Testbed Experiments for Improving the Cost-Effectiveness of the Conservation Reserve Program

Peter Cramton[1], Daniel Hellerstein[2], Nathaniel Higgins[3], Richard Iovanna[4], Kristian López-Vargas[5], Steven Wallander[6]

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Abstract

The Conservation Reserve Program (CRP), the world's largest conservation program, pays farmers to voluntarily establish conservation cover on approximately 30 million acres of environmentally sensitive cropland. We conduct a laboratory study of several auction alternatives for the CRP and test their performance in terms efficiency and cost-effectiveness. We focus on (1) the current price cap format studying the impact of different degrees of price-cap *tightness,* and, (2) on comparing the price-cap auctions with two alternative formats based on *reference prices* – one in which the reference is determined exogenously and another in which it is determined endogenously. We find that, as expected, excessive tightening of price caps forces participants out, damaging efficiency and cost effectiveness. Second, substantial relaxation of the price cap does not hurt efficiency nor participation, but it does hurt cost-effectiveness by allowing higher rents. In balance, relaxing price caps is preferable to tightening them in terms of cost effectiveness. Third, the *exogenous* reference price format allows medium-cost bidders to submit offers that are competitive against low-cost bidders. This hurts both efficiency and cost-effectiveness. The *endogenous* reference price, outperforms the exogenous reference price in terms of cost-effectiveness by increasing participation and reducing rents.

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[1] Department of Economics, University of Maryland, College Park, MD 20742 USA.

[2] United States Department of Agriculture, DC 20250 USA.

[3] United States Department of Agriculture, DC 20250 USA.

[4] United States Department of Agriculture, DC 20250 USA.

[5] Economics Department, University of California, Santa Cruz, CA 95064 USA. (klopezva@ucsc.edu)

[6] United States Department of Agriculture, DC 20250 USA.

1. Introduction

The Conservation Reserve Program (CRP), which may be the world's largest conservation program on private lands, spent \$1.9 billion in fiscal year 2012 to pay farmers to voluntarily establish conservation cover on 29.6 million acres of environmentally sensitive cropland. The program relies on two approaches to enroll land: a competitive system known as *General Signup* and a first-come, first-served system called *Continuous Signup*. General Signup is a competitive auction through which offers to enroll land are ranked according to an index of environmental benefits and cost. Each bid is constrained by a parcel-specific *price cap*. In contrast, Continuous Signup focuses on enrolling land in targeted geographic regions or for sets of high-value conservation practices, delivering payments set by the Farm Service Agency (FSA) to offers that meet fairly strict eligibility criteria.

Economic theory and practical experience from other types of government auctions (e.g., timber sales, toxic asset purchase, and communication spectrum sales) suggest that a modified auction structure could make CRP more cost-effective. This paper reports on a laboratory study of alternative auction mechanisms and how they perform in controlling costs and achieving efficiency. We focus on the current price cap format using different degrees of cap "tightness," as well as on two alternative formats based on reference prices: one in which the reference is determined exogenously and another in which it is determined endogenously.

In our experimental setting, there are 16 bidders each with an object (parcel), and one buyer (the program) who has a goal to buy (enroll) eight objects (parcels). Opportunity cost per object (representing rental price of parcels) are assigned randomly and distributed privately. All studied auction formats are pay-as-bid type and we assess their performance using the following outcomes: participation (percentage of bidders that opt in), bidding behavior (bids for a given opportunity cost), allocative efficiency (proportion of overlap between auction outcome and efficient allocation) and cost-effectiveness (the auction payment to buy eight objects relative to the sum of the eight lowest costs).

In our first analysis (Analysis 1), we study the impact of the variation of price cap tightness where bidders are restricted to submit offers at or below an object-specific cap based on an unbiased, yet noisy estimate of opportunity costs plus a *markup* μ. The buyer buys from the bidders with eight lowest bids and pays each of them what they ask. In the theoretical *benchmark price cap* format (BPC) the markup value is chosen to be minimal, provided that participation is always (at least weakly) preferred.[7] In the *relaxed price cap (RPC),* μ is three times as big as in BPC. We also study price cap tightness levels that are too tight (setting μ levels that are below its ideal value) as well as different tightness levels that are higher (more relaxed) than its ideal level. In our second analysis (Analysis 2), we compare two price cap tightness levels (BPC and RPC) with two formats based on reference prices. In the *exogenous reference price* auction (ExogRP), there is no cap in terms of bidding. Instead, a scoring system is used to determine the winners of the auction. The score has two additive components: (i) the normalized bid relative to a *reference*

[7] As explained below, this format, although useful as an ideal benchmark, it is not feasible in practice.

set equal to the estimated opportunity cost; and (ii) another that penalizes the bidder for having a high estimated cost. The first component aims to generate price competition among bidders of different costs, the second aims to reduce allocative inefficiencies. In the *endogenous reference price* auction (EndoRP), the score function is the same and there is no price cap. However, the reference is set equal to the average bid of other bidders with similar estimated costs. Because the score in this format depends on the behavior of others (therefore "endogenous"), bidders do not know with certainty their score at the time of bidding.

In Analysis 1, we find, as expected, that setting tightness levels below the ideal level reduces participation dramatically, even among low cost bidders, because tight price caps directly clash with individual rationality – force bidders out of the auction. Since low-cost bidders are often out of the auction, high-cost bidders win the auction frequently and this hurts allocative efficiency and cost-effectiveness substantially. When, instead, the markup parameter is above the ideal level (i.e. it is "relaxed"), participation rates increase but efficiency remains at roughly the same levels for any markup at or above its ideal level. However, as higher level of markups allow for higher rents, the cost-effectiveness of the program worsens substantially as the tightness of the price cap is increasingly relaxed. The main lesson of this analysis is that attempts to reduce costs making the price cap tighter are likely to cause severe inefficiencies and be counterproductive in terms of cost-effectiveness. Relaxing the price-caps, on the other hand, does not hurt allocative efficiency but does reduce cost effectiveness.

In Analysis 2 on price-cap versus reference prices, we find that for both price cap treatments (ideal and loose), as well as for the exogenous reference price, participation rates are in the range of 80% to 84% (no statistical difference). The endogenous reference price, however, has a higher participation rate at 90.8% (statistically higher than the other three treatments). On bidding behavior, BPC keeps offers relatively low, as it mechanically enforces low rents, and loosening up the price cap does not increase competition substantially and only allows for more rents. In fact, winning bids under RPC are the highest of all formats. In the exogenous reference price, participation is as low as in BPC and accepted offers are nearly as high as in RPC. In the endogenous reference price, via higher participation, stronger competition makes winning offers to be the lowest after BPC. In allocative efficiency, BPC, RPC and the endogenous reference price perform equally well (92.9%, 93.2% and 91.7%, respectively); all significantly better than the exogenous reference price (88.3%). In cost-effectiveness, the BPC performs best, with the lowest over-cost measure (18.3%). RPC performance is substantially worse (37.6%) mainly because it allows bidders to extract high rents compared to BPC. Exogenous reference price performs statistically not different than the RPC (35.1%). Finally, the endogenous reference price auction performs better than RPC and ExoRP with an over-cost index of 30.8%.

Our results reveal potential benefits and drawbacks the mechanisms based on reference prices might face in practice. However, further laboratory work and field research is recommended to study other potential formats and the optimal parameterization of the chosen formats.

The rest of the paper is organized as follows. Section 2 describes the Conservation Reserve Program (CRP) and its currently known issues. Section 3 presents the alternative auction formats we study (relaxed price caps, exogenous reference price and endogenous reference price). Section 4 describes the experiment design, setting, sessions and protocols. In Section 5 we present and discuss our laboratory results. Section 6 presents a market design discussion and Section 7 concludes.

2. The Conservation Reserve Program (CRP)

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. There are many CRP practices, ranging from relatively straightforward native grasses or tree plantings, to structural practices such as grassed waterways and constructed wetlands.[8]

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 ("cost share"). Where parcels are located and how their annual payments are set determine overall program cost.

The program enrolls land using two types mechanisms: a competitive system called *General Signup* and a first-come, first-served system called *Continuous Signup*. General Signup is a competitive auction through which offers to enroll land are ranked according to an index of environmental benefits and cost. Some version of competitive General Signup has been utilized since the program began in 1985. General Signups have tended to take place annually and usually last four weeks. During this time, the FSA maintains an open call for bids from landowners. The Continuous Signup focuses on enrolling land in targeted geographic regions or for sets of high-value conservation practices, delivering Agency–determined payments to offers that meet minimum criteria.

An offer to enroll in General Signup specifies the conservation practice that the producer seeks to establish, the parcel on which the practice is proposed, and the annual payment that the producer proposes to receive, i.e., the bid. The bid can be no greater than a parcel-specific estimate that FSA generates. This estimate is intended to reflect the (minimum) annual payment the producer is willing to accept (WTA) to enroll in CRP or, equivalently, the opportunity cost of or reservation value for participation.

Since 1996, the General Signup has ranked offers on the basis of a multi-dimensional index (the Environmental Benefits Index, or EBI) that reflects both cost (the bid) and anticipated environmental benefits. Offers are ranked according to the EBI; those above a cutoff set by the Secretary of Agriculture are enrolled.

Also since 1996, Continuous Signup has been used to encourage establishment of relatively intensive practices to address serious conservation concerns. This signup is year-round and non-competitive, with eligible offers enrolled on a first-come, first served basis. Continuous signup

[8] Practices can vary by region and state. For examples of eligible practice, see the Michigan state NRCS office website for a detailed description of common practices:

http://www.nrcs.usda.gov/wps/portal/nrcs/detail/mi/programs/?cid=nrcs141p2_024527,

and the Pennsylvania state NRCS office:

http://www.nrcs.usda.gov/wps/portal/nrcs/detail/pa/programs/?cid=nrcs142p2_018173.

acreage often qualifies for extra financial incentives (such as Signup Incentive Payments and Practice Incentive Payments), which can push total payments above the parcel's price cap.

Total enrollment in CRP is subject to acreage caps at the practice[9], county[10], and national levels. The acres signed up in a given year cannot exceed the national cap set by the Farm Bill, less the active contract acres that will not be expiring at the end of the year. Accordingly, this constraint varies considerably from year to year and is the most restrictive.

As of December 2013 approximately 260,000 contracts covering almost 20 million acres had entered the program through General Signup, and about 410,000 contracts covering nearly 6 million acres had entered the program through Continuous Signup.[11] The average size of General and Continuous Signup enrollments are 75 acres and 14 acres, respectively, reflecting the fact that former tends to enroll whole fields and the latter parts of fields. For a detailed account of the evolution of the of the mechanisms used by the CRP see Hellerstein (2017)

Known Issues of the Current CRP Auction

General Signup operates as a procurement auction, and, as such, the CRP can utilize competition to control costs. That is, costs can be driven down because bidders might want to reduce their asking prices in order to increase their chances of being selected, i.e., winning the auction. In pay-as-bid auctions like the CRP, participants will want to submit a bid that is low enough to be accepted, yet high enough to be profitable.

In the CRP, like in other auctions, some participants are very certain of their prospects of winning if, other things equal, their opportunity cost is low. In this way, those bidders are able to extract relatively large profits from the auction. Similarly, other auction participants who are certain to be rejected are unlikely to make any offer to enroll.

In the General Signup CRP, the piece of information which farmers can use to predict the likelihood that their offer will be accepted is the EBI. By having particularly environmentally valuable land or land with unusually low agricultural productivity, or both, CRP bidders know that they can ask for an annual payment significantly higher than their opportunity cost and still be confident that their offer will be accepted. The fact that General Signup is a *repeated* auction may exacerbate the situation. Past auction outcomes can inform potential participants in General Signup auctions how large an acceptable bid can be. In fact, empirical examinations of CRP signups generally find there are substantial differences between farmer bids and their "reserve rents". Kirwan, Lubowski and Roberts (2005) find that landowners are, on average, paid 20% above their opportunity costs. Similarly, Horowitz, Lynch and Stocking (2009) find that bids in

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[9] Practice caps only apply to continuous signups—since many continuous signup acres enroll under "initiatives" (such as the State Acres for wildlife enhancement initiative) that set aside a fixed number of acres that must use a limited set of conservation practices.

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

[11] http://www.fsa.usda.gov/Internet/FSA_File/julysummary13.pdf

an auction where the state purchases farmland development rights are 5-15% above landowner opportunity costs.

USDA has implemented price controls in the form of price caps for the General Signup precisely to prevent excessive payments to bidders. The particular intent is to limit farmers' annual rental payments to an *estimate* of their opportunity costs. This is why the price caps are based on *soil rental rates* (SRRs). SRR are in turn based on county-average dryland cash-rent estimates, soil-specific adjustment factors, and professional judgment.[12] The key feature of these price caps, however, is that they are inherently imprecise and, possibly, subject to bias. Unobserved heterogeneity in land quality and limited number of observations with cash rental agreements are likely sources of error.[13]

Despite its goal to lower the costs of the program, the parcel-specific price caps are likely having counterproductive consequences. Under imprecise and possibly biased estimates of the SRRs, the price caps may be causing higher costs for the General Signup auction due to their negative impact on participation rates. Even small imprecisions in the opportunity cost estimates can drive a mass of potential bidders to an unprofitable region (receiving a price cap below actual opportunity costs), dissuading them from auction participation. And, with fewer participants, the cost effectiveness of the program is negatively affected via two channels. First, in order to satisfy an acreage target, the program needs to accept parcels with high opportunity costs to replace dissuaded lower-cost bidders. Second, strategic, non-dissuaded bidders can exploit the lack of competition that gives them good chances to win the auction by submitting higher offers than they would otherwise submit.

Relaxing the cap (setting each price cap equal to the estimated opportunity plus a "markup") is an obvious way to reduce a cap's negative effects on participation. However, the more relaxed they are, the less binding caps become, and so the cost-reducing potential of the price caps vanishes. There is a cap level that balances the participation effects discussed with the potential for bid reduction. However, as discussed in (Hellerstein and Higgins, 2010) and in our experimental data, striking the right balance is difficult and to a large extent unattainable outside controlled settings.[14]

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[12] "FSA bases rental rates on the productivity of the soils within each county and the average dryland cash rent" http://sustainableagriculture.net/publications/grassrootsguide/conservation-environment/conservation-reserve-program/

[13] In regions where share rents predominate, imprecise formulae that map share fractions to cash rentals are often used.

[14] Hellerstein and Higgins (2010) find that auction efficiency peaks in the neighborhood of the ideal cap. They compare observed payments to the cost of a feasible Vickrey auction, and price caps 20 percent above or below cost perform relatively worse than caps around participant cost. However, the role of participation is not explicitly studied here.

3. Studied Auction Formats

Given that the current approach in the CRP is to set tight price caps, it is natural to explore the impact of relaxing the caps to varying degrees. As argued below, the participation incentives of the price cap format as well as the precision of the estimates of the opportunity costs are key in determining the adequate tightness of the price cap. By varying the degrees of tightness, we empirically explore the trade-off that emerges between reducing expected rents and dissuading bidders from entering the auction. We also consider two variants of an alternative auction design based on reference prices. Like caps, the reference-price approach still uses available cost estimates, but the constraints it imposes on bidders are less direct and therefore it does not dissuade bidders from participating in the same magnitude as a tight price cap does.

3.1. Price-Cap Auctions

Two particular price-cap auctions deserve special discussion: the benchmark price cap (BCP) and the relaxed price-cap (RPC). The *benchmark price cap* is the price-cap auction where the tightness is set to minimize the cost of implementing the program. It is possible to implement such an auction in the laboratory because we control and know the distribution of opportunity costs and, more importantly, the accuracy of the opportunity costs estimates. In fact, one of the benefits of running experiments is precisely the possibility to build an benchmark of this type. In real life, however, this is likely not feasible as the control and knowledge necessary for this approach are hardly ever achieved and formats that are more robust to errors in the estimation of SRRs.

The *relaxed price cap* (RPC) is a modest departure from the current General Signup where the program sets the price caps equal to an opportunity cost estimate, plus a an allowed "markup". large enough to make it rational for all or most bidders to participate. If the effect of increased participation from the relaxed price cap outweighs the increase in price paid to existing participants, this approach could potentially reduce the program's costs. Athey et. Al. (2002) use a *limit price* with 30% from the estimated value. The analog in the reverse auction of the CRP, this would mean setting price cap 130% above the estimated opportunity cost.

3.2. Reference-Price Auctions

Point estimates of opportunity costs could also be used to normalize bids instead of serving as caps. That is, they can serve as *reference prices*. Normalized bids can form scores and be ranked in the similar fashion as the ranking of raw bids in the current format. In that sense, an auction based in reference prices would relay in similar information as the system based on price cap.[15]

Theoretically, reference prices can have contrasting effects. On one hand, the reference price mechanism, unlike the price cap, makes bids above the SRR admissible and pushes no one out of the auction in a direct manner. This could increase price competition and cost-effectiveness. On the other hand, however, ranking bidders by the attractiveness of their offers relative to their

[15] The current CRP offer ranking already includes a *cost factor* that provides improved ranking for offers that bid down to a greater extent relative to their price cap.

reference price (or estimated SRRs) is an equalizing force across the cost range. This can cause undesirably high-cost bidders to win the auction often, impacting cost-effectiveness negatively. To reduce the second negative effect, we can set a scoring function that uses as inputs bidders offers relative to SRRs and a penalty increasing with the likelihood of being a high cost bidder. This is a different approach than the one taken in Hellerstein, Higgins and Michaels (2015) where the penalty was a function of the bid itself.

The first reference-price auction we study sets a score system that depends only on each bidder's own estimated opportunity cost and bid. We call this format *exogenous reference price* because the normalizing magnitude of one's bid does not depend on anyone else's bidding. In this format, references (based on SRRs) would be announced to farmers before they submit a bid as it currently happens with price caps.

The second reference-price auction we consider is the *endogenous reference price*. This format constitutes a less direct (and even optional) way to use SRRs. In this system, the normalizing formula depends, endogenously, on the average bid of a set of similar, comparable, or neighboring parcels.[16] In this mechanism, the reference price for each parcel would not be known to the farmers at the time of the auction, but would be calculated after all bids are submitted.

Making the reference unknown and uncertain for bidders may reduce asking prices and rents. However, not announcing a reference price upon which to base their bid could be unsettling to some bidders and cause them to opt out of the auction. Also, endogenous references might suffer from collusion, and attempts to minimize collusive forces (larger, less obvious matching) could exacerbate or generate other issues.

As in the case of exogenous reference prices, a penalty that is increasing with the likelihood of being a high cost bidder can be included in this mechanism as well, in order to attenuate the equalizing forces of a reference price mechanism.

Participation effects and collusion in reference price settings are not straightforward to model and therefore the laboratory evidence can be particularly insightful on those regards; even more so when the scoring formulae are not simple ratios as it is our case.

4. Related Literature

We use economic experiments to inform an exercise of market design. This approach has been used in many contexts of Government auctions in the last four decades (Roth, 2015; Milgrom, 2004). In the early 90s the U.S. Treasury conducted an experiment that led to the establishment of the uniform-price auction of Government bonds in 1998 (see Back and Zender, 1993, for a survey on Government bonds). Similarly, before the 90s, the Federal Communications Commission (FCC) assigned the spectrum case by case (and even by lottery, for a few years), but in 1994, the FCC established the Nationwide Narrowband Personal Communication Service

[16] Similar with respect to the information available to the Program.

auction (see Cramton, 2002, for a survey on spectrum auctions). The USDA Forest Service uses a pricing system that is based in auction (see Athey et al., 2011). A combination of auction theory and experiments has also informed the debate about Centers for Medicare and Medicaid Services (Cramton et al., 2015, Merlob et al 2012). Likewise, economic theory and experimentation have also been used to study possible design improvements in Non-government auctions and regulated markets. This has been the case in internet auctions (see, e.g., Roth and Ockenfels, 2002; Ariely et al., 2005), medical labor markets (e.g., Roth and Peranson, 1999; Niederle and Roth, 2019), airport runways (Grether et al 1981; Cramton et al 2006; Ball et al, 2007) financial markets (Budish et al, 2015, Aldrich and Lopez-Vargas, 2017), and many others.

Several studies have analyzed the functioning of conservation programs. Hamilton (2010) highlights how the specific rules of the program that are actually implemented (as opposed to just the broad design) have first order impact in the outcomes of the program. Arnold et al. (2013) argues that, in the context of conservation and under budget constraints, screening contracts can outperform discriminatory reverse auctions. Stoneham et al. (2003) and Eigenraam (2005) study conservation auctions in Australia, and Messer et al (2013) study the conservation auctions implemented in Scotland.

Auctions with bid caps based on estimated bidders' values (or cost) have been utilized in several Government auctions and natural resource contexts. British Columbia, for example, calculates an *upset price* (an estimate of bidders value) for timber stands that they wish to sell at auction. Athey, Cramton, and Ingraham (2002) find that using a limit price equal to about 70% of this value is optimal. This limit price represents a 30% "rollback" from the estimated value. The analogous in a reverse auction like the CRP would be to set the price caps at approximately 130% of estimated opportunity cost. In a more closely related study is Hellerstein and Higgins (2010) analyze the impact of bid caps using an experiment. They find that bid caps where the cap is tight (so that participation is not profitable for at least 1/5 of the bidders) performs poorly in cost-effectiveness. Hellerstein et al. (2015) offer a detailed discussion how to use theory and experiments to improve conservation programs. It discusses crucial aspects that are relevant for this paper too. The authors discuss how understanding the limits of the available information is crucial for the success of the auction design. They discuss a reference price auction that is different than the one we study in this paper but their findings—namely that reference prices can improve upon open auctions or (too-)tight price-caps auction—are compatible with ours.

Broader work on *scoring auctions* is relevant to our paper as well. These are auctions where bids are not directly compared. Instead a scoring function that depends on the submitted bids and other information is used to rank the bidders. Scoring auctions are typically used to allow the designer to take quality (or other relevant dimension of the good) into account. The reference price auctions studied in this paper are a type or scoring auction. These type of auction has been implemented 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). Other reference-price (scoring) auctions have been successfully implemented in financial markets. The U.S. Treasury used a reference price auction to purchase toxic assets under TARP legislation, following the 2008 financial crisis. These auctions allowed the Treasury to compare bids on securities of different values. In the conservation context, this type of auction could help reduce the rents extracted from farmers with lower opportunity cost, by incentivizing all farms to participate and bid competitively. Experimental work on auctions with reference prices can be found in Ausubel et. al. (2013) and Armantier, Holt, and Plott (2013).

5. Laboratory Experiment

We study the auction alternatives described in the previous section in a laboratory setting. These experiments aim to inform the discussion and redesign of the CRP auctions by shedding light on the virtues of (and issues raised by) the potential new formats. It is expected that field work will be a next, intermediate step towards the redesign. A field experiment will provide more precise measures of the impact of the final candidate formats.

5.1. Design

In a given period, each of the $N > 1$ bidders holds an *object* which he might or might not aim to put for sale. Bidder $i \in \{1,2,\ldots,N\}$ privately observes a signal c_i representing his value or *opportunity cost* of the object. If bidder i sells the object to the buyer for *price* p_i, he forgoes the private value of the object and receives the price p_i, instead. Bidders' *costs* are i.i.d. draws from a uniform distribution with all integers from 10 to 100 as support.

$$c_i \sim_{iid} U[10, 100]$$

That is, we are in an independent private cost model setup. There is a single buyer with a fixed demand $Q^d < N$ that sets up a mechanism to buy as many units as possible up to Q^d. In all experiments reported in this paper, $N = 16$ and $Q^d = 8$. In the context of the program, bidders represent farmers, objects represent parcels, and the buyer represents the CRP.

In the laboratory implementation, subjects collected economic profit calculated as the difference between the price p_i and c_i if i is able to sell the object and zero otherwise. However, all formats we study in this paper are pay-as-bid. That is, if i sells, the price will always be equal to i's bid b_i ($p_i = b_i$). Therefore, profits can always be represented as:

$$\Pi_i = 1_{\{i\ sells\}}(b_i - c_i)$$

and different formats will simply change the conditions under which bidder i sells or does not sell his object.

There is an imprecise estimate of each bidder's opportunity cost $\widehat{c_i}$ available to the buyer. This estimate follows this process.

$$\widehat{c_i} = c_i + \epsilon_i$$

where:

$$\epsilon_i \sim_{iid} U[-5, +5]$$

Finally, since players (representing farmers) in this environment can only have one direction of transaction, *sell*, we use the terms "bid" and "offer" interchangeably to refer to their stated/asked minimum compensation to part with their corresponding objects; i.e., their stated WTA.

5.1.1. Auction Formats

Price-Cap Formats

The buyer sets bidder-specific price caps. Bidder i's price cap equals the estimated cost $\widehat{c_i}$ plus an allowed (average) *markup* of μ experimental currency units (ECUs). That is:

$$Cap_i = \widehat{c_i} + \mu$$

We will also refer to the parameter μ as the tightness level of the price cap. At the beginning of the auction, bidder i privately observes his own c_i and his specific Cap_i, and then decides whether to participate in the auction or not. If he decides to participate, he then submits a bid (offer), denoted by b_i that cannot exceed the corresponding Cap_i. The buyer accepts the eight lowest offers and rejects the remaining participating offers. If less than eight offers are submitted, the buyer accepts all offers. Sellers makes profit of $(b_i - c_i)$ and non-seller make null profit.

The parameter μ captures the tightness level of the price cap or what the average markup of a winning bidder would be, if they were to bid sincerely. As we shall see below, when $0 < \mu < 5$, and in particular closer to zero, many bidders decide to opt out of the auction (because it is irrational or nearly irrational to participate) and this generates vast inefficiency. On the other extreme, when μ is large, the price cap is non-binding and the format approaches a simple pay-as-bid auction.

We will study six values of μ: 1, 3, 5, 8, 12, and 15. It can be argued that tightness levels of $\mu = 1, 3$ represent the current design that most likely discourages participation. Also, we define as the ***Benchmark Price Cap (BPC)*** as the tightest price cap format for which every bidder finds it individually rational to participate in the auction, regardless of their corresponding estimated cost, $\widehat{c_i}$. Formally, the μ^{BPC} is the lowest markup such that $Cap_i \geq c_i$ for all i with certainty. In our setup, $\mu^{BPC} = 5$, because it cancels the worst realization of estimation error any bidder can get ($\epsilon = -5$). Markups below 5 necessarily generate non-participation among rational bidders, and markups above 5 are less than ideal because (under complete information) hurt the cost effectiveness of the program. Similarly, we define the format with the most permissive markup, i.e., least tight cap ($\mu = 15$) as the ***Relaxed Price Cap (RPC)***. In short, we study two values of μ below the ideal benchmark value (BPC) and two values between this benchmark and the RPC.

Exogenous reference price (ExogRP)

The buyer sets bidder-specific reference prices based on estimated costs. Bidder i's reference price equals the estimated cost $\widehat{c_i}$. At the beginning of the auction bidder i privately observes his own c_i and his specific reference price (buyer's estimation of his cost), and then decides whether to participate in the auction or not. If he decides to participate, he then submits an offer. The buyer collects all offers from participating bidders and computes everyone's score following this rule:

$$\text{Score}_\text{i} = \frac{\text{b}_\text{i}}{\text{Reference Price}_\text{i}} + \frac{\text{Reference Price}_\text{i}}{50}$$

Where the $\text{Reference Price}_\text{i} = \widehat{c_i}$. The second term in the Score formula is the high-cost-bidder penalty discussed above. The buyer accepts the eight lowest scores and rejects the remaining participating offers. If less than eight offers are submitted, the buyer accepts all offers. As before, selling bidders make a profit of $(b_i - c_i)$; non-selling bidders make null profits.

Endogenous reference price (EndoRP)

At the beginning of the auction, bidder i privately observes his own c_i and buyer's estimation of his opportunity cost $\widehat{c_i}$. He then decides whether to participate in the auction or not. If he decides to participate, he must submit an offer. The buyer collects all offers from participating bidders and computes everyone's score following the same rule as in the exogenous reference price (i.e. $\text{Score}_\text{i} = \text{Offer}_\text{i}/\text{Reference Price}_\text{i} + \text{Reference Price}_\text{i}/50$). Except now the $\text{Reference Price}_\text{i}$ is the average offer of the four bidders that are closest to i in terms of the estimated cost. The rest of the auction format is identical to the endogenous reference price.

Two of its relevant conceptual features need to be noted. First, bidders in this format possess less information of their chances of winning, conditional on their (c_i, ϵ_i) pair, as they would do in all three other formats. This additional uncertainty could positively impact participation, because (as we document below) slim chances of winning are a major factor in non-participation decisions. Second, the bidding behavior set by this format is theoretically more robust to the moments of ϵ_i, the estimation error of the opportunity costs. In particular, equilibrium bidding is invariant to bias, $\mathbb{E}[\epsilon_i] \neq 0$, as this would not alter grouping therefore nor the neighbors' average bid faced by any bidder.

5.2. Experimental Sessions and Protocols

We conducted 11 sessions, to conduct two separate analyses. In the first analysis, we study the impact of price cap tightness (different levels of μ) on participation, bidding behavior, allocative efficiency, and cost of the Program. In the second analysis, we compare the performance of price caps versus reference prices. More precisely, we contrast the benchmark price cap (BPC), the relaxed price cap (RPC), the endogenous reference price (EndRP) and the exogenous reference price (ExoRP) on the aforementioned outcomes.

Each session implemented three or four different auction formats, in different orders (see Table 1). We used six different sets of realizations for cost and estimated costs, henceforth *Draws*. Each draw consists of a full set of cost and estimated costs for the whole session. All draws provided values for 15 subjects. Draws 1, 2 and 3 had 15 periods each, and draws 4, 5 and 6 had 20 periods each. Within each of the two analyses, the set of draws is perfectly matched and balanced across auction formats.

For the first analysis (on price cap tightness) we use sessions 1 through 4 and 9 through 11 with draws 4, 5, and 6. This amounts to a total of 960 individual decisions per markup level (20 rounds times 3 draws times 16 bidders). For the second analysis (price caps versus reference prices) we use sessions 1-8 and draws 1, 2, 3, 4, 5, 6. This amounts to a total of 1680 individual bidder decisions per market format (20 rounds times 3 draws times 16 bidders, plus 15 rounds times 3 draws times 16 bidders).

When a session had three (four) formats, subjects were paid based on 6 (8) randomly selected rounds, two for each type of auction in the session. The exchange rate between Experimental Currency Units (ECUs) to U.S. Dollars is 3; that is, 3ECUs = US$ 1.

Table 1: Experiment Design

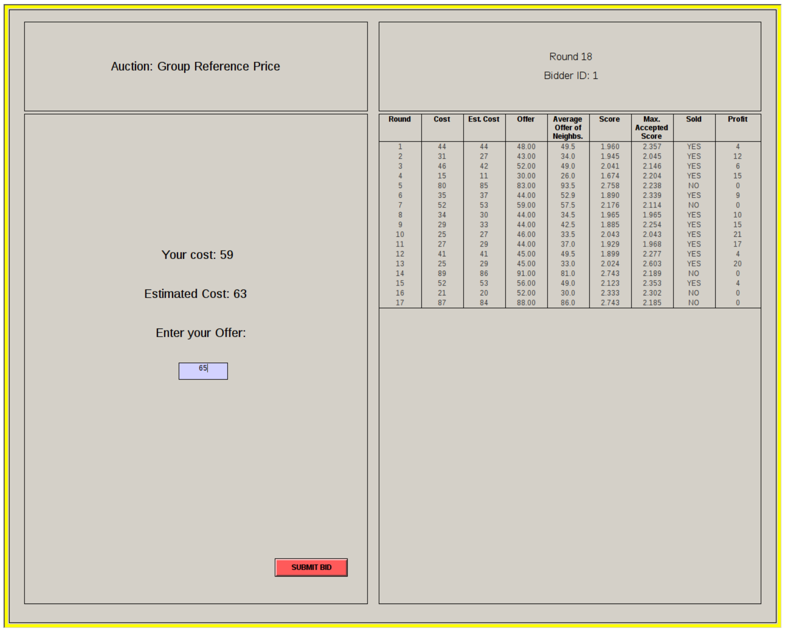
Sessions	Treatments (Draws) [in order of implementation]	Rounds per treatment	Number of Bidders
1	ExoRP, RPC, EndoRP (4, 4, 4)	20	16
2	BPC, ExoRP, RPC (5, 5, 5)	20	16
3	EndoRP, BPC, ExoRP (6, 6, 6)	20	16
4	RPC, EndoRP, BPC (6, 5, 4)	20	16
5	EndoRP, BPC, ExoRP (2, 2, 2)	15	16
6	BPC, RPC, EndoRP (3, 2, 3)	15	16
7	RPC, ExoRP, RPC (1, 3, 3)	15	16
8	ExoRP, EndoRP, BPC (1, 1, 1)	15	16
9	Price Caps: $\mu = 8, 12$; EndoRP'; EndoRP'' (4, 4, 4, 4)	20	16
10	Price Caps: $\mu = 12, 3, 8, 1$ (5, 6, 5, 6)	20	16
11	Price Caps: $\mu = 8, 1, 12, 3$ (6, 5, 6, 5)	20	16

Note: EndoRP', EndoRP'' in session 9 (not discussed in the paper) implemented different scoring formulas for endogenous reference price without participation decisions.

Participants received a copy of written instructions at the beginning of each session. Once the session started, the experimenter provided general instructions. Before each auction type started, the experimenter read the format-specific instructions aloud and provided numerical examples as well as a description of the computer interface. Individual questions from participants were allowed after the reading of each format-specific instructions.

All auction interfaces shared main features. As seen in Figure 1, the left side of the screen displayed bidder's private information for the current period. At the action stage, this side of the screen also contained the corresponding buttons and fields where bidders could opt in or out of the auction. After submitting their decision, that side of the screen turned into a waiting screen. Once the results for the current period were processed, those were displayed in detail in that side of the screen too. The right side of the screen permanently displays the history table with all the relevant information from previous periods.

Figure 1: Sample Experimental Interface



6. Experiment Results

This section details the findings from the analyses we conducted on (1) the impact of price-cap tightness levels, and (2) the comparison between two price-caps levels (ideal and relaxed) and two reference price formats (endogenous and exogenous).

Outcomes

Our analysis focuses on (i) participation rates, (ii) bidding behavior, (iii) *allocative efficiency* and (iv) *cost-effectiveness*. For *participation rates*, we use the percentage of bidders that opt into the auction (i.e. decide to submit a bid). For bidding behavior, we characterize submitted bids at different levels of private cost. For allocative efficiency, we use an object-level efficiency indicator of whether an object (parcel) was efficiently allocated by the auction in or out of the program. For those who are among the eight lowest cost bidders in the auction, this indicator takes a value of 1 for bidder i, if i sells the object, and 0 otherwise. For those who are among the eight highest cost bidders in the auction, this indicator takes value of 1 for bidder i, if i does not sell the object, and 0 otherwise. In a perfectly efficient auction the program will buy from bidder i if and only if i is among the eight lowest cost bidders.

To study cost-effectiveness we use an over-cost measure:

$$\text{Over} - \text{cost} = \frac{\text{Observed Payment}}{\text{Efficient Payment}} - 1$$

measures the actual cost of achieving the target purchase level of eight objects (in the context of the CRP, the room remaining under an acreage cap available for enrollment) relative to the efficient payment. This measure of *over-cost* is bounded below at zero and unbounded above. The efficient payment is assumed to be the minimum feasible cost -- the sum of the eight lowest costs -- which is what the buyer (program) would pay under complete information on the actual costs.

Results Summary

Table 2 provides summary statistics of the main studied outcomes. Before we discuss particulars, note that we found no strong evidence of learning.[17] Excluding the first five periods of every session-treatment conducted yields nearly identical results in most calculations. Our report will be mostly based on all data-points and mention results from excluding the first five periods when necessary.

In our analysis of price-cap tightness levels (*Analysis 1*), we find that, as expected, setting tightness levels below the ideal level (i.e. μ<5) reduces participation dramatically with respect to the benchmark price cap (BPC, μ=5), across low and high-cost bidders. While participation rates are above 80% for BPC, they rapidly decline to 72% for μ=3 and to 59% for μ=1. Participation rates are reduced with tight price-caps more than with any feature of any studied format, simply because price caps that are too tight have a direct clash with individual rationality. The non-participation of low-cost bidders for formats with μ<5 impacts efficiency negatively, because it implies that higher-cost bidders win the auction often. Allocative efficiency is reduced from 94% for μ=5 to 61% for μ=1. Tight price caps also affect the cost-effectiveness of the program: the measure of over-cost goes from 18% for μ=5 to 52% for μ=1.

When, instead, the markup parameter is above the ideal level (i.e. $\mu \geq 5$) participation increases as more bidders are allowed for positive rents. Allocative efficiency, on the other hand, remains statistically constant for any markup level at or above ideal level ($\mu \geq 5$). However, as higher level of markups allow for higher rents, the cost of the program goes up substantially as μ increases -- cost effectiveness of the program worsens. The over-cost of the program increases mostly linearly in μ, going from 18.1% for μ=5 to 37.4% for μ=15.

The main lesson of this analysis on price-cap tightness is that attempting to reduce program costs by making the price-cap tighter is likely to cause severe inefficiencies and is actually counterproductive in terms of cost-effectiveness. On the other hand, relaxing the price caps does not hurt efficiency and simply increases over-cost at a much lower rate than a tighter cap. In sum, from the policy perspective, erring on the side of caution with price caps (making them tight) can be highly damaging to the program's goals.

For our analysis on price-cap versus reference prices (*Analysis 2*), we find that for both price cap treatments (ideal and loose), as well as for the exogenous reference price, participation rates are in the range of 80% to 84% (statistically equal). The endogenous reference price, however, has a

[17] In the regressions for all outcomes, the coefficient of Period is statistically zero, at a significance level of 0.05.

higher participation rate at 90.8% (statistically higher than the other three treatments). This pattern illustrates, again, that directly unprofitable auctions (e.g. price cap with null or tight markups) discourage participation, but so do auctions where a subset of bidders know they will lose the auction with near certainty.[18]

Table 2: Summary Statistics

Auction Format	All Periods (averages)				
	Participation	Winning Offers	Allocat. Effic.	Over-Cost	Profit
	Analysis 1: Price Cap Tightness (μ)				
$\mu = 1$	0.591	50.889	0.610	0.519	2.766
$\mu = 3$	0.722	44.275	0.779	0.354	3.617
$\mu = 5$ (BPC)	0.805	38.830	0.940	0.181	4.452
$\mu = 8$	0.868	40.725	0.931	0.242	6.475
$\mu = 12$	0.864	43.556	0.935	0.332	9.619
$\mu = 15$ (RPC)	0.846	44.870	0.942	0.374	11.414
	Analysis 2: Price Cap vs. Reference Prices				
BPC	0.824	38.815	0.929	0.183	4.284
RPC	0.842	44.799	0.932	0.376	11.224
ExogRP	0.818	43.879	0.883	0.351	8.366
EndoRP	0.908	42.505	0.917	0.308	7.880

Notes: Analysis 1 uses draws 3 4 and 5, and Analysis 2 uses all draws: 1 through 6.

In terms of bidding behavior, as in Analysis 1, BPC keeps offers low as it mechanically enforces low rents. This is precisely why the BPC format corresponds to the most desirable implementation of a price cap format (it achieves minimal rents and individual rationality for all). Also, loosening up the price cap does not increase participation, so no extra competition force drives down bids in the relaxed price cap treatment RPC compared to BPC. As a consequence, winning bids under RPC are the highest of all formats. In the exogenous reference

[18] There are several reasons for which this could happen: costly processing of optimal bidding and behavioral biases associated to perception of loss are two of them.

price, the typical bidding behavior (detailed below) implies that the auctioneer picks high-cost bidders more often. This causes winning offers to be nearly as high as in RPC. Finally, in the endogenous reference price, higher participation promotes bid competition and winning offers are lowest after BPC.

In allocative efficiency, BPC and RPC perform equally well (92.9% and 93.2%, respectively) and significantly better than the exogenous reference price (88.3%). Statistically, the endogenous reference price (91.7%) performs as well as the price cap formats.

As before, the benchmark price cap performs best in this measure of cost-effectiveness, with an over-cost of 18.3%. Relaxed price cap format performs poorly in cost effectiveness (over-cost of 37.6%) mainly because it allows bidders to extract high rents compared to BPC. Exogenous reference price (35.1%) does perform slightly better than the relaxed price cap, but the difference is not statistically significant. Finally, the endogenous reference price auction performs well relative to RPC and ExoRP with an over-cost index of 30.8%.

6.1. Analysis 1: Price Caps Tightness

Participation

In our setup, participation was individually rational if $\mu \geq 5$. However, participation is far from complete in all auction formats (see Figure 1). When tightness levels are below the benchmark, ideal level (i.e. μ=1, 3) participation is rather low as expected compared to the benchmark price cap (μ=5). This is because price-cap conflicts directly with individual rationality, forcing bidders out of the auction. While, participation rates are at 80.5% for BPC, they rapidly decline to 72% for μ=3 and to 59% for μ=1.

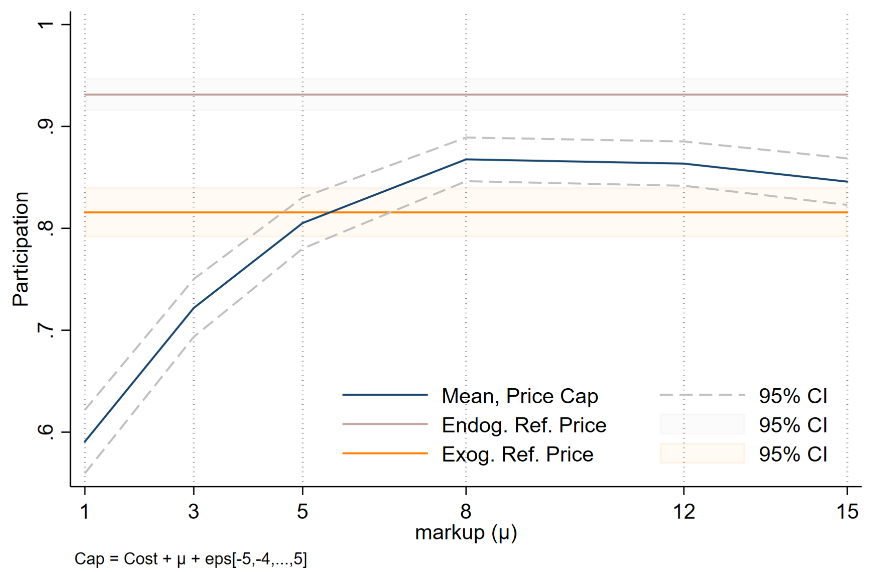
We conduct a binary regression estimation and Table 3 shows the results in terms of marginal effects. In this table, μ=5 is the comparison group, and columns 2 through 5 compute marginal effects using with baseline probability at cost=55. All regressions include session fixed effects. Specification in column (1) displays the specification with nothing else but the dummies for tightness levels, while in column (2) cost is added as regressor. In columns 3 and 4 controls for draws and period are added. Finally, column (5) reports the estimation dropping the first five periods--results are nearly identical. Let us take column 4, we find that the change in probability of participation with respect from BPC to μ=3 is -7.4% and from BPC to μ=1 us -17.7%, both statistically significant.

Table 3: Participation Decisions – Probit Regression – Average Marginal Effects

	(1)	(2)	(3)	(4)	(5)
$\mu = 1$	-0.1757***	-0.1811***	-0.1811***	-0.1767***	-0.1600***
	(0.0168)	(0.0161)	(0.0160)	(0.0143)	(0.0169)
$\mu = 3$	-0.0757***	-0.0832***	-0.0832***	-0.0744***	-0.0690***
	(0.0176)	(0.0167)	(0.0166)	(0.0148)	(0.0174)
$\mu = 8$	0.0710***	0.0696***	0.0688***	0.0619***	0.0728***
	(0.0192)	(0.0178)	(0.0178)	(0.0176)	(0.0206)
$\mu = 12$	0.0657***	0.0674***	0.0669***	0.0589***	0.0753***
	(0.0191)	(0.0176)	(0.0175)	(0.0174)	(0.0203)
$\mu = 15$	0.0441**	0.0498***	0.0496***	0.0436***	0.0435**
	(0.0188)	(0.0170)	(0.0169)	(0.0167)	(0.0192)
Cost		-0.0040***	-0.0040***	-0.0043***	-0.0046***
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
Controls for Individual Draw	NO	NO	YES	YES	YES
Controls for Period	NO	NO	NO	YES	YES
Only Period > 5	NO	NO	NO	NO	YES
Baseline probability	0.8052	0.8274	0.8419	0.7858	0.7601
Obs.	5760	5760	5760	5760	4320

Notes: μ=5 is the comparison group. For columns 2 through 5, baseline probability is for Cost=55. All regressions include session fixed effects. Significance levels: * 0.10 ** 0.05 *** 0.01

Figure 1: Mean Participation by Cap Variation



When tightness levels are above the ideal level (i.e. μ=8, 12, 15) participation increases with respect to BPC: from 80.5% in BPC to 86.8% for μ=8, to 86.4% for μ=12 and to 84.6% for μ=15. According to this analysis, these increments in the probability of participation with respect to BPC are statistically significant regardless of the specification. This finding is interesting, in that even for auctions where profits are allowed to be strictly positive, participation is below 90%. As we discuss below, we conjectured this is due to the near null probability of winning for bidders above cost=70, regardless of μ.

Bidding Behavior

As benchmarks for winning offers, in this setup, notice that the average opportunity cost among efficiently enrolled parcels is 32.5 ECUs.[19] Also, the average opportunity cost among enrolled by a pure random assignment is 55 ECUs. In actuality, the average winning offers depend on both allocative efficiency, as well as how much profit/rent bidders collect in a given format.

BPC has an average accepted offer not too far from this lower bound: 38.8 ECUs. For μ below BPC, things get closer to random assignment. For μ=1 the average winning offer is 50.8 ECUs. For μ=3 the average winning offer is 44.2 ECUs. Bidding behavior reacts much less dramatically to relaxations of the price caps. For μ values of 8, 12 and 15, the average winning offer is 40.7,

[19] This is the same as the average payment under efficiency and sincere bidding

43.5 and 44.9 ECUs, respectively (see Table 2). This means that although higher rents are allowed as μ goes up, competition prevents these rents from increasing in direct proportion to μ.

Allocative Efficiency and Cost Effectiveness

Making price caps tight could be seen as a naïve design choice trying to reduce the cost of the program by limiting the rents of bidders (land owners). In fact, this indeed reduces bidders' rents, but, at the same time, generates a massive inefficiency that worsens cost effectiveness, so the consequences of this naïve design are severely negative on balance. When price caps are too tight (μ<5), the average profit of winning bidders is indeed low (2.77 ECUs for μ=1 and 3.62 ECUs for μ=3) but by forcing a mass of low-cost bidders out of the auction, higher cost bidders win the auction more frequently compared to BPC. This directly, and dramatically, hurts allocative efficiency reducing it from 94% for μ=5 to 78% for μ=3, and to only 61% for μ=1 (See Table 2 and Figure 2). Furthermore, since these winning bidders have on average higher cost compared to winners in BPC, by submitting profitable offers they the cost-effectiveness of the program. While the over-cost under BPC is 18%, it goes up to 35% for μ=3, and to 52% for μ=1. That is, the closer the price cap gets to an unbiased estimator of the opportunity cost, the lower the cost effectiveness of the program. These results are shown in Figure 2 and Tables 2 and 3. In the two panels of Figure 2, the horizontal axes represent the markup parameter μ. In panel (a), efficiency declines steeply to the left of μ=5 (BPC), and, in panel (b), over-cost increases steeply to the left of μ=5. Table 3 reports on our regression analyses. We can see that the worsening of efficiency and cost-effectiveness is statistically significant. Compared to BPC, setting μ=1 decreases efficiency by 24.9 percentage points and increases the over-cost of the program by 32.2 percentage points.

Figure 2: Efficiency and Cost-Effectiveness by Price Cap Variation

(a) Efficiency (b) Over-cost

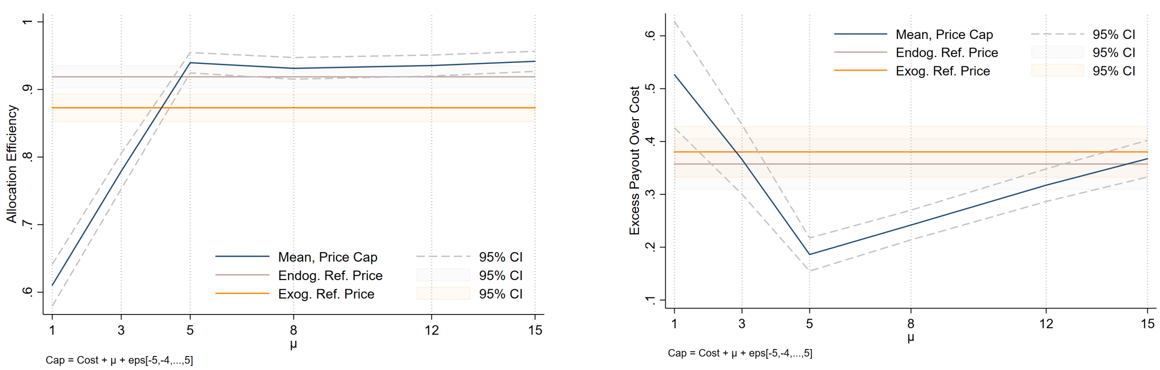


Table 3: Regression Analysis – Efficiency and Cost-Effectiveness

	(a) Parcel-Level Efficiency (Probit – Marg. Effects)		**(b) Auction-Level Over-cost** (Random Effects Model)	
	All Periods	Period > 5	All Periods	Period > 5
$\boldsymbol{\mu = 1}$	-0.2490***	-0.2499***	0.3223***	0.3893***
	(0.0143)	(0.0166)	(0.0388)	(0.0581)
$\boldsymbol{\mu = 3}$	-0.1529***	-0.1553***	0.1543***	0.1964***
	(0.0152)	(0.0176)	(0.0368)	(0.0552)
$\boldsymbol{\mu = 8}$	-0.0130	-0.0043	0.0574*	0.0579
	(0.0174)	(0.0203)	(0.0349)	(0.0523)
$\boldsymbol{\mu = 12}$	-0.0071	0.0072	0.1503***	0.1448***
	(0.0176)	(0.0207)	(0.0336)	(0.0504)
$\boldsymbol{\mu = 15}$	0.0026	-0.0012	0.1930***	0.1964***
	(0.0179)	(0.0204)	(0.0336)	(0.0504)
Controls for Cost	Yes	Yes	N/A	N/A
Controls for Period	Yes	Yes	Yes	Yes
N	5760	4320	360	180

Notes: Comparison group is $\boldsymbol{\mu = 5}$, Auction 1: Benchmark Price Cap. Standard errors in parentheses. Significance levels: * 0.10 ** 0.05 *** 0.01

When the markup parameter is above the ideal level (i.e. $\mu > 5$), participation is at least as high as in BPC. Bidders are allowed higher rents as μ increases, although they sort themselves in similar fashion as in BPC and therefore efficiency rates remain similar to BPC levels. This can be seen in Figure 2A where efficiency is flat for all μ values at or above 5; and in the regression Table 3A where the marginal effects of μ=8, 12, 15 are insignificant.

Cost effectiveness does deteriorate when μ increases because allowing higher rents directly hurts the cost of the program, even though efficiency levels remain high. Relaxing μ from 5 to 12, increases over-cost by 15 percentage points compared to BPC (see regression results in Table 3B) and relaxing it all the way to μ=15 increases it by 19.3 percentage points.

It is important to notice that, although relaxing the price caps hurts cost effectiveness, it does so to a much lesser degree than tightening the price cap. In fact, from regression results, we can calculate that the incremental impact on over-cost of reducing (*tightening*) μ from its BPC level (μ=5) is 4 to 5 times higher than the impact of increasing (*relaxing*) μ. Again, from the policy perspective, setting price caps that are too tight is more damaging than setting price caps that are relatively permissive.

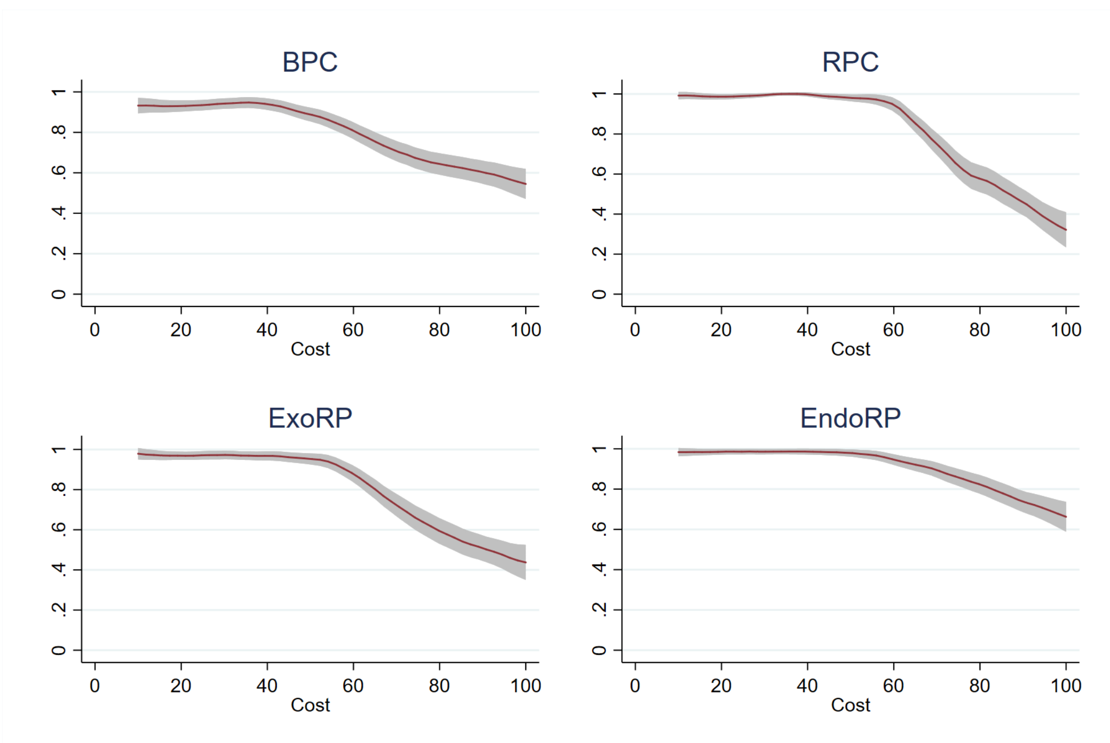
6.2. Analysis 2: Price Caps versus Reference Prices

Participation

In every auction, participation was individually rational – bidding can never lead to losses. However, participation is far from complete in all auction formats (see Table 2 and Figure 3).

It is expected that participation in BPC is lower than in other formats: there is a 1/11 chance of getting a cap equal cost; in which case opting out or setting offer equal to cost both lead to the same null profit. However, it seems participation decisions do not simply obey (weak) individual rationality, but respond to the chances of winning (which they could infer from the history table that shows maximum accepted offers) and the size of the attainable profit. The participation rate when attainable profits are zero or one ECUs and costs are at or above 70 is as low as 45.4%.

Figure 3: Mean Participation Rates by Auction Format



Note: Local polynomial estimation with 95% confidence interval.

In RPC, where it is always individually rational to opt in, participation rates sharply decline for costs over 60 ECUs. In particular, when attainable profits are 10 or 11 ECUs and costs are at or above 70 ECUs, participation rate is only 49.1%. With these forces in play, the level of overall participation in RPC (84.2%) is slightly higher than under BPC (82.4%) but this difference is not significant (see Table 4). This is a relevant insight for the redesign of the CRP auction. It suggests that relaxing the markup has limited positive effects on participation and (from Analysis 1) only matters when the markup is below ideal level. Above the value that makes participation rational for enough bidders, further increases in the markup do not generate a surge in participation rates.

Interestingly, participation rates are also low for the exogenous reference price format (81.8%). Similar to what happens in the price cap formats, here again bidders receive in the history table a clear indication of their near null chances of winning and opt out (see Figure 3, bottom left panel).

These points provide an additional insight for the redesign of the CRP: designing an auction where the information available to the bidder is not fully informative of his winning chances could, in some cases, be beneficial to encourage participation. In fact, that seems to be the virtue of the last format: the endogenous reference price (EndoRP). In the EndoRP, bidders do not have a clear signal of their chances of winning (their exact score will depend on what other similar bidders do) and so they opt-in more often. See in Figure 3 (bottom right panel) that the EndoRP format has in fact the slowest decline of participation in cost. As a consequence, on average, this format has the highest participation rate: 90.8%.

These results are confirmed by our regression analysis reported in Table 4. Statistically, participation rates of all formats are equal, except for the endogenous reference price format that exhibits 8.2% higher participation rates than in BPC. This finding is robust to a series of different specifications and to restricting the sample to Period>5.

Our data also shows that in both price cap formats the participation rates slightly decline after the fifth period. These findings are consistent with the idea that processing the bidding strategy is slightly costly and, therefore, when the chances of winning a positive profit are sufficiently low it is optimal to opt out.

Bidding Behavior

Observed behavior follows the patterns of theoretical insights for the price-cap formats. Theory suggest bidding function takes this form $b_i = \min\{cap_i, \tilde{b}(c_i)\}$, where $\tilde{b}(c_i)$ is a latent function that is increasing in cost. That is, low cost bidders bid the cap because they will win the auction with near certainty and are able to extract as much rents as allowed. There is a range of cost bidders who participate and bid below the cap and above the cost and have a non-trivial chance of winning. High cost bidders, having a near null chance to win the auction, opt out or submit bids with near null profits. These patterns are observed in the laboratory. The two top panels of Figure 4 show bidding data from BPC and RPC. Indeed, low-cost bidders ($c_i \leq 40$) nearly always participate if their cap allows for profit and submit bids equal to their corresponding caps (98.2% in BPC and 99.1% in RPC). And high-cost bidders ($c_i \geq 70$) either opted out or submitted bids with near null potential profits (2 ECUs or less) (52.6% in BPC and 57.2% in RPC). Consistent with theory predictions on rent extraction, winning bids are much higher under RPC compared to BPC (p-value =0.0003)

Table 4: Participation Decisions – Probit Regression – Average Marginal Effects

	(1)	(2)	(3)	(4)	(5)
RPC	0.0101	0.0040	0.0040	-0.0016	-0.0030
	(0.0150)	(0.0135)	(0.0134)	(0.0129)	(0.0156)
ExogRP	0.0059	0.0072	0.0066	0.0005	0.0172
	(0.0139)	(0.0126)	(0.0126)	(0.0121)	(0.0145)
EndoRP	0.0897***	0.0882***	0.0874***	0.0825***	0.1050***
	(0.0120)	(0.0112)	(0.0111)	(0.0106)	(0.0127)
Cost		-0.0053***	-0.0053***	-0.0054***	-0.0060***
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
Controls for Individual Draw	NO	NO	YES	YES	YES
Controls for Period	NO	NO	NO	YES	YES
Only Period > 5	NO	NO	NO	NO	YES
Test: RPC = ExoRP prob > |t|	0.7671	0.7910	0.8313	0.8631	0.1624
Test: RPC = EndoRP prob > |t|	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
Test: ExoRP = EndoRP prob > |t|	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
Baseline probability	0.8235	0.8565	0.8576	0.8384	0.8294
Obs.	6720	6720	6720	6720	4800

Note: For columns 2 through 5, baseline probability is for Cost = 55. All regressions include session fixed effects.

For the ExogRP format, behavior in the laboratory seems to follow this pattern. Bidders discover after few periods that an approximate score threshold k exists below (above) which chances of winning are rather high (low). This score level is not always profitably attainable for a bidder, given their cost and estimated cost. If the bidder can only profitably attain much higher score values than this approximate threshold k, then they typically either opt out of the auction or submit a bid reflecting minimal profit: 80.4% of bidders with $c_i \geq 70$ either opt out of the auction or bid for a profit of two ECUs or less. Those who can attain a score value of k or lower choose the offer that gives them a score value near k, not much below. This is because, typically and conditional on winning, higher profits are associated with higher scores. These behavioral pattern is clearly observed in the data too. For those with competitive costs, targeting an approximate score value of k seem to be quite common (as shown in the left panel of Figure 5 that plots chosen scores against bidders' cost). Typically, bidders with $c_i \leq 50$ exhibit an average score function that is flat (at score = 2.059) with respect to cost. A theory insight would predict this value to be determined so that, on average, eight bidders are able to attain score k and the rest are not able to attain this value. The data seems to follow that insight as the estimate for k is not far from a theoretical value of $k = 2.103$, calculated by simple simulation. This score targeting allows very low cost bidders to extract rents since they know achieving the score is all that matters.

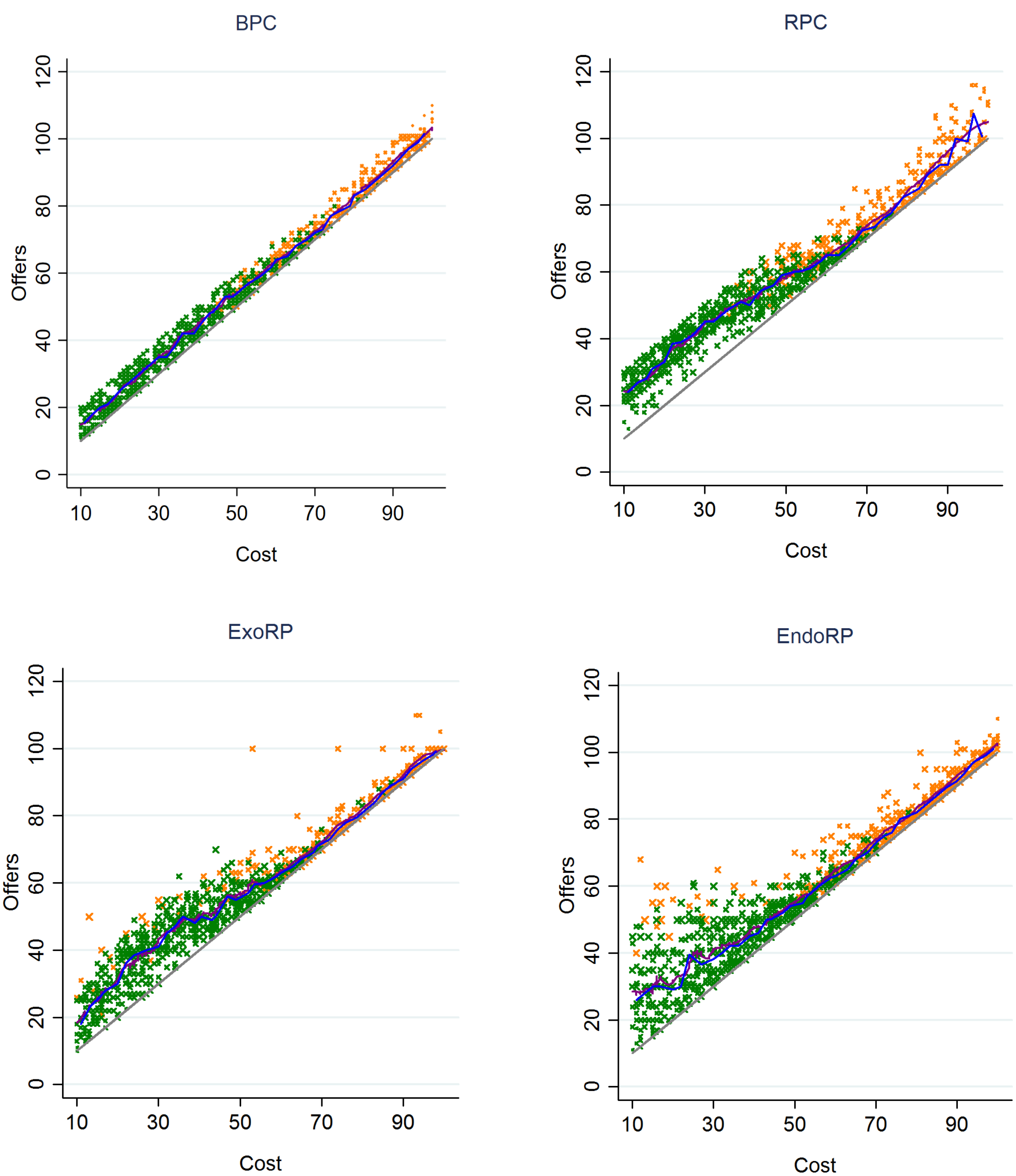
The theoretical insights for the endogenous reference price are subtler: without information on their reference price or exact scores, bidders would focus more on making competitive offers. This seems to be the case. Compared to ExogRP, winning bids in EndoRP are lower (p-value < 0.0001). Score behavior does not follow a flat pattern for low-cost bidders as it did for the exogenous reference price format (see bottom-right panel of Figure 5). This non-flat pattern reflects how this format without a score to target incentivizes bidders to be more competitive.

Allocative Efficiency and Cost Effectiveness

The allocative efficiency index is reported in Table 2. In this metric, BPC and RPC formats perform similarly well (91.8% and 92.7%, respectively) and significantly better than the exogenous reference price (87.8%). The endogenous reference price (91.3%) performs as well as the price cap formats and clearly outperforms the exogenous reference price. Regression analyses that control for cost and period effects are reported in Table 4 and confirm the result: all treatments perform equivalently, except ExogRP which underperforms all the other three.

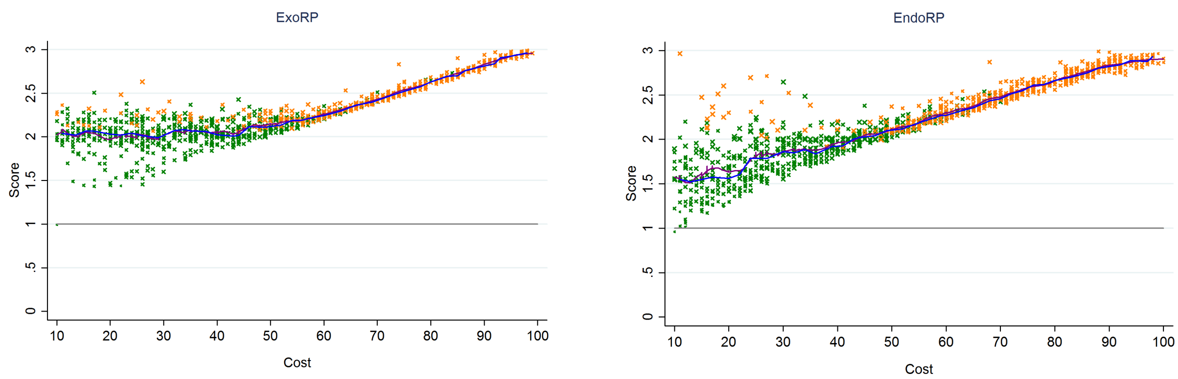
In sum, i) in terms allocative efficiency the endogenous reference price performs as well as the benchmark price cap (BPC) format; ii) relaxing the price cap does not hurt allocative efficiency as compared to the benchmark price cap (BPC); iii) the exogenous reference price does worse than all the other studied formats. We discuss in the following subsection the sources of ExogRP underperformance in terms of allocative efficiency.

Figure 4: Data on Bidding Behavior



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

Figure 5: Score Behavior in Reference Price Formats



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

Table 4: Regression Analysis – Efficiency and Cost-Effectiveness

	Parcel-Level Efficiency (Probit – Marg. Effects)		**Auction-Level Over-cost** (Random Effects Model)	
	All Periods	Period > 5	All Periods	Period > 5
Relaxed price cap	0.0029	0.0077	0.1755***	0.1826***
	(0.0088)	(0.0109)	(0.0218)	(0.0307)
Exog. Ref Price	-0.0446***	-0.0395***	0.1670***	0.1976***
	(0.00995)	(0.0122)	(0.0205)	(0.0297)
Endo. Ref Price	-0.0114	-0.0042	0.1215***	0.1473***
	(0.0091)	(0.0112)	(0.0201)	(0.0293)
RPC = ExogRP prob > |t|	0.0000	0.0001	0.6904	0.6239
RPC = EndoRP prob > |t|	0.1172	0.2796	0.0128	0.2479
ExogRP = EndoRP prob > |t|	0.0011	0.0041	0.0266	0.0909
Controls for Cost	Yes	Yes	N/A	N/A
Controls for Period	Yes	Yes	Yes	Yes
N	6720	4800	420	300

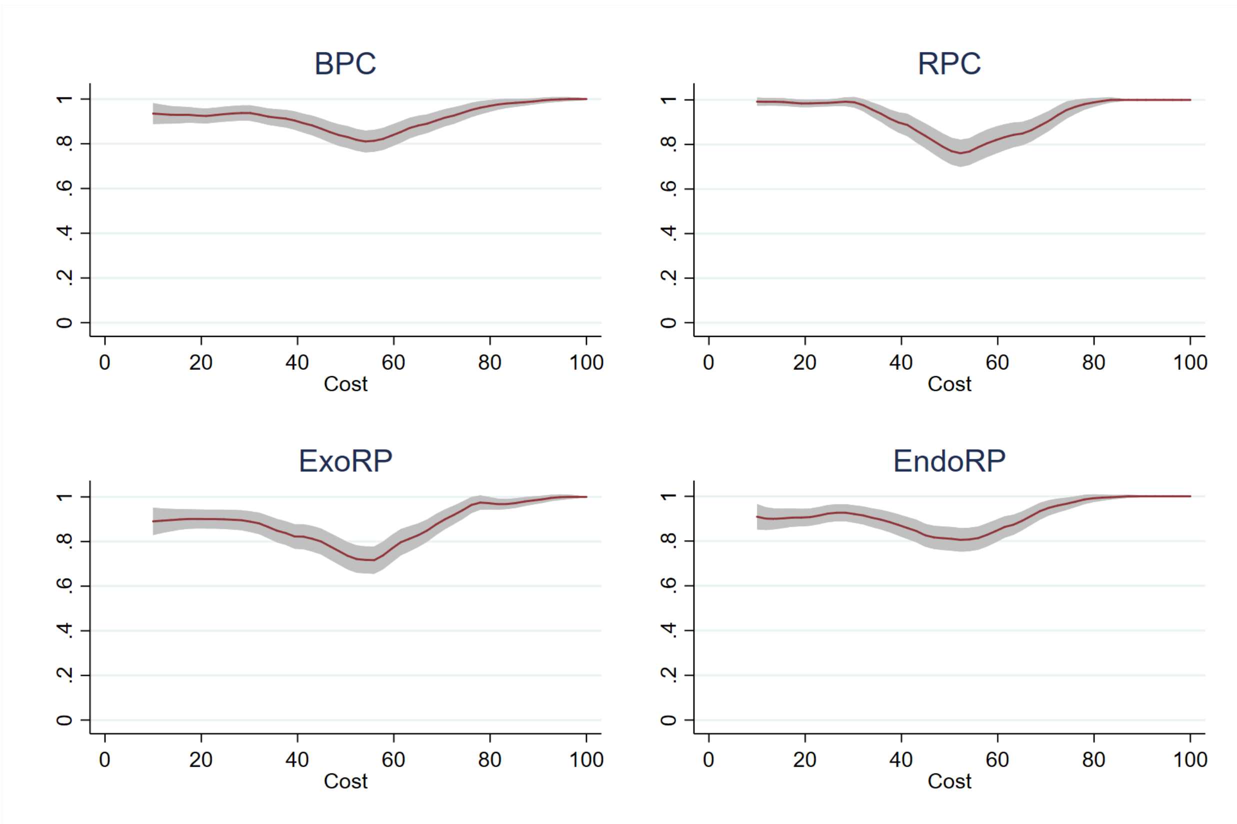
Note: Comparison group is Benchmark Price Cap. Standard errors in parentheses. Significance levels: * 0.10 ** 0.05 *** 0.01

In terms of cost effectiveness, as expected, the benchmark format BPC displays a low over-cost of 18.3%. It must be highlighted that this value provides a lower bound of over-cost under unlikely conditions in the implementation of a price cap system and it is for that reason referential, so the other formats' over-cost are not thought as departures from zero over-costs.

Among the rest of formats, RPC performs worst with 37.6% of over-cost. That is, RPC performs well in terms of allocative efficiency (comparable to the BPC), it performs rather poorly in terms of cost effectiveness. This is mainly because low-cost bidders in RPC are allowed to extract high rents without altering their chances of winning.

Exogenous reference price performs similarly to RPC with an over-cost index of 35.1%. The endogenous reference price auction exhibits an over-cost of 30.8%, the best among the feasible formats, outperforming RPC and ExoRP. Our regression analysis reported in the last two columns of Table 4 confirms this ranking.[20]

Figure 6: Probability of being in the efficient allocation at different cost levels



Note: Local polynomial regressions and 95% confidence intervals.

We explore the sources of inefficiency in the ExogRP format. In figure 6, we can see the ExogRP format under-performs all the other formats in the efficient allocation of medium and low-cost bidders. This is mainly because, in this format, most low and mid cost bidders pursue

[20] When we exclude the first five periods, the ordering becomes statistically less significant. EndoRP still performs better than ExogRP, but RPC and ExogRP are now statistically equivalent in the over-cost measure.

the same score level. Targeting the same score, low and medium cost bidders receive similar probability of winning the auction, when -by chance- more than eight bidders are able to attain a score of k (this pattern can be observed in the bottom left panel of Figure 6). On the other hand, the EndoRP format is highly efficient because uncertainty regarding their actual score gives bidders the incentive to focus on competitive offers, making score behavior to be roughly monotonic in cost. Interestingly, as it can be observed in the top left and bottom right panels of Figure 6, the efficiency pattern of BPC (our unfeasible benchmark) and EndoRP are quite similar.

7. Discussion

This laboratory exercise has provided relevant insights on the properties of the different formats to be considered when implementing any of these auctions outside the lab. The first insight is that the correct calibration in the implementation of the price-cap format is crucial; and that is difficult and unlikely to strike the optimal tightness of the cap outside controlled environments. Furthermore, even at its ideal tightness level, the price-cap auction exhibits substantial over-costs. When the price cap is too tight, the auction forces bidders towards inefficient non-participation generating rather high inefficiencies and over-cost. When the cap is too loose, bidders realize there is room for higher rents and over-cost measures get large too. Indeed, this format is highly vulnerable to bias and inaccuracy in the estimation of $\widehat{c_i}$. Possible biases make the choice of μ more difficult and larger estimation error of the SRRs relative to the variance of true costs implies higher chances of inefficient non-participation and, at the same time, larger rents of winning bidders – both hurting cost effectiveness.

This evidence suggests that, if the estimates of the SRRs are sufficiently imprecise, it might be appropriate to relax substantially the price cap (adopt RPC) allowing high rents or choose a format that is more robust to these errors. On one hand, in terms of allocative efficiency, the exogenous reference price format underperforms the benchmark price cap (as expected) and the EndoRP (counter to our expectations). This is because the ExogRP generates a behavior by which all low and medium cost bidders target the same score value, forcing the buyer to pick a costly set of sellers more frequently than in other auctions. The format also did not excel in terms of cost effectiveness.

One the other hand, the endogenous reference price format turns out to be an interesting alternative candidate. EndoRP outperforms ExogRP in terms of efficiency and it is comparable to RPC. In terms of cost effectiveness, the EndoRP outperforms to ExogRP and RPC, although the comparison with RPC is not robust. Finally, theory insights for the EndoRP say that this format should be invariant to bias in cost estimates and it is less impacted by the imprecision of such estimates. Given its satisfactory performance in the laboratory, we recommend studying further the endogenous reference price format.

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Appendix

Table A1: Summary Statistics for Period > 5

Auction Format	(averages) Parti-cipation	Winning Offers	Allocat. Effic.	Over-Cost	Profit
	Analysis 1: Price Cap Tightness (μ)				
$\mu = 1$	0.594	51.327	0.601	0.527	2.859
$\mu = 3$	0.708	44.931	0.764	0.366	3.617
$\mu = 5$ (BPC)	0.785	39.185	0.931	0.186	4.468
$\mu = 8$	0.860	40.992	0.928	0.242	6.469
$\mu = 12$	0.858	43.331	0.936	0.317	9.561
$\mu = 15$ (RPC)	0.826	44.912	0.931	0.367	11.188
	Analysis 2: Price Cap vs. Reference Prices				
BPC	0.803	39.070	0.918	0.192	4.330
RPC	0.820	44.776	0.927	0.377	11.171
ExogRP	0.812	44.298	0.878	0.365	8.935
EndoRP	0.908	43.082	0.913	0.329	8.440