Journal of Environmental Economics and Management 108 (2021) 102439

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

# Improving the cost-effectiveness of the Conservation Reserve Program: A laboratory study☆

Peter Cramton [a], Daniel Hellerstein [b], Nathaniel Higgins [c], Richard Iovanna [d], Kristian López-Vargas [e,*], Steven Wallander [b]

[a] University of Cologne, University of Maryland, Germany
[b] Economic Research Service (ERS), United States Department of Agriculture (USDA), USA
[c] Google Inc., USA
[d] USDA, USA
[e] University of California, Santa Cruz, USA

ARTICLE INFO

*Article history:*
Received 21 September 2018
Revised 21 February 2021
Accepted 23 February 2021
Available online 8 March 2021

*JEL classification:*
C91
D47
N52

*Keywords:*
Auctions
Market design
Conservation
Conservation reserve program
Price cap
Bid cap
Reference price
Procurement auction

ABSTRACT

The Conservation Reserve Program (CRP) is arguably the world's largest payments-for-ecosystem services program, with $1.8 billion paid to farmers in 2017 for practices on 23.4 million acres. The CRP uses a pay-as-bid, reverse auction with field-specific price caps to enroll most of the land in the program. Economic theory and empirical studies from other domains suggest that the restrictive price-cap auction format used in the current design of the CRP exhibits issues in terms of efficiency and cost-effectiveness. Using a laboratory experiment, we study the impact of varying the tightness of the price-cap auctions. We also examine two alternative auction formats based on reference prices. We find that excessively tight bid caps reduce efficiency and cost effectiveness by discouraging participation. Conversely, bid caps set too high also reduce cost-effectiveness by allowing higher rents. An exogenous reference price ranking format, which makes medium-cost sellers more competitive against low-cost sellers, reduces both efficiency and cost-effectiveness. An endogenous reference price format increases cost-effectiveness by increasing participation and reducing rents.

© 2021 Published by Elsevier Inc.

## 1. Introduction

Reverse auctions are a popular structure for conservation programs that provide payments for ecosystem services. Since these are voluntary programs, achieving cost-effective and efficient outcomes is formidable challenging and depends upon often complex program rules and ranking formats (Claassen et al., 2008).

☆ We thank the two anonymous referees and the editor who provided constructive comments that improved our paper significantly, and Bryan Pratt for excellent research assistance. This research was supported by the U.S. Department of Agriculture, Economic Research Service through a cooperative agreement. The findings and conclusions in this publication are those of the authors and should not beconstrued to represent any official USDA or U.S. Government determination or policy.

* Corresponding author.
*E-mail address:* klopezva@ucsc.edu (K. López-Vargas).

https://doi.org/10.1016/j.jeem.2021.102439
0095-0696/© 2021 Published by Elsevier Inc.

Among the best known and largest of these programs is the Conservation Reserve Program (CRP), administered by the United States Department of Agriculture (USDA), which pays landowners to convert environmentally sensitive or vulnerable cropland to a perennial cover of grasses or trees for at least 10 years.

Most CRP acres are enrolled through what is known at the General Signup, in which interested landowners submit an offer consisting of the parcel boundary to be enrolled, specific conservation practice to which the cropland will be converted, and a desired annual payment (the bid). Offers are then scored and ranked on the basis of an Environmental Benefits Index (EBI), which weighs the bid against the anticipated environment gain from the conservation practice. After the auction closes, a minimum acceptable cutoff EBI is selected by USDA, based on program acreage constraints and other considerations, and all proposals with an EBI above the cutoff are enrolled.

In addition to the use of an auction, to reduce rents through competitive pressure, the program also constrains rents through the use of field-specific bid caps.[1] These estimates of opportunity cost are inherently imprecise and can adversely affect program performance by both driving away potential bidders when they are lower than actual opportunity cost and enabling remaining participants to extract information rents when they are higher (Kirwan et al., 2005; Hellerstein, 2017).

This study follows the literature on using laboratory experiments of simulated auctions to evaluate alternative conservation auction formats (Schilizzi, 2017). While a number of the earlier studies have looked at design considerations such as the revelation of agency preferences for environmental quality (Cason and Gangadharan, 2004; Messer et al., 2017), transaction costs (Palm-Forster et al., 2016), types of program constraints (Boxall et al., 2017), and coordination incentives (Banerjee et al., 2015), only a few conservation studies have looked at the tightness of the bid caps and the formula underlying the cost ranking format (Hellerstein and Higgins, 2010).

In this paper, we look at three main auction formats: bid caps, exogenous reference prices, and endogenous reference prices. In the case of bid caps we study multiple configurations where we vary how "tight" the bid cap is with respect to the parcel-specific opportunity cost estimate. The exogenous reference price is based on the opportunity cost information available to the program and the endogenous reference price on the offers of sellers with similar cost information.

With respect to bid caps, we find that making the cap tighter (i.e., reducing the potential for markups) reduces participation dramatically, even among low-cost sellers, making the caps counterproductive in terms of cost-effectiveness. Conversely, loosening up the bid cap does not increase competition and mainly enables sellers to obtain high rents, hurting cost-effectiveness. There is a cap level that balances the participation effects discussed with the potential for reducing offer values. However, as discussed in Hellerstein and Higgins (2010) (and in our experimental evidence below), striking the right balance is to a large extent unattainable outside controlled experimental settings.[2]

Comparing bid caps to reference prices, we find that participation rates in the exogenous reference price are statistically equal to those of modest and loose bid caps, but higher than in tight bid caps. In contrast, the endogenous reference price auction exhibited a noticeably higher participation rate, enhancing competition.

In terms of cost-effectiveness, the exogenous reference price performance is comparable to a loose bid cap. Interestingly, the endogenous reference price outperforms the exogenous reference price and the tight bid caps. There is also mild evidence that it also outperforms the very relaxed bid caps. While the endogenous reference price auction was not as cost effective as the auction in which bid caps were relaxed just enough so no seller would be dissuaded from entry, we argue such caps are only implementable in an experimental setting.[3]

Our results highlight both how the current design of the CRP auction discourages participation among low cost bidders, hurting efficiency and cost effectiveness, and the advantages of relaxing bid caps or replacing them with reference prices in a program redesign.

The rest of the paper is organized as follows. Section 2 provides relevant background information on the CRP. Section 3 reviews the related literature on auction design. Section 4 presents formally the auction formats we study, the corresponding theoretical predictions, and the experimental design. In section 5, we present and discuss our results, and Section 6 concludes.

## 2. The Conservation Reserve Program

The CRP pays farmers to voluntarily take environmentally sensitive cropland out of production for a contract period of 10–15 years and instead establish a conservation cover of grass or trees. The program's main objectives are to minimize soil erosion, enhance water quality, and create wildlife habitat. CRP practices vary considerably in terms of complexity and the effort involved, ranging from the establishment of a simple perennial grass mix, to a bottomland hardwood stand, to structural practices such as grassed waterways and constructed wetlands. Producers are provided an annual *rental payment* to compensate for the opportunity cost of foregone crop production, as well as assistance paying for practice establishment (known as "cost share").

[1] We will use "bid cap" and "price cap" interchangeably.

[2] Hellerstein and Higgins (2010) find that auction cost effectiveness peaks when price caps are set at 90% of the maximum possible induced cost of the auctioned item, where actual costs vary across participants – which implies that 10% of participants cannot profit from the auction. However, the role of participation is not explicitly studied.

[3] This is because in reality it is difficult to have sufficient information of the true distribution of the estimation error.

The program enrolls land using two types of mechanisms: an auction mechanism called *General Signup* and a first-come, first-served system called *Continuous Signup*.[4] This paper focuses in the General Signup, where offers to enroll land are first ranked according to an index of environmental benefit and cost.[5]

Each competing proposal in the General Signup specifies the conservation practice that the landowner seeks to establish, the boundary of the parcel on which the practice is proposed, and the *bid* (the annual payment that the landowner seeks to receive). The bid must be no greater than a parcel-specific cap that Farm Service Agency (FSA) generates. This cap is intended to reflect the minimum payment the producer is willing to accept (WTA) to enroll in CRP or, equivalently, the opportunity cost of participation. The program ranks offers according to a multi-dimensional index (the Environmental Benefits Index, or EBI) that reflects both the cost to the USDA (the bid) and the anticipated environmental benefit. Those above a cutoff set by the Secretary of Agriculture are enrolled and the rest of the offers are rejected.

Total enrollment in CRP is subject to acreage caps at the county and national levels.[6] The acres signed up in a given year cannot exceed the national cap set by the Farm Bill, minus the active contract acres that will not be expiring at the end of the year. Since expiration dates vary considerably, the effect of the national acreage cap for the General Signup varies considerably from year to year.[7]

The General Signup, as a procurement auction, uses competition to control costs. That is, farmers have an incentive to reduce their bids to increase their chances of being selected. In pay-as-bid auctions like the CRP, participants want to submit a bid that is low enough to be accepted, yet profitable. Since there is heterogeneity in opportunity cost and environmental benefits, participants with relatively low opportunity cost or high benefits may realize their prospects of winning are high even after inflating their bid with a large markup. Conversely, other auction participants who are certain to be rejected are unlikely to make any offer to enroll.

Empirical examinations of CRP signups generally find there are substantial differences between farmer bids and their opportunity cost. Kirwan et al. (2005) find that landowners are, on average, paid 20% above their opportunity cost, which they estimate by predicting the counterfactual offers if all EBI scores were set to zero. Similarly, Horowitz et al. (2009) find that offers in an auction where the state purchases farmland development rights are 5–15% above landowner opportunity cost.

The USDA has implemented price controls in the form of bid caps for the General Signup to prevent excessive payments to farmers. The intent is to limit farmers' annual payments to an estimate of their opportunity cost. The bid caps are based on soil rental rates (henceforth SRRs), which are estimated using county-average dryland cash-rent estimates, soil-specific adjustment factors, and professional judgment (Hellerstein, 2017). These estimates, of course, are inherently imprecise.

Despite the intention to lower the costs of the program, the parcel-specific price caps may be having counterproductive consequences. Under imprecise (let alone possibly biased) estimates of the SRRs, the price caps may be increasing the cost of General Signup auction due to their negative impact on participation rates. Even small deviations in the opportunity cost estimates can drive a mass of potential participants to an unprofitable region—receiving a bid cap below actual opportunity cost—dissuading them from auction participation. This reduction in participation negatively impacts the cost effectiveness of the program via two channels: First, to satisfy an acreage target, the program is obliged to accept parcels with higher opportunity cost to replace dissuaded lower-cost farmers. Second, strategic, remaining participants can exploit the lack of competition to win the auction with higher bids than they would otherwise submit.

## 3. Related literature

Other programs reminiscent of CRP have cropped up since its inception in 1985. Important examples include the Nature Conservancy's BirdReturns program (started in 2014) that implements a reverse auction used for habitat restoration in the U.S. – also one of the primary objectives of CRP. BirdReturns uses a closed bid, single round format auction to compensate California rice farmers to flood their fields in the spring and fall in order to provide temporary critical habitat for migrating waterfowl and shore and wading birds (Golet et al., 2018). The auction is conducted semi-annually and offers are ranked and selected according to bid amount as well as anticipated benefit, i.e., habitat value. Contract terms are limited to a single season. While considered a success, the scope and scale of the program are relatively modest.

Internationally, Australia has had considerable experience with conducting reverse auctions for the sake of private lands conservation, which have also used a closed bid, single round format (Rolfe et al., 2017). However, the scale of the programs (e.g., Bush Tender) individually and even in the aggregate has been much smaller than CRP. Further, nearly all of the thirty-four programs assessed by Rolfe et al. (2017) were active for just one or two years. Finally, Australia's initial enthusiasm for such programs appears to have waned, with very little activity reported over the past several years.

[4] The Continuous Signup enrolls land in targeted geographic regions or high-value conservation practices, delivering Agency-determined payments to offers that meet specific criteria.

[5] Some version of competitive General Signup has been utilized since the program began in 1985. General Signups have taken place every few years over the past decade and will be conducted annually going forward. They usually last four weeks. During this time, the Farm Service Agency (FSA) maintains an open call for offers from landowners.

[6] CRP's enabling legislation limits per-county CRP enrollment to be less than 25% of cropland acres.

[7] As of September 2017, approximately 204,000 contracts covering over 16 million acres had entered the program through General Signup, and about 434,000 contracts, covering over 7.3 million acres, entered the program through Continuous Signup (CRP monthly summary report, 2017). For a detailed account of the evolution of the CRP, see Hellerstein (2017).

In the case of China's Grain-to-Green program (GTG), millions of steeply sloped cropland acres have been converted to pasture and forest since 1999 in the Yellow and Yangtze river basins. As CRP has decreased in spatial extent over the last three Farm Bills, GTG has expanded to be the largest program of its kind, 20M hectares by 2014. However the GTG program is not a reverse auction but rather a fixed rate payment system.

Beyond the experiences of analogous and related programs, our paper draws from and contributes to several strands of economics literature on conservation programs and auction mechanisms that make those programs more cost-effective. Latacz-Lohmann and Van der Hamsvoort (1997) were the first to point out that the fixed-rate payments systems, which were the most common in programs before the 2000s, did not address the information asymmetries between landowners (who know their true opportunity cost) and the regulator (who are better aware of the environmental benefit). These authors proposed the use of research on auctions to induce cost revelation.

Early studies focused on the increase in cost-effectiveness relative to fixed-rate payments. For example, Schilizzi and Latacz-Lohmann (2007) devise an experiment to compare Australian conservation auctions to their fixed price counterfactual that found performance to improve ten to sixty percent. Uchida et al. (2005) found the fixed payments to Chinese farmers from GTG to be several times larger than those of the CRP.

One of the earlier studies to compare the effectiveness of alternative auction designs, Cason et al. (2003) devised an experiment to study the effects of revealing the environmental benefit (EB) of their land to landowners during an auction. Sellers significantly increase offers when they know that EB is high, so high EB lands are more frequently rejected.

Relevant to the CRP, Hellerstein and Higgins (2010) analyze bid caps' impact in reverse auctions using an experiment. They find that tight bid caps, which make participation unprofitable for at least a fifth of the bidders, perform poorly in cost-effectiveness. The opposite of a bid cap of a reverse auction is a minimum bid, or reserve price, in a forward auction. As predicted by theory, empirical research shows that reserve prices have a positive impact on revenue for pay-as-bid auction formats (see, e.g., Reiley, 2006; Ostrovsky and Schwarz, 2011; Choi et al., 2016).

Several studies from the broader literature that examine whether reserve prices should be kept secret or made public arrive at different conclusions. From a theoretical perspective, Vincent (1995) shows that, under some conditions, making the reserve price secret can increase revenue via higher participation. Katkar and Reiley (2007) find that secret reserve prices hurt the seller, deterring participation. Grether et al. (2016) found no relevant impact of secret reserve prices on revenue.

Reference prices are the other major market mechanism and involve incorporating an expected or desired bid amount into the function used to score and rank offers. Reference price auctions have been implemented in several contexts, especially in financial markets. The U.S. Treasury used a reference price auction to purchase toxic assets under the Troubled Asset Relief Program (TARP), following the 2008 financial crisis. These auctions allowed the Treasury to compare bids on securities of different values (see, e.g., Ausubel et al., 2013; Armantier et al., 2013). Scoring auctions are used in construction contracts, for example, to express the auctioneer's trade-off between payment and time to completion (Lewis and Bajari, 2011; Asker and Cantillon, 2008).

Hellerstein et al. (2015) discuss the policy design implications associated with the information available to the CRP and suggest that reference price auctions could be considered in a redesign of the program. We will evaluate the use of reference prices, both public and secret, as alternatives to price caps in our experiment.

## 4. Experiment

In this section, we present a formal description of the auction formats we study. We then discuss their corresponding theoretical predictions. Finally, we describe the design of the treatments and implementation of the experiment.

### 4.1. Auction formats and theoretical predictions

After we introduce the environment and each auction format formally, we present features and implications of the equilibrium behavior in each format. We use symmetric Bayes-Nash as our equilibrium notion and assume risk neutrality.[8]

#### 4.1.1. Environment and metrics

The buyer seeks to purchase $k > 1$ units from $n$ sellers, with $k < n$, and implements a multi-object pay-as-bid reverse auction to buy these objects. In the context of the CRP, this represents that the Program wants to secure the environmental service of $k$ parcels from $n$ farmers. Each seller (farmer) seeks to sell (rent) her object (parcel) trying to maximize expected

[8] We should note that the theoretical predictions presented here were derived in a post hoc exercise. We include this section following a suggestion from the editor. We originally designed this study without a comprehensive theoretical analysis because of the following reasons. First, there were already specific formats that were being implemented (price caps auctions) or considered (reference price auctions). Second, we had not devised a form to solve these equilibrium bidding functions. Third, the environment and studied formats were sufficiently complex so that large deviations from theoretical predictions were expected. We thank the editor for suggesting this additional analysis. Although our main initial conjectures were confirmed, this exercise did generate new insights and provided more precise predictions that improved the paper. For a detailed presentation of this theoretical exercise, see Klevans and López Vargas (2020). Being this an post hoc exercise, it is more proper not to formulate the predictions in terms of hypotheses, because those were not formulated before the data was collected.

profits. It is also assumed that each seller owns only one object and that the auction is a one-shot interaction.

Seller $i$'s opportunity cost of selling her object is denoted by $c_i$, and it is a random variable with support in a bounded positive interval. That is, $c_i \sim F$, with support in the interval $[\underline{c}, \overline{c}]$.[9] The buyer posses an estimate or signal, $\widehat{c}_i$, of each seller $i$'s opportunity cost. This signal has an additive error or noise:

$$\widehat{c}_i = c_i + \epsilon_i \tag{1}$$

where $\epsilon_i \sim H$ with support in $[\underline{\epsilon}, \overline{\epsilon}]$.

The buyer might use this information in the auction. Furthermore, it is assumed that the seller $i$ observes $\epsilon_i$ directly or indirectly.

We study the following three formats: (1) a family of price-cap auctions; (2) an exogenous reference-price auction; and (3) an endogenous reference-price auction. All three formats of reverse auctions are analogues to sealed bid, pay-as-bid formats in standard, forward auctions. Therefore, the payoff always takes the form of this equation:

$$\pi_i(b_i, c_i, \epsilon_i) = (b_i - c_i)\Pr[i \text{ wins}] \tag{2}$$

where $b_i$ is $i$'s offer. The probability of winning, $Pr[i \text{ wins}]$, is shaped by each particular auction set of rules and the equilibrium bidding behavior of competitors.

In the theoretical predictions as well as in the experiment, $F$ and $H$ will be the uniform distributions. In particular, unless stated otherwise we will have that $n = 16, k = 8, F = U\{10, 100\}, H = U\{-5, +5\}$. This also corresponds to the parameterization used in the experiment.

Finally, before we formally present each auction format and its predicted outcomes, let us define the four main metrics we use to contrast these formats both in the model and in the experiment.

1. *Participation rate* is measured at the auction level as the percentage of sellers that opt into the auction (i.e., decide to submit an offer).
2. *Average winning offer* is measured at the auction level as the average payment to the $k$ winning sellers or the per unit cost of the objects.
3. *Allocative efficiency* can be measured at the object level and at the auction level. Object $i$ is said to be allocated efficiently when it is sold *if and only if* $c_i$ is among the $k$ lowest costs. The auction-level efficiency is calculated as ratio of the number of objects allocated efficiently divided by $n$.
4. *Cost excess* is a measure of cost effectiveness and it is defined as:

$$\frac{\text{payment to the } k \text{ winning sellers}}{\text{sum of } k \text{ lowest costs}} - 1. \tag{3}$$

It takes values from zero (in perfectly cost-effective auctions) to infinity.

Cost excess is a particularly important outcome in a our setting because conservation programs typically have a fixed budget constraint (in dollar terms) or a target quantity. We should also note that cost excess is linked to, yet different from, allocative efficiency. An auction format can implement the efficient allocation at a very high cost and thus be highly cost ineffective. However, for an auction to be perfectly cost effective, it must also be efficient.[10] This also implies that this measure of cost effectiveness is not only affected by allocative efficiency but also by sellers' rents. For this reason, our measure of cost effectiveness is a good summary of auction performance.

#### 4.1.2. Price cap auctions (PC)

In this auction, the buyer sets a maximum allowed offer specific to each seller, using the noisy signal of the corresponding opportunity cost, $\widehat{c}_i$. However, the cap for seller $i$ is not necessarily equal to $\widehat{c}_i$. Instead, the buyer sets the cap by adding a uniform markup $\mu$ to the estimated opportunity cost, as shown in equation (4).

$$Cap_i = \widehat{c}_i + \mu \tag{4}$$

The markup parameter $\mu$ represents the degree of tightness or looseness in the price-cap auction. Lower (higher) values of the markup $\mu$ make the price cap tighter (more loose).

At the moment of the auction, each seller observes their private information, $\{c_i, \widehat{c}_i\}$ ($\mu$ is assumed to be public knowledge). Then each seller decides simultaneously whether to participate or not in the auction. Conditional on participation, each seller also decides and submits their offer, $b_i$, which cannot exceed the corresponding cap ($b_i \leq Cap_i$). The buyer accepts the $k$ lowest offers and rejects the remaining offers. If less than $k$ offers are submitted, the buyer accepts all offers. A selling bidder $i$ makes a

[9] In the context of the CRP, $c_i$ represents the opportunity cost of renting the parcel to the Program.

[10] Proof: If the auction is not efficient, then we could replace a winning seller with another with a lower cost, and also reduce payments reducing cost excess.

**Table 1**
Theoretical predictions of efficiency and cost effectiveness.

| | Price Cap | | | | | | Reference Price | |
|---|---|---|---|---|---|---|---|---|
| | PC1 | PC3 | PC5 | PC8 | PC12 | PC15 | XRP | NRP |
| Participation Rate | 0.60 | 0.80 | 1 | 1 | 1 | 1 | 1 | 1 |
| Winning Offer | 51.2 | 43.7 | 38.7 | 41.6 | 45.1 | 47.3 | 46.5 | 82.7 |
| Efficiency Rate | 0.613 | 0.794 | 0.969 | 0.979 | 0.987 | 0.993 | 0.993 | 0.685 |
| Excess Cost | 0.584 | 0.309 | 0.151 | 0.24 | 0.353 | 0.427 | 0.396 | 1.516 |

*Notes*: Figures computed as the average over 1000 simulations.

profit of $b_i - c_i$; non-sellers make zero profit.

As shown in Klevans and López Vargas (2020), only very loose auctions (infinite or nonbinding $\mu$) have a closed-form solution.[11] When $\mu$ is binding, there is no closed-form solution. However the authors devised a method to solve the equilibrium function with analytical and numerical methods. They show the symmetric equilibrium bidding can be characterized as follows:

$$b^*(c_i, Cap_i; \mu) = \min\{Cap_i, \widetilde{b}_i(c_i; \mu)\} \tag{5}$$

where $\widetilde{b}_i(c_i; \mu)$ is a latent bidding function indicating the optimal offer when the cap is not personally binding. Note this latent function does not depend on the $Cap_i$.

The latent bidding function depends on $\mu$, as expected. We solved the equilibrium for six markup values: $\mu \in \{1, 3, 5, 8, 12, 15\}$. These also correspond to the values we use in the experiment (see Section 4.2). From now on, we will refer to each of these parameterizations of different price cap auctions by their markup value. For example, the auctions with $\mu = 1$ and $\mu = 3$ will be denoted by PC1 and PC3, respectively. As intuition suggests, equilibrium solutions have qualitatively different properties whether for $\mu < 5$ and for $\mu \geq 5$.

For $\mu < 5$, the probability of receiving a cap that is individually irrational (not profitable) increases as $\mu$ decreases, and it approaches 1/2 as $\mu$ approaches to zero. Lower $\mu$ reduces participation and with fewer competitors make high-cost bidders to win more often. This in turn incentivizes participating sellers to increase their bids to the cap level. In fact, for our parameterizations PC1 and PC3, equilibrium latent offers are high enough so that sellers always use offer their caps (see plot A.2 in Appendix A). This greatly reduces both efficiency and cost effectiveness. These predictions can be observed in Table 1. For example, when the price cap has a markup as low as 1 (PC1), efficiency goes down all the way to 61.3% and excess cost is 58%. We should note that a very tight price cap (such as PC1) is qualitatively analogous to how the General Signup of the CRP is currently implemented.

For $\mu \geq 5$, it is always individually rational to participate, so the main impact of the markup is not mediated via participation, but through higher rents. As $\mu$ becomes larger, the latent bid $\widetilde{b}_i(c_i, \mu)$ approximates the analytical solution for the non binding $\mu$ (see footnote 11). That is, as $\mu$ increases the bidding function is more monotonic with respect to cost, increasing efficiency rates. For the two most loose auctions, PC12 and PC15, the efficiency rate are 98.7% and 99.3%, respectively. The issue is, however, that with higher, looser caps, rents become larger and the theoretical (expected) excess cost levels rise to 35.3% and 42.7%, respectively, for PC12 and PC15.

#### 4.1.3. *Exogenous Reference Price (XRP)*

In this format, there is no price cap but the noisy signals of the opportunity costs are used to normalize offers. That is, they serve as a form of *reference price*. We call this format exogenous because the reference value does not depend on anyone's choices but simply the signal of each bidder's cost.

It is assumed that the cost, $c_i$, and the reference value, $\widehat{c}_i$, are both part of the private information set of bidder $i$ at the moment she decides to participate and submit her offer, $b_i$. Once all auction participants submit their offers, the buyer computes everyone's score following this rule:

$$\text{Score}_i = \frac{b_i}{\text{Reference Price}_i} + \gamma \times \text{Reference Price}_i \tag{6}$$

In the XRP, Reference Price$_i = \widehat{c}_i$. The first term of the right-hand side is the normalized bid. The second term of the right-hand side is the high-cost seller penalty, and $\gamma$ is the relative weight of this penalty.

In the theoretical solution, as well as in the experiment, there are 16 sellers and the buyer accepts the bids from the eight lowest scores and rejects the remaining offers. If fewer than eight offers are submitted, the buyer accepts all offers. Also, $\gamma$ is

[11] For example, for the case of $n = 16$, $k = 8$, $F = U[10, 100]$, $H = U[-5, +5]$ and $\mu > 50$, the optimal bidding is given by: $b^*(c_i) = 55 + [45\binom{n-1}{k-1}\left(\frac{c-10}{90}\right)^k]/[\sum_{i=0}^{k-1}\binom{k-1+i}{k-1}\left(\frac{c-10}{90}\right)^i]$ (see plot A.1 in Appendix A). In this case, the bidding function is strictly increasing in cost. Therefore, low cost sellers always win making the auction perfectly efficient but, at the same time, those sellers extract rather high rents hurting cost effectiveness.

always equal to 0.02.[12]

The theoretical predictions for this auction are as follows. First, the XRP auction always admits profitable offers. Therefore participation is always rational. Second, competition is now in terms of scores and there is no cap for bids. This implies the equilibrium scoring function follows a pattern analogous to the bidding function of the uncapped auction described in footnote 11. That is, the equilibrium score – as a function of cost – is convex and weakly increasing, with majority of winning scores in a small range (between 2 and 2.1).[13] This can be seen in panel (b) of Fig. A.3 in Appendix A. The near perfect monotonicity of the equilibrium score function with respect to cost explains why theoretical efficiency rate is rather high (99.3%), as indicated in Table 1.

The properties of the equilibrium bidding are derived from the incentive of the score formula and the equilibrium score function.[14] In contrast with the price cap auction, equilibrium bidding in the XRP auction does not generate high rents for low-cost bidders because in this format higher-cost bidders can also achieve competitive scores. This happens because the first term of the score formula (Equation (6)) is an equalizer force across cost levels. Consequently, higher-cost bidders win the auction more often and cost effectiveness is severely hurt. As indicated in Table 1, the theoretical excess cost of XRP is 39.6%, comparable to highly loose price caps (PC12 and PC15). The behavior of equilibrium scoring and bidding can be seen in panel (a) of Fig. A.3 in Appendix A.[15]

#### 4.1.4. Endogenous Reference Price (NRP)

The structure and timing of this auction is the same as in the XRP, except for one important difference. In the NRP, the $\text{ReferencePrice}_i$ of Equation (6) equals the average offer of a group of sellers that are closest to $i$ in terms of the estimated cost, $\widehat{c}_i$. In the equilibrium solution as well as in the experiment, the size of that comparison group is four. As in the XRP, $\gamma$ is set to 0.02.

In the theoretical equilibrium of the NRP, it is always rational to participate, as profitable offers are always admissible. However, discovering the optimal bidding is arguably more complex than in the XRP. For example, sellers cannot map their offers into a deterministic score as in the XRP –they do not know the offers of the other sellers in their group. From the game-theoretical and computational perspective, finding the equilibrium is also complex and only a numerical approach can be implemented.[16]

Interestingly, the equilibrium bidding function in the NRP is mostly flat for low- and medium-cost sellers, weakly increasing and convex (see Fig. A.3 in Appendix A). In particular, nearly all winning offers are around $b = 80$, with an approximate score of 2.6. This equilibrium implies high rents for winning sellers and suggests that there is a high degree of coordination among low- and medium-cost sellers who can achieve this offer level. In terms of auction outcomes, this coordination on a high offer level impacts efficiency negatively, which goes down to 68.5% (only comparable to the two worst price cap auctions) and also cost effectiveness, making excess cost climb to 151.6%, by far the worst among all studied formats.

### 4.2. Treatments design

We designed and conducted a laboratory experiment to study the three types of auction formats discussed above: (1) the price cap that resembles the current structure of the CRP General Signup, (2) the exogenous reference price and, (3) the endogenous reference price. Each treatment in our experiment is defined by the pair (auction format, auction parameterization). A total of eight different treatments were studied. We implement six different parameterizations of the price cap auction and a single parameterization for each of the two reference-price auction formats.

All our treatments shared the same underlying environment, closely following the description provided in subsection 4.1. Each auction procured eight objects (parcels) from a total of 16 competing sellers. A seller's private information consisted of her cost, $c_i$, and the signal of this cost available to the buyer with an additive noise ($\widehat{c}_i = c_i + \epsilon_i$). The noise is distributed uniformly over all integers between $-5$ and $+5$, inclusive. All studied auctions are analogous to sealed, pay-as-bid formats. Costs are distributed uniformly over all integers between 10 and 100, inclusive, and independently across sellers. That is, following the notation from the theoretical subsection, in the experiment, we set $n = 16$, $k = 8$, $\epsilon_i \sim_{iid} U\{-5, +5\}$, and $c_i \sim_{iid} U\{10, 100\}$. These specifications applied in all auctions of all eight studied treatments:

- **PC1, PC3, PC5, PC8, PC12, PC15**: Price cap auction treatments for $\mu = 1, 3, 5, 8, 12, 15$, respectively.
- **XRP**: Exogenous reference price auction with score formula given by Equation (6), $\mathit{ReferencePrice}_i = \widehat{c}_i$, and $\gamma = 0.02$
- **NRP**: Endogenous reference price auction with score formula given by Equation (6), $\mathit{ReferencePrice}_i$ equal to the average offer of the four closest bidders in terms of $\widehat{c}_i$, and $\gamma = 0.02$

[12] This was chosen as a close number to 1/55, where that 55 is the expected average cost.

[13] The equilibrium score function is not increasing only for very low-cost bidders that also have a negative $\epsilon_i$. This is an implication of Equation (6) and the fact that, for these bidders, the minimum score they can attain is above the "winning range".

[14] Conditional on, $\epsilon_i$, the equilibrium bidding function is increasing in $c_i$. Conditional on costs, it is weakly increasing in $\epsilon_i$.

[15] See Klevans and López Vargas (2020) for the technical details of this solution.

[16] KlevansandLópezVargas (2020).

**Table 2**
Summary statistics.

| Treatment | Participation | Winning Offers | Allocative Efficiency | Excess Cost | Seller Profit |
|---|---|---|---|---|---|
| | | | (a) | | |
| PC1 | 0.591 | 50.889 | 0.610 | 0.519 | 2.766 |
| PC3 | 0.722 | 44.275 | 0.779 | 0.354 | 3.617 |
| PC5 | 0.805 | 38.830 | 0.940 | 0.181 | 4.452 |
| PC8 | 0.868 | 40.725 | 0.931 | 0.242 | 6.475 |
| PC12 | 0.864 | 43.556 | 0.935 | 0.332 | 9.619 |
| PC15 | 0.846 | 44.870 | 0.942 | 0.374 | 11.414 |
| | | | (b) | | |
| PC5 | 0.824 | 38.815 | 0.929 | 0.183 | 4.284 |
| PC15 | 0.842 | 44.799 | 0.932 | 0.376 | 11.224 |
| XRP | 0.818 | 43.879 | 0.883 | 0.351 | 8.366 |
| NRP | 0.908 | 42.505 | 0.917 | 0.308 | 7.880 |

*Notes*: All columns show averages of the corresponding outcome across all auction periods. As discussed in section 4.2, we used six different $16 \times T$ arrays of cost and error (called *draws*) in this experiment where 16 is the number of sellers in each auction and $T$ is the number of repetitions of the same treatment in a session. We deployed the same three draws for PC1, PC3, PC8, PC12; and deployed all six draws for PC5, PC15, XRP, and NRP. This allows us to conduct two comparisons that are balanced in terms of draws. First, showed in Panel (a), the contrast among all PC auctions (treatments PC{1, 3, 5, 8, 12, 15}) using the same three draws. Second, showed in Panel (b), the contrast among treatments PC5, PC15, XRP, and NRP, using all six draws.

We implemented each of these treatments in multiple rounds to account for learning effects, as is standard in auction experiments. Our design is a mixture of within-group and between-group, where each human participant interacts in more than one treatment, but not all. The distribution of treatments across sessions is reported in Appendix B. This design mainly allowed us to cover the relatively large number of treatments in the price-cap auction.

We balanced the realizations of cost and errors across treatments as follows. A *draw* in our experiment is an $n \times T$ array of realizations for $(c_i, \epsilon_i)$ pairs, where $n$ is the number of sellers in an auction (16 in all auctions), and $T$ is the number of consecutive rounds of the same treatment within the session. We used a total of six different draws in our experiment. We deployed the same three draws for PC1, PC3, PC8, PC12; and deployed all six draws for PC5, PC15, XRP, and NRP. With this, our design allows us to conduct two perfectly balanced comparisons (1) across all PC auctions, and (2) among PC5, PC15, XRP, and NRP treatments. Using the first comparison, we study the impact of price-cap tightness. With the second, we contrast the price-cap formats to the alternative ones based on reference prices. Appendix B presents the distribution of draws across sessions.

### 4.3. Experiment procedures

We conducted 11 experimental sessions with a total of 176 participants at the LEEPS Laboratory of the University of California, Santa Cruz. In all sessions, 16 human subjects participated as sellers in our procurement auction. Eight sessions contained three treatments each, and the remaining three contained four treatments each. The order of treatments was varied systematically to be able to control for order effects in the analysis.

Participants received a copy of written instructions at the beginning of each session. Before each treatment started, the experimenter read the instructions aloud and provided numerical examples for that treatment. Students were given the opportunity to ask questions. At the end of all rounds, two rounds per treatment were chosen at random for payment. The exchange rate between Experimental Currency Units (ECUs) to U.S. Dollars was 3 ECUs per $1. Experiment interface and instructions can be found in Appendix C.

## 5. Results and discussion

We divide the analysis of our experiment data in two parts. First, we study the impact of price-cap tightness, and second, we contrast two price-cap benchmarks (PC5 and PC15) with the two reference price formats (XRP and NRP).

Table 2 provides summary statistics of the main outcomes. Top panel (a) uses the balanced data behind the analysis of the price cap tightness. Bottom panel (b) uses the balanced data behind the analysis that contrasts price cap auctions with reference price auctions.[17]

Before we proceed to the detailed analyses, we should note that our discussion is based mainly on a set of regression analyses implemented on data samples that use balanced draws (as in Table 2). Regression analysis allows us to control for cost, period, and order effect when appropriate. We also implemented standard nonparametric tests as well as regressions with pooled

[17] See subsection 4.3, for the description of balanced draws.

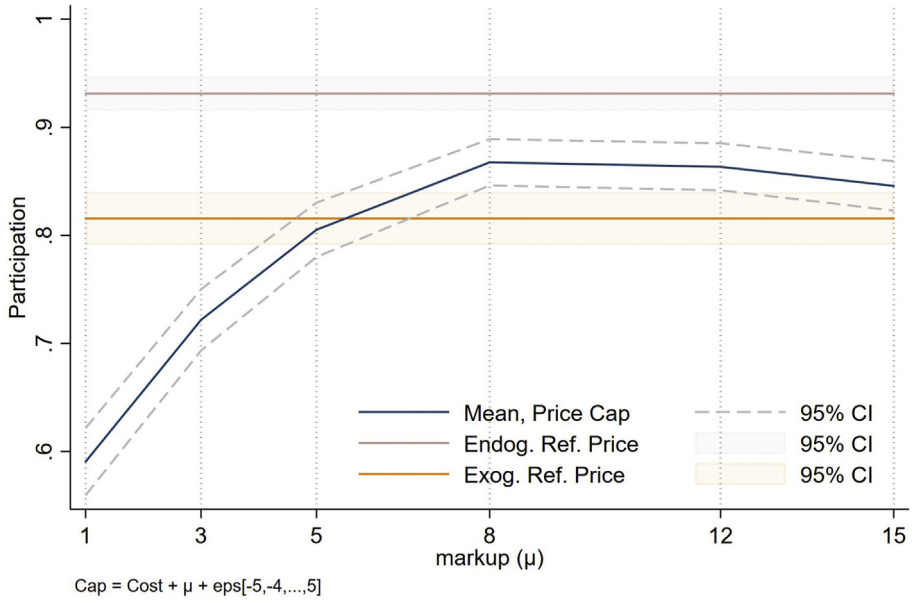



**Fig. 1.** Mean participation by cap variation.

unbalanced data. These robustness checks tell the same story as in our main analysis.

We did not find strong evidence of learning: in nearly all regressions for all outcomes, the coefficient of Period is not statistically different from zero, at conventional significance levels. Also, excluding the first five periods of every treatment within the session yields nearly identical results in most estimations. Our report will be based on all data-points and mention results from excluding the first five periods when necessary.

### 5.1. The impact of price-cap tightness

In this environment, since the largest downside error ($\epsilon_i$) in the estimation of the opportunity cost is $-5$, all participants would be expected to submit an offer if $\mu \geq 5$. Interestingly, we do not observe full participation in PC5 or even at higher markup levels (see Table 2 and Fig. 1). This implies that there is an additional driver to non-participation. For example, sellers might experience a cognitive or psychological costs of computing and submitting an offer. In that case, participation will only be rational if the expected profits are positive and not close to zero. Consistent with this idea, opting out is indeed more prevalent among sellers with near null expected profits due to low chances of winning or caps that are too tight.[18] Nonetheless, there is a clear negative relation between tighter, less profitable price caps and participation rates, suggesting that sellers behave, to a large extent, rationally when assessing their decision to withhold their offer. When the allowed markup is below 5 (i.e., in PC1 and PC3), participation is low as expected compared to PC5, as predicted by theory. This is because the price cap conflicts directly with individual rationality, forcing sellers out of the auction. While participation rates are at 80.5% for PC5, they decline to 72% for PC3 and to 59% for PC1.

We estimate a binary choice regression model with participation as the dependent variable. The details of this exercise and its results can be found in Table C.2 in the Appendix. We find that reducing the markup from five to three (i.e., going from PC5 to PC3) reduces the probability of participation by 7.4 percentage points. If we reduce the markup from five to one, participation decreases by 17.7 percentage points. Both results are statistically significant at conventional levels regardless of the specification.

When tightness levels are above PC5 (PC8, PC12, PC15), participation increases from 80.5% in PC5 to 86.8% for PC8, 86.4% for PC12, and 84.6% for PC15. In the regression analysis, these differences in the probability of participating with respect to PC5 are confirmed (statistical differences are significant at standard levels, regardless of the specification). This finding is particularly relevant. Even for auctions where participation is always individually rational, participation rates are below 90%. Consistent with our previous conjecture, non participation is lowest among sellers with near zero probability of winning (sellers with $c_i \geq 70$, regardless of $\mu$).

In sum, participation partially conforms with the theoretical predictions. As expected, low markups (PC1 and PC3) has the lowest participation rates. However, full participation predicted for auctions with $\mu \geq 5$ is never reached. Overall, observed

[18] Alternatively, sellers might experience aversion to losing the auction, or anticipate the regret of participating under such a low chances of winning or earning positive amounts.

participation is below the theoretical prediction.

Let us now discuss offer behavior. Besides theory predictions in Table 1, there are other two benchmarks for winning offers: (i) the expected opportunity cost among efficiently enrolled parcels which is 32.5 ECUs,[19] and (ii) the expected opportunity cost of winning sellers if enrollment occurs by random assignment which is 55 ECUs.

Relative to the theoretical average of winning offers, observed behavior closely follows the predicted pattern across different values of $\mu$. Relative to the two benchmarks, also as expected, PC5 has an average accepted offer of 38.8 ECUs, closer to efficient costs than the rest of price cap auctions. For $\mu$ below PC5, things get closer to random assignment. For PC1, the average winning offer is 50.8 ECUs. For PC3, the average winning offer is 44.2 ECUs. Interestingly, offer behavior reacts less to loosening the price caps (higher $\mu$). For PC8, PC12 and PC15, the average winning offer is 40.7, 43.5 and 44.9 ECUs, respectively (see Table 2). Although higher rents are allowed as $\mu$ goes up, competition prevents these rents from increasing in the same scale as increments of $\mu$.

The results for efficiency and cost effectiveness are interesting as well. First, making price caps tight may appear to be a way to reduce the cost of the program by limiting the rents of sellers. However, as predicted by theory, while a tighter cap does reduce rents, it also forces a mass of low-cost sellers out of the market. This generates inefficiency and worsens cost effectiveness. Thus, the impact of tightening the price cap is negative.

As we reduce the markups making price caps tighter, allocative efficiency decreases from 94% for PC5 to 78% for PC3, and to 61% for PC1 (Table 2 and Fig. 2). The efficiency levels for PC1 and PC3 are not statistically different than their corresponding theory prediction. Furthermore, since winning sellers of tighter price caps have, on average, higher costs compared to the winners in PC5, the cost-effectiveness of the program is harmed as well. While excess cost under PC5 is 18%, it goes up to 35% for PC3, and to 52% for PC1. Although these values do not match theoretical values statistically, they follow the same steep increase as $\mu$ decreases. In sum, as the price cap tightens and gets closer to an unbiased estimator of the opportunity cost ($\mu = 0$, as in the current CRP design), the auction gets less efficient and less cost effective.

We implement a parcel-level binary regression for efficiency and an auction-level linear regression for excess cost. The results discussed above on estimated efficiency and excess cost are confirmed by this regression analysis (see Table 3, Fig. 2). Going from PC5 to PC3 decreases efficiency by 15.3 percentage points and increases the over-cost of the program by 15.4 percentage points. Going from PC5 to PC1 decreases efficiency by 24.9 percentage points and increases the over-cost of the program by 32.2 percentage points.

Regression analysis also confirms that for price caps above five, efficiency remains unchanged, but cost effectiveness deteriorates due to higher rents. All marginal effects of PC8, PC12, and PC15 on efficiency are insignificant, with PC5 as the comparison setting. All effects of PC8, PC12 and PC15 on excess cost are positive and significant. In particular, relaxing the price cap from PC5 to PC15 increases excess cost by 19.3 percentage points. Theory does predict the same qualitative patterns of efficiency and excess cost as price caps loosen. However, observed efficiency levels of all loose PC auctions is below theoretical prediction. Statistically, observed excess cost is higher than predicted in PC5, same as predicted in PC8, and lower than predicted for PC12 and PC15.

There is an asymmetry in the effects of price caps on cost-effectiveness. Although relaxing the price caps hurts cost effectiveness, it does so to a much lesser degree than tightening the price cap relative to PC5. In fact, we can calculate that the incremental impact on excess cost of tightening the price cap below PC5 is 4–5 times higher than the impact of loosening it above PC5. Importantly, highly relaxed price caps, which allow for information rents about 20 percentage points higher than in PC5, are more cost effective than extremely tight price caps which lead to excess costs equivalent to information rents between 30 and 40 percentage points higher than in the PC5. In short, from the policy perspective, setting price caps that are too tight (as it occurs with current CRP design) is more damaging than setting price caps that are relatively permissive.

In this analysis, we use PC5 as the comparison format. However, it is important to highlight that PC5 is an unattainable benchmark outside the lab. This is because outside the lab, we are less certain about the distribution of errors in cost estimation. As an example, suppose the program is trying to implement PC5 but there is a small (underestimating) bias of size $-2$. In this context, the effective markup would be $\mu = 3$ and, following the evidence in this subsection, the performance of the auction would be substantially diminished relative to the intended PC5.

### *5.2. Alternative formats: price caps versus Reference Price auctions*

As we have seen in the previous subsection, the performance of the price cap auction is highly sensitive to the allowed markup. The effective markup, however, is not known, because in practice, farmers' opportunity costs are estimated not only with error, but also with bias. Consequently, policymakers may not be able to choose $\mu$ with certainty. In this context, it is worth considering alternative auction formats that are potentially more robust to bias and possible large imprecisions in the estimation of opportunity costs.

In this section, we present and discuss how the exogenous reference price (XRP) and the endogenous reference price (NRP) compare to two price-cap auctions that we use as benchmarks: PC5 and PC15. We use PC5 as a comparison format that is ideal although, as explained before, also largely unattainable outside the lab. PC15, on the other hand, is a more realistic and therefore informative benchmark since performance metrics are less sensitive to errors in cost estimation around $\mu = 15$.

[19] This is the same as the average payment under efficiency or truthful offer behavior or complete information.

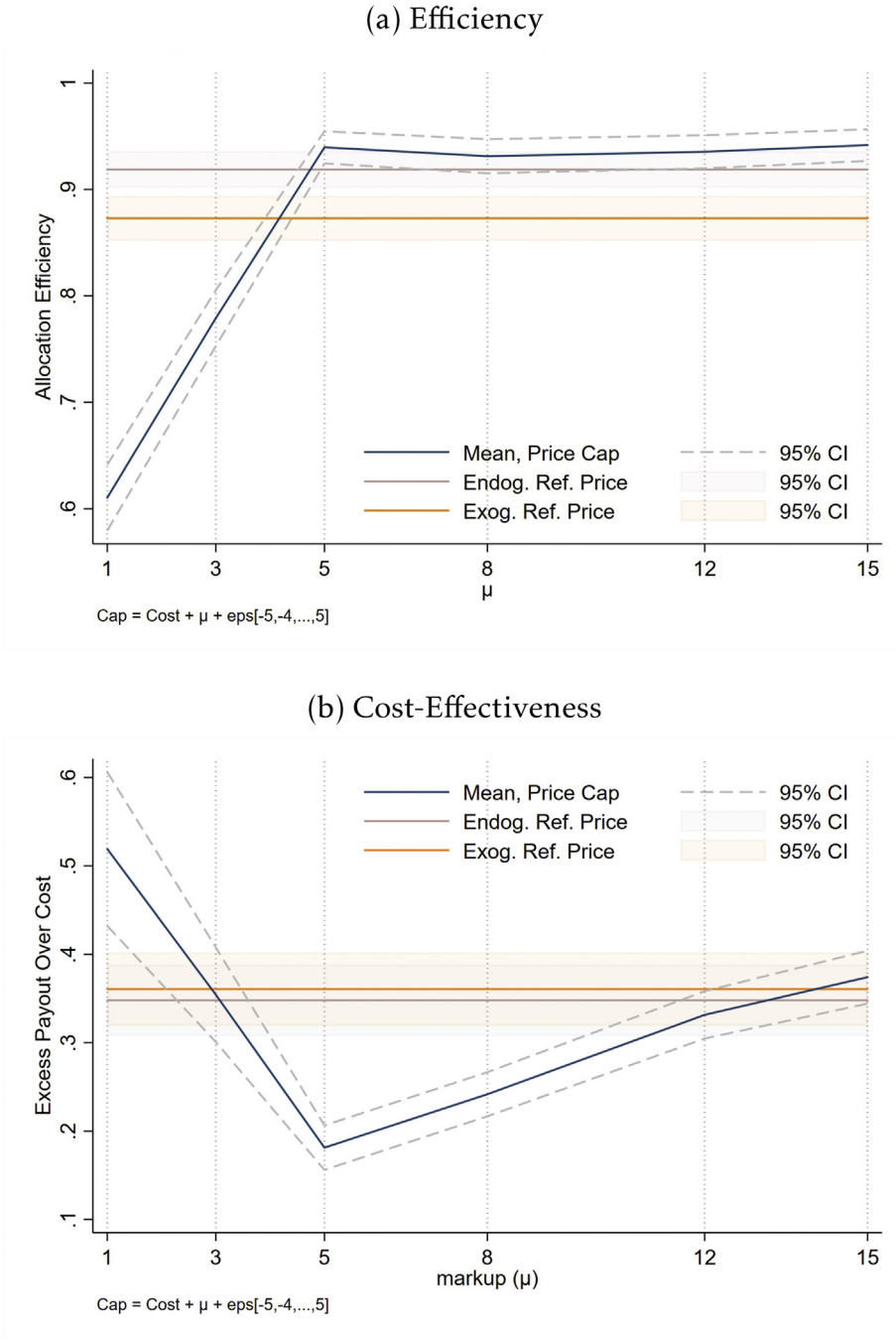



**Fig. 2.** Efficiency and cost-effectiveness by price-cap variation.

Let us start with a discussion of participation decisions. In all auctions considered in this analysis, PC5, PC15, XRP and NRP, participation is individually rational and therefore predicted participation is 100% in all of them. However, as before, participation is far from complete. Once again, our data strongly suggests sellers are sensitive to the available information on their chances of winning.

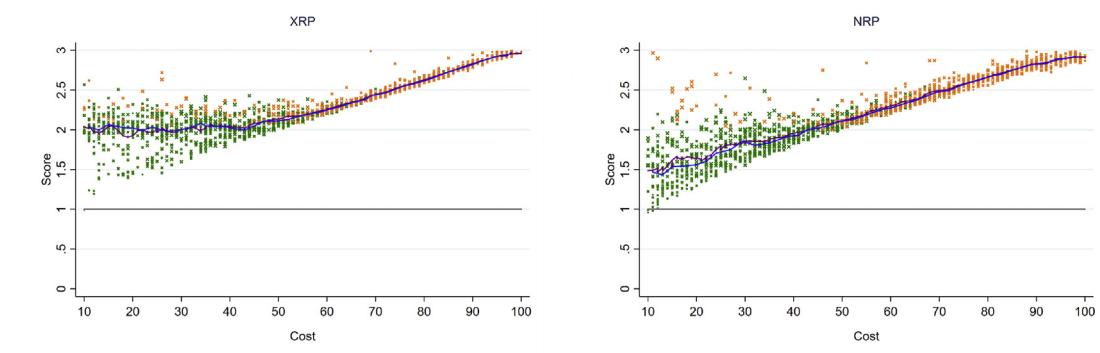
In the case of price caps, as discussed in subsection 5.1, relaxing the markup from PC5 to PC15 has limited positive effects on participation. Interestingly, participation rates are also low for the XRP (81.8%). The NRP, in contrast, exhibits the highest participation rate (90.8%).

This pattern of participation is a clear deviation from theoretical prediction. We conjecture that this difference arises because in PC5, PC15 and XRP sellers receive (from current auction information and play history) a clear indication of when their chances

**Table 3**
Efficiency and cost-effectiveness by cap tightness.

| | (a) Parcel-Level Efficiency (Probit - Marg. Effects) | (b) Auction-Level Excess Cost (Random Effects Model) |
|---|---|---|
| PC1 | −0.2490*** | 0.3223*** |
| | (0.0143) | (0.0388) |
| PC3 | −0.1529*** | 0.1543*** |
| | (0.0152) | (0.0368) |
| PC8 | −0.0130*** | 0.0574*** |
| | (0.0174) | (0.0349) |
| PC12 | −0.0071*** | 0.1503*** |
| | (0.0176) | (0.0336) |
| PC15 | 0.0026*** | 0.1930*** |
| | (0.0179) | (0.0336) |
| Controls for Cost | Yes | N/A |
| Controls for Period | Yes | Yes |
| N | 5760 | 360 |

Notes: Comparison group is PC5. Standard errors in parentheses.
Significance levels: * 0.10 ** 0.05 *** 0.01.




Note: Green (orange) stars denote winning (losing) offers. Blue and purple lines depict a non-parametric estimation of the conditional mean and median, respectively.

**Fig. 3.** Score Behavior in Reference-Price Formats. Note: Green (orange) stars denote winning (losing) offers. Blue and purple lines depict a non-parametric estimation of the conditional mean and median, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

of winning are near zero and opt out when winning chances are null. In the NRP, in contrast, sellers do not opt out as often because they do not have certainty about their chances of losing. In short, unlike the PC and XRP, in the NRP format, sellers are not directly discouraged from participation. The data supports this conjecture: mid and high cost sellers in the NRP participate more than in the other formats. In fact, the NRP has the slowest decline of participation rates with respect to costs among all four formats (see Fig. D.6 in Appendix).

We estimate a set of binary choice regressions (see Table D.3 reported in the Appendix) which confirms that NRP exhibits higher participation rates than the rest of formats – and the rest of formats exhibit statistically equivalent participation rates among themselves. These findings are robust to a series of different specifications and to excluding the first five periods.[20] Needless to say, theory predictions are statistically rejected.

Let us now discuss offer behavior. In the XRP, sellers seem to target an approximate score threshold $\widetilde{s}$. Below (above) this threshold score, chances of winning are rather high (rather low). This score level is not always profitably attainable for a seller, given their cost and estimated cost. If the seller can only profitably attain much higher values than this approximate threshold, then they typically either opt out of the auction or submit an offer reflecting minimal profit. In fact, 80.4% of sellers with $c_i \geq 70$ either opt out of the auction or offer for a profit of two ECUs or less. Those who can approximately attain target score or lower choose the offer that is compatible with such target. This behavior is shown in the left panel of Fig. 3 that plots winning scores against sellers' cost. Typically, sellers with $c_i \leq 50$ exhibit an average score that is flat at score $= 2.059$ with respect to cost. This value lies within the theoretical range. As predicted by theory, score targeting allows low-cost sellers to extract rents since they know achieving the score is nearly sufficient to win the auction.

[20] Our data also shows that in both price cap formats the participation rates decline slightly after the fifth period.

**Table 4**
Relative efficiency and cost-effectiveness of alternative auction formats.

| | Parcel-Level Efficiency (Probit - Marg. Effects) | Auction-Level Excess Cost (Random Effects Model) |
|---|---|---|
| PC15 | 0.0029*** | 0.1755*** |
| | (0.0088) | (0.0218) |
| XRP | −0.0446*** | 0.1670*** |
| | (0.00995) | (0.0205) |
| NRP | −0.0114*** | 0.1215*** |
| | (0.0091) | (0.0201) |
| Test: PC15 = XRP prob > \|t\| | 0.0000*** | 0.6904** |
| Test: PC15 = NRP prob > \|t\| | 0.1172*** | 0.0128** |
| Test: XRP = NRP prob > \|t\| | 0.0011*** | 0.0266** |
| Controls for Cost | Yes | N/A |
| Controls for Period | Yes | Yes |
| N | 6720 | 420 |

Notes: Comparison group is PC5. Standard errors in parentheses.
Significance levels: * 0.10 ** 0.05 *** 0.01.

The theoretical insights for the endogenous reference price are interesting. First, relative to all other studied auctions, behavior in the NRP differs from theoretical equilibrium the most in terms of offer behavior. The average winning offers of the NRP 42.5, almost one half of the predicted value 81.6. The score behavior does not follow a flat pattern for low-cost sellers as it did for the XRP (see right panel of Fig. 3), implying that this format encourages sellers to be more competitive.

In allocative efficiency (reported in Table 4), all formats perform statistically the same, except XRP, which underperforms the other formats. PC5, PC15, and NRP exhibit statistically equivalent efficiency rates of 92.9%, 93.2% and 91.3%, respectively.[21] The XRP, in contrast, reaches an efficiency level of 88.8%. Our regression analysis at the object-level that controls for cost and period effects (reported in Table 4) confirms the same ordering in efficiency performance.

We explored the sources of inefficiency in the XRP format. Fig. D.6, reported in the Appendix, identifies the root of this under-performance as behavior among low- and medium-cost sellers. In this format, most low- and mid-cost sellers pursue the same score, and therefore receive similar probabilities of winning the auction. Interestingly, the efficiency pattern of PC5 (our infeasible format) and NRP are quite similar.[22]

In terms of cost effectiveness, as expected, PC5 displays a low excess cost of 18.3%. It should be noted that this value mainly provides a lower bound of excess cost, attainable under controlled conditions, unlikely to be feasible in practical implementations of the price cap format. Among the rest of the formats, PC15 performs worst with a 37.6% of excess cost. As theory suggested, this is mainly because low-cost sellers in PC15 extract high rents without altering their chances of winning. The XRP exhibits a cost excess of 35.1%, statistically equivalent to that of PC15. This contradicts the theory prediction that the XRP would be more cost effective than PC15 (see Table 1). Interestingly, the observed behavior of the NRP auction exhibits the largest deviation from the theory prediction. While the predicted cost excess is 158% (the highest among all formats), in the experiment, the NRP exhibited an excess cost of only 30.8%, outperforming PC15 and XRP. Our regression analysis reported in the last column of Table 4 confirms this ranking.[23]

Given that the NRP performed better than predicted and expected, it is therefore important to highlight other conceptual advantages of this format relative to the other formats. Theoretically, for example, the offer behavior shaped by this format is robust to bias in the estimation of the opportunity costs, $E[\epsilon_i] \neq 0$. This is because in the NRP (unlike PC and XRP) only the ordering of $\widehat{c}_i$ matters for grouping, and not the exact values.

### 5.3. Robustness checks

We also conducted nonparametric two sided, Wilcoxon matched-pairs tests for our main four metrics (participation rate, average winning offers, allocative efficiency and cost excess). For this purpose, we used the six averages (corresponding to different draws) per treatment. This exercise yields the same results as our regression analysis. Detailed reports of these tests can be found in Appendix D.

Finally, we also conducted a regression analysis pooling all data (i.e., using imperfectly balanced data across formats). This exercise allows us to compare all six PC auctions and both reference price formats. We find that this analysis yields results consistent with the ordering suggested in Table 2 and in Figs. 1 and 2. That is, that PC1 –the auction closest to the current implementation of the general sign-up of the CRP– does worse than all other auctions in all considered metrics. PC1 has the

[21] The findings regarding PC5 and PC15 are consistent with the analysis in subsection 5.1.
[22] This can be observed in the top left and bottom right panels of Fig. D.6 reported in the Appendix.
[23] Although, it should be noted that when we exclude the first five periods, the ordering becomes statistically less significant.

lowest participation rates, the highest average winning offers, the lowest efficiency rates and the highest cost excess.

## 6. Conclusion

This paper provides insights on the properties of the current auction format used in the CRP as well as on plausible alternative formats. In particular, our experimental design allowed us to study the impact of loosening the current price cap format, and to study two auctions based on reference prices. We use participation, average winning offer, allocative efficiency, and cost excess (a measure of cost effectiveness) as metrics of auction performance in this context.

The first insight is that there is a Goldilocks level for a price cap when one is employed in an auction. When the price cap is too tight, participation in the auction is low even among low-cost sellers, and consequently, allocative efficiency and cost effectiveness are low as well. When the cap is too loose, sellers realize that there is room for higher rents, and excess cost measures are larger. As it happens, the caps currently being applied in the General Signup CRP are, in fact, tighter than the tightest treatment we studied, which was the worst performer in our experiment. However, the proper calibration of bid caps to attain an optimal level presents a formidable challenge outside a highly controlled, experimental setting. The performance of the price cap format is susceptible to how soil rental rate estimates reflect forgone returns to crop production. Since this is effectively unknown, so too is the markup that minimizes the program's total cost.

Regarding the exogenous reference price auction, we find it is less efficient than relatively loose price caps. We also find that it underperforms the endogenous reference price auction, counter to our expectations. This is because the exogenous reference price enables sellers to discover the minimally acceptable score and bid accordingly, increasing the total cost of the selected offers. The inefficiency of this format also hurts its cost effectiveness.

By contrast, an endogenous reference price turns out to be an interesting alternative candidate. In terms of efficiency, the endogenous reference price outperforms the exogenous reference price as well as the tight and loose price cap auctions. In fact, it is comparable to the optimal (and unattainable) price cap auction in terms of efficiency. Regarding cost effectiveness, the endogenous reference price also outperforms the exogenous reference price, the tight price cap, and the loose price cap.

Given the evidence and insights presented here, we believe future research should study more closely auction formats that are likely to outperform the current design. Studying the endogenous reference price and the loose price cap in the field would be a natural next step.

In terms of the study's applicability to the program, it is worth noting that General Signup CRP can be said to combine a tight bid cap with an exogenous reference price. The latter manifests as two additive cost-related terms and in a way somewhat less straightforward than the specification we present.

Applying what we have learned in this experiment to the General Signup would appear to be a relatively straightforward simplification of current policies, i.e., relaxing the caps and perhaps adjusting the manner in which the reference price enters in the EBI calculation. The results of this study suggest the potential to reduce programs costs by doing so. In addition, this change may enhance the customer experience to the degree landowners are frustrated by effectively being told by the Program what they should be willing to accept to enroll, which is based on an often imprecise estimate of foregone returns.

However, it seems unlikely that a change would be considered for the whole of General Signup in advance of piloting it in the field. Even that approach may be fraught as conducting the signup differently in different locations or for different landowner pools, even through random selection, runs the risk of the criticism that some landowners are being unfairly disadvantaged.

A pilot that makes use of the study's insights or field experimentation may be more feasible under Continuous Signup, as a host of distinct sub-programs already exist within it that may allow for experimentation. The Conservation Reserve Enhancement Program (CREP), may be a promising fit, although this CRP variation would require participation and buy-in from a partner agency or conservation organization.

Were a pilot or field experiment to be implemented, its impact is likely to be muted by the existence of other CRP opportunities available to landowners in the region. In other words, landowners seeking to enroll in a particular practice could conceivably do so competitively via a CREP pilot or non-competitively through standard Continuous Signup, the latter effectively establishing a guaranteed floor on the annual payment.

Ideally, such a pilot would be conducted multiple times in order to ascertain whether treatment effects attenuate over time as a result of learning. Conversely, it may take a few iterations to pique the interest of landowners who have long assumed CRP was unable to pay what they were willing to accept.

Finally, we note that the setting we study abstracts away relevant aspects of the CRP in order to focus on the pricing mechanisms. Of course, an actual General Signup auction does not involved multiple rounds occurring in rapid succession, nor is there a firm sense on the seller's part of the number of offers that will be selected. Rather, the auction occurs at most once a year, which may limit the potential for learning behavior. The offers or acres selected or, equivalently, the score cutoff is determined after the signup period closes and the offers are compared, albeit bounded by the difference between the acres currently enrolled and the statutorily mandated National acreage cap. And as noted above, in addition to an opportunity to participate in an CRP auction, a landowner would typically also be able to enroll non-competitively.

Prior work suggests that price caps may adversely impact both cost and environmental outcomes in such settings. However, we have considered objects that are homogeneous in their environmental outcome. In order to focus our attention on pricing

mechanisms and cost heterogeneity, we assume away rents associated with the environmental outcomes of enrolled land.[24]

In reality, environmental outcomes not only vary considerably across offers as results of location-specific endowments, such as soil type, but landowners can typically choose from a range of perennial covers and conservation practices, which affect those outcomes. Further some of the environmental outcomes manifest on-site and some off-site, with the former potentially interacting with the offer amount.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeem.2021.102439.

## References

Armantier, Olivier, Holt, Charles A., Plott, Charles R., 2013. A procurement auction for toxic assets with asymmetric information. Am. Econ. J. Microecon. 5 (4), 142–162.
Asker, John, Cantillon, Estelle, 2008. Properties of scoring auctions. Rand J. Econ. 39 (1), 69–85.
Ausubel, Lawrence, Cramton, Peter, Feliz-Ozbay, Emel, Higgins, Nathaniel, Ozbay, Erkut, Stocking, Andrew, 2013. Handbook of Market Design. Oxford University Press, pp. 489–554. Chap. Common-Value Auctions with Liquidity Needs: An Experimental Test of a Troubled Assets Reverse Auction.
Banerjee, Simanti, Kwasnica, Anthony, M., Shortle, James S., 2015. Information and auction performance: a laboratory study of conservation auctions for spatially contiguous land management. Environ. Resour. Econ. 61 (3), 409–431.
Boxall, Peter C., Perger, Orsolya, Packman, Katherine, Weber, Marian, 2017. An experimental examination of target based conservation auctions. Land Use Pol. 63, 592–600.
Cason, Timothy N., Gangadharan, Lata, 2004. Auction design for voluntary conservation programs. Am. J. Agric. Econ. 86 (5), 1211–1217.
Cason, Timothy N., Gangadharan, Lata, Duke, Charlotte, 2003. A laboratory study of auctions for reducing non-point source pollution. J. Environ. Econ. Manag. 46 (3), 446–471.
Choi, Syngjoo, Nesheim, Lars, Rasul, Imran, 2016. Reserve price effects in auctions: estimates from multiple regression-discontinuity designs. Econ. Inq. 54 (1), 294–314.
Claassen, Roger, Cattaneo, Andrea, Johansson, Robert, 2008. Cost-effective design of agri-environmental payment programs: US experience in theory and practice. Ecol. Econ. 65 (4), 737–752.
Golet, Gregory, Low, Candice, Avery, Simon, Andrews, Katie, McColl, Christopher, Laney, Rheyna, Reynolds, Mark, 2018. Using ricelands to provide temporary shorebird habitat during migration. Ecol. Appl. 28 (2), 409–426.
Grether, David M., Porter, David, Shum, Matthew, 2016. Public vs. Secret reserve prices in auctions: evidence from combining field and lab experiments. In: Secret Reserve Prices in Auctions: Evidence from Combining Field and Lab Experiments April 18, 2016.
Hellerstein, Daniel, 2017. The US conservation reserve program: the evolution of an enrollment mechanism. Land Use Pol. 63, 601–610.
Hellerstein, Daniel, Higgins, Nathaniel, 2010. The effective use of limited information: do offer maximums reduce procurement costs in asymmetric auctions? Agric. Resour. Econ. Rev. 39 (2), 288–304.
Hellerstein, Daniel, Higgins, Nathaniel, Roberts, Michael, 2015. Options for Improving Conservation Programs: Insights from Auction Theory and Economic Experiments. Tech. rept.. U.S. Department of Agriculture, Economic Research Service.
Horowitz, John, Lynch, Lori, Stocking, Andrew, 2009. Competition-based environmental policy: an analysis of farmland preservation in Maryland. Land Econ. 85 (4), 555–575.
Katkar, Rama, Reiley, David H., 2007. Public versus secret reserve prices in eBay auctions: results from a pokémon field experiment. B E J. Econ. Anal. Pol. 5 (2).
Kirwan, Barrett, Lubowski, Ruben, Roberts, Michael J., 2005. How cost effective are land retirement auctions? Estimating the difference between payments and willingness to accept in the conservation reserve program. Am. J. Agric. Econ. 87, 1239–1247.
Klevans, Gregory, López Vargas, Kristian, 2020. Price Caps and Scores in Multi-Object,Pay-As-Bid Procurement Auctions. https://ssrn.com/abstract=3746774.
Latacz-Lohmann, Uwe, Van der Hamsvoort, Carel, 1997. Auctioning conservation contracts: a theoretical analysis and an application. Am. J. Agric. Econ. 79 (2), 407–418.
Lewis, Gregory, Bajari, Patrick, 2011. Procurement contracting with time incentives: theory and evidence. Q. J. Econ. 126 (3), 1173–1211.
Messer, Kent D., Duke, Joshua M., Lynch, Lori, Li, Tongzhe, 2017. When does public information undermine the efficiency of reverse auctions for the purchase of ecosystem services? Ecol. Econ. 134, 212–226.
Ostrovsky, Michael, Schwarz, Michael, 2011. Reserve prices in internet advertising auctions: a field experiment. EC 11, 59–60.
Palm-Forster, Leah, H., Swinton, Scott, M., Redder, Todd, M., DePinto, Joseph, V., Boles, Chelsie, M.W., 2016. Using conservation auctions informed by environmental performance models to reduce agricultural nutrient flows into Lake Erie. J. Great Lake. Res. 42 (6), 1357–1371.
Reiley, David H., 2006. Field experiments on the effects of reserve prices in auctions: more magic on the internet. Rand J. Econ. 37 (1), 195–211.
Rolfe, John, Whitten, Stuart, Windle, Jill, 2017. The Australian experience in using tenders for conservation. Land Use Pol. 63, 611–620.
Schilizzi, Steven, 2017. An overview of laboratory research on conservation auctions. Land Use Pol. 63, 572–583.
Schilizzi, Steven, Latacz-Lohmann, Uwe, 2007. Assessing the performance of conservation auctions: an experimental study. Land Econ. 83 (4), 497–515.
Uchida, Emi, Xu, Jintao, Rozelle, Scott, 2005. Grain for green: cost-effectiveness and sustainability of China's conservation set-aside program. Land Econ. 81 (2), 247–264.
Vincent, Daniel R., 1995. Bidding off the wall: why reserve prices may Be kept secret. J. Econ. Theor. 65 (2), 575–584.

[24] We thank an anonymous referee for suggesting we highlight this difference between our setting and the actual implementation of the CRP.