

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

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Abstract

Market mechanisms encourage the delivery of environmental services at low cost, but targeting payments to participants whose behavior is affected by the incentive — “additionality” — is complicated by information asymmetry. We explore this market design challenge in the context of auctions for conservation contracts in one of the largest Payments for Ecosystem Services mechanisms in the world, the US Conservation Reserve Program. We use a regression discontinuity design to estimate that three of four marginal bidders would have counterfactually retired land in the absence of the incentive, and we show that heterogeneity in counterfactual land use introduces adverse selection in the market. We develop and estimate a joint model of bidding and land use (additionality) to quantify the implications of this market failure for the performance and design of procurement mechanisms and competitive offset markets. We find that feasible procurement schemes that set incentives based on heterogeneity in additionality generate substantial welfare gains. In offset markets, adverse selection limits trade (-15%) and reduces welfare (-5%) relative to optimal incentives, but feasible differentiated pricing reduces this gap. Our results highlight that, especially when well-designed, markets for environmental services can deliver welfare gains even in the presence of non-additionality.

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1 Introduction

Land-use change contributes 9% of global greenhouse gas emissions (Le Quéré et al., 2015) and leads to 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). “Additionality” drives this divergence: successful market design is challenging when only some participants’ behavior are affected by the market incentive. Will additionality drive markets to failure, undermining the widespread adoption of environmental incentive policies and the promise of offset markets (Salzman et al., 2018; Kosoy et al., 2015)?¹ Or can environmental markets be designed to achieve their promise of low-cost climate change mitigation (Griscom et al., 2017)?

We address these questions by analyzing additionality as a market failure of information asymmetry. Landowners may possess and potentially act upon private information about the probability that the incentive will impact their behavior, i.e. their additionality (Roy, 1951; Jack and Jayachandran, 2019). This presents the fundamental challenge to these markets as information asymmetry can drive them to failure (Akerlof, 1970; Manelli and Vincent, 1995). Analyzing additionality as a problem of information asymmetry also presents the opportunity that we take up in this paper: to use a well-developed set of tools to analyze, test, quantify, and remedy this classic market failure.

We conduct our analysis in the context of the United States Department of Agriculture’s Conservation Reserve Program (CRP), the oldest and largest Payments for Ecosystem Services (PES) mechanism in global history.² The CRP incentivizes the retirement of agricultural land and the adoption of conservation activities via procurement auctions of conservation contracts. We assemble a unique dataset linking landowner bids to their eventual land use, regardless of the success of their bids. Crucially, the data on land use — which we obtain via satellite imagery — allows us to measure additionality. Combined with this data, the CRP auction provides an ideal empirical setting for each step of our analysis: assessing the extent of additionality, testing for information asymmetry, and quantifying their implications for

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

²Integrated 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.

welfare under current and alternative market designs. The insights gained from this rich setting are broadly applicable: CRP contracts are structured similarly to other PES programs,³ to contracts traded in global offset markets ([Engel et al., 2008](#)), and to private competitive agricultural offset markets in the US.

We first formalize the connection between additionality and information asymmetry and their implications for welfare and market design in the graphical welfare framework of [Einav et al. \(2010\)](#). Landowners differ in both their willingness to accept a contract to provide an environmental service — the minimum dollar amount they would need to be paid to accept the contract — and their additionality — the probability that contracting will impact their behavior. The value of a contract to a buyer depends on a landowner’s additionality but her choices depend only on the market incentive. This divergence generates the possibility of inefficient selection, and when a landowner’s willingness to accept a contract is low because that contract is unlikely to change her behavior, adverse selection in the market. This presents the challenge to market design. In procurement, adverse selection can erode achievable surplus ([Manelli and Vincent, 1995](#); [Lopomo et al., 2023](#)). In competitive offset markets, adverse selection can prevent efficient trades, as buyers of contracts take expectations over the expected additionality of *all* market participants, not only those contracting at the margin ([Akerlof, 1970](#)). These challenges can be remedied if markets can be 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 graphical analysis highlights that the quantitative importance of these market design challenges and opportunities for remedy depend on two curves: (i) an *incremental value* curve — the value of contracting beyond baseline, which depends on additionality ([Heckman and Vytlacil, 2001, 2005](#)) — and (ii) a *willingness to accept* curve, which governs choices in the market. Our model is agnostic about the relationships between these curves, following [Jack and Jayachandran \(2019\)](#), who highlight the importance of capturing a complex relationship — based on hassle costs, imperfect foresight, or other factors — between landowners’ contracting decisions and their additionality.⁴ The scope of additionality, the existence and extent of adverse selection, and together, their quantitative implications for the function and design of environmental markets are all empirical questions.

We begin with the first of these empirical questions and examine the extent of additionality. While a crucial input into the design and evaluation of environmental markets, credible es-

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

⁴Indeed, [Jack and Jayachandran \(2019\)](#) do not detect evidence of adverse selection, despite its clear theoretical possibility.

timates of additionality — particularly in large-scale, mature markets — are scarce, as they require knowledge of an unobserved counterfactual (Rubin, 1974). We use the discontinuity in contracting around the winning bid to evaluate additionality at the margin of acceptance. We document that landowners substitute away from row-crop agriculture to natural vegetation and grasslands upon contracting. We calculate additionality by comparing our estimated regression discontinuity treatment effects to the magnitude of land contracting at the margin. We find that only one quarter of landowners are additional: non-additionality is quantitatively important in this setting.

To test for asymmetric information about additionality, we relate heterogeneity in additionality to heterogeneity in willingness to accept. We simplify the causal problem with two assumptions — perfect compliance and no leakage, both of which we test and validate — to obtain an i -specific measure of additionality for *all* rejected bidders (82% in our most restrictive auction). We examine the relationship between i -specific additionality and i -specific bids following classic tests for information asymmetry in insurance markets Chappori and Salanie (2000) and auctions (Athey and Levin, 2001). We document substantial heterogeneity in additionality and a positively 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 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.

Our analyses quantifying the extent of non-additionality and the existence of adverse selection provide clear evidence on the challenges to environmental market design. But the implications of these challenges for the performance of environmental markets requires a quantitative economic framework, namely, the incremental value and willingness to accept curves. In the second half of the paper, we develop and estimate a joint model of bidding and additionality to obtain these objects. Our model and estimation strategy first infers willingness to accept from revealed preferences in bidding behavior alone, and then obtains both the level of additionality and its relationship to willingness to accept using the same assumptions, variation, and patterns presented in the first half of the paper.

The CRP's auction mechanism again provides an ideal empirical setting. Landowners submit multi-dimensional bids across heterogeneous contracts, which are ranked by a scoring rule. This multi-dimensional auction provides an exceptionally rich environment for analyzing opportunities for market design, as both the menu of contracts and observable predictors provide tools to increase social welfare in the presence of non-additionality. We develop a

model of bidding that accommodates both this complex bidding environment and our central aim to capture adverse selection in this market. We first 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. We use the insight that the bidding problem can be solved as an “inner” single-agent discrete choice problem and an “outer” one-dimensional game. We further specify an additional dimension of landowner type, her additionality, which we define as the conditional expectation of each bidder’s change in land use, given both observable characteristics and the unobserved landowner types that govern optimal bidding. This conditional expectation — a Marginal Treatment Effect (MTE) curve ([Heckman and Vytlacil, 2001, 2005](#)) — is the model primitive that captures heterogeneity in the value 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 ([Hortaçsu, 2000](#); [Hortaçsu and McAdams, 2010](#); [Agarwal et al., 2023](#)). We first estimate bidder beliefs via simulation then bidder types via revealed preferences. We rely on variation in the scoring rule for identification of the distribution of willingness to accept across contracts. In the final step, we estimate additionality and its dependence on unobserved landowner types by matching the levels of additionality and the relationship between additionality, observable characteristics, and optimal bids presented in our descriptive analyses. We use our estimates of additionality to calculate the incremental value of contracting based on valuations of environmental services from the CRP literature and the USDA’s revealed preferences implied by the scoring rule, both of which assume full additionality ([Claassen et al., 2018](#)).⁵

We examine our estimates in our graphical welfare framework. Despite estimates that capture both non-additionality and adverse selection, we find that a uniform-price market for the base contract of land retirement can deliver substantial welfare gains in procurement regimes (\$22.79 per acre-year) and in competitive offset markets (\$21.57 per acre-year). The divergence between these two market structures (-5%) reflects the trade-limiting effects (-15% relative to the efficient quantity) of adverse selection in competitive markets ([Akerlof, 1970](#)). This simple graphical analysis illustrates a primary conclusion of our quantitative economic framework: despite the existence of non-additionality and adverse selection — factors that could lead to complete market failure — we find that this market *can* succeed. Although adverse selection would limit trade and reduce welfare, offset markets for CRP contracts would not completely unravel.

⁵“Benefit-cost indices are used to rank applications for acceptance in all major USDA conservation programs... Existing indices, however, implicitly assume full additionality.” ([Claassen et al., 2018](#))

This optimism is accompanied by both challenges and further opportunities for improvements to market design. First, achieving these gains requires optimal price-setting, which depends on estimates of the population distributions of both additionality and willingness to accept (Eisenhauer et al., 2015). Mis-pricing that ignores the possibility of non-additionality can erode 27% of surplus. Second, not all contracts succeed. We examine heterogeneity across contracts — made possible by our model of bidding on discrete contract features — and demonstrate that adverse selection among forestry contracts, similar in structure to controversial forestry offsets, is more severe. The extent of adverse selection in markets for these contracts can prevent a regulator from achieving the first best and completely unravel competitive markets for forestry offsets. Finally, we document heterogeneity in our estimates of willingness to accept and additionality across observable characteristics.

We evaluate the implications of this graphical analysis for the performance of the CRP auction mechanism and alternative market designs. In the presence of non-additionality, the welfare effects of the CRP mechanism are ambiguous; we estimate that it generates welfare gains of between \$340 and \$590 million per auction. However, the status quo falls far short of a first best allocation. Achieving this allocation with an incentive compatible mechanism is infeasible as our estimates of adverse selection imply that social surplus is not monotone in bidder type (Myerson, 1981). We instead design feasible, asymmetric Vickrey-Clarke-Groves (VCG) auctions that increase welfare by \$250-\$450 million per auction. VCG mechanisms that do not account for heterogeneity in additionality across observable characteristics and contract choices leave achievable surplus on the table. Designing the scoring rule to more closely align socially optimal allocations, which depend on additionality, and landowner-optimal choices, which do not, generates welfare gains of at least 10% of the status quo. Differentiated posted prices regimes deliver welfare gains via similar mechanisms.

We conclude by discussing offset market design. Competitive markets introduce distinct welfare considerations: a differentiated offset market may or may not be more efficient than a uniform one. We find that feasible contract differentiation based on readily available covariates would increase welfare in a counterfactual competitive offset market by 16%, reducing both inefficient selection and inefficiently-limited trade due to adverse selection. Next, we consider which contracts could be successfully traded. Building on our graphical analysis, we find that only forestry offsets would unravel, while welfare losses from adverse selection in alternative markets — grasses, habitats — are limited to at most 5%, even with uniform pricing.

Together, our results highlight that although non-additionality and adverse selection both exist and in theory, pose an existential challenge to environmental market design, 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 types that determine choices, but crucially, the implications of these choices for additionality, social welfare, and the success of the market.

Related Literature Most generally, our paper contributes to a recent literature that evaluates market designs based on their impact on treatment effects, rather than revealed-preference measures of participant welfare alone. These ideas have been applied empirically to organ allocation problems (Agarwal et al., 2020), foster care (Robinson-Cortés, 2019), and education (Barahona et al., 2023; Kapor et al., 2022; Larroucau and Rios, 2023), and typically require estimating a relationship between revealed preference choices and outcomes — in our setting, additionality. In doing so, we relate to an empirical literature analyzing multi-dimensional screening problems with moral hazard (Chade et al., 2022; Gaynor et al., 2023) as well as theoretical work on contracting under asymmetric information in our specific context of PES and offset markets (Li et al., 2022; Mason and Plantinga, 2013; Haupt et al., 2023).

Our model to evaluate the impact of additionality on market designs brings together the literature on Roy-selection and policy-relevant treatment effects (Heckman and Vytlacil, 2001, 2005; Eisenhauer et al., 2015; Ito et al., 2021) with (i) a large literature on the analysis of selection markets (Akerlof, 1970; Einav et al., 2010; Bundorf et al., 2012) and (ii) a smaller literature on adversely selected procurement auctions (Manelli and Vincent, 1995; Laffont and Tirole, 1987; Lopomo et al., 2023; Carril et al., 2022). In our setting, Roy-style selection into contracting generates adverse selection that can erode achievable surplus in procurement and limit trade in competitive markets. We develop a new approach to analyze this selection, relating Marginal Treatment Effects to types revealed by optimal bidding in an auction.

Methodologically, our auction model and estimation strategy builds on a literature advancing the analysis of auctions (Asker and Cantillon, 2008; Che, 1993; Jofre-Bonet and Pesendorfer, 2003; Agarwal et al., 2023; Hortaçsu, 2000; Hortaçsu and McAdams, 2010; Hanazono et al., 2020) and contributes to a recent empirical literature analyzing scoring (Bolotnyy and Vasserman, 2023; Allen et al., 2023) and other multi-dimensional auctions (Kong et al., 2022).

Most directly, our paper contributes to the literature on PES and a small literature on offset market design (Aronoff and Rafey, 2022; Calel et al., 2021). Papers studying PES have focused primarily on estimating average treatment effects of incentive payments (Alix-Garcia et al., 2015; Jack, 2013; Jayachandran et al., 2017; Jack and Jayachandran, 2019; West

et al., 2020; Calel et al., 2021; Rosenberg et al., 2022). While others have highlighted the possibility of selection, evidence detecting it has been mixed (Montero, 1999; Jack, 2013; Jack and Jayachandran, 2019). Our primary contribution relative to this literature is two-fold. First, we provide estimates of additionality — treatment effects relative to both the zero effect and a 100%-additional benchmark — and clear evidence of adverse selection, both in a large-scale, mature market. Second and more importantly, we develop a framework to evaluate the welfare and market design consequences of these descriptive facts in both procurement and offset market settings. Though our application is related to conservation incentives, our general framework applies broadly to ubiquitous voluntary environmental regulation (Allcott and Greenstone, 2017; Borenstein and Davis, 2016; Boomhower and Davis, 2014).

2 Theoretical Framework

We begin with a simple graphical framework to formalize the challenge of additionality and its implications for welfare, market design, and empirical analysis.

2.1 Model

We consider a population of landowners, indexed by i , each making a binary decision to contract, $x \in \{0, 1\}$, to obtain a transfer, p . The contract involves a promise to provide an environmental service, $a = 1$, for $a \in \{0, 1\}$. In our setting, $a = 1$ denotes agricultural land retirement, versus cropping, $a = 0$. The action $a = 1$ generates social value from positive environmental externalities. The buyer of the contract — either a regulator or a buyer in an offset market — values these benefits from $a = 1$ at $B > 0$, creating the possibility of gains from trade.

Contract Value The action $a_i = 1$ delivers value in the absence of a contract because the social value B is delivered whenever i chooses $a_i = 1$, *regardless* of x_i . The surplus generated by contracting with i is therefore only the *incremental value* $B \cdot (a_{i1} - a_{i0})$, where a_{i1} denotes i 's action with the contract, and a_{i0} denotes i 's action without the contract. Under perfect compliance, $a_{i1} = 1$. However, a_{i0} is unobserved whenever $x_i = 1$ (Rubin, 1974), and is therefore non-contractible. This hidden action is the basis of the market failure introduced by non-additionality.

Landowner Types Each landowner i is characterized by two objects. The first is a landowner’s private transaction-relevant type, WTA_i , or her willingness to accept the contract. This is defined as the minimum transfer p required for a landowner to choose $x_i = 1$. The second object, τ_i , governs the value of contracting with i , and is defined as:

$$\tau_i \equiv \mathbb{E} [a_{i1} - a_{i0} | \mathcal{I}] \quad (1)$$

where \mathcal{I} denotes the information set of a market designer, and includes information that could be observed or elicited (WTA_i). We will refer to τ_i as i ’s *additionality*, or the expected change in a_i with versus without the contract for landowner i . In our stylized setting, absent any observable characteristics, $\tau_i = \mathbb{E} [a_{i1} - a_{i0} | WTA = WTA_i]$. In other words, τ is the Marginal Treatment Effect of contracting (Heckman and Vytlacil, 2001, 2005).

We briefly make two comments on this formulation of landowner types. First, we use (WTA_i, τ_i) as model primitives, which serve as sufficient statistics for welfare under the status quo and counterfactuals that hold this distribution fixed.⁶ Second, we consider an unrestricted relationship between WTA_i and τ_i . WTA_i and τ_i could be related, as landowners may have a low WTA_i for the same reason that they have a low τ_i — unprofitable land — but the exact form of this relationship is complex in realistic settings (Jack and Jayachandran, 2019). Landowners may have imperfect foresight over future a_i , and contracting frequently involves activities beyond $a = 1$ that impose (heterogeneous) hassle costs that enter WTA_i .⁷ The relationship between WTA_i and τ_i is therefore an empirical question.

Social and Landowner Incentives We define the expected social surplus of contracting with i as:

$$SS_i = B \cdot \tau_i - WTA_i \quad (2)$$

Gains from trade arise when the incremental value of environmental services are higher than a landowner’s willingness to accept the contract. Landowners make contracting decisions:

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

The divergence between Equations (2) and (3) illustrates a fundamental challenge: i transacts

⁶In other words, we integrate over the complex type distribution discussed above. This approach is common in both empirical (Einav et al., 2010) and theoretical (Lopomo et al., 2023) treatments of selection markets.

⁷These include complying with mandates to purchase specific seed mixes, paperwork burdens to process payments, and audits to manage compliance, and any taste or distaste for participating in an environmental market.

based only on the transfer p and her WTA_i , but efficient selection depends on τ_i , or i 's additionality.

Market Structure We consider two market structures. In both, non-contractibility of a_{i0} and the heterogeneity in $B \cdot \tau_i$ that it introduces will generate challenges to market design than can erode or even reverse the possibility of gains from trade. But the distinct market structures will lead to distinct sources of welfare loss.

Surplus-Maximizing Regulator First, we consider a regulator or market designer maximizing social surplus. Let $\theta_i = (WTA_i, \tau_i)$ and $F(\theta)$ define the population of landowners. For ease of exposition, we focus on the following price-setting problem:⁸

$$\max_p \int SS(\theta) \cdot x^*(p; \theta) dF(\theta) \quad (4)$$

where a regulator sets a single price to maximize welfare, given knowledge of the population distribution $F(\theta)$ but not each θ_i .⁹

Trade in Offset Markets Second, we consider a competitive offset market, which facilitates the trade of contracts for the incremental value of environmental services between decentralized buyers and landowners. Offset contracts are defined by a single price, p , and pool together all landowners willing to contract at p . As in the regulator's case, buyers know the distribution $F(\theta)$ but cannot distinguish across contracting landowners. Buyers in offset markets purchase a contract when its expected value $\mathbb{E}[B \cdot \tau_i | WTA_i \leq p]$ is greater than or equal to its price p .

2.2 Graphical Analysis

We analyze welfare using the graphical framework of [Einav et al. \(2010\)](#) in Figure 1. We begin by analyzing the regulator's problem who seeks to maximize social surplus with a single price. Figures 1a and 1b plot two distinct markets, each containing the same two curves, defined by different population distributions of $\theta_i = (WTA_i, \tau_i)$.

⁸While we have written Equation (4) as a price-setting problem, we note that it is isomorphic to a regulator searching for efficient quantities and implementing an allocation, given those quantities, with an efficient auction.

⁹For now, we abstract away from observable characteristics that would allow for differentiated pricing and any costs arising from the need to finance payments via distortionary taxation.

The first curve is the WTA curve, or the CDF of the population distribution of WTA_i . The second is the incremental value curve $B \cdot \tau$, which calculates the value of $B \cdot \tau_i$ at each point on the WTA curve. Note that the incremental value curve lies weakly below B — the social value of $a = 1$ — reflecting non-additionality of landowners. Figure 1 displays an upwards-sloping $B \cdot \tau$ curve, reflecting the fact that expectations over a_{i0} — whether a landowner would retire or crop her land in the absence of the contract — may influence WTA_i .¹⁰ This upwards-sloping $B \cdot \tau$ curve captures adverse selection in the market: landowners with the lowest WTA_i are also the least additional and therefore deliver the least incremental environmental value.¹¹

Recall from Equation (2) that social surplus is defined as the difference between these two curves: the area underneath the incremental value curve $B \cdot \tau$ and above the WTA curve represents social welfare gains. Conversely, in any regions where the WTA curve lies beneath the incremental value curve $B \cdot \tau$, contracting will *reduce* social surplus. In these regions, the costs imposed on landowners do not outweigh the incremental environmental gains of contracting.

The Regulator’s Problem In Figure 1a, despite the existence of adverse selection, the first best outcome can be achieved by setting p^* at the intersection of the incremental value and the WTA curves. Contracting with all landowners with $WTA_i \leq p^*$ delivers social welfare gains in triangle ABC. However, the simplicity of this solution belies the challenge that additionality poses, even when a regulator can achieve the first best. This optimal price depends on the shape of $B \cdot \tau$, which depends on heterogeneous treatment effects at each point along the WTA curve. Mis-pricing generates welfare losses. Consider instead a regime that ignores the possibility of non-additionality and prices at B . This generates welfare losses in triangle CDE, that, in the market defined by Figure 1a, erodes almost all gains from trade realized in triangle ABC.

Figure 1b demonstrates an alternative market. Now, the $B \cdot \tau$ curve lies below the WTA curve at the bottom of the distribution, reflecting very low additionality at low, but still positive, levels of WTA_i . This causes the $B \cdot \tau$ curve to cross the WTA curve more than once. In this market, the regulator *cannot* achieve the first-best allocation, triangle ABC, as any price that induces contracting in triangle ABC also yields social welfare losses in triangle CDE. In

¹⁰A positive relationship between WTA_i and τ is an instance of “selection on slopes” or “selection on moral hazard” in the terminology of (Einav et al., 2013).

¹¹We note that the exact shape of the $B \cdot \tau$ curve (as well as the WTA curve) are merely for illustrative purposes and, and both are ultimately empirical question. Indeed, the purpose of contrasting Figures 1c and 1d is to show how different $B \cdot \tau$ and WTA curves can generate substantially different conclusion, motivating the need for empirical analysis.

fact, the optimal price is $p^* = 0$: adverse selection unravels the opportunity for a regulator to offer a market at all, despite the existence of gains from trade. This occurs because of the divergence between Equations (2) and (3): the regulator cannot induce efficient selection because it cannot observe and set differentiated incentives based on τ_i . More generally, in the market defined by Figure 1b, *no incentive compatible mechanism* can achieve the first best (triangle ABC) — or in this example, positive surplus at all — because the relationship between social surplus and transaction-relevant types (WTA_i) is not monotone (Myerson, 1981; Manelli and Vincent, 1995).

Offset Market Equilibrium In Figures 1c and 1d, we illustrate how the same economic challenge — heterogeneity in $B \cdot \tau_i$ that can lead to adverse selection — generates further welfare losses and design challenges in offset markets, exactly as in the classic lemons market of Akerlof (1970). In Figure 1c, we have re-created the market defined in Figure 1a, with the addition of one curve. This curve, the *average incremental value*, plots the expected value of an offset contract as we vary the equilibrium price across the distribution of WTA_i in the population: $\mathbb{E}[B \cdot \tau_i | WTA_i \leq p]$. Recall that this average incremental value is exactly the willingness to pay of buyers in an offset market. At the socially optimal price, $\mathbb{E}[B \cdot \tau_i | WTA_i \leq p^*] < p^*$ because — in the adversely selected market illustrated in Figure 1c — the contract includes all of the lower WTA_i types with lower additioality, τ_i . In the presence of adverse selection, trade in offset markets will be limited, leading to the welfare loss in triangle CDE. Even when a regulator can achieve the first best, an offset market can unravel completely, as demonstrated in Figure 1d.

Empirical Questions Figure 1 illustrates that the welfare implications of additioality hinge on the shapes of the WTA and $B \cdot \tau$ curves: these will be our key empirical objects of interest. While illustrative of the economics of additioality, this stylized model was limited in its scope to achieve welfare improvements with additional tools, or to consider how other factors, e.g. the need to finance payments out of distortionary taxation, can exacerbate welfare losses. Our empirical implementation will consider a richer set of contracts and observable characteristics that can enter \mathcal{I} . These will allow us to explore not only the possibility of *welfare losses* from additioality, but the potential for *welfare gains* from market designs that induce more favorable selection via differentiated transfers and the design of the menu of contracts.

3 Empirical Setting and Data

3.1 The Conservation Reserve Program

Our empirical setting is the Conservation Reserve Program (CRP), a Payments for Ecosystem Services (PES) scheme incentivizing conservation on agricultural land administered by the United States Department of Agriculture (USDA). Established in 1985, the CRP pays landowners approximately two billion dollars per year to retire highly erodible and other environmentally sensitive cropland and adopt additional conservation activities for a contract duration of 10 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.¹² Moreover, the structure of the CRP and its incentivized activities are similar to other government financed PES schemes,¹³ to offset contracts traded in voluntary markets,¹⁴ and most specifically, to a burgeoning private agricultural offset market in the US.¹⁵ 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.¹⁶

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.¹⁷ 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.

¹²By 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 payments programs similar to the CRP administered by 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).

¹³China's Sloping Land Conversion Program and the U.K.'s Environmental Stewardship Program are notable examples. See citations in (Kinzig et al., 2011).

¹⁴Over 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.

¹⁵As of 2021, at least 10 companies had established platforms for the trade of agricultural offset contracts(Stubbs et al., 2014)

¹⁶See <https://www.congress.gov/bill/117th-congress/senate-bill/1251> for more details.

¹⁷In 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).

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.¹⁸ The uncertain acreage threshold, in combination 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 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.¹⁹ 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.²⁰

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 by avoiding the harmful environmental effects of row-crop agriculture, the possibility that some landowners conserve in the absence of the CRP ($a_{i0} \neq 0$) presents the additionality concern in this setting.

¹⁸There 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.

¹⁹The 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.

²⁰The 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.

3.2 Data

The key feature of our dataset is that we links bids to 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).

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 three complementary datasets.

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 CDL classifies the binary indicator of crop versus non-crop — our primary outcome of interest — with extremely high accuracy ([Lark et al., 2021](#)). 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. We use both datasets due to their complementary strengths.

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 measures that we can observe — the binary decision to crop versus retire land — and we will assess results under a range of assumptions about how additionality interacts with the value of these “top-up” actions.

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

Panel A presents land use outcomes in the year prior to bidding. Approximately 21% of bidders’ land is cropped prior to bidding (18-21% on bid fields), compared to approximately 30% nation-wide, 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.²¹ 80% of bidders are awarded contracts across the auctions in our sample, with the average auction including 36,763 bidders.

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

4 Evidence on Additionality and Adverse Selection

4.1 Regression Discontinuity Estimates of Additionality

An estimate of additionality is a crucial input into the evaluation and design of environmental markets, but obtaining such an estimate requires a research design to credibly estimate counterfactual behavior in the absence of a contract. We address this challenge by exploiting 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 outcome of interest is whether land is cropped or retired, the primary incentivized activity of the CRP.

Our main specification takes advantage of the panel nature of our dataset and estimates the following estimating equation, for landowner (or bidder) i , in auction g , and year relative to auction r :

$$y_{igr} = \sum_{r'} \beta_r \cdot \mathbb{1}\{S_{ig} \geq \underline{S}_g\} \cdot \mathbb{1}\{r' = r\} + f_r(S_{ig} - \underline{S}_g) + \epsilon_{igr} \quad (5)$$

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

$$y_{igr} = \beta \cdot \mathbb{1}\{S_{ig} \geq \underline{S}_g\} + f(S_{ig} - \underline{S}_g) + \epsilon_{igr} \quad (6)$$

When estimated when $r \leq 0$, Equation (6) provides a test of validity, as there should be no discontinuity ($\beta = 0$), and when estimated on $r > 0$, β provides an estimate of the pooled treatment effect.

We estimate Equations (5) and (6) 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 randomness in the ex-post location of the winning score threshold. While bidders may possess information ex-ante about the distribution of the threshold, which they use to construct their bids, we assume that bidders

do not know the threshold's precise ex-post location. Testing this assumption translates to standard smoothness and manipulation tests for RD analyses. If (certain) bidders were able to predict the exact location of the score threshold, we would observe bunching in the distribution of scores reflecting bidders who optimally locate just above it. We may also observe differences in land use before the auction that reflect sorting around the threshold.

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 present our pooled (across years and auctions) RD plot on *pre-period* land-use. We plot the raw data and fit parameters from Equation (6), restricted to only $r \leq 0$. We see no evidence of differential land use at the discontinuity before the auction, providing further support for the validity of our RD design.

The second assumption necessary for interpretation of Equations (5) and (6) is 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 (6) for $r > 0$, and demonstrates a first stage close to one. Based on Figure 2c, we will interpret the RD coefficients in Equations (5) and (6) 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 (6) for $r > 0$. As the CRP's primary goal is to incentivize agricultural land retirement, our outcome of interest is the share of each bidder's land that is cropped. The discontinuity in land use outcomes — winning fields crop 8% less of their land — rejects the null hypothesis of no treatment effect of the program ($\tau = 0$). This land is instead put into natural vegetation and grassland (trees, shrubs, wetlands and grasses), as incentivized by the CRP (Figure 3b). Because we present estimates at the bidder level, cropping outcomes do not go to zero for winners, who typically only contract on a subset of their land. These clear treatment effects reject the most pessimistic views of environmental markets: that no participants change behavior, leading to no scope for welfare gains from incentivizing the provision of environmental services.

We estimate our main dynamic RD specification in Equation (5) 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 $\tau = 1$ or full additionality benchmark.

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 behavior — 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.²²

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 less than the $\tau = 1$ full additionality benchmark. Figure 4 demonstrates that approximately one in four bidders is additional, or conversely, that three of four bidders are non-additional, or do not generate incremental value from land retirement upon contracting. This highlights that non-additionality does indeed pose a potentially severe challenge to the performance and design of environmental markets.

Table 2 summarizes results from Figures 2, 3, and 4, presenting estimates for the pooled specifications in both datasets (Equation (6)). 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% additionality. We also present estimates on other land use outcomes (Panel B).²³

²²Indeed, 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).

²³Appendix Figures C.2 and C.3 present additional corresponding RD figures.

Discussion Our estimates of additionality at the margin have clear welfare and market design implications in the context of the conceptual framework in Section 2. First, the incremental value curve $B \cdot \tau$ lies substantially below B . Setting prices based on B alone could therefore lead to inefficient selection and welfare loss. A second, more subtle implication of our estimates is the need to accommodate a flexible relationship between willingness to accept and additionality to capture the shapes of the WTA and $B \cdot \tau$ curves. If, alternatively, willingness to accept and additionality could be summarized by a single index — in which bidders with positive values of WTA_i are additional, and bidders with values of WTA_i equal to zero are non-additional — then at the margin, additionality should be either zero or one.²⁴ Our results clearly reject both of these null hypotheses.

Mechanisms: Testing Leakage and Non-Compliance We argue that our estimates are driven by heterogeneous land use behavior, absent the contract, 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 such that retiring some fields makes it less likely to crop others. We see no evidence of either of these hypotheses.²⁵

In theory, the lack of additionality could be two-sided, driven by both conservation without a CRP contract and cropping with a CRP contract (non-compliance). We assess the CRP’s compliance regime by systematically inspecting ultra-high resolution (0.6-1m) aerial photographs of over 1,000 enrolled fields.²⁶ 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. As described in more detail in Appendix B, we find no evidence of

²⁴Technically, because there exist bidder characteristics (asymmetry) and additional action choices that shift the score, and because we pooled sign-ups with different thresholds, the RD results in Figure 3 and Table 2 could be estimating a mixture of purely marginal ($\tau = 0$) and purely inframarginal ($\tau = 1$) types. We rule this out in Appendix Table C.1, which presents RD estimates split by the location of the threshold — parameterized by the amount a bidder would need to bid for the base contract to achieve \underline{S} — and finds that $0 < \tau < 1$ across groups.

²⁵The 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.

²⁶Specifically, 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.

non-compliance.

Implications Together, these two results — no leakage 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 i , a measure of (ex-post) additionality, $a_{i1} - a_{i0}$. In other words, we can simplify our causal problem into a “selective labels” problem (Lakkaraju et al., 2017; Chan et al., 2022; Arnold et al., 2022).

4.2 Testing for Adverse Selection

Our framework’s main premise is that in the presence of non-additionality, environmental markets are — potentially — selection markets. In this section, we test for asymmetric information and adverse selection directly.

Empirical strategy We observe both an i -specific measure of ex-post additionality, $a_{i1} - a_{i0}$, and an i -specific bid, a function of WTA_i , among all rejected bidders. We use these two observations to conduct a test for information asymmetry in the spirit of Chiappori and Salanie (2000) and Athey and Levin (2001). We estimate the following regression specification:

$$a_{i1} - a_{i0} = \beta \cdot \mathbf{b}_i + \pi \cdot \mathbf{z}_i + f(\mathbf{z}_i^s) + \epsilon_i \quad (7)$$

where $a_{i1} - a_{i0}$ denotes i ’s (ex-post) 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, $f(\mathbf{z}_i^s)$ 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 (7), 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 $a_{i1} - a_{i0}$ is indicative of adverse selection. We estimate Equation (7) in the one auction in which we observe the delineations of the bid fields (the 2016 auction), which is required to construct $a_{i1} - a_{i0}$. This auction is also the most restrictive auction in our sample: $a_{i1} - a_{i0}$ is unmasked for the vast majority of bidders (82%).

Results Figure 5a presents a binned scatterplot of the correlation between ex-post additionality and the dollar amount bid per acre per year, residualized of $f(\mathbf{z}_i^s)$. Figure 5a

demonstrates a positive relationship between higher bids — reflective of higher willingness to accept — and additionality. Bidders have a higher willingness to accept in part because of their private information about land use in the absence of the CRP contract. In other words, the results in Figure 5a provide evidence of adverse selection. Figure 5b takes the analysis one step further and shows that bids remain correlated with ex-post 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 adverse selection on contract features by replacing 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 contracts choices reveal information about additionality, providing additional tools to a market designer. 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 $f(\mathbf{z}_i^s)$ but excluding any endogenous bid choices from the regression specification. These estimates of soil productivity are collected by the USDA and are designed to approximate the amount that a landowner would be able to earn on a given parcel of land. 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 increase welfare by differentiating across types using this feasible predictive characteristic that is not currently incorporated in the scoring rule.

Discussion The analysis in Sections 4.1 and 4.2 provide clear evidence on the challenges facing environmental markets: non-additionality is substantial and it introduces adverse selection in the market. To understand the implications of these challenges for the function of markets, we require a quantitative economic framework — specifically, the *WTA* and $B \cdot \tau$ curves from Section 2 — adapted to a richer contracting environment that can capture the heterogeneity documented in this section as tools for improvements to market design.

5 Empirical Model of Bidding and Additionality

We use the controlled strategic environment of the auction to estimate bidders' willingness to accept various contracts based on revealed preferences and relate these estimates to additionality using the patterns in the previous section. We extend the multi-dimensional bidding models of [Asker and Cantillon \(2008\)](#) and [Che \(1993\)](#). Landowners are characterized by a multi-dimensional private transaction-relevant type and bid on discrete contracts, differentiated by heterogeneous conservation actions, in response to a non-linear scoring rule. As in the stylized model of Section 2, landowners also differ in their additionality, τ_i , which we allow to depend on both observable characteristics and bidders' multi-dimensional transaction-relevant types, capturing adverse selection.

5.1 Model

Landowner Types Each landowner, or bidder, i is characterized by a type vector $((c_i, \kappa_i), \tau_i)$ for $\kappa_i = \{\kappa_{ij}\}$. The first component, (c_i, κ_i) , defines landowner i 's transaction-relevant type. These are the cost parameters that determine i 's willingness to accept a contract j . c_i is the base cost of contracting, common across contracts, and κ_{ij} is the top-up cost associated with contract j , with $WTA_{ij} = c_i + \kappa_{ij}$.

As in the stylized framework in Section 2, τ_i is defined as:

$$\tau_i = \mathbb{E} [a_{i1} - a_{i0} | \mathbf{z}_i, c_i, \kappa_i] \quad (8)$$

or the expected difference in land retirement with (a_{i1}) , versus without (a_{i0}) the contract, as a function of observable characteristics \mathbf{z}_i and bidder types (c_i, κ_i) .

Contract Value As in Section 2, additionality, or τ_i , governs the *incremental value* of contracting. We note that although WTA_{ij} is now multi-dimensional, τ_i only represents the single dimension of land retirement, a_i . This is due to (i) fundamental data limitations — the specifics of the contracted top-up actions, e.g. the species of grasses, are unobserved — and (ii) the dramatic simplification it allows while still capturing non-additionality on the key dimension of CRP contract value, land retirement.

To accommodate this assumption, we will consider two polar cases of contract value: (i) additive separability, in which the incremental value of the top-up action, relative to the base action, is additively separable, delivering value regardless of additionality — $B_i^0 \cdot \tau_i + B_i^j$ —

and (ii) perfect complementarity, in which the full value from the contract is derived only when i is additional — $(B_i^0 + B_i^j) \cdot \tau_i$. B_i^0 denotes the social value of the base action of land retirement $a_i = 1$, and B_i^j denotes the social value of the top-up action, relative to the base action. Social value is indexed by i to reflect differences in environmental sensitivity across landowners, and by j to reflect differences in social value across contracts.

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 S according to a known scoring rule 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: $S = s(\mathbf{b}_i, \mathbf{z}_i^s)$. 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 score S given uncertain realizations of two distributions. The first is expectations over i 's competitors, specifically the joint distribution of the scores, acreages, and number of competing bidders.²⁷ The second is over the magnitude of the acreage limit determined by Congress in the Farm Bill.²⁸ Because we assume that landowners do not condition on their own characteristics when forming these expectations, all landowners face the same probability of winning at a given score, which we denote by the CDF $G(S)$.

Payoffs and Optimal Bidding Each landowner i solves:

$$\mathbf{b}_i^* = \underset{(r, \mathbf{x})}{\operatorname{argmax}} \left\{ \underbrace{(r - c_i - \mathbf{x} \cdot \kappa_i)}_{\text{Payoff to } i \text{ conditional on bid } (r, \mathbf{x})} \times \underbrace{G(s((r, \mathbf{x}), \mathbf{z}_i^s))}_{\text{Probability of } i \text{ winning with bid } (r, \mathbf{x})} \right\} \quad (9)$$

where a landowner chooses her bid $\mathbf{b}_i = (r_i, \mathbf{x}_i)$ to maximizes her payoff conditional on

²⁷We assume that i does not observe either the number or the observable characteristics of her competitors, consistent with that fact that bidding is decentralized and involves thousands of bidders across dozens of states. We also assume that each bidder does not condition on her own characteristics when forming expectations about the distribution of \underline{S} .

²⁸Because the number of bidders is large — the average auction in our sample has over 36,000 bidders — the uncertain acreage limit, which varies across years, is a key driver of randomness in \underline{S} . Appendix Figure D.1 provides empirical support for the assumption of quantity uncertainty: the distributions of submitted scores are essentially identical across sign-ups with large differences in acreage limits.

winning, multiplied by the probability of winning at that bid, given her type (c_i, κ_i) .

Additionality In the contract period following the auction, landowners make land use decisions. If awarded a contract $x_{ij} = 1$ and $a_{i1} = 1$. If not, landowners choose a_{i0} , which is not contractible. At the time of bidding, additionality types τ_i in Equation (8) reflect a market designer’s expectations of this behavior. We treat this conditional expectation as a primitive of the model.²⁹

Remarks We briefly note some features and simplifications in the model presented above. First, we highlight that landowners are competing on both price and contract features. We incorporate this to capture the setting, in which quality competition is an important component of the bidding environment,³⁰ and to assess how additionality varies with landowners’ private costs of specific contract features. Second, the formulation of (9) demonstrates 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.

Third, we note that although the contracting and choice environment is now more complex, the basic market failure introduced by additionality is the same as in the stylized graphical set-up of Section 2. Bidders make choices that depend on the scoring rule $s(\mathbf{b}_i, \mathbf{z}_i^s)$ and their transaction-relevant type, (c_i, κ_i) . However, contract value depends on τ_i . As the scoring rule does not condition on τ_i , this divergence can lead to inefficient selection.

Finally, we note two simplifications in our formulation of the bidder’s problem. First, we assume bidding is costless; we do not model a bid preparation cost or selection into bidding.³¹ 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, dynamic considerations are not non-existent. In a dynamic framework, the cost parameters estimated from the formulation in (9) can be interpreted as *pseudo-costs*

²⁹Note that we do not directly model the choice of a_{i0} , and instead estimate the conditional expectation function in Equation (8) and use it as a sufficient statistic for welfare and counterfactuals. See the discussion in Section 2 for more details on this choice.

³⁰From 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.”

³¹This 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.

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.

5.2 Identification and Estimation

Identification The identification of (c_i, κ_i) relies on revealed preferences from Equation (9) (Agarwal et al., 2023). The revealed preferred $\mathbf{b}_i^* = (r_i, \mathbf{x}_i)$ contract-bid combinations yield inequalities that generate identified sets containing the true population distribution of (c_i, κ_i) . We obtain inequalities because of the discrete contract choice, and rely on choice shifters that vary the relative returns to actions 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 entire distribution of (c_i, κ_i) conditional on observable characteristics \mathbf{z}_i . Appendix Figure D.2 provides a graphical explanation.

Identification of τ_i uses the fact that we observe the joint distribution of $a_{i1} - a_{i0}$, exogenous characteristics \mathbf{z}_i , and optimal bids $\mathbf{b}_i^* = (r_i, \mathbf{x}_i)$ to estimate a conditional expectation function that rationalizes this joint distribution observed in the data (analyzed in Section 4). However, $a_{i1} - a_{i0}$ is masked for the 18% of bidders who win in our most restrictive auction. We therefore require additional instruments that shift a landowner's probability of winning via $s(\mathbf{b}_i, \mathbf{z}_i^s)$, but are excluded from a_i .³²

Parameterization We parameterize (c_i, κ_i) as:

$$c_i \sim N(c(\mathbf{z}_i), \sigma_c^2(\mathbf{z}_i)) \quad \kappa_{ij} = p_j(\mathbf{z}_i) + u_j(\mathbf{z}_i) + \epsilon_{ij} \quad \epsilon_{ij} \stackrel{iid}{\sim} N(0, \sigma_\kappa^2(\mathbf{z}_i)) \quad (10)$$

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 (10) parsimoniously captures key differences across contracts.³³

³²If we observed an infinitely restrictive auction, in which landowners submitted bids but everyone was rejected, we would not require additional instruments.

³³Landowners 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

Finally, we parameterize τ_i as:

$$\tau(\mathbf{z}_i, c_i, \kappa_i) = \pi \cdot \mathbf{z}_i + \beta \cdot c_i + \alpha \cdot \kappa_i \quad (11)$$

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

Estimation Our estimation strategy proceeds in three steps. In the first step, we estimate landowner beliefs about $G(S)$. In the second step, we estimate the transaction-relevant type distribution (c_i, κ_i) via revealed preferences. We then use the results from the first half of the paper to estimate $\tau(\mathbf{z}_i, c_i, \kappa_i)$, allowing the data to inform the relationship between willingness to accept and addititonality. The first two steps are a common approach to the empirical analysis of auctions ([Guerre et al., 2000](#); [Hortaçsu and McAdams, 2010](#); [Agarwal et al., 2023](#)) and the second two steps are a common approach to the empirical analysis of selection markets ([Bundorf et al., 2012](#); [Tebaldi, 2022](#)).

Step 1: Estimate $G(S)$ 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.3 provides more detail.

Step 2: Estimate the Distribution of (c_i, κ_i) Our next step estimates the distribution of (c_i, κ_i) conditional on observable bidder types \mathbf{z}_i using the optimality of bids from Equation (9).

We classify bidders into 32 distinct categories of bidder types that consistute the observable heterogeneity in \mathbf{z}_i that we use to parameterize (c_i, κ_i) . These types are based on interactions of quartiles of soil productivity, prior CRP status, and prior land use status. These characteristics are likely highly predictive of bidder costs and allow us to flexibly capture observable heterogeneity.

covers beyond the five dimensions in \mathbf{p}_j (twelve total) that each can be combined with an upgrade option. See Appendix A for more detail.

We use two sources of variation 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. A useful feature of this unusual policy experiment is that we can directly test that landowners are indeed 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. We also use the fact that bidders in Wildlife Priority Zones³⁴ 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, κ_i) . Figure D.3 illustrates these sources of variation.

We estimate (c_i, κ_i) using a Maximum Simulated Likelihood (MSL) estimator, which maximizes the likelihood of each bidder's observed score-contract combination (\mathbf{b}_i^*) . Estimation is challenging 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, while maintaining the full dimensionality of the optimal solution to the bidder's problem in (9).³⁵ Second, we use the change of variables and importance sampling techniques proposed by Ackerberg (2009) to reduce the computational burden associated with searching over a high dimensional bid space. We discuss the details of this estimation procedure in more detail in Appendix D.3.

Step 3: Estimate Additionality $\tau(\mathbf{z}_i, c_i, \kappa_i)$ We interpret the patterns from Section 4 within the framework of the model. We do so by estimating $\tau(\mathbf{z}_i, c_i, \kappa_i)$ via the Method of Simulated Moments (MSM), where we search for the parameters in $\tau(\mathbf{z}_i, c_i, \kappa_i)$, $\theta^\tau = (\pi, \beta, \alpha)$, that rationalize the level of additionality from the RD, the covariance between additionality and observable characteristics \mathbf{z}_i , and the relationship between (c_i, κ_i) and additionality reflected in the patterns of adverse selection in Figures 5b and 5c.

Specifically, we draw simulations (c_i^k, κ_i^k) from our estimated distribution, solve for the optimal \mathbf{b}_i^* using Equation (9), and search for the parameters θ^τ that match: (i) additionality at

³⁴Wildlife Priority Zones, or WPZs, are determined by state governments to focus conservation efforts on habitats of certain species or certain environmentally sensitive land, like wetlands.

³⁵Specifically, 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.3.

the RD, (ii) additionality among all rejected bidders and by observable characteristics, (iii) the covariance between additionality and chosen scores, and (iv) the additionality within chosen contracts. We match model implied functions of τ_i to observed functions of τ_i , which as in Section 4.2, we calculate in the data using the fact that we can “read off” ex-post measures of additionality, $1 - a_{i0}$, among rejected bidders. Importantly, all of the moments that we match are conditional on optimal bids being below the score threshold. We thus account for the fact that the relationships in Figure 5 are estimated in a selected sample using our now *known* data generating process that governs this selection: optimal bidding in Equation (9) based on the estimated (c_i, κ_i) distribution from Step 2 .

To ensure that our results are not sensitive to the distributional assumptions of (c_i, κ_i) , we rely on the existence of variation in the scoring rule $s(\mathbf{b}_i, \mathbf{z}_i^s)$ that is excluded from $\tau(\mathbf{z}_i, c_i, \kappa_i)$. Specifically, we assume that whether a bidder is in a Wildlife Priority Zone (WPZ) or an Air Quality Zone (AQZ) is unrelated to τ_i , as these variables depend on the sensitivity of wildlife or the importance of air quality, which, especially conditional on the rich set of observable bidder types, \mathbf{z}_i , seems plausibly unrelated to land use decisions. We discuss this step in more detail in Appendix D.3, which includes a test of this exclusion restriction motivated by Angrist and Rokkanen (2015). We use as observable predictors of τ_i the 32 bidder types that parameterize (c_i, κ_i) and the remaining components of the scoring rule.

5.3 Parameter Estimates

Estimates of the (c_i, κ_i) distribution Figures 6a and 6b plot the estimated distributions of c_i and κ_{ij} .³⁶ 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 action 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, κ_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

³⁶ Appendix Table D.1 presents parameter estimates for select example cells of \mathbf{z}_i and standard errors.

see strong evidence of a positive relationship — higher c_i landowners have higher additio-

nality, 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.3 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 (10), and model-implied costs are similar in rank and in magnitude to the administrative data.

Estimates of Additio-nality $\tau(\mathbf{z}_i, c_i, \kappa_i)$ In Table 4, we present select parameter estimates in $\tau(\mathbf{z}_i, c_i, \kappa_i)$. We focus on describing the relationship between additio-

nality and unobserved bidder types (c_i, κ_i). The remaining parameters capture the projection of $\tau(\mathbf{z}_i, c_i, \kappa_i)$ onto observable characteristics as illustrated, for the case of soil productivity estimates, in Figure 5d.

In column (1), we include only scoring rule controls and in column (2) we add the full set of observable bidder types that parameterized (c_i, κ_i) . In columns (1) and (2), we only allow for a relationship between c_i and τ_i , i.e. we impose that $\alpha = 0$. Consistent with the residual positive relationship between bids and additio-

nality in Figure 5b, we see that landowners possess and act upon residual private information about additio-

nality, 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 additio-

nality by eight percentage points, or 31% of our baseline additio-

nality estimate of 26%. This result highlights the substantial information asymmetry and adverse selection introduced by non-additio-

nality.

Columns (3) and (4) allow for a relationship between κ_i and τ_i . In column (3), we only allow tree-related action costs to impact τ_i , reflecting the strong tree-specific adverse selection in Figure 5c. Once we allow κ_{ij} to influence τ_i , we see that much of the positive relationship between a landowner’s willingness to accept and additio-

nality can be captured by tree-related costs. 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 τ_i and κ_{ij} , we see that the entirely of the residual relationship between transaction-relevant types and additio-

nality loads onto κ_{ij} , though tree-related contracts are still by far the most adversely selected. This will have implications for the welfare effects of markets that incentivize environmental services across heterogeneous contracts.

Our model-implied estimate of additio-

nality at the RD margin is between 22-23%, within our range of estimates of 21%-31%. It is closest to our pooled remote-sensing based estimate, which is most similar to our estimator of $\tau(\mathbf{z}_i, c_i, \kappa_i)$ in data and estimation strategy.

6 Welfare and Alternative Market Designs

Armed with estimates of the joint distribution of $WTA_{ij} = c_i + \kappa_{ij}$ and τ_i , the final outstanding ingredient is the valuation of contracted actions, B_i^j . We take estimates of B_i^j from the literature quantifying the environmental value of CRP activities (Johnson et al., 2016; Feather et al., 1999; Hansen, 2007) and relative valuations across landowners i and contracts j from the scoring rule (Ribaudo et al., 2001). Importantly, these valuations — either relative, across i and j , or in levels — do not consider counterfactual behavior, i.e. they are constructed under the assumption that $\tau_i = 1$ for all i (Claassen et al., 2018). We therefore consider social welfare under the revealed preferences of B_i^j by the USDA. Appendix E discusses our process of obtaining estimates of B_i^j and the construction of the incremental value curve in more detail.

6.1 Graphical Analysis

Base contract Figure 7 presents the empirical analogue of Figure 1, graphing the WTA , incremental value ($B \cdot \tau$), and average incremental value curves for the base contract. Our two main facts from Section 4 are reflected in Figure 7. The incremental value curve lies substantially below B , reflecting non-additionality, and is upwards-sloping, consistent with our documented patterns of adverse selection.

Figure 7 yields three implications of these descriptive facts for the function and design of environmental markets. First, the incremental value curve crosses the WTA curve only once — the empirical market described by Figure 7 appears more like Figure 1a than Figure 1b — and a regulator can achieve the surplus of \$22.79 per acre-year in region ABC without suffering an efficiency loss. In other words, the existence of substantial non-additionality and adverse selection — facts that, absent an economic framework, may lead skeptics to conclude that these markets are doomed to fail — do not unravel the opportunity for a regulator to offer a surplus-increasing market for the base contract.

Second — still considering the regulator’s pricing problem — Figure 7 documents the possibility of efficiency losses when prices are not set at the intersection of the WTA and incremental value curves. We consider instead a regime with pricing at B , yielding welfare losses of \$6.19 per acre-year in triangle CDE, eroding 27% of the gains in triangle ABC. This presents the challenge to a regulator: inducing efficient selection depends on the shape of the $B \cdot \tau$ curve — a marginal treatment effect object (Heckman and Vytlacil, 1999, 2001, 2005) — and the WTA curve. Successful market design therefore requires careful quantitative analysis of these curves.

Third, Figure 7 documents the welfare losses due to adverse selection in an alternative market structure: a competitive offset market. This welfare loss arises due to the divergence between the incremental value curve, which governs social surplus, and average incremental value curve, which governs what offset buyers are willing to pay for a contract (Akerlof, 1970). This divergence only occurs if the market is adversely (or advantageously) selected. Adverse selection limits trade in offset markets from the efficient quantity q^* to the equilibrium quantity q^c (a 15% reduction), yielding welfare losses in the triangle CFG, equal to 5.3% of the gains with the optimal uniform price (triangle ABC). Though the adverse selection introduced by additionality (i) exists in the market and (ii) limits trade and reduces welfare, it does not go so far as to completely unravel the opportunity for trade in offset markets. This conclusion is in stark contrast to critics of offset markets who argue that the basic endeavor of offset trading futile.

The shape of the incremental value curve in Figure 7 is of note for interpreting the conclusions above: at low levels of WTA_i , the market does not appear adversely selected at all. This helps prevent the market from completely unravelling. But if the social costs of environmental degradation, B , are revised upward, the welfare costs of adverse selection in offset markets could increase as triangle CFG grows in size.

Heterogeneity across landowners and contracts Our empirical implementation provides the opportunity to go beyond the single contract uniform price setting problem analyzed in Section 2. Figure 8a re-creates Figure 7 for tree contracts. We focus 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. Moving beyond the base contract requires us to use one of our assumptions — additive separability versus perfect complementarity — about the relationship between the social value of the top-up action incentivized by the contract and additionality. For the purposes of analyzing Figure 8a, we assume perfect complementarity, i.e. that the full social value of the contract is delivered only when landowners are additional.³⁷

Figure 8a demonstrates that, for the particularly adversely selected tree contracts, the incremental value curve crosses the WTA curve more than once, leading to welfare losses at the bottom of the WTA distribution, as in Figure 1b. We caution that this exercise requires substantial out of sample extrapolation, but we highlight it as illustrative of how alterna-

³⁷While other contracts offer value that is plausibly additively separable from land use decisions — for example, constructing habitats tailored to the preferences of the USDA — tree-related actions seem better-suited to the assumption of perfect complementarity, as our measure of non-additionality captures any non-crop behavior, including the presence of trees.

tive WTA and incremental value curves can generate different conclusions across two broad classes of contracts in our empirical setting. Figure 8a demonstrates that to obtain the region of surplus in BC, a regulator must suffer the welfare losses in region AB. In other words, in the market described by Figure 8a, a regulator cannot implement the first best allocation because in some regions, the incremental value curve increases more steeply than the WTA curve, i.e. social surplus is not monotone in WTA_i (Myerson, 1981; Manelli and Vincent, 1995; Lopomo et al., 2023). This steepness has further implications for competitive offset markets. Offset markets trading tree contracts would completely unravel, though there are gains from trade to be achieved.

Figures 8b and 8c examine heterogeneity by observable characteristics. Figures 8b and 8c plot separate curves — for the base contract, as in Figure 7 — by whether a landowner is in the lowest versus highest quintile of the soil productivity distribution. Both the WTA and incremental value curves look very different across these two populations, leading to (i) differences in optimal prices — that differ from the optimal uniform price — and reductions in the sizes of the triangles that denote the welfare losses in competitive offset markets.

We now turn to quantifying the implications of these patterns of heterogeneity — across observables, and across contracts — for the performance of current and alternative market designs.

6.2 Alternative Market Designs: Differentiating Incentives

We build on the graphical analysis, now considering the full choice environment of landowners, choosing across contracts, and full information set available to a market designer of observable characteristics, \mathbf{z}_i . Because social welfare depends on additionality but landowner choices do not, we consider market designs that exploit the information about additionality contained in observables and landowners' choices of contracts to yield more efficient allocations. We investigate three broad classes of markets: posted prices and auctions — both procurement regimes — and competitive offset markets, which will have distinct welfare considerations.

Building on the status quo scoring rule, we consider differentiated incentives of the following form:

$$p_i^j = \mathbf{w} \cdot \mathbf{z}_i + \tilde{B}^j \quad (12)$$

where \mathbf{w} are weights on observable characteristics that can potentially influence incentives, \mathbf{z}_i , and \tilde{B}^j are differentiated incentives across contracts, with the tilde representing that \tilde{B}^j

and B^j may not align.³⁸ We define the social surplus of contracting with i for contract j , building on Equation (2) to one of:

$$\underbrace{B_i^0 \cdot \tau_i + B^j}_{\text{Additively separable}} - c_i - \kappa_{ij} - \lambda \cdot p_i^j \quad \underbrace{(B_i^0 + B^j) \cdot \tau_i}_{\text{Perfect complements}} - c_i - \kappa_{ij} - \lambda \cdot p_i^j \quad (13)$$

depending on our assumptions about how additionality impacts the value of top-up actions. We will present results under both assumptions, which beyond illuminating which conclusions are sensitive to which assumptions, will provide insights regarding the mechanisms behind improvements to market designs. Under the additively separable assumption, the scope for non-additionality to impact market function is limited by the value of the top-up actions, which provide value regardless of additionality. We have also now introduced the realistic feature of a potentially non-zero cost of public funds, λ , based on the need to finance payments via distortionary taxation. Landowners choose contracts that maximize $p_i^j - c_i - \kappa_{ij}$, with the option to refuse a contract and receive a payoff of zero. Our empirical exercises search for values of the pricing equation in (12) that maximize social surplus subject to landowner choices.

Differentiated posted prices We begin with a regulator's price-setting problem, building directly on our graphical analysis. We investigate the increase in social surplus attainable as we differentiate incentives, relative to a baseline of an optimal *uniform* instrument to adjust for additionality. We design the baseline so that incentives are set optimally to reflect (i) additionality in levels, using only a single instrument and (ii) heterogeneity in the value of top-up actions, B^j .³⁹ The results in Figure 9 therefore isolate the gains from additional instruments to differentiate incentives based on heterogeneity in τ_i .⁴⁰

In the first pricing regime in Figure 9, we only change B^j to the incentives \tilde{B}^j that maximize social surplus, i.e. we assess the gains from redesigning the menu of contracts. We observe gains of between 0.1% and 3%. The differences within this range highlight mechanisms. When the value of top-up actions is additively separable, top-ups represent a substantial share of the surplus at stake and any distortions away from pricing at the incremental value

³⁸We now abstract away from the heterogeneity in B^j across WPZ and non-WPZ landowners for simplicity.

³⁹We use two different baselines across our two assumptions to focus only on the gains differentiation, not mis-pricing in levels: under perfect complementarity, we set $p_i^{*j} = p^* + B^j$ for a uniform optimal p^* and under additive separability, we find an optimal scaling factor to set $p_i^{*j} = (B^0 + B^j) \cdot \theta^*$.

⁴⁰We focus on gains from accounting for τ_i instead of adjusting prices to reflect heterogeneity in the value of contracts B^j to (i) focus attention on our main object of interest, additionality, and (ii) because the gains from differentiating by B^j rely heavily on valuations of B^j (in addition to the distribution of κ_{ij}), the valuations of which we do not view as our primary strength of contribution.

of the top-up action, B^j , will destroy substantial surplus for any screening gains of the base contract, $B^0 \cdot \tau_i$. On the other hand, when the incremental value of actions themselves is also impacted by τ_i , the gains from re-pricing are higher, as attracting low τ_i types with high B^j contracts — e.g. tree contracts — reduces the value associated with *both* the base contract and top-up action.

However, using menu design is indirect relative to setting incentives differentiated across i . First, we incorporate only the observable characteristics used in the current scoring rule, but with weights \mathbf{w} set to incorporate differences in τ_i . Then, we add a single additional dimension, a “feasible” predictor of τ_i , which we construct by projecting τ_i on deciles of soil productivity and wind and water erosion. We find that these simple, feasible differentiated pricing schemes can achieve welfare gains of up to 18%.⁴¹ The heterogeneity across social welfare assumptions is again informative. The gains from differentiated pricing are substantially larger with a cost of funds, as gains accrue not only via reductions in inefficient selection — represented by, e.g., the divergence between p_5^* and p^* in Figure 8c — but also from limiting transfers to less additional types, as illustrated in Figure 8b.

Asymmetric Auctions Next, we turn to auctions. We analyze Vickrey-Clarke-Groves (VCG) auctions and benchmark their performance against the status quo auction mechanism and a first best allocation. We define asymmetry in our VCG mechanisms as in Equation (12). Our auctions implement the differentiated posted prices regime investigated above for any given (status quo) quantity. This auction pays each landowner i $\mathbf{w} \cdot \mathbf{z}_i + \tilde{B}^j$ for contract j — which governs asymmetry, analogous to posted prices — plus the positive externality generated by her participation in the mechanism⁴². Because the mechanics of differentiated incentives are equivalent to the posted pricing regime, we focus our attention on the comparisons it affords between the status quo mechanism, an infeasible first best allocation, and feasible alternative auctions. For this analysis, we ignore the possibility of a cost of funds.

Figure 10 presents results and demonstrates that the status quo mechanism generates welfare

⁴¹ Again, the smaller gains under the additively separable assumption reflect the fact that less than 70% of surplus at stake is impacted at all by additionality.

⁴² Specifically, the VCG incentive payment is:

$$\begin{aligned} & \mathbf{w} \cdot \mathbf{z}_i + \tilde{B}^j + \\ & \sum_{i' \neq i} \sum_{j'} \left(\mathbf{w} \cdot \mathbf{z}_{i'} + \tilde{B}^{j'} - c_{i'} - \kappa_{i'j'} \right) \cdot x_{i'j'}^* ((c, \kappa)_{i,-i}) - \sum_{i' \neq i} \sum_{j'} \left(\mathbf{w} \cdot \mathbf{z}_{i'} + \tilde{B}^{j'} - c_{i'} - \kappa_{i'j'} \right) \cdot x_{i''j'}^* ((c, \kappa)_{-i}) \end{aligned}$$

where $x_{ij}^* ((c, \kappa)_{i,-i})$ denoting the allocation that maximizes $\sum_{i'} \sum_{j'} \left(\mathbf{w} \cdot \mathbf{z}_{i'} + \tilde{B}^{j'} - c_{i'} - \kappa_{i'j'} \right)$ given all reports of (c_i, κ_{ij}) and $x_{ij}^* ((c, \kappa)_{-i})$ denoting the allocation that maximizes it without i .

gains of between \$340 and \$590 million per auction. Given the divergence between social and landowner incentives introduced by non-additionality, the welfare effects of the status quo mechanism are *ex ante* ambiguous but empirically positive. This finding is not sensitive to our choice of ignoring a cost of funds: we also find welfare gains of \$140-\$340 million in the presence of a cost of funds. Second, the status quo mechanism falls far short of the first best allocation — what could be achieved if a regulator could set allocations based on observables and the full vector of (c_i, κ_i) . However, this allocation is not implementable, as social surplus is not monotone in bidder types. This is driven by the adverse selection in the market introduced by (non)-additionality and stems from the same fundamental problem preventing a regulator from achieving the first best in Figure 8a. This underscores the complications introduced when a market designer is seeking to maximize an objective that depends on landowners' private information but that diverges from a pure choice-theoretic welfare criterion.

The remaining bars evaluate welfare under asymmetric VCG auctions. Regardless of our assumptions about contract value, we find that we can achieve welfare gains of between 69-75% of the status quo mechanism, or between \$250 and \$440 million per auction. The different sources of welfare gains across the two assumptions of additive separability and perfect complementarity are related to the the posted prices results. The switch to VCG alone — using the original scoring rule, without incorporating τ_i — represent a substantial share of the gains under the assumption of additive separability because it efficiently incentivizes contract choices, which comprise a substantial share of surplus at stake. However, even under this assumption — which limits the impact of additionality on social welfare — incorporating differentiated incentives based on predictors of τ_i deliver 13% of the gains, and much more under alternative assumptions.

The results in Figures 9 and Figure 10 highlight the gains — in excess of 10%, even under conservative assumptions and relative to sophisticated market designs — from simple, feasible changes that align landowner and socially optimal choices in the presence of non-additionality.

Offset Market Design Finally, we turn to the design of competitive offset markets, where decentralized buyers and landowners trade contracts. Market design in this context is more nuanced, as differentiated incentives no longer necessarily increase welfare. We examine the effect of differentiating offset contracts by observable characteristics, focusing for simplicity on only the base contract, in Figure 11a. We plot the percent reduction in quantity traded and welfare lost in a competitive market, relative to the optimal price, under our three

differentiated pricing regimes: (1) uniform, (2) scoring rule characteristics, and (3) a feasible prediction of τ_i based on soil productivity estimates and erosion. We also include on Figure 11a the welfare per acre-year obtained under each of these offset market designs. We find that feasible differentiated pricing schemes reduce the extent of welfare losses from adverse selection from 5% to less than 2% of the optimal price, and increase welfare by 16% overall via more efficient trades in the market. The gains from differentiated incentives are thus high even in competitive markets, supporting efforts to collect and price upon detailed information to predict τ_i .⁴³

Our second question concerns which contracts can and cannot be successfully traded in offset markets, building on the graphical comparison of Figures 7 and 8a. Figure 11b plots the reductions in quantities traded and welfare — relative to the optimal uniform price — across the three broad categories of contracts in our setting: grasses, trees, and habitats. The main result of Figure 11b echoes the graphical analysis. Only tree-related contracts potentially unravel: welfare losses for the remaining contracts are limited to at most 5%. The comparison between our two assumptions of contract value in Figure 11b presents another opportunity for improvements to market design. If contracts provide value that accrues even when non-additional, for example specific ways of maintaining the trees, this value can “push up” the incremental value curve and reduce the welfare lost from adverse selection. This supports on-going efforts that emphasize the “co-benefits” of offset contracts.

We conclude by discussing why this market can succeed in the presence of non-additionality and adverse selection. First, the existence of non-additionality is counter-balanced by landowners’ low willingness to accept: though the value of contracts is reduced by non-additionality, these contracts provide environmental services cheaply. Second, the eligibility requirements for the CRP are stringent enough — a requirement of historically working farmland — that some landowners are additional, even at the bottom of the willingness to accept distribution. Third, because contracts generally require specific activities — whether hassle costs or productive — other factors influence willingness to accept, and potentially contract value, which mutes the extent of adverse selection (Jack and Jayachandran, 2019). Finally, agricultural decisions are relatively easy to understand and predict, offering covariates to increase surplus in environmental markets in the presence of non-additionality.

⁴³All of the largest private procurers of clean energy, such as Google and Microsoft, have outlined methodologies to calculate the “additionality” of the energy project. Other firms are developing products to “estimate additionality” among privately owned forests, like NCX.

7 Conclusion

We examine the performance and design of environmental markets in the presence of non-additionality. We cast the market design challenge introduced by additionality as a market failure of information asymmetry and use this formulation to apply insights from a well-developed toolkit for the analysis and design of selection markets. We conduct our analysis using a unique dataset generated by the auction mechanism of the the Conservation Reserve Program, one of the largest voluntary environmental market mechanisms in the world.

We begin by providing clear evidence in support of the challenge of additionality. We use a regression discontinuity design to demonstrate that non-additionality is descriptively severe: only one quarter of landowners are additional. Moreover, we show that that it generates adverse selection in the market.

We quantify these forces, analyze welfare, and explore the performance of alternative procurement and offset market designs by developing and estimating a joint model of bidding and additionality. Despite the existence of both substantial non-additionality and adverse selection — features of this market thought to doom it to failure — we find that the market can deliver welfare gains in both procurement settings and in competitive offset markets. Moreover, we find substantial gains to feasible market designs that set differentiated incentives using only the design of contracts and readily available covariates.

We highlight two distinct avenues for future work. First, our analysis focused on the single friction of information asymmetry on welfare and market design. Investigating additional features of voluntary environmental markets, for example offset demand, the incentives of platforms and certifiers that facilitate trade, and the design of markets in the presence of complementarities in ecosystem services across space, all present interesting avenues for future research.

More broadly, our results highlight that successful market design often involves considerations beyond maximization of total agent welfare in the market. While the divergence between socially optimal outcomes and privately optimal choices is a classic motivation for government intervention in markets, empirical evaluations of the design of markets typically focus on choice-theoretic criteria for evaluation. Future research should continue to bridge this gap.

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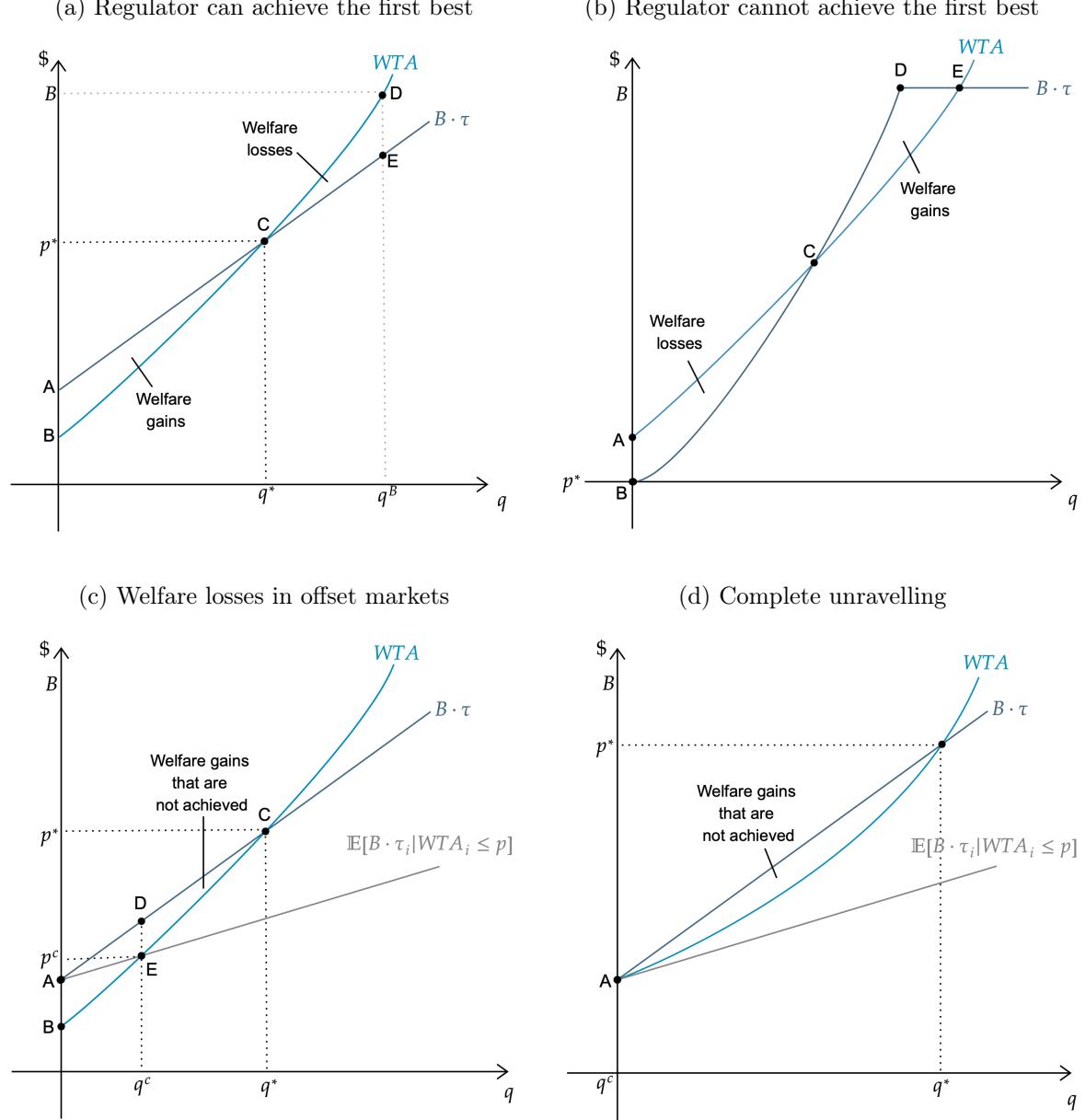
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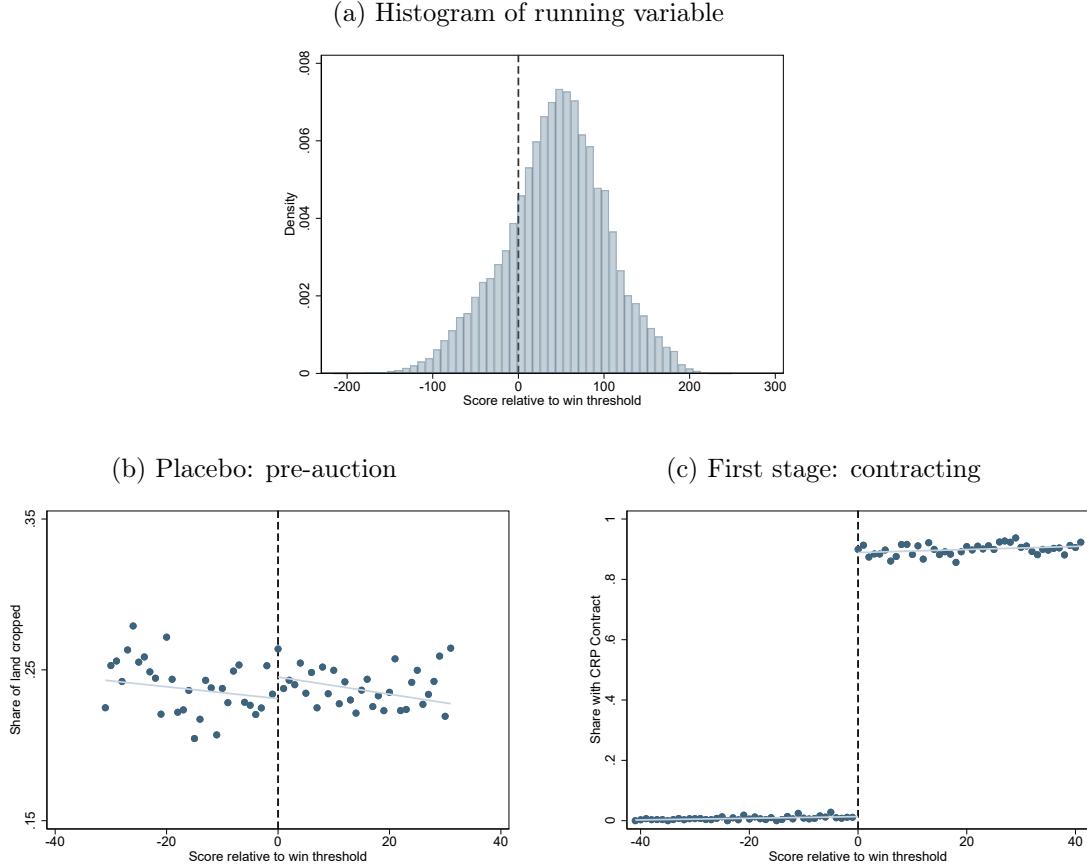
Figures and Tables

Figure 1: Graphical welfare analysis



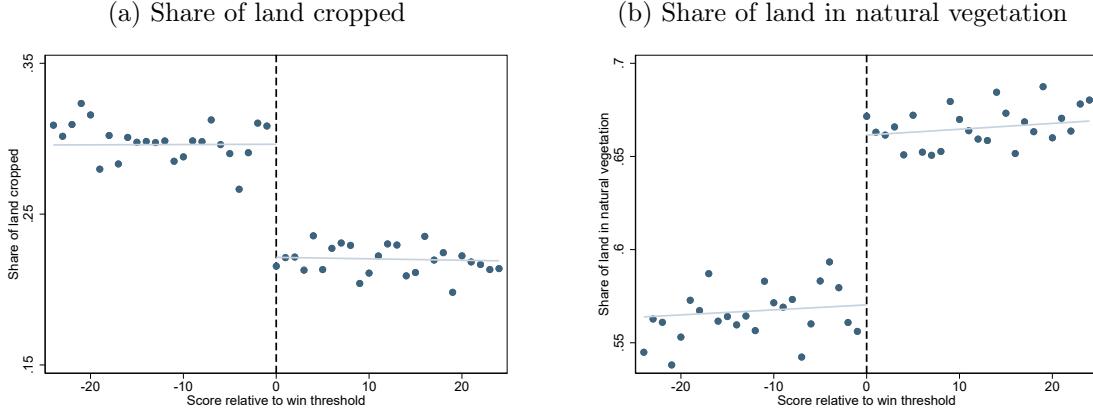
Notes: All figures describe markets as characterized by WTA and incremental value $B \cdot \tau$ curves. B denotes the value of the environmental service $a = 1$, whereas $B \cdot \tau$ denotes the incremental value of contracting, relative to no contract, “deflated” to account for non-addititonality. The area between the $B \cdot \tau$ and the WTA curves represent social welfare gains from contracting (see Equation (2)). Sub-figures (a) and (b) denote the regulator’s optimal pricing problem, where the regulator can achieve the first best (a) and cannot (b). Sub-figure (a) also demonstrates the welfare losses from mis-pricing (at B). Sub-figure (c) and (d) add in the average incremental value curve, $\mathbb{E}[B \cdot \tau_i | WTA_i < p]$ which defines the value of an offset contract (an offset buyer’s willingness to pay). The intersection of the WTA and average incremental value curves define an offset market equilibrium. The upwards-sloping $B \cdot \tau$ curve, indicative of adverse selection, limits trade in competitive markets and lead to welfare losses (triangle CDE) relative to the (achievable) first best (c) or even a complete unravelling of the market (d).

Figure 2: RD validity and first stage



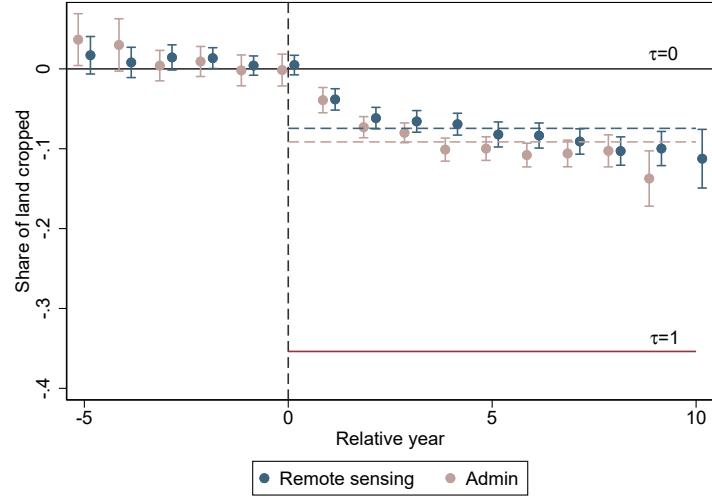
Notes: Sub-figure (a) presents a histogram of bidders' scores relative to the win threshold (the running variable for the RD analysis, $S_{ig} - S_g$), pooled across auctions. Bidders above zero win. Sub-figures (b) and (c) present raw data and estimated parameters from Equation (6) with a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Calonico et al., 2014). Panel (b) is estimated for only $r \leq 0$ (pre-auction), and panel (c) is estimated for only $r > 0$ (post-auction). Sub-figure (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. Sub-figure (c) plots the share of bidders that obtain a CRP contract. Positive numbers in the RD figures correspond to winning, negative numbers correspond to losing. Each observation is a bidder.

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



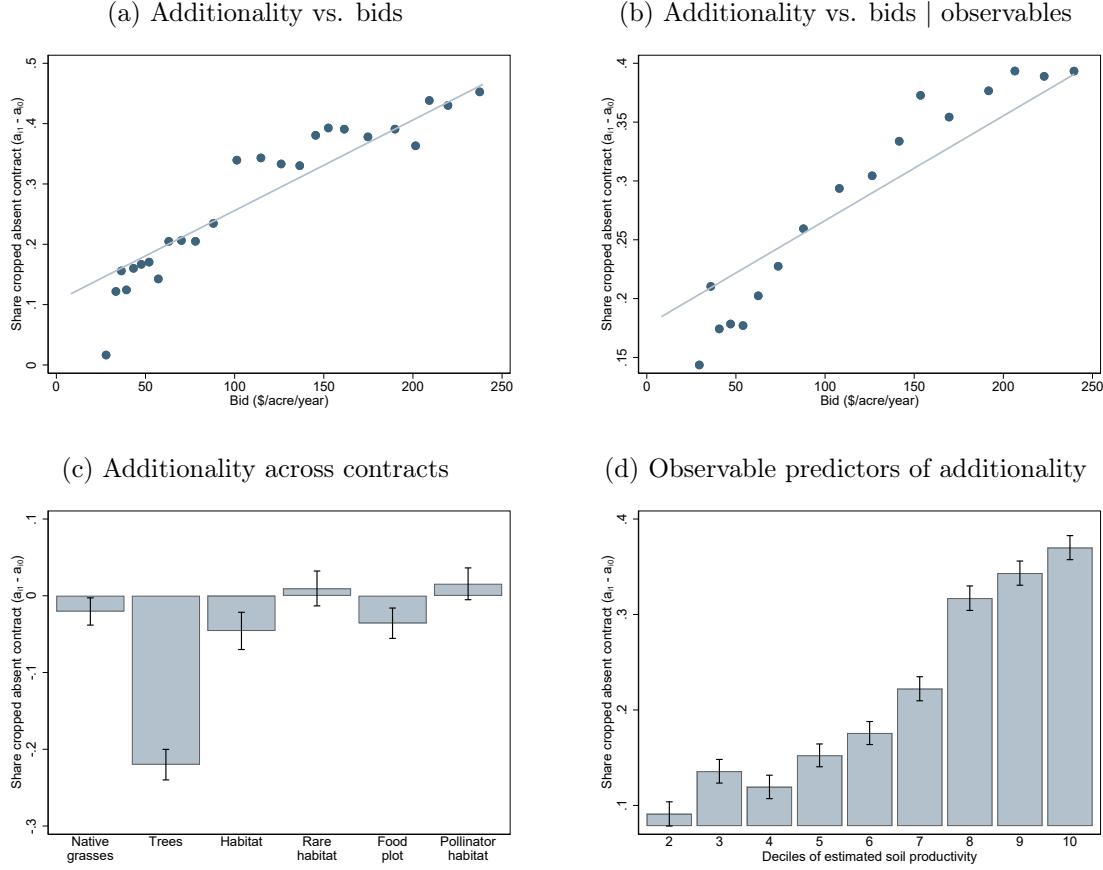
Notes: Sub-figures (a) and (b) present raw data and estimated parameters from Equation (6) with a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Calonico et al., 2014) for $r > 0$ (post-auction). Land-use outcomes are measured as the share of the bidding tract that is cropped (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 in the RD figures correspond to winning, negative numbers correspond to losing. Each observation is a bidder. Corresponding coefficient estimates and standard errors presented in Table 2.

Figure 4: RD estimates of additionality



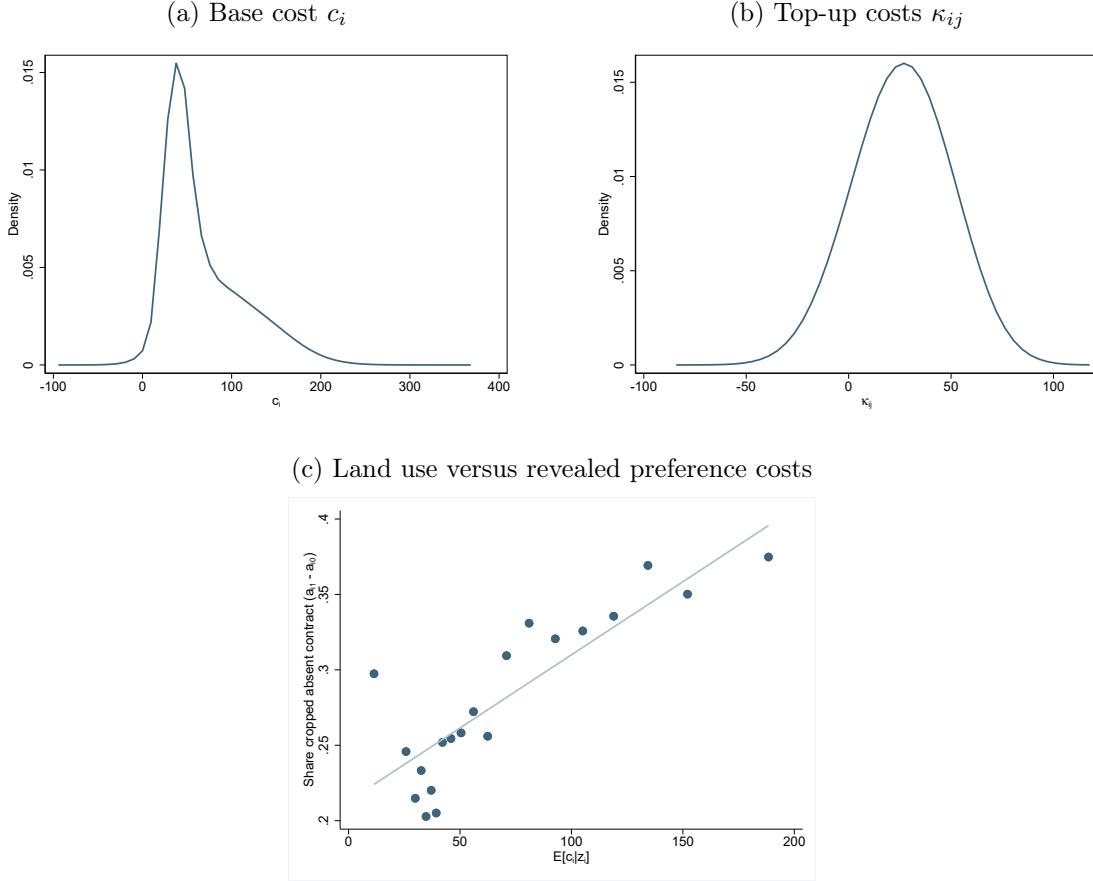
Notes: Figure plots coefficients from Equation (5), using a local linear specification in the MSE-optimal bandwidth (Calonico et al., 2014), on the outcome of cropped land, measured with both remote sensing and administrative datasets. Dashed lines indicate the pooled treatment effects (Equation (6) estimated for $r > 0$). 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. Standard errors are clustered at the bidder level. Positive years in Figure (d) correspond to post-auction years. Each observation is a bidder. $\tau = 1$ represents the “full additionality” benchmark and is calculated as the total acreage offered into the CRP mechanism among marginal bidders. 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 and adverse selection



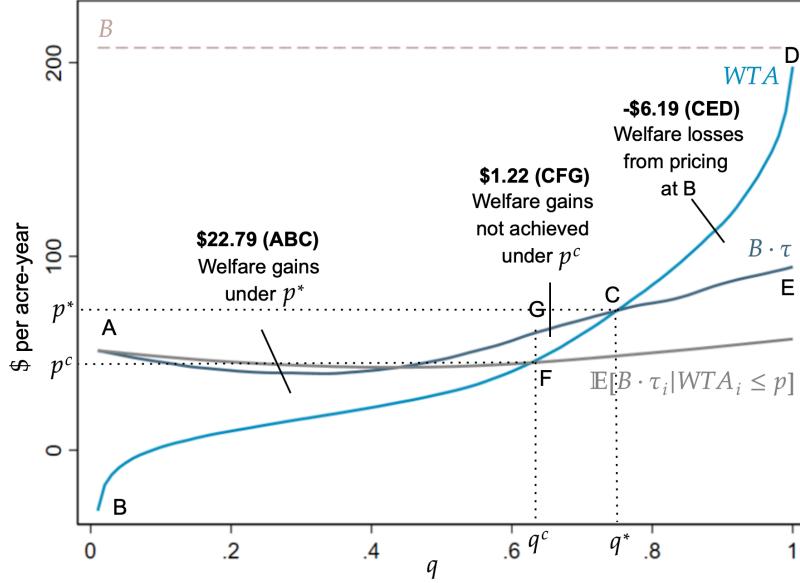
Notes: Figures present visual representations of coefficient estimates of various specifications of Equation (7). A positive relationship between bids, or specific contract features, and additionality indicates adverse selection. All regressions control for characteristics that are incorporated in the 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). Sub-figure (a) correlates the dollar bid component (per acre, year year) with additionality, conditional on only characteristics included in the scoring rule. Sub-figure (b) adds interaction terms of prior land use (quartiles of prior cropped interacted with re-enrolling CRP status) and deciles of estimated soil productivity. Sub-figure (c) investigates additionality by contract features, relative to a base contract feature of introduced grasses, again controlling for scoring rule characteristics. Sub-figure (d) examines relative additionality, residualized of score characteristics, by deciles of the estimated soil productivity distribution. Standard errors clustered at the bidder level.

Figure 6: Estimated landowner cost distributions



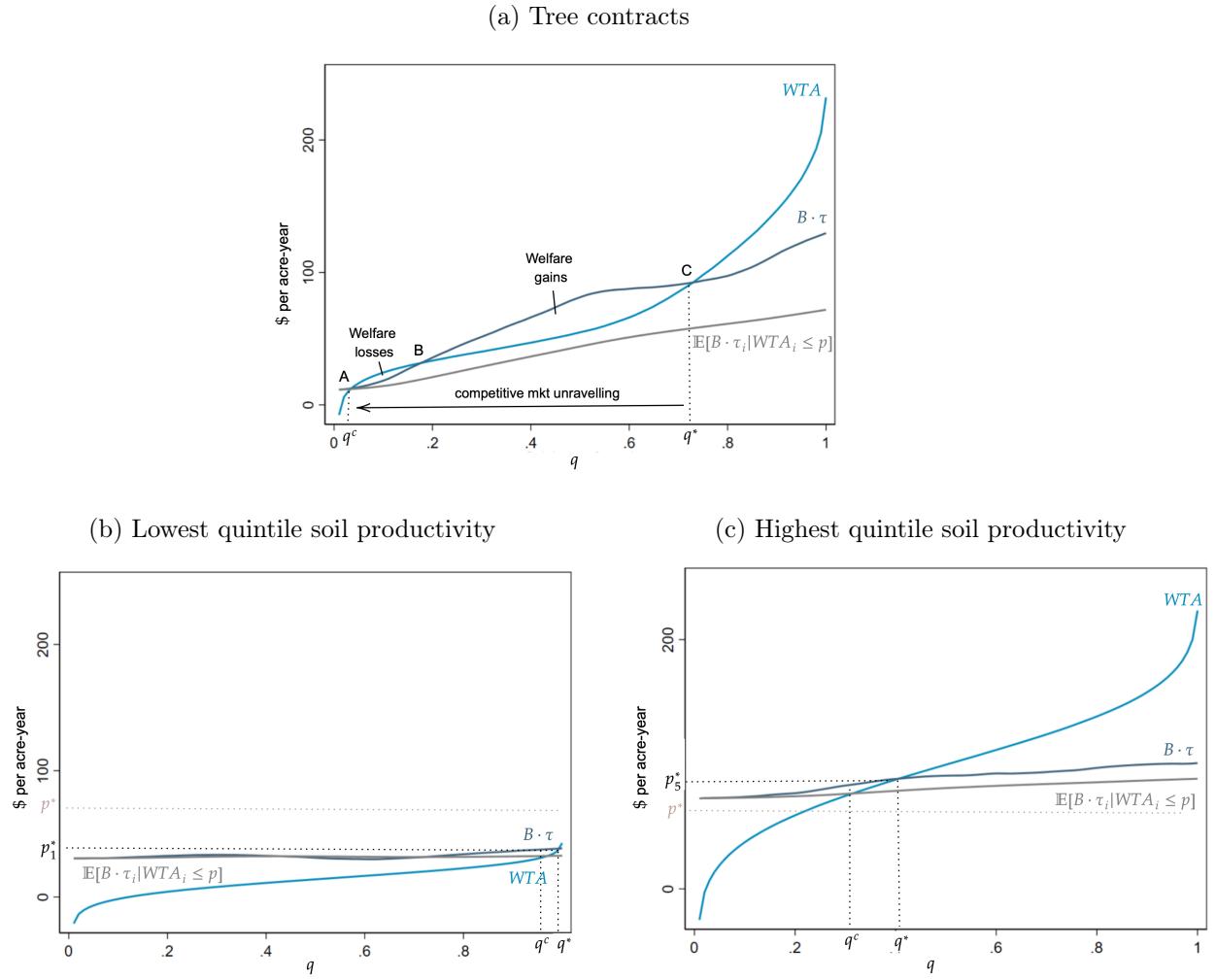
Notes: Figures present kernel density plots of estimates of the base cost c_i (a) and top-up cost κ_{ij} (b) for all auctions in our sample, where $WTA_{ij} = c_i + \kappa_{ij}$. These costs are estimated based on revealed preferences in bidding behavior. See the discussion in Section 5.1 for estimation details. Sub-figure (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 sub-figure (c) are measured using the remote sensing data.

Figure 7: Empirical graphical welfare analysis



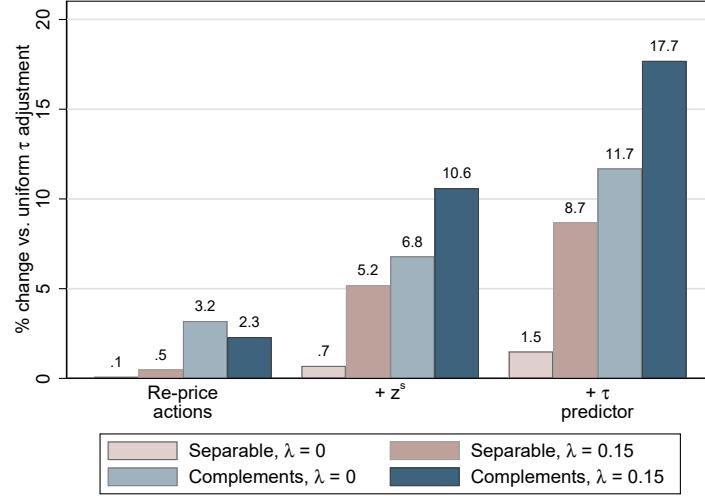
Notes: Figure presents empirical counterparts of the curves in Figure 1 for the base contract. WTA is calculated as the minimum cost across all possible contracts and is not sensitive to the normalization of κ_{ij} . B denotes the value of the environmental service $a = 1$, calibrated as defined in Appendix E, whereas $B \cdot \tau$ denotes the incremental value of contracting, relative to no contract, “deflated” to account for non-additionality. The area between the $B \cdot \tau$ and the WTA curves represent social welfare gains from contracting (see Equation (2)). The intersection of the WTA and $B \cdot \tau$ curve denotes the solution to the regulator’s pricing problem. Triangle ABC represents welfare gains under this optimal price. The area CDE represents welfare losses from mis-pricing at B : in this triangle the incremental value of contracting does not exceed a landowner’s willingness to accept the contract. The average incremental value curve, $E[B \cdot \tau_i | WTA_i < p]$ defines the value of an offset contract. The intersection of the WTA and average incremental value curves define an offset market equilibrium. This equilibrium leads to welfare losses (triangle CFG) by limiting efficient trades.

Figure 8: Graphical analysis: heterogeneity across contracts and observables



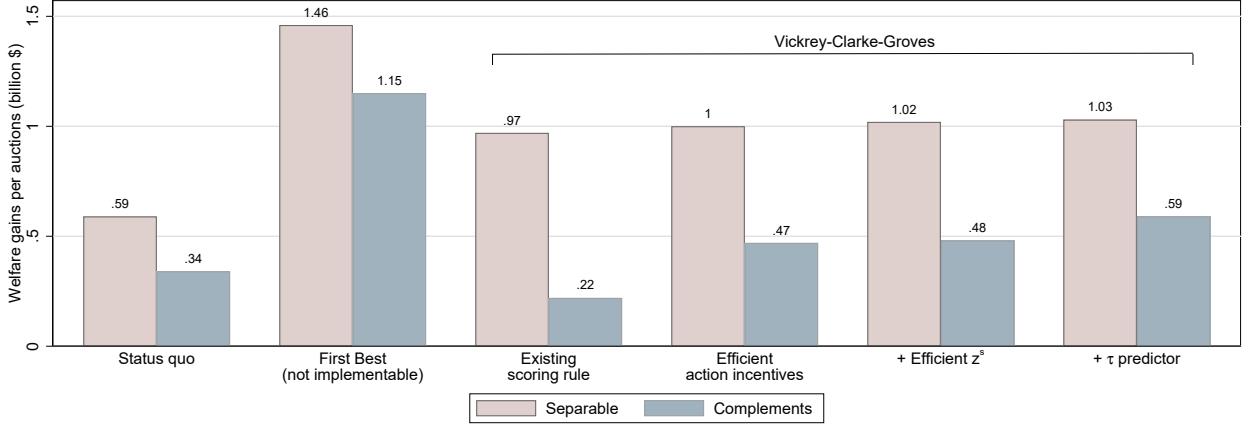
Notes: Figure presents empirical counterparts of the curves in Figure 1. In sub-figure (a), WTA is calculated as the minimum WTA to achieve any tree contract, in sub-figures (b) and (c) it is for the base contract. $B \cdot \tau$ denotes the incremental value of contracting, relative to no contract. The area below $B \cdot \tau$ and above WTA denote social welfare gains from contracting (see Equation (2)). The average incremental value curve, $\mathbb{E}[B \cdot \tau_i | WTA_i \leq p]$ defines the value of an offset contract. The intersection of the WTA and average incremental value curves define an offset market equilibrium. In sub-figure (a) it is assumed that the full value of the contract – including the additional social value of trees, relative to the base contract— is delivered only when landowners are additional (perfect complementarity). Sub-figure (a) demonstrates that, at the levels of non-additionality and adverse selection estimated for tree contracts, the regulator cannot achieve the first best and offset markets will completely unravel. Sub-figures (b) and (c) denote heterogeneity by estimates of soil productivity. These will be our primary predictors of additionality for differentiating incentives.

Figure 9: Gains from differentiated pricing schemes



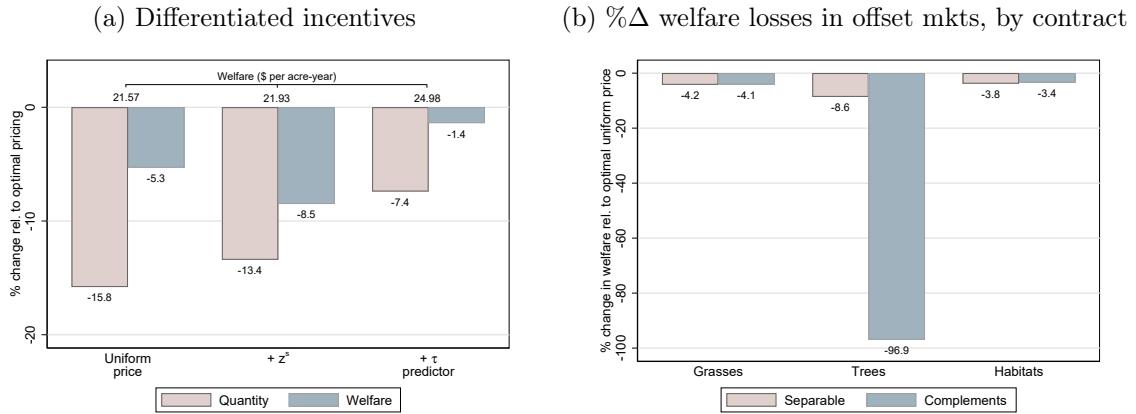
Notes: Figure demonstrates the gains from differentiated incentives, defined in Equation (12), relative to a baseline with a uniform instrument to account for additionality. We consider welfare under four regimes, defined by our two assumptions about the top-up value of actions: additive separability, where all incremental value of the action relative to the base contract is delivered, and perfect complementarity, where value is delivered only when the landowner is additional. We also consider a regime with a cost of funds $\lambda = 0$ and without $\lambda = 0.15$. We define our baseline so that it accounts for both the level of additionality in the population and heterogeneity in the value of heterogeneous contracts. We use two different baselines across our two assumptions to focus only on the gains differentiation, not mis-pricing in levels: under perfect complementarity, we set $p_i^{*j} = p^* + B^j$ for a uniform optimal p^* and under additive separability, we find an optimal scaling factor to set $p_i^{*j} = (B^0 + B^j) \cdot \theta^*$. Re-price actions involves finding the action prices that maximize social welfare under each of the assumptions, subject to landowner choices. Adding scoring rule controls find optimal weights on the characteristics already included and priced by the scoring rule. Adding feasible τ predictors involves adding an additively separable projection of τ on to observable characteristics of soil productivity and erosion. Under the additively separable assumption, approximately 70% of the surplus at stake is impacted by additionality, i.e. the additively separable top-up actions account for approximately 30% of surplus.

Figure 10: Welfare under alternative auctions



Notes: Figures presents estimates of the welfare gains of the status quo auction, an infeasible first best allocation with the same quantity constraint as the status quo, and asymmetric VCG auctions. We calculate welfare gains per auction under our two assumptions about the top-up value of actions: additive separability, where all incremental value of the action relative to the base contract is delivered, and perfect complementarity, where value is delivered only when the landowner is additional. Under the additively separable assumption, approximately 70% of the surplus at stake is impacted by additionality, i.e. the additively separable top-up actions account for approximately 30% of surplus. The status quo calculates welfare under our estimated distribution of (c_i, κ_{ij}) and estimates of additionality by simulating optimal bids. Existing scoring rule implements an asymmetric VCG mechanism with the existing scoring rule. The remaining columns further adjust the scoring rule and asymmetries based on Equation (12). Efficient action incentives involves finding the action prices that maximize social welfare, efficient scoring rule weights find the optimal weights on the characteristics already included and priced by the scoring rule, and adding feasible τ predictors involves adding an additively separable projection of τ onto observable characteristics of soil productivity and erosion to bidders' asymmetric incentives.

Figure 11: Offset market design



Notes: Figures describe welfare and quantities traded under a competitive offset equilibrium versus an optimal price. Sub-figure (a) analyzes the base contract and reports welfare relative to optimal prices under an undifferentiated, differentiated by scoring rule characteristics, and differentiated including a predictor of τ regime. The numbers above the bars tabulate total welfare in the market. Sub-figure (b) analyzes three different sub-markets, each considering only one type of contract being traded, under our two assumptions about the top-up value of actions: additive separability, where all incremental value of the action relative to the base contract is delivered, and perfect complementarity, where value is delivered only when the landowner is additional.

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	0.302	0.282	0.209	0.213	0.211	0.183
Corn	0.110	0.108	0.073	0.076	0.071	0.057
Soybean	0.105	0.097	0.061	0.072	0.068	0.071
Fallow	0.017	0.007	0.031	0.013	0.051	0.025
Natural vegetation or grassland	0.546		0.695		0.652	
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 = establish grasses		0.638				
		(0.481)				
Contract action = establish trees		0.111				
		(0.315)				
Contract action = establish 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 (0.007)	0.009 (0.006)
Post-auction (pooled sign-ups)	-0.075 (0.007)	-0.091 (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 (0.003)	-0.023 (0.003)
Soybean	-0.018 (0.003)	-0.026 (0.003)
Fallow	-0.008 (0.002)	-0.011 (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 (0.015)	-0.000 (0.015)
N bidders	258,286	258,286
N bidder-years	3,099,432	1,808,002

Notes: Table presents coefficient estimates from Equation (6), 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 data limitations. All results are based on a specification using a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Calonico et al., 2014). Standard errors are clustered at the tract level.

Table 3: Summarized mean cost (c_i, κ_{ij}) estimates

	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, or transaction-relevant types, for the base cost c_i and top-up cost κ_{ij} for all auctions in our sample, where $WTA_{ij} = c_i + \kappa_{ij}$. These 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: The dependence of additionality on unobserved landowner types

	(1)	(2)	(3)	(4)
β : coefficient on base cost (c_i)	0.0018 (0.0002)	0.0020 (0.0002)	0.0007 (0.0003)	-0.0002 (0.0004)
α : coefficient on top-up cost (κ_{ij})				
Trees		0.0035 (0.0002)	0.0046 (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 transaction-relevant types (Equation (11)). Coefficients measure the effect on additionality of a \$1 per acre, per year change in c_i or κ_{ij} . Parameter estimates obtained via the Method of Simulated Moments estimator described in Section 5.1. This estimator relates observed patterns of land use among rejected bidders to bids, given estimated distributions of (c_i, κ_{ij}) and optimal bidding in Equation (9). 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 $a_{i1} - a_{i0}$) 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, κ_{ij}) distribution used to simulate optimal bids. Positive coefficients indicate a positive relationship between WTA and additionality, or adverse selection in the market.

A Institutional Appendix: The CRP Mechanism

The scoring rule depends on exogenous 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.⁴⁴

Exogenous 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.

The characteristics are exogenous in the sense that they depend on a bidders location and not the actions they choose to provide. These characteristics, and the points that each bidder is able to obtain based on their location alone, are known for every field in the US.

⁴⁴See <https://www.fsa.usda.gov/Assets/USDA-FSA-Public/usdaproducts/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.

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/conifers/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

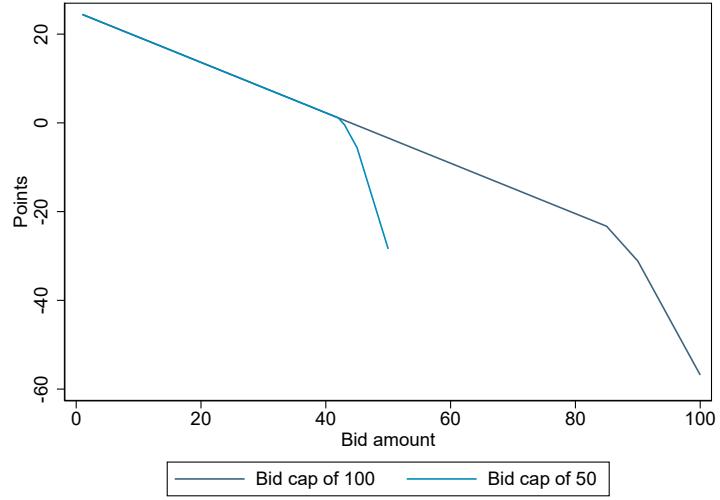
Notes: Table describes the menu of upgrade actions.

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 treatment of 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 $r_i > \bar{r}_i$, where \bar{r}_i denotes the i specific bid cap. These bid caps are determined based on the productivity of soils and are known for all tracts in the US. Second, the score introduces non-linearities based on the amount a bidder bids before the bid cap with kinks at 10% and 15% below the bid cap (see Figure A.1 for a demonstration).⁴⁵ 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.

⁴⁵Encouragingly, 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 implied payoff at thresh-old score	Market share	Average implied payoff at thresh-old score	Market share	Average implied payoff at thresh-old score	Market share
	No upgrade		+ wildlife flood plot		+ pollinator habitat	
Grasses 1	28.63	0.140	35.21	0.015	52.91	0.007
Grasses 2	74.30	0.104	77.86	0.022	86.00	0.019
Grasses 3	43.64	0.067	49.37	0.005	64.68	0.009
Grasses 4	81.00	0.201	83.59	0.023	90.34	0.056
Trees 1	65.13	0.039	69.44	0.003	79.54	0.000
Trees 2	94.73	0.020	96.45	0.003	101.47	0.001
Trees 3	73.29	0.012	76.52	0.001	85.06	0.000
Trees 4	79.54	0.002	82.40	0.000	89.65	0.000
Trees 5	98.14	0.029	99.83	0.003	104.71	0.002
Habitat 1	75.29	0.032	78.72	0.006	86.60	0.001
Habitat 2	81.73	0.039	84.25	0.007	90.84	0.014
Habitat 3	93.07	0.077	94.82	0.009	99.91	0.025

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

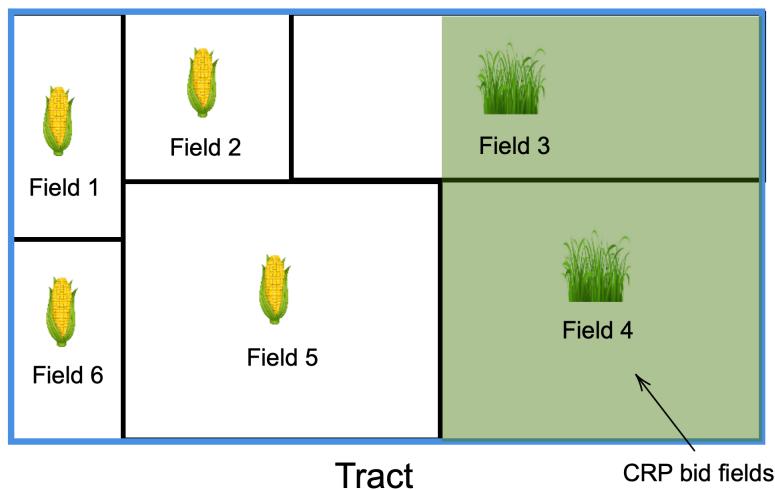
B Data Appendix

B.1 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 in 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.⁴⁶ 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 firm / bidder in our analysis. This tract contains six fields, these are administrative delineations of a tract, each with a single land use. The green shaded area represents an example area bid into the CRP. This could follow field boundaries (as for field 4) or cut into fields (as for field 3).

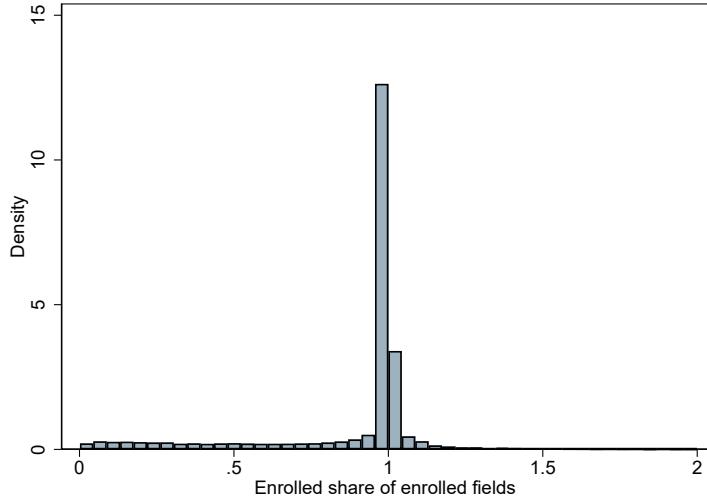
A tract is a collection of fields under one common ownership that is operated as a farm or part of a farm (a tract is a landowner, or bidder, in our setting). The average tract includes 4.75 fields. Each tract can submit at most one bid into a CRP auction. This bid can include

⁴⁶See https://www.fsa.usda.gov/Assets/USDA-FSA-Public/usdaffiles/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 trained on administrative data submitted to the USDA for crop insurance purposes (Form 578, discussed in more detail below). The CDL has been used in prior economics research studying cropping and land use ([Scott, 2013](#); [Hagerty, 2022](#)).

Our primary analysis aggregates these categories into super-classes of crop versus non-crop, following ([Lark et al., 2017](#)). Note that our crop classification excludes alfalfa / hay and fallow / idle cropland. The super-class accuracy of the CDL is very high with > 99% producer's (classified as cropped when truly cropped) and > 98% user's (truly cropped when classified as cropped) accuracy. Despite this high super-class accuracy, remote sensing classifications are

subject to measurement error in classification ([Alix-Garcia and Millimet, 2022; Torchiana et al., 2022](#)), particularly when analyzing land use transitions, that we take seriously. In order to improve accuracy, some states in some years use prior years' CDL as an input into the training algorithm, providing a further source of bias stemming from the classification algorithm.

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

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

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

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

this process in more detail in the next sub-section.

B.2 Validating compliance

While our RD result provides unbiased estimates of the marginal treatment effect at the score threshold, regardless of compliance, to obtain an i -specific measure of additionality ($a_{i1} - a_{i0}$) we need to assess compliance in the status quo regime. Under perfect compliance, we face only a one-sided missing data, or a selective labels, problem.

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 ultra 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: $Y_i(1) = 0 \forall i$

	All post-period years (1)	Drop first two years (2)
Share of enrolled fields classified as cropped	0.054 (0.008)	0.024 (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? We briefly note why we conducted this involved exercise to classify compliance by eye using ultra-high resolution photographs instead of the derived remote sensing product (the CDL). We do so for three reasons. First, these photographs are much higher resolution (1 m vs. 30m pixels), allowing a higher degree of accuracy for a sensitive question (is this program being enforced?). Second, conducting tests by eye allows for more flexibility in the face of measurement error than the derived product, e.g. by only focusing on cases where our reviewers agree. And third, and most importantly,

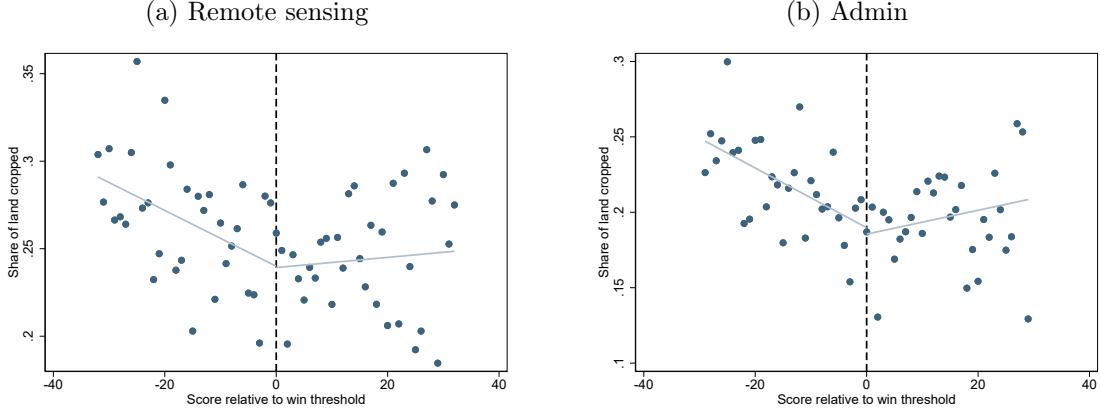
the fact that the CDL uses lagged CDLs in its classifier makes it impossible to distinguish non-compliance from classification error.

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

C Supplemental Figures and Tables

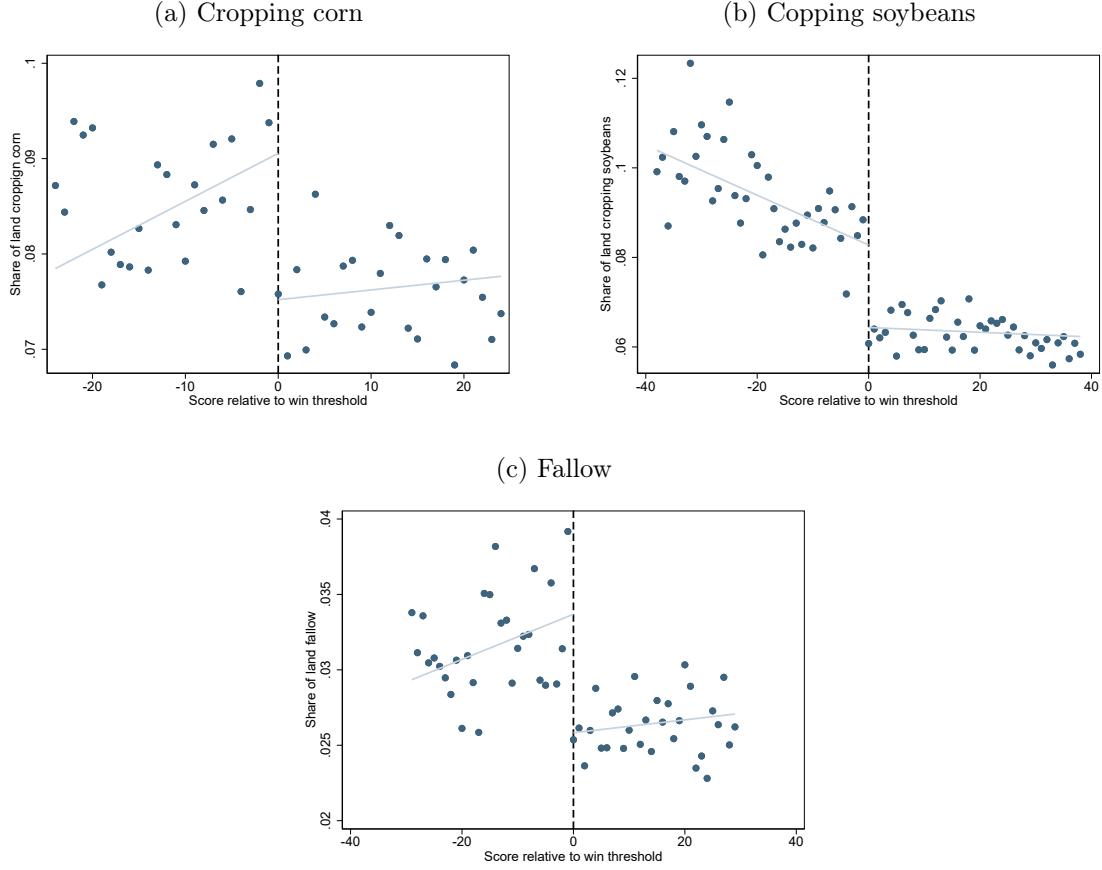
C.1 RD

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



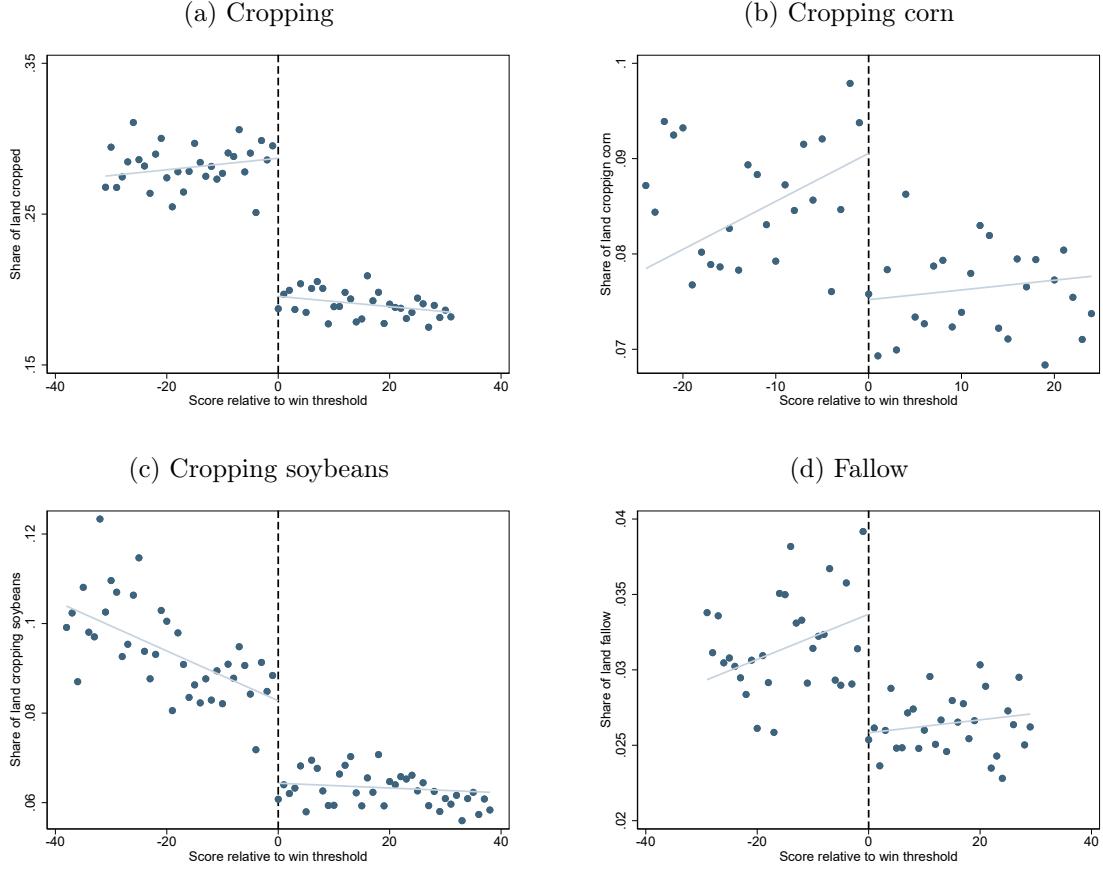
Notes: Figures present raw data and estimated parameters from Equation (6) with a local linear regression on either side of the win threshold in the MSE-optimal bandwidth ([Calonico et al., 2014](#)) for $r > 0$ (post-auction). Regression is estimated at the field level, restricting to non-bid fields for bidding landowners. Estimates are restricted to the 2016 auction where delineations of bidding and non-bidding 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 in the RD figures correspond to winning, negative numbers correspond to losing. Each observation is a bidder. Corresponding coefficient estimates and standard errors presented in Table 2.

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



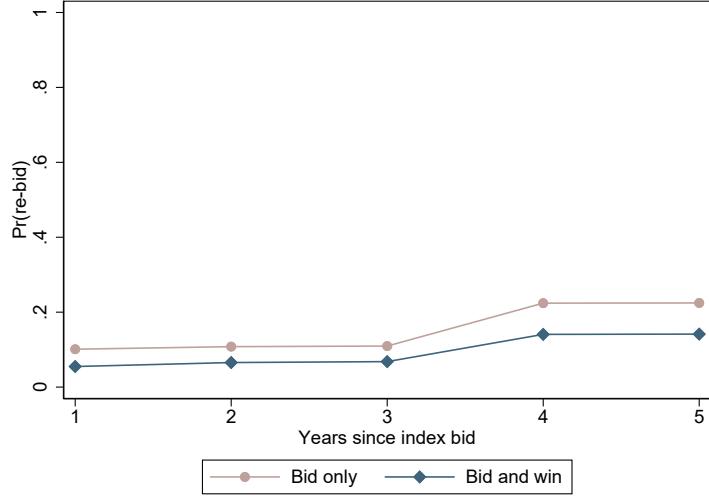
Notes: Figure presents raw data and estimated parameters from Equation (6) with a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Calonico et al., 2014) for $r > 0$ (post-auction). Land-use outcomes are measured using crop classifications in the remote sensing data. The running variable is the difference between each bidder's score and the threshold score. Positive numbers in the RD figures correspond to winning, negative numbers correspond to losing. Each observation is a bidder. Corresponding coefficient estimates and standard errors presented in Table 2.

Figure C.3: Additional RD plots: admin data



Notes: Figure presents raw data and estimated parameters from Equation (6) with a local linear regression on either side of the win threshold in the MSE-optimal bandwidth (Calonico et al., 2014) for $r > 0$ (post-auction). Land-use outcomes are measured 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 in the RD figures correspond to winning, negative numbers correspond to losing. 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 losers who have rebid at least once in the years following an index auction, split by all bidders (beige) and successful bidders (blue). Restricted to only bidders who the index bid. By five years out, fewer than 20% of losing bidders have ever successfully rebid.

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

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

Notes: Table presents pooled RD coefficients (Equation (6) for $r > 0$) split by the rental rate required for the base contract to achieve the threshold rule. This uses both variation across sign-ups and variation within sign-ups across bidders: bidders with land that is more environmentally sensitive can bid 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. The positive relationship is also generally indicative of adverse selection, but does not control for variation in the scoring rule.

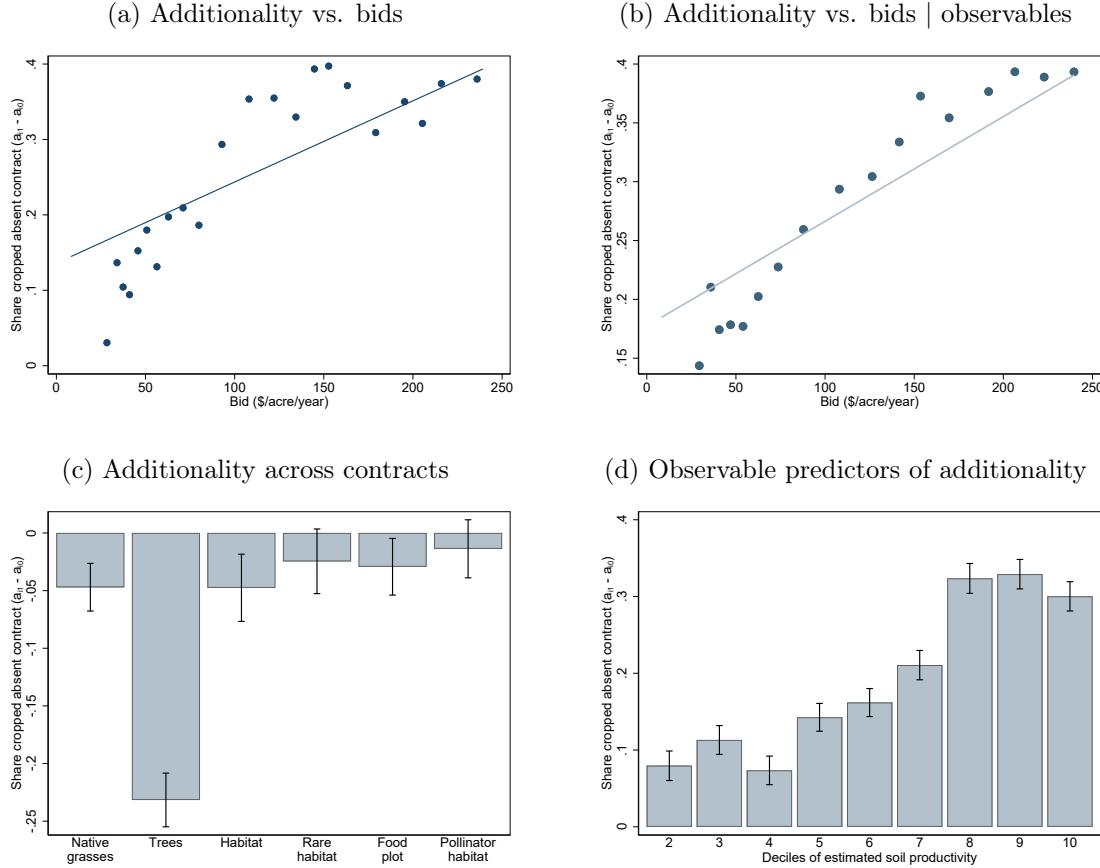
Table C.2: RD evidence: coefficient estimates, > 5 acre offers

	Remote sensing (1)	Admin (2)
Panel A: Main outcome: share of land cropped		
Pre-sign-up (placebo)	0.016 (0.007)	0.014 (0.006)
Post-period (pooled sign-ups)	-0.076 (0.007)	-0.095 (0.006)
Post-period (full contract duration: 2010-2020)	-0.117 (0.020)	
Panel B: Other outcomes		
Corn	-0.016 (0.003)	-0.023 (0.003)
Soybean	-0.021 (0.003)	-0.027 (0.003)
Fallow	-0.009 (0.002)	-0.011 (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 (0.015)	-0.000 (0.015)
N bidders	236,593	236,593
N bidder-years	2,839,116	1,656,151

Notes: Table presents coefficient estimates from Equation (6), 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 sign-ups 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 satellite imagery; only cropped outcomes are reported in the admin data. Calculations of implied additionality divide the treatment effect estimates by 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 data limitations. All results are based on a specification using a local linear regression on either side of the win threshold in the MSE-optimal bandwidth ([Calonico et al., 2014](#)). Standard errors are clustered at the tract level. Standard errors are clustered at the tract level. Restricted to the 92% of bidders offering more than 5 acres into the CRP, per best practices for the analysis of CDL data discussed in ([Lark et al., 2017, 2021](#)).

C.2 Testing for Information Asymmetry

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

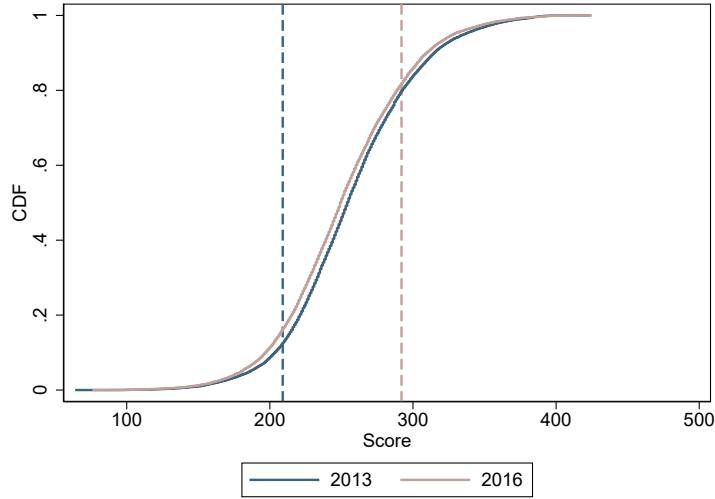


D Model and Estimation Details

D.1 Information Environment

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

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



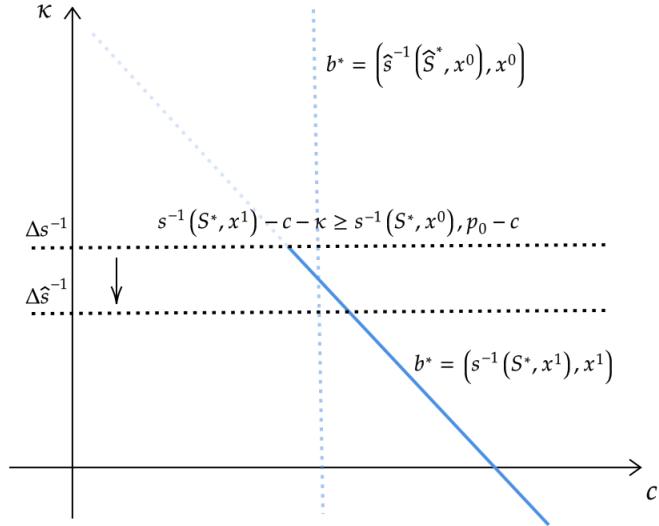
Notes: Figure presents ex-post win thresholds and ex-ante bid distributions for the 2013 and 2016 auctions.

D.2 Identification

Figure D.2 describes the graphical identification argument in the simple case with only two actions (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 . The identified set is a line because of the combination of the continuous and discrete bidding problem. The choice of score in this environment, rather than identify a point as

in Guerre et al. (2000) thus identifies a line. 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. Non-linearities in the scoring rule add in additional inequalities, but the basic argument is the same. See Agarwal et al. (2023) a much more in-depth discussion.

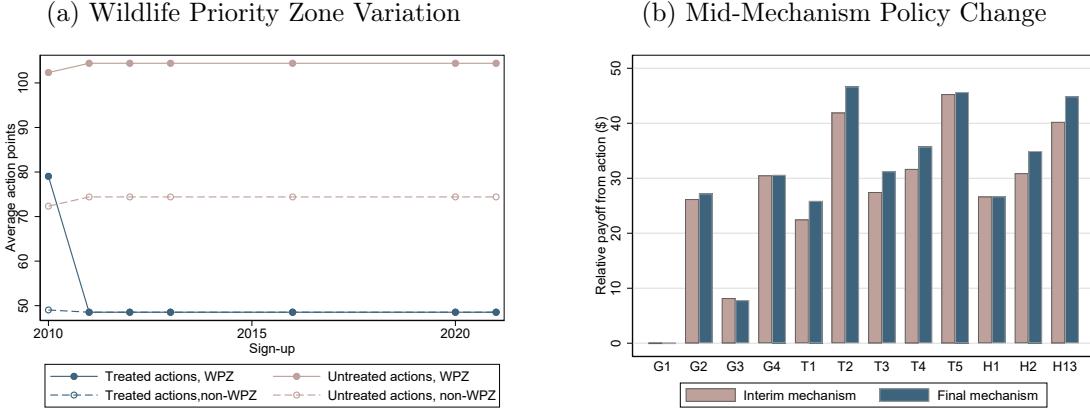
Figure D.2: Graphical identification argument



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

Figure D.2 makes clear the need for variation in the scoring rule. Figure D.3 describes this variation in our context.

Figure D.3: Sources of variation in the relative returns to actions

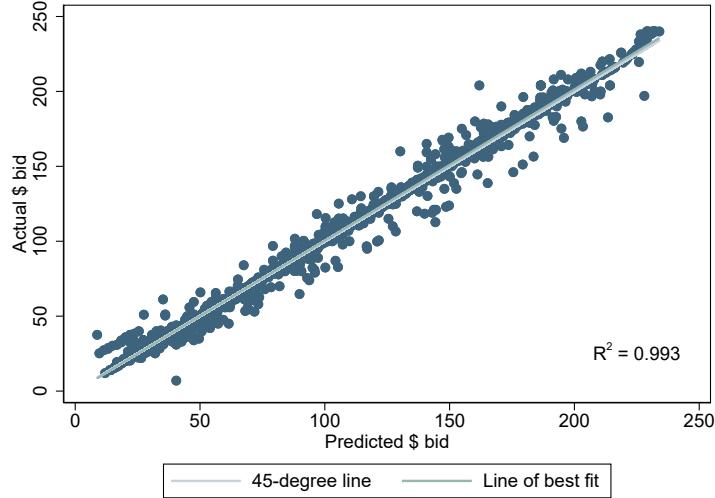


Notes: Figure presents sources of policy variation in the scoring rule that yield variation in returns to actions. Sub-figure (a) plots average action points award for a set of “treated” actions, actions for which after the 2011 auction WPZ bidders no longer got WPZ points, and “untreated” actions, whose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

D.3 Estimation

Pre-Estimation: reconstructing the scoring rule We construct the entire function, $s(\mathbf{b}_i, \mathbf{z}_i^s)$ from the EBI Factsheets. Figure D.4 confirms that our reconstruction performs extremely well: at observed actions, our predictions of the required bid to achieve the true score predicts the observed bid with an R^2 of over 0.99.

Figure D.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 $s(\mathbf{b}_i, \mathbf{z}_i^s)$.

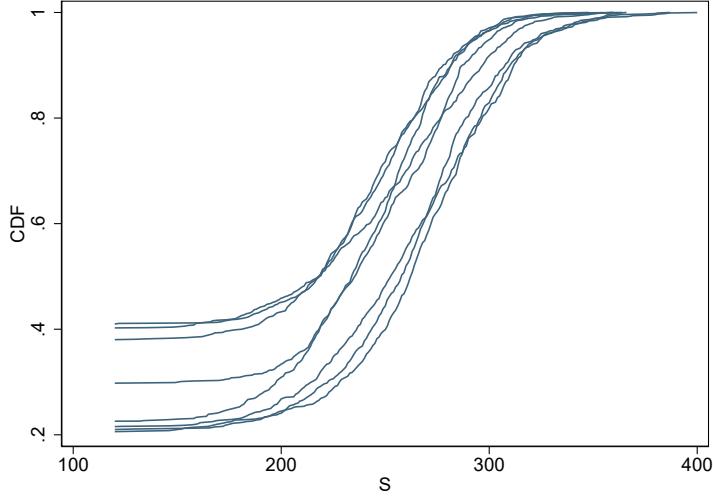
Step 1: Obtain bidder beliefs via simulation Our resampling procedure to obtain win probabilities follows [Hortaçsu \(2000\)](#); [Hortaçsu and McAdams \(2010\)](#). Specifically, we:

1. Fit a Beta distribution⁴⁷ to the observed distribution of acreage thresholds across auctions. For this, we use additional historic data on auctions starting in 1999. This provides us with 12 auctions.
2. Fit a Beta distribution to the observed distribution of number of opposing bidders across auctions. For this, we again use additional historic data on auctions starting in 1999. This provides us with 12 auctions.
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 $G_g(S)$.

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

⁴⁷We fit a Beta distribution instead of a log normal distribution to avoid using an unbounded distribution.

Figure D.5: CDF of $G_s(S)$ across auctions



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

Step 2: Estimate (c, κ_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 (c_i, κ_i) . We use as our proposal distribution parameter estimates obtained from a simplified version of the model, where bidders choose a score using only their expectations of their κ_{ij} draws, then given that score, choose an optimal contract. Under this informational environment, 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.** Next, we draw simulations from the proposal distribution and solve the bidder's problem in [Equation \(9\)](#). Bidder's can only bid integer scores, so bidders search over all feasible score-contract combinations among integers in the support of observed scores.
3. **Coarsen the space of choice probabilities.** Because the full set of bids is 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 is low. We address this 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 $(\tilde{S}_i, \tilde{x}_i)$ denote this chosen action in this coarsened action set.

4. **Reweighting 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, $(\tilde{S}_i, \tilde{x}_i)$, given parameters to be estimated, θ , is:

$$\mathcal{L}_i = \frac{1}{K} \sum f\left((\tilde{S}_i, \tilde{x}_i) | (c^k, \kappa_i^k)\right) \frac{p\left((c^k, \kappa_i^k) | \theta\right)}{g\left((c^k, \kappa_i^k)\right)} \quad (14)$$

where $f\left((\tilde{S}_i, \tilde{x}_i) | (c, \kappa_i)\right)$ calculates whether the coarsened action $(\tilde{S}_i, \tilde{x}_i)$ was chosen as revealed preferred in the solution to the bidding problem in Step 2, $p\left((c^k, \kappa_i^k) | \theta\right)$ is the probability of observing simulation draw (c^k, κ_i^k) given parameter guess θ , and $g\left((c^k, \kappa_i^k)\right)$ calculates the probability of observing (c^k, κ_i^k) given the proposal distribution from Step 1.

5. **Find θ to maximize the log likelihood.** I suppressed dependence in (14) 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.
6. **Repeat:** We repeat Steps 2-5 several times, using estimates from (5) in 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 MSL estimators ([Train, 2009](#)).

We calculate standard errors using the negative inverse of the Hessian.

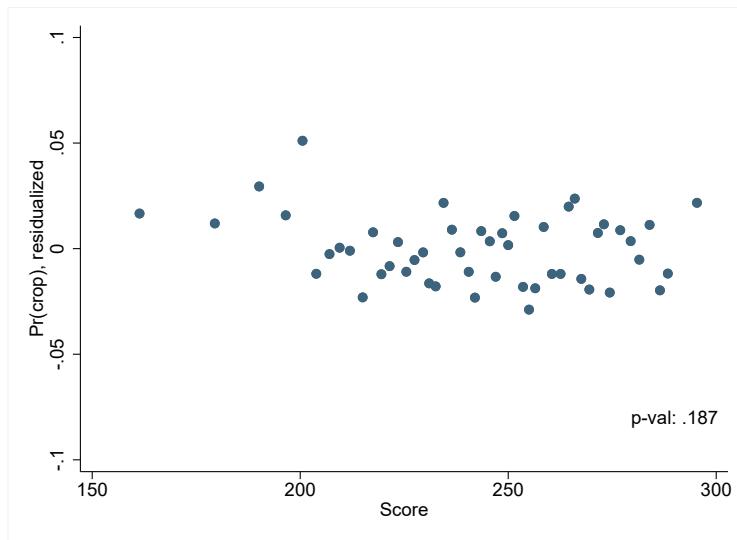
Step 3: Estimate $\tau(\mathbf{z}_i, c_i, \kappa_i)$ Our final step involves estimating the conditional expectation function $\tau(\mathbf{z}_i, c_i, \kappa_i)$, where we match model implied functions of τ_i to observed functions of τ_i , which as in Section 4.2, we calculate in the data using the fact that we can “read off” ex-post measures of additionality, $1 - a_{i0}$, among rejected bidders. Specifically: we search for θ^τ that maximizes $\hat{g}(\theta^\tau)' A \hat{g}(\theta^\tau)$ for weighting matrix A and sample moments: $\hat{g}(\theta^\tau) = \hat{\mathbb{E}} [m_i - \frac{1}{K} \sum_k m_i (\theta^\tau | c_i^k, \kappa_i^k) | \mathbf{z}_i]$, where $\hat{\mathbb{E}}$ denotes the sample expectation. We use as m_i :

- Additionality at the RD: $\tau_i \cdot \mathbb{1}[\underline{S} - b < s(\mathbf{b}_i^*, \mathbf{z}_i^s) < \underline{S}]$ for bandwidth b .
- Additionality by observable characteristics: $\tau_i \cdot \mathbb{1}[s(\mathbf{b}_i^*, \mathbf{z}_i^s) < \underline{S}] \cdot \mathbf{z}_i$.
- Covariance between additionality and chosen scores: $\tau_i \cdot s(\mathbf{b}_i^*, \mathbf{z}_i^s) \cdot \mathbb{1}[s(\mathbf{b}_i^*, \mathbf{z}_i^s) < \underline{S}]$.
- Additionality within chosen contracts: $\tau_i \cdot \mathbb{1}[x_{ij} = 1] \cdot \mathbb{1}[s(\mathbf{b}_i^*, \mathbf{z}_i^s) < \underline{S}]$

We note that all moments estimate relationships conditional on $s(\mathbf{b}_i^*, \mathbf{z}_i^s) < \underline{S}$. We use as A the two-step optimal GMM weight matrix. 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.

To ensure that our estimates are not reliant on the normal functional form assumptions for (c_i, κ_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.

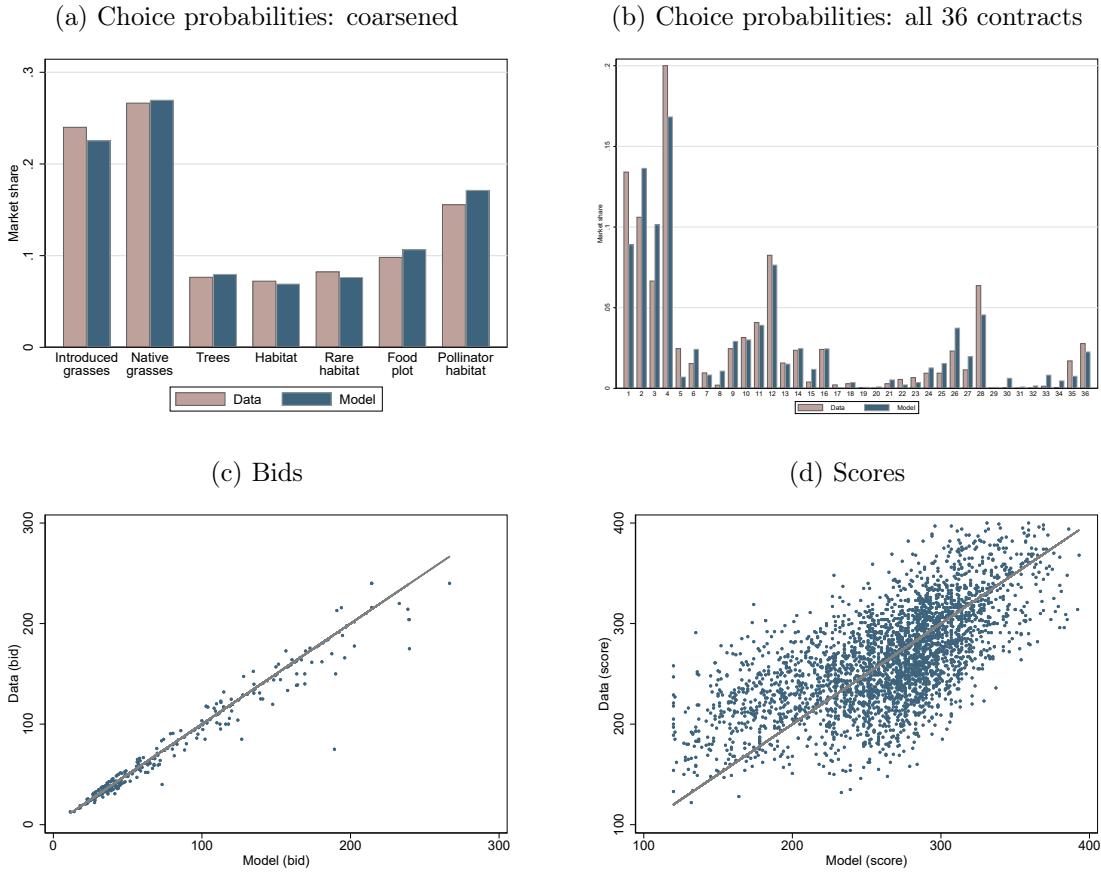
Figure D.6: Residualized relationship between score and cropping



Notes: Figure presents the relationship between a binary indicator 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.

Results: example parameter estimates and model fit The tables and figures below present parameter estimates and assess the fit of the bidding model.

Figure D.7: Assessing model fit



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.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)
Rate 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 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 $G(S)$.

Table D.2: Comparison between estimated and administrative cost estimates

	Estimates	Median admin cost	Average admin cost
		(1)	(2)
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 Monetizing Benefits

Recall that the value of contracting is given by either $B_i^0 \cdot \tau_i + B^j$ or $(B_i^0 + B^j) \cdot \tau_i$. To calculate these values we must obtain values for B_i^0 and B^j . Technically, B^j varies across whether or not a bidder is in a Wildlife Priority Zone. We abstract from this heterogeneity in our valuations and counterfactuals for simplicity.

We assume that the weights in the scoring rule reflect the relative weight that the planner places on B_i^j , assuming $\tau_i = 1$ for all i . The assumption that $\tau_i = 1$ for all i is discussed in [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.* This also assumes that the weights reflect the USDA's preferences, i.e. that they are not distorted to optimally screen types. There is no evidence to support this ([Ribando et al., 2001](#)). Because the USDA values transfers to agricultural landowners, we assume that the USDA maximizes overall social welfare when designing its auction and scoring rule. Finally, we choose to use these USDA revealed-preferred values of B_i^j , which may not align with the true environmental benefits or social value across B_i^j for a number of reasons, including political concerns ([Ribando et al., 2001](#)). We choose to take this USDA-revealed-preferred approach, versus calibrating B_i^j from an external integrated assessments model,⁴⁸ to focus on additionality as the primary friction, rather than miscalibrated values. Specifically, we note that scoring rule is separable in the actions incentivized by contracts and the bid amount:

$$s(\mathbf{b}_i, \mathbf{z}_i^s) = \underbrace{s^a(\mathbf{x}_i, \mathbf{z}_i^s)}_{\text{action points (incl. base action)}} + \underbrace{s^r(r_i)}_{\text{non-linear function of rental rate}} \quad (15)$$

and we assume that

$$s^a(\mathbf{x}^j, \mathbf{z}_i^s) \cdot \Upsilon = (B_i^0 + B^j) \quad (16)$$

where \mathbf{x}^j denotes the contract vector corresponding to $x_{ij} = 1$, for some scaling factor Υ that scales points into dollars. The remaining piece of information required is therefore an estimate of Υ .

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

$$\frac{\hat{\Upsilon}}{\sum \mathbb{1}\{S_i \geq \bar{S}\}} \sum_{i|S_i \geq \bar{S}} s^a(\mathbf{x}_i, \mathbf{z}_i^s) = \hat{\Omega} \quad (17)$$

⁴⁸See <https://naturalcapitalproject.stanford.edu/software/invest> for one such example.

for any estimate of the value of the CRP, $\hat{\Omega}$. So we can use Equation 17 to obtain an estimate for $\hat{\Upsilon}$. Because valuations, and revealed preferred estimates of willingness to accept, are constructed for the long-run estimates for the full contract duration, we scale our estimates of τ_i , which are estimated on only 4 post-period years and incorporate a transition period, to the full contract period using our estimated dynamic treatment effects. We discount the stream of benefits over the contract period by 5%. 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 be an under-estimate.

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

1. Our first estimate sums the recreational,⁴⁹ public works,⁵⁰ and air quality benefits⁵¹ from [Feather et al. \(1999\)](#) and adds estimates of the value of greenhouse gas reductions from sequestered CO₂ (over the 10-year contract) and reduced fuel and fertilizer use (permanent) monetized at \$43 per metric ton. This leads to an overall estimated value of the CRP of \$98.34 per acre, per year.
2. Our second estimate takes the global valuation of the CRP from [Hansen \(2007\)](#), which is equal to \$255.70, per acre, per year.
3. Our third and fourth estimate take a conservative and generous value of the non-GHG CRP benefits from [Johnson et al. \(2016\)](#) and adds estimates of the value of greenhouse gas reductions from sequestered CO₂ (over the 10-year contract) and reduced fuel and fertilizer use (permanent) monetized at \$43 per metric ton. This leads to estimates of \$367.96 and \$456.04, per acre, per year.

The description above highlights the difficulties of monetizing the value of the all of the environmental benefits of the CRP. We emphasize that our focus is not on obtaining estimates of B_i^j . We use these simply to scale our primary object of interest, τ_i .

⁴⁹Includes sport-fishing, small-game hunting, noncompetitive viewing, and waterfowl hunting.

⁵⁰Includes cost savings associated with reduced maintenance of roadside ditches, navigation channels, water treatment facilities, municipal water uses, flood damage, and water storage.

⁵¹Includes reduced health risks and cleaning costs associated with blowing dust.