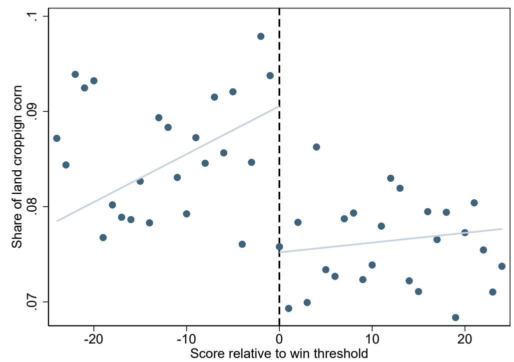
Notes: Figure presents raw data and estimated parameters from equation (7) with a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Calonico et al., 2014) for $r(i,t) > 0$ (post-auction). Land-use outcomes are measured using crop classifications in the remote sensing 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. Corresponding coefficient estimates and standard errors presented in Table 2.

Figure C.3: Additional RD plots: admin data

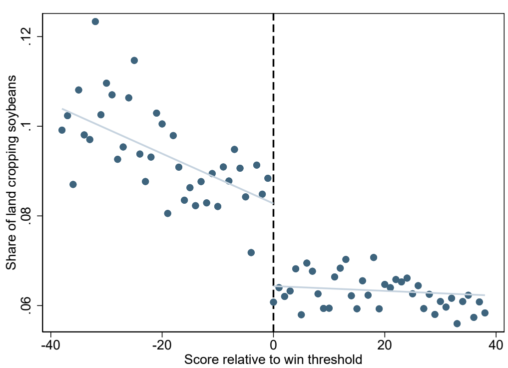
(a) Cropping



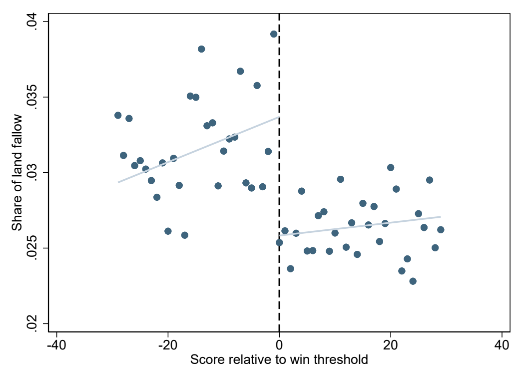
(b) Cropping corn



(c) Cropping soybeans

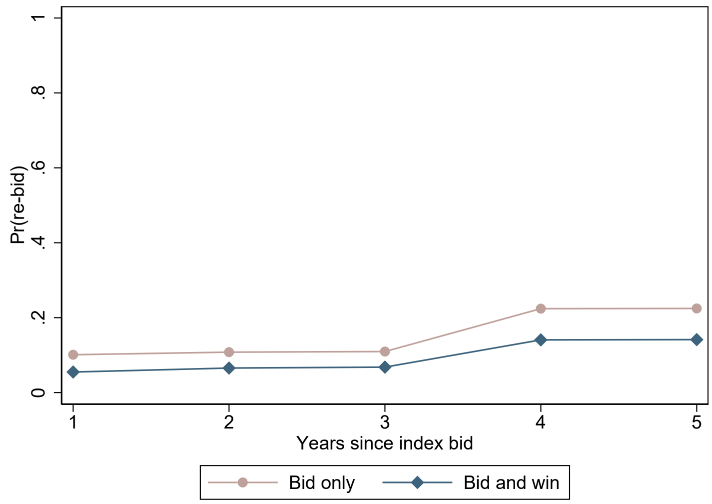


(d) Fallow



Notes: Figure presents raw data and estimated parameters from equation (7) with a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Calonico et al., 2014) 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. 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: split by location of threshold rent of base contract

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

Notes: Table presents pooled RD coefficients (Equation (7) for $r(i,t) > 0$ (post-auction) split by the rental rate required for the base contract to achieve the threshold rule. This uses both variation across auctions and variation within auctions across bidders: bidders with land that is more environmentally sensitive can bid bid a lower rate to obtain a given threshold than those whose lands are given fewer points for environmental sensitivity. Standard errors clustered at the tract level. The outcome is share cropped measured in the remotely sensed data.

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

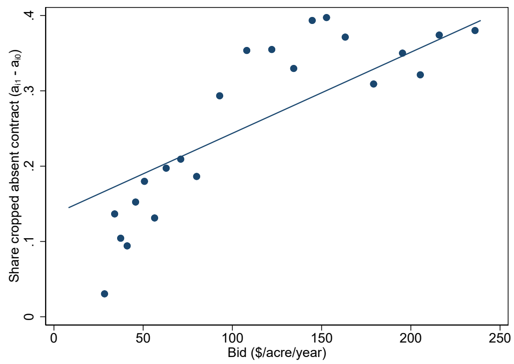
	Remote sensing	Admin
	(1)	(2)
Panel A: Main outcome: share of land cropped		
Pre-sign-up (placebo)	0.016	0.014
	(0.007)	(0.006)
Post-period (pooled sign-ups)	-0.076	-0.095
	(0.007)	(0.006)
Post-period (full contract duration: 2010-2020)	-0.117	
	(0.020)	
Panel B: Other outcomes		
Corn	-0.016	-0.023
	(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), estimated with land use outcomes measured in both the remotely sensed data (column 1) and the administrative data (column 2). The full-contract duration focuses only on the 2009 auction, in which we have a long enough post period to measure outcomes over the full contract duration, others pool all auctions for which we have post-period data: auctions in 2009, 2011, 2012, 2013, and 2016. On average the pooled post-period includes 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 at the RD margin. Panel C estimates the effect of a CRP contract on non-bid, and therefore non-contracting, fields to test for spillovers. We restrict this analysis to the 2016 auction due to a requirement of bid field delineations. All results are based on a specification using a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Calonico et al., 2014). Standard errors are clustered at the tract level.

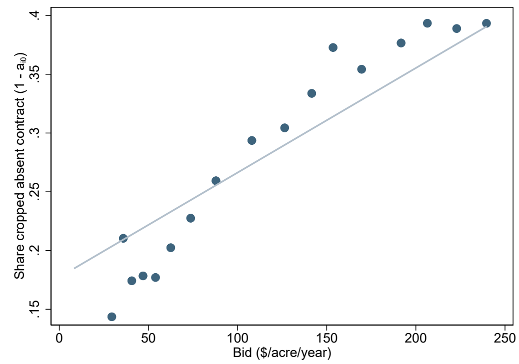
Testing for Asymmetric Information

Figure C.5: Testing for asymmetric information and adverse selection: admin data

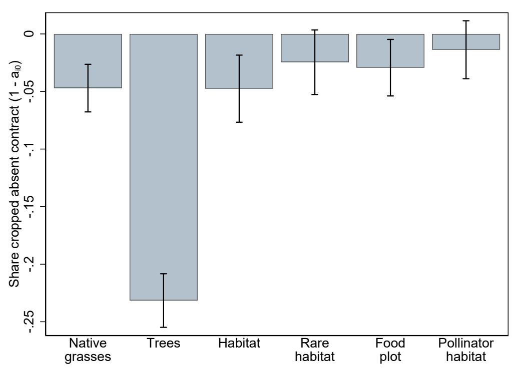
(a) Additionality vs. bids



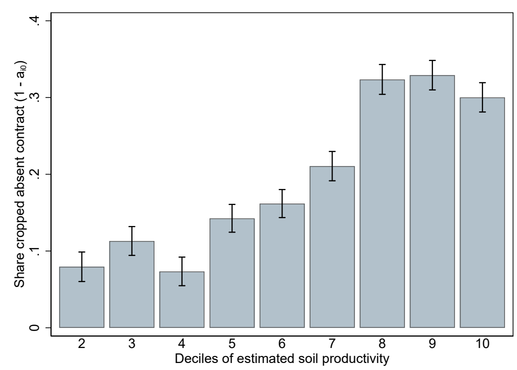
(b) Additionality vs. bids | observables



(c) Additionality across contracts



(d) Observable predictors of additionality



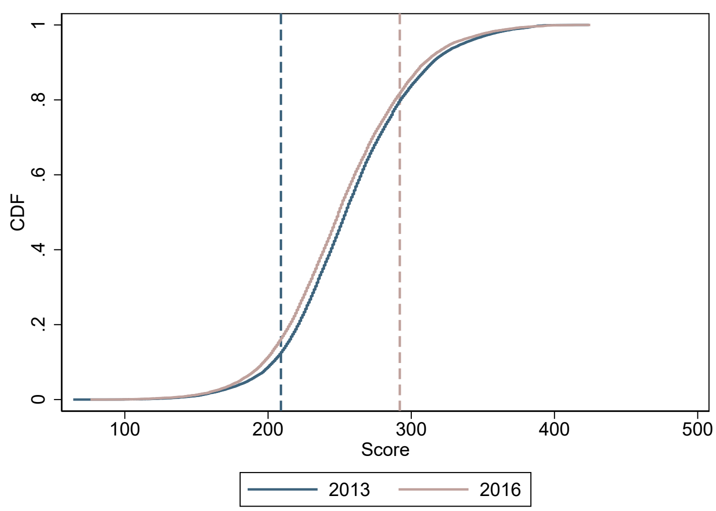
Notes: Figures present visual representations of coefficient estimates of various specifications of equation (8). A positive relationship between bids, or specific contract features, and additionality indicates adverse selection. All regressions control for characteristics that are incorporated in the scoring rule: whether a bidder is in a wildlife priority zone, estimates of groundwater quality, estimates of surface water quality, estimates of win and water erosion (deciles), air quality impacts, and whether or not a bidder is in a air quality zone. Additionality is measured as the share of fields offered into the CRP mechanism that are cropped post auction, conditional on rejection. Estimates are restricted to the auction in 2016, in which 82% of bidders are rejected and the delineations of bid fields are observed. Additionality is measured in 2017-2019 in the administrative data (Form 578). Panel (a) correlates the dollar bid component (per acre, year year) with additionality, conditional on only characteristics included in the scoring rule. Panel (b) adds interaction terms of prior land use (quartiles of prior cropped interacted with re-enrolling CRP status) and deciles of estimated soil productivity. Panel (c) investigates relative additionality by contract features, relative to a base contract feature of introduced grasses. Panel (d) examines relative additionality by deciles of the estimated soil productivity distribution. Standard errors clustered at the bidder level.

D Model and Estimation Details

Information

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

Figure 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 bid distributions for the 2013 and 2016 auctions.

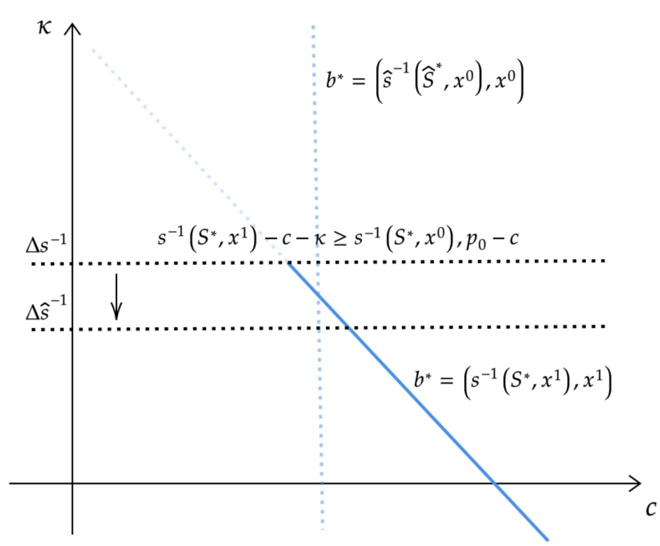
Identification

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 an example menu in Table A.3 for a concrete example of this function). The choice to bid S^* and x^1 at relative payoffs in the scoring rule defined by s identifies the blue line containing the true parameters c and κ. Why a line? The cost of choosing x^1 is $c + \kappa$. The choice of S^* can therefore be inverted as in Guerre et al. (2000) to point identify $c + \kappa$: this is the blue line presented in Figure D.2. Why a line segment? The observation that x^1 was chosen to reach score S^*, and not x^0, given the different payoffs associated with x^0 and x^1 in the scoring rule, bound the magnitude of κ: if κ were higher than the horizontal line defining the blue line segment, it would have been optimal to obtain 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 types as bidders change choices in response to the change in 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 the more complex features of our setting, including 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



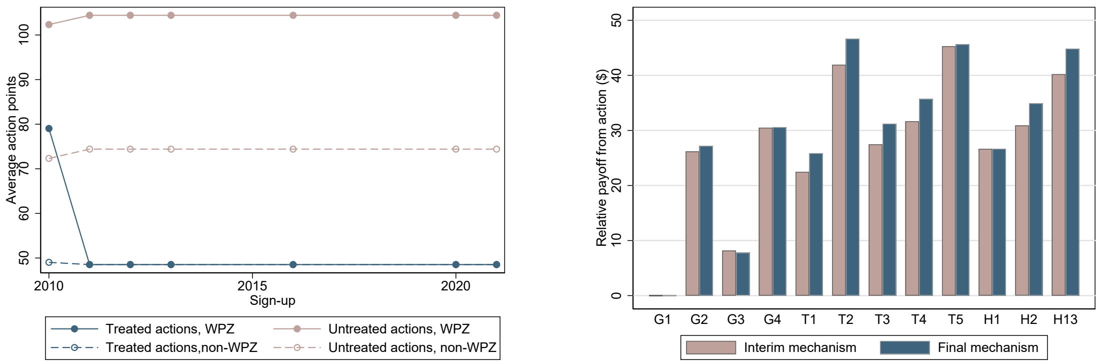
Notes: Figure presents a graphical identification argument. See text for details.

As discussed in the main text, the final component of our model, $\tau\left(\mathbf{z_i}, c_i, \kappa\right)$, is identified by also observing a_{i0} jointly with optimal bids (including as they change with the variation described in Figure D.2) in the thought experiment of an infinitely restrictive auction.

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

Figure D.3: Sources of variation in the scoring rule: choice shifters

(a) Wildlife Priority Zone Variation (b) Mid-Mechanism Policy Change

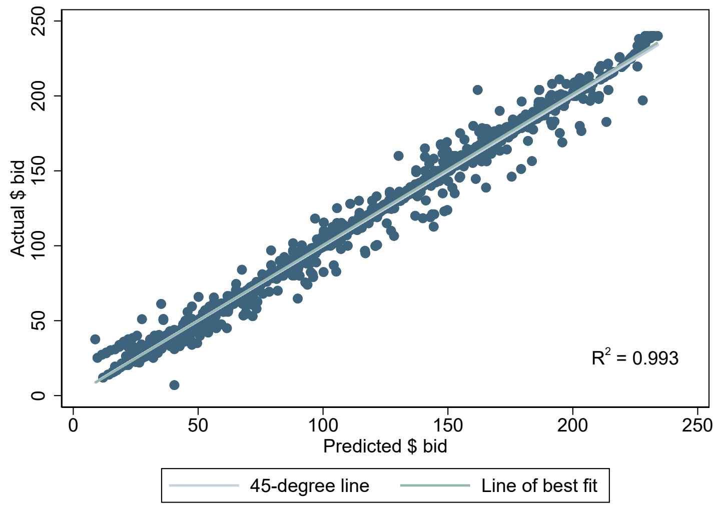


Notes: Figure presents sources of policy variation in the scoring rule that yield variation in returns to contracts. Panel (a) plots average action points award for a set of "treated" actions, actions for which after the 2011 auction WPZ bidders no longer got WPZ points, and "untreated" actions, whose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

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 to achieve the score chosen in the data predicts the observed bid with an R^2 of over 0.99.

Figure D.4: Relationship between predicted and actual bid at observed scores and actions



Notes: Figure presents a scatter plot of actual bids against predicted bids, given observed actions and scores, based on our construction of $s\left(\mathbf{b_i}, \mathbf{z_i^s}\right)$.

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

1. Fit a Beta[59] 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 (1) and the number of opposing bidders, N, in (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.

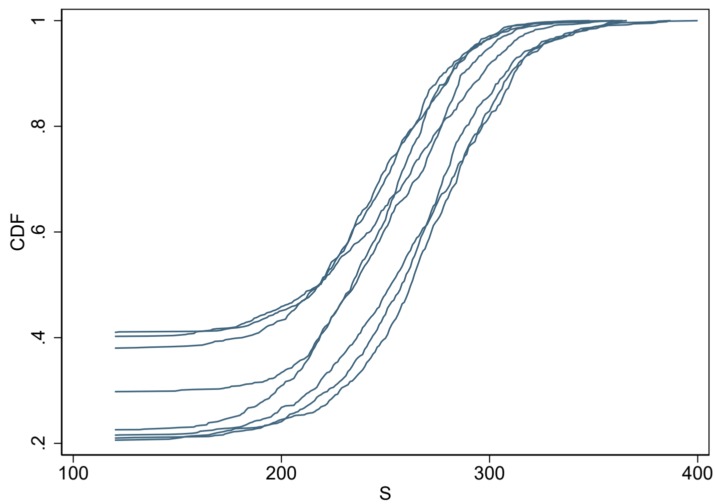
4. Repeat step (3) to obtain an auction specific probability of winning at any given score $G_g(S)$.

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

We do not re-sample separately in each asymmetry class, as in Hortaçsu (2000); Hortaçsu and McAdams (2010), given the information assumptions discussed in the main text. 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.

Figure D.5 plots the output of our simulation procedure across all auctions in our sample.

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 the Distribution of $(c, \kappa_{\mathbf{i}})$ Our estimation procedure is as follows:

1. **Construct a proposal distribution.** Following Ackerberg (2009), we begin by constructing a proposal distribution from which to draw proposal $(c_i, \kappa_{\mathbf{i}})$ 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 separable discrete choice problem and an inversion following Guerre et al. (2000). We obtain parameter estimates from this simplified model, then fit normal distributions to the means and variances (inflating the variance by 25%) for our proposal distribution.

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 $\left(c_i^k, \kappa_{\mathbf{i}}^{\mathbf{k}}\right)$ from the proposal distribution and solve the bidder's problem in equation (10) for each

bidder and each simulation draw. Bidder's can only bid integer scores, so to solve (10), we search over all feasible (based on the bid cap) score-contract combinations among integers in the support of observed scores. This approach 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) used to estimate parameters.

3. **Coarsen choice probabilities.** Because the dimension of possible bids is large (on the order of 10,000 choices), we face the challenge that, absent an extremely large number of simulation draws, the probability of simulating each choice observed in the data is exceedingly low. We address this challenge by coarsening the space of optimal actions, having already solved the problem with the full choice set (step 2). We coarsen these actions into the cartesian product of the two dimensions of choices. The first is deciles of the scoring rule. The second is contract choices, which we coarsen from the full 36 set of contracts to seven dimensions in p_j and u_j. Specifically, we coarsen choices into (1) the five distinct dimensions that comprise p_j when u_j is the no upgrade option, plus the two choices of upgrade options. Let $\widetilde{\mathbf{b}^*} = \left(\tilde{S}_i, \tilde{x}_i\right)$ denote the optimal coarsened bid observed in the data (where we note that this in terms of score and contract choice, not rental rate and contract choice as in the main text).

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, $\widetilde{\mathbf{b}^*} = \left(\tilde{S}_i, \tilde{x}_i\right)$, given parameters to be estimated, θ, is:

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

where $\widetilde{\mathbf{b}^{*\mathbf{k}}}$ is the coarsened optimal bid given simulation draw $\left(c_i^k, \kappa_{\mathbf{i}}^{\mathbf{k}}\right)$, the solution to the bidder's problem in equation (10), and the coarsening described in Step 3. Equation 17 then re-weights simulation draws, for a given parameter guess θ by the ratio of $p\left(\left(c^k, \kappa_{\mathbf{i}}^{\mathbf{k}}\right)|\theta\right)$ is the probability of observing simulation draw $\left(c^k, \kappa_{\mathbf{i}}^{\mathbf{k}}\right)$ given parameter guess θ, and $g\left(\left(c^k, \kappa_{\mathbf{i}}^{\mathbf{k}}\right)\right)$ the probability of observing $\left(c^k, \kappa_{\mathbf{i}}^{\mathbf{k}}\right)$ given the proposal distribution from Step 1. We use log transformations of the PDF of the multi-variate normal to avoid issues of numerical instability.

5. **Find θ to maximize the log likelihood**. We suppressed dependence in (17) on $\mathbf{z_i}$. We estimate θ separately for each of our 32 cells of observable heterogeneity for a sample of 1,000 bidders in each cell in each auction. as our computational capabilities are

somewhat limited on the USDA servers. Another benefit of the importance sampling approach of Ackerberg (2009) is that it results in a differentiable objective function, allowing for the use of a gradient-based optimizer.

6. **Repeat**: We repeat Steps 2-5 several times, using estimates from the solution to Step 5 as new the proposal distribution to ensure that results are not sensitive to simulation error based on our initial proposal distribution. Our final estimates use 10,000 simulation draws to minimize the simulation bias in maximum simulated likelihood estimators (Train, 2009).

We calculate standard errors in Table D.1 using the negative inverse of the Hessian.

Step 3: Estimate $\tau(\mathbf{z_i}, c_i, \kappa_i)$ Our final step involves estimating the conditional expectation function $\tau(\mathbf{z_i}, c_i, \kappa_i) = \mathbb{E}[1 - a_{i0} \,|\, \mathbf{z_i}, c_i, \kappa_\mathbf{i}] = \pi \cdot \mathbf{z_i} + \beta \cdot c_i + \alpha \cdot \kappa_\mathbf{i}$. We match model implied moments of additionality $(\tau(\mathbf{z_i}, c_i, \kappa_i))$ to observed moments of additionality, $1 - a_{i0}$ among rejected bidders (as in Section 4.2). We call these moments m_i. We search for $\theta^\tau = (\pi, \beta, \alpha)$ that minimizes $\hat{g}(\theta^\tau)' A \hat{g}(\theta^\tau)$ for weighting matrix A and sample moments: $\hat{g}(\theta^\tau) = \hat{\mathbb{E}}\left[m_i - \frac{1}{K}\sum_k m_i\left(\theta^\tau | c_i^k, \kappa_i^k\right)\right]$, where $\hat{\mathbb{E}}$ denotes the sample expectation. We use as m_i:

- 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: $(1 - a_{i0}) \cdot \mathbb{1}[x_{ij} = 1] \cdot \mathbb{1}\left[s\left(\mathbf{b_i^*}, \mathbf{z_i^s}\right) < \underline{S}\right]$.

Each of the moments above is observed in the data, conditional on the score being below the winning score threshold, or $s\left(\mathbf{b_i^*}, \mathbf{z_i^s}\right) < \underline{S}$. We therefore condition all of our moments on this selected sample.

Our estimation approach follows the following steps:

1. Draws simulations $\left(c_i^k, \kappa_\mathbf{i}^\mathbf{k}\right)$ from the distribution estimated in Step 2 (via MSL).
2. Calculate optimal bids $\mathbf{b_i^*}(c_i^k, \kappa_\mathbf{i}^\mathbf{k})$ using optimal bidding in equation (10).
3. Calculate $m_i\left(\theta^\tau | c_i^k, \kappa_i^k\right)$ by replacing $1 - a_{i0}$ with $\pi \cdot \mathbf{z_i} + \beta \cdot c_i + \alpha \cdot \kappa_\mathbf{i}$ and observed bids with simulated optimal bids for each simulation draw k and parameter guess θ^τ.

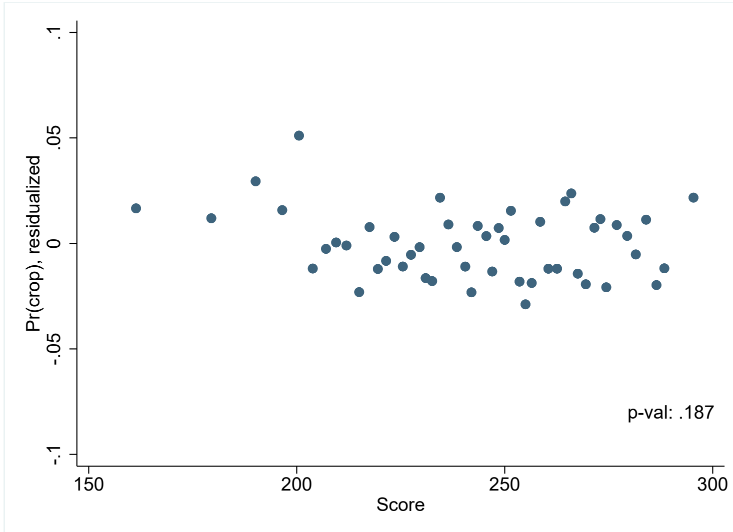
4. Minimize the objective $\hat{g}(\theta^{\tau})' A \hat{g}(\theta^{\tau})$.

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 $\tau(\mathbf{z_i}, c_i, \kappa_i)$ using only the single 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 $\tau(\mathbf{z_i}, c_i, \kappa_i)$ in this auction can be extrapolated to the other auctions in our sample, and that $\tau(\mathbf{z_i}, c_i, \kappa_i)$ 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 rejected bidders, not those transitioning into land retirement.

To ensure that our estimates are not relying exclusively on the normal functional form assumptions for $(c_i, \kappa_\mathbf{i})$, we require instruments that shift $s(\mathbf{b_i^*}, \mathbf{z_i^s})$ but that are conditionally independent of a_{i0}. We use landowners' Wildlife Priority Zone and Air Quality Zone status as instruments. While testing the exclusion restriction directly is impossible, we conduct a test 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 this point identified c_i and the remaining controls. This suggests that the residual variation in the score — which includes variation in these instruments — is conditionally independent of a_{i0}. Of course, this is estimated using a different model where we can more easily "control for" the endogenous component of the score. Figure D.6 is therefore only suggestive, but at least encouraging, that our instruments are valid.

Figure D.6: Residualized relationship between score 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 a scoring rule characteristics except for Wildlife Priority Zone and Air Quality Zone, and the score. Estimated among losing bidders in the 2016 auction only.

We calculate standard errors via bootstrapping. Our final bootstrapped estimates will bootstrap over the entire estimation procedure, incorporating variance from estimators in earlier steps. The current standard errors do not incorporate estimation error in $(c_i, \kappa_{\mathbf{i}})$.

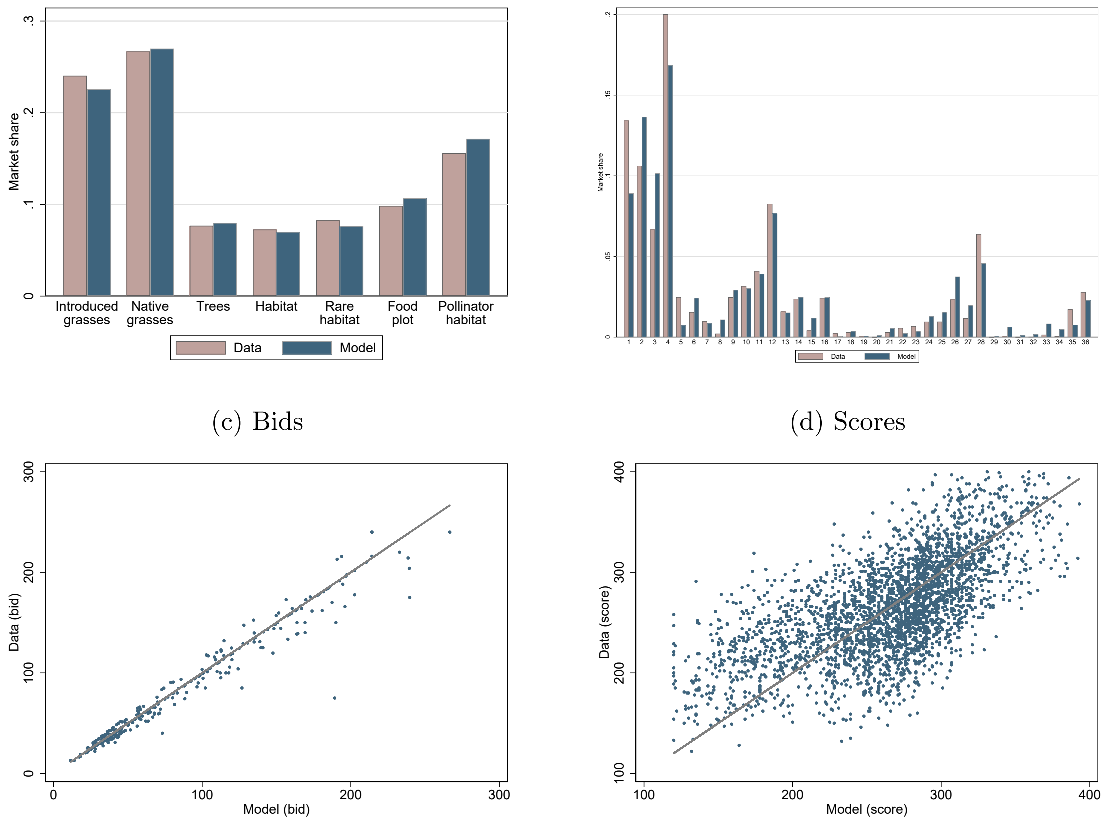
Results: Select Parameter Estimates and Model Fit The tables and figures below present parameter estimates and assess the fit of the bidding model.

Table D.1: Example (c_i, κ_{ij}) estimates

	Former CRP = 0				Former CRP = 1			
Former 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: Assessing model fit



(a) Choice probabilities: coarsened

(b) Choice probabilities: all 36 contracts

(c) Bids

(d) Scores

Notes: Figures summarize model fit by comparing simulated choices of contracts, bids, and scores to the data. Coarsened actions fit better than the full set of actions because we are matching 36 contracts with only 7 parameters. Similarly, bids fit better than scores, since scores incorporate the discrete choice of action.

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 reflect the relative weights (in dollars) that the planner places on $B_j(\mathbf{z_i^s})$ across j and $\mathbf{z_i^s}$, assuming $a_{i0} = 0$ for all i. The main idea is that the mechanism implicity makes trade-offs in the scoring rule that monetize relative 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.* Seond, 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. Therefore, the assumption that the USDA maximizes overall social welfare when designing its auction and scoring rule, which it does by announcing its preferences in the scoring rule, further makes this assumption palatable. It also motivates our focus on efficient auctions.

However, the USDA revealed-preferred values of $B_j(\mathbf{z_i^s})$ may not necessarily align with the true "environmental benefits" or social value across $B_j(\mathbf{z_i^s})$ for a variety of reasons, chief among them political concerns in the design of the scoring rule (Ribaudo et al., 2001). We choose to take this USDA-revealed-preferred approach, versus calibrating n $B_j(\mathbf{z_i^s})$ from an external integrated assessments model,[60] to focus on additionality as the primary source of social welfare losses, rather than miscalibrated values.

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 amount:

$$s\left(\mathbf{b}_i, \mathbf{z_i^s}\right) = \underbrace{s_a\left(\mathbf{x}_i, \mathbf{z_i^s}\right)}_{\text{action points}} + \underbrace{s_r\left(r_i\right)}_{\text{non-linear function of rental rate}}, \tag{18}$$

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. Based on conversations with USDA officials, the fact that different bidders face different quasi-linear scoring rules based on their bidcap

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

does not reflect differential valuation of environmental benefits across bidders, nor does it reflect differential additionality. Therefore, we use the median $s'_r(r_i)$.

Using our "quasi-linearized" approximation to the scoring rule, we now 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 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. If a CRP contract award induces changes to the environment beyond the 10-year contract, our valuations will thus be an under-estimate.

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

1. Our first estimate sums the recreational,[61] public works,[62] and air quality benefits[63] 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 (permanent) 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 global valuation of the CRP from Hansen (2007), which is equal to $255.70, per acre, per year.

3. Our third and fourth estimate take a conservative and generous value of the non-GHG CRP benefits from Johnson et al. (2016) and adds estimates of the value of greenhouse gas reductions from sequestered CO_2 (over the 10-year contract) and reduced fuel and fertilizer use (permanent) monetized at $43 per metric ton. This leads to estimates of $367.96 and $456.04, per acre, per year. These may be an over-estimate because they 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 and in terms of ultimately monetizing them. As an example, these estimates

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

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

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

do note incorporate the adverse health impacts of insecticide use documented in (Taylor, 2022). We emphasize that our focus is not on obtaining estimates of $B_j(\mathbf{z_i^s})$, but rather how additionality $\tau(\mathbf{z_i}, c_i, \kappa_i)$ impacts welfare and market design. We use these estimates only to scale our primary object of interest, $B_j(\mathbf{z_i^s})$. Our results can easily be recalculated for any alternative valuation of $B_j(\mathbf{z_i^s})$. Quantifying the environemental value of ecosystem services is an important complementary area of research.