Competition-Based Environmental Policy: An Analysis of Farmland Preservation in Maryland

by

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COMPETITION-BASED ENVIRONMENTAL POLICY: AN ANALYSIS OF FARMLAND PRESERVATION IN MARYLAND

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Abstract

This paper studies bidder behavior in an innovative program in which farmers compete to sell their development rights to the State. We derive a reduced form bidding model that includes both private value and common value components. This model allows us to estimate the role of bidder competition, the winner's curse correction, and the underlying distribution of private values. We find that competition reduces bid mark-ups, by roughly 0.2 percent for each additional bidder. We further find that bidders adjust for a possible winner's curse by increasing their bids by roughly 10 percent over their reservation values. Using the inferred reservation values, we compare this program to an alternative take-it-or-leave-it offer. We find that a take-it-or-leave-it offer of 50 percent of development values would have preserved more farmland for an equivalent budget than the current reverse auction setup.

Keywords: farmland preservation, first-price auctions, interdependent values, winners curse

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1. Introduction

A large proportion of environmental problems stem from destructive land use. Such problems include biodiversity loss and threat of species extinction due to land conversion and habitat loss, carbon release due to deforestation and land cultivation practices, nonpoint water pollution from agriculture, flood control, and loss of amenities such as scenery, local climate, and wildlife viewing. Indeed, it often appears that a large portion of U.S. environmental problems would be solved if land use decisions could be optimized to include environmental externalities.

This prominent role for land use is important because the legal means used to regulate land use in the U.S. are very different from those used to regulate pollution. In the case of pollution, Federal regulations directly limit what polluters can do. The Clean Water Act, for example, uses what is termed a "permitting approach" in which major releases of water pollution are forbidden without an authorizing permit. In contrast, land use in the U.S. outside of urban areas faces much looser regulation.[1] Instead, the primary "regulatory" tool is to *pay* landowners to undertake the actions that we as a society would like them to undertake. Exceptions exist, of course, but the general principle is that for land use, the rights are inherent in the property, whereas for pollution, the environmental rights are held by the public, in the hands of the government. This difference affects the policies and policy implementation issues that must be considered.

Because of this tradition, policymakers have sought land use policies with low budgetary costs but that are nonetheless cost-effective. The most promising of these are *competition-based*

[1]The Federal government retains some regulatory control over land use through the Endangered Species Act, the Surface Mining Control and Reclamation Act, the Coastal Zone Management Act, and sections of the Clean Water Act. These controls apply to only a small proportion of decisions on non-governmental lands. Furthermore, this legislative approach largely stopped with the rise of the property rights movement (Echevarria, 2005). Local governments regulate land use through zoning, which is weaker than pollution regulation.

policies in which landowners compete for shares of a fixed budget. Competition-based policies are modeled after auctions and they rely on economic arguments governing auction efficiency to motivate their use. Examples include the Conservation Reserve Program (CRP), a Federal program under which landowners submit bids to take environmentally sensitive agricultural land out of production for a 10 or 15 year period. Lowest bids (per environmental benefit) are enrolled first, with enrollment continuing until the budget is exhausted. Non-U.S. examples include Australia's Auction for Landscape Recovery, the U.K.'s Challenge Funds and initial auctions for greenhouse gas reductions, and Germany's Grassland Pilot. Competition-based policies are likely to be important components of future policies for two major U.S. environmental issues: nonpoint water pollution and carbon sequestration.

Although competition-based schemes have many desirable properties, there is much that remains unknown about their optimal implementation. For example, while it is generally believed that increased competition will reduce acquisition costs, the magnitude of this effect is largely unknown. Auction information structures may be quite complicated and may therefore distort bidding, again in ways that have not been much explored. These and other factors cause competition-based programs to be potentially less efficient than other programs with more certain and straightforward payment structures. This paper attempts to shed light on these issues.

This paper studies bidder behavior in the Maryland Agricultural Land Preservation Foundation (MALPF) program, an innovative program in which farmers compete to sell the right to develop their property to the State. The state then retires these development rights in perpetuity, ensuring that the property remains undeveloped.

Several unique features of this auction allow us to identify the informational components in the bidders' strategies. We thus are able to develop a simple reduced form bidding model that includes both the relevant private value and common value elements. This model forms our first contribution to the literature. While there has been some theoretical work on competition-based land use policies, their empirical analysis is largely absent from the literature. In this paper, we demonstrate that our reduced-form auction model is quite rich for examining the effectiveness of the MALPF auction.

Using this bidding model with data from 22 auction rounds over 19 years, we examine the effects of competition, information, and bidder entry and selection on bidding behavior in the MALPF auction. We find that competition reduces bid mark-ups, by roughly 0.2 percent for each additional bidder. We further find that bidders adjust for a possible winner's curse by increasing their bids by roughly 10 percent over their reservation values. These measurements represent our second contribution to the literature.

Our third contribution is a unique approach to inferring reservation values. We argue that because low reservation value bidders enter earlier and win more often, we can use the relationship between bids and the number of previously accepted bidders to infer the underlying distribution of landowners' reservation values. This distribution is essentially the supply curve of enrolling parcels. We then use this inferred distribution to assess the performance of this program relative to a take-it-or-leave-it offer, roughly analogous to the design question of Bulow and Klemperer (1996). A take-it-or-leave-it approach is an alternative to the MALPF auction that uses the same program components and thus forms a natural benchmark for comparison. We argue that the state could have enrolled a greater number of acres for a given budget had they made a take-it-or-leave-it offer of 50 percent of parcels' market easement values.

Together, the results from this long-running auction suggest that competition does drive bids downward, as auction proponents argue, but not to the reservation value, and that a form of winner's curse also leads bidders to bid above their reservation values. Therefore, the competition-based approach may not be achieve lower costs than a non-competition-based take-it-or-leave-it approach. Our paper explains the derivation and limitations of this conclusion.

2. Overview

2.1 MALPF program design and alternatives

Maryland established the MALPF program in 1977 as one of the nation's first statewide programs to purchase landowners' development rights. By 2003 the MALPF had acquired the development rights on 228,854 acres, which is 4 percent of State land and 10 percent of its agricultural acres. The sale of the development rights typically entails a *conservation easement*, a restriction on the deed that proscribes most forms of development. The owner of a parcel that has sold its development rights is free to sell the land but any new owners are, of course, similarly prohibited from developing the property. The program's acquisition expenditures for these development rights for the fiscal year 2002 were $37.6 million, with a statewide average per-acre cost of $1,960. We study bids from Carroll County, an urbanizing county just west of Baltimore. We chose this county because: (i) it experienced substantial development pressure during the period of study yet also had 178,000 acres of agricultural land at the start of the MALPF program, (ii) it actively promoted the MALPF auctions, and (iii) there was no other competing preservation program during the study period.

In each round of bidding, interested eligible landowners submit offers to sell their parcels' development rights. After the offers are submitted, the program pays for professional appraisals of the market value of the unconstrained property. The agricultural value of the property (that is, its value if it were constrained to remain in agriculture) is then computed by program procedures. The state calculates the "market easement value" as the difference between the property's unconstrained market value and its constrained agricultural value.

The landowner's submitted offer is then converted into a ratio by dividing it by the market easement value. These ratios are ranked and the program purchases development rights starting with the lowest ratio offer. The landowner is paid the amount of his submitted offer (with exceptions described below); thus, this program is a type of first-price auction. The program works its way up this line-up of ratios until the annual budget is exhausted. In this way, the program buys development rights that are the least expensive relative to the assigned market easement value. Because of the auction-like approach we refer to the landowners' offers as bids.

The ratio approach represents an innovative design feature for farmland preservation. If the state were to purchase development rights from the lowest bidders, without further adjusting the bids, it would end up purchasing rights from properties that were least likely to be developed. By comparing bids to the market's assessment, the state acquires easements that are cheapest relative to the market price; this adjustment is presumably no longer biased toward low development probability parcels. Our paper does not address the optimality of this feature, nor do we model the underlying objective function that motivates the MALPF policy design.

Like all government programs, the MALPF program has many twists that complicate the analysis. For ratios greater than one, the program may offer to purchase the development rights at the market easement value, assuming the budget has not been exhausted by parcels with ratios less than one. For these parcels, this payment would of course be lower than the landowner's requested payment. Landowners can either accept this offer or decline it. Furthermore, when ratios exceed one and remaining funding is available the administrator selects parcels for auxiliary offers based on unspecified criteria and not necessarily on the lowest-ratios-first rule.

Participants who are not accepted, either because their ratio was too high for the given budget-round or because they were not willing to accept the offered market easement value, can re-bid in any future round. Multiple rebidding is allowed and indeed is common.

There are several broader issues to note about the MALPF program, unrelated to its competition-based approach. In the selection of parcels to enroll the program does not account for the effect of restricting a given parcel's development on the development of other non-restricted parcels. In other words, the decision to acquire development rights from parcel i is made without considering whether other parcels are more likely to be developed as a result. The selection rule also does not account for other public goods provided by the parcels, such as wildlife habitat.

Even within its narrow context, however, alternatives to the MALPF auction are available. For example, the cut-off ratio could be changed; there are reasons why a cut-off ratio either above or below one could be better. Alternatively, the state could eliminate the bidding entirely and offer only a standing take-it-or-leave-it offer to buy development rights from all interested sellers at a given percentage of their market easement value, say 75 percent. Interested participants would apply to the state, their market easement value would be determined, and the bidders could accept or reject an offer of 75 percent of the market easement value on a first-come, first-serve basis. This pure take-it-or-leave-it approach would be less expensive than the current set-up if the MALPF auction's bids were greatly above landowners' reservation values. This determination can only be ascertained through empirical analysis.

Although this paper focuses on competition-based policy, it is worth mentioning two other, more prevalent voluntary enrollment, payment-based land use policies. One such category is *formula-based* payments, sometimes called fixed-rate, in which the state offers a payment to enrollees that is based solely on observable parcel characteristics. Formula-based payments are used for the Conservation Reserve Enhancement Program. This is also the main format of programs internationally (see Pfaff, Robalino, and Sánchez, 2006). The take-it-or-leave-it offer described above is a form of formula-based payment.

The other category is *negotiation-based*, which is the way most land ownership transactions are conducted. This is also the method by which non-governmental organizations such as The Nature Conservancy acquire easements.

Other land use policies such as Transferable Development Rights have a regulatory aspect linked to the voluntary enrollment component and are not covered by this paper.

2.2 The MALPF procedure as auction

The argument for competition-based policies relies on the principles that underlie auction theory. Insights and prescriptions from auction theory in turn depend on the underlying information environment. Therefore, we first lay out the basic information paradigm as it applies to the MALPF auction.

It is common in the auction literature to distinguish between auctions with independent private values and more general information structures that include affiliation either among bidders or between bidders and the auctioneer, often with a focus on some form of common value. In the land preservation context, private value refers to a landowner-specific measure of the easement value, some element of which is known only by the current operator. This value also likely includes the landowner’s utility from farming and, more relevant, utility from future generations farming the land.

We also consider a form of common value that stems from the parcel’s market easement value. We refer to this as a common value element because landowners bid without knowing their parcel's market easement value and the market easement value would likely affect the value the bidder places on his easement.

Much of the empirical literature focuses on distinguishing between pure private value and pure common value environments with the assumption that one of these paradigms dominates the auction under consideration (Athey and Haile, 2002; Hendricks and Paarsch, 1995; Hendricks, Pinkse, and Porter, 2003; Paarsch, 1992). This dichotomy is not particularly relevant for the MALPF auction which clearly has both information elements.

2.3 Literature

Competition-based land use policies such as the Conservation Reserve Program (CRP) have been the subject of some theoretical work (Smith, 1995; Latacz-Lohmann and Van der Hamsvoort, 1997) but most of the empirical analysis has not made use of the auction paradigm. An exception is Kirwan, Lubowski, and Roberts (2005), who estimate a reduced form model and infer reservation values from assumptions based on the portion of the reservation value that is observable. Only private values are likely present in the CRP context. A second exception is Vukina, Levy, and Marra (2006), who use a reduced form model to examine how plot-specific environmental scores, which increase the probability of winning, ceteris paribus, affect bids. Our auction set-up and data are richer than these models and this richness allows us to develop a more concrete, though still reduced-form, model and to estimate a broader set of relationships.

Another prominent competition-based program is the Georgia Irrigation Reduction Auction, under which farmers with irrigation permits submitted bids to stop irrigating for a single growing season (Cummings, Holt, and Laury, 2004). The most relevant result to our analysis is that a preliminary field experiment found mark-ups of 7-12 percent above costs, which is comparable to our results. In their experiment almost 20 percent of the offers were below the assigned reservation value. Below-cost bidding may also be occurring in our auction.

Stoneham et al. (2003) analyzed auctions for conservation contracts in Australia and compared the existing first-price auction with an alternative fixed offer. They assumed that bids were equal to reservation values, however, so that the auction always does better than the fixed offer.

The theoretical auction literature provides guidance on optimal auction design. These papers provide useful intuition but do not tell us whether the MALPF auction should be thought of as superior to alternative set-ups. The MALPF auction and its alternatives are similar to the model of Bulow and Klemperer (1996) in which they compare an English auction with N+1 bidders to an auction with N bidders in which the auctioneer makes a take-it-or-leave-it offer to the winner after observing all submitted bids. They argue that regardless of the information structure, the pure auction always yields higher expected revenue than any take-it-or-leave-it offer with fewer bidders. This finding suggests that the MALPF set-up might be superior to any take-it-or-leave-it approach[2] and that, in general, policymakers should adopt competition-based policies. There are several key differences between our setting and theirs, however, including the infeasibility of an English auction and the lack of a well-defined objective function for the MALPF program.[3] We therefore cannot take it as given that the MALPF auction is an optimal farmland preservation policy.

[2]The current MALPF set-up includes the possibility of a take-it-or-leave-it offer for losers at the auctioneer's reservation value of one. The analogous question in the Bulow and Klemperer model is whether the cut-off ratio should be below one.

[3]For example, the state's objective is neither to maximize the acreage enrolled, in which case it would ignore market easement values, nor to maximize the market value of the acquired easements, in which case it would evaluate parcels based on the difference between the bid and market easement value, not the ratio. This lack of an analytically-sound objective function that is consistent with welfare principles prevents us from using many of the optimal-auction prescriptions in the auction literature.

Although it is generally optimal in common-value-type auctions for the auctioneer to reveal all information, Vincent (1995) argues that in some environments it may be optimal for the auctioneer to keep the reservation value secret. This result is relevant because the MALPF auction is analogous to a set-up in which the auctioneer sets a bidder-specific reservation value that is unknown to the bidder. Vincent's information structure is different from the MALPF auction, however, so that again we cannot conclude that the MALPF auction is optimal.

Our paper provides empirical estimates of the effect of competition on bids, the winner's curse correction, and the distribution of the private value element. By far the most attention in the literature has been devoted to the relationship between bids and number of bidders. In a pure private value environment, a higher number of bidders is predicted to lead to a more competitive auction, which in our case means lower bids (Milgrom and Weber, 1982; McAfee and McMillan, 1987; Matthews, 1987). In an environment with interdependent values, a category that includes ours, the prediction that more bidders will lead to more competitive (lower) bids no longer holds. Menezes and Monteiro (2000) demonstrate that if bidder entry is endogenous, a higher number of bidders may result in lower seller revenue, which is analogous to higher bids in our context. Pinkse and Tan (2005) also suggest that the auctioneer may sometimes benefit from reducing auction competitiveness to reduce the winner's curse correction. Bajari and Hortacsu (2003), for example, found in a regular auction that adding one more bidder decreases bids by 3.2 percent. Hong and Shum (2002), analyzing procurement contracts, also found that more bidders led to less competitive bids. The intuition that more competition is better is hard to relinquish, however without stronger and more relevant evidence.

Empirical studies must often account for endogenous numbers of bidders. Haile, Hong, and Shum (2007) describe examples of instruments such as the number of firms requesting bidding information, the number of local firms in an industry, the number of eligible bidders, or the number of bidders ever to bid in a comparable auction.

A further important issue is how even to even define the competitiveness of an auction such as the MALPF's, in which an undetermined number of bidders may be accepted. The most relevant study for our purposes is Tenorio (1993) who, examining bidding for a share of fixed amount of foreign currency, considered both the number of bidders and total quantity demanded, that is, the sum of all bids. The total dollar amount bid is not usable in our model since it cannot be known ex ante and is correlated with the regressors, namely market easement values.

3. Model

3.1 Land value and the value of development rights

We start with a standard model of land conversion. Let $V(t)$ represent the value of a specific parcel were it to be developed at time t. We assume that this value is random and exhibits geometric Brownian motion, $dV(t) = \alpha V(t)\mathrm{d}t + \sigma V(t)\mathrm{d}z$, where dz is an increment of a Wiener process. $V(t)$ is the discounted value of the sum of housing services that would be accrued if the parcel were to be developed at time t.

Development incurs two sorts of costs, the cost of constructing the housing stock and related infrastructure and the foregone profits from agriculture. The latter is most important for this analysis. Let x represent annual net returns from agriculture on this parcel; for simplicity these returns are assumed non-stochastic. Let ρ be the risk-free discount rate. Since x is assumed non-random, the discounted returns from agriculture, and thus the market value of the land absent any opportunity for development is $X = x/\rho$.

The landowner's decision is the date τ at which to develop the parcel. When the parcel is converted the landowner gives up the remaining stream of x, valued at $Xe^{-\rho\tau}$. The parcel is converted when $V(t)$ exceeds X plus the option of waiting for a higher offer. Thus the value of an undeveloped parcel given current realization V is:

$$F^m(V) = \max_{\tau} X + E[(V(\tau) - X)e^{-\rho\tau}] \qquad (1)$$

This is a standard investment under uncertainty problem, easily solvable by methods described in Dixit and Pindyck (1994). See Plantinga, Lubowski, and Stavins (2002) for its use in the land conversion context, although they assume a different stochastic process for dV. Note that (1) can be rewritten as $F^m(V)$ = max $E[X(1-e^{-\rho\tau}) + V(\tau)e^{-\rho\tau}]$, which makes clearer the two income streams. The cost of land conversion is assumed to be zero in this model but such a cost would not change the underlying structure of the problem. Making X stochastic would make the subsequent expressions more complex but again without changing the basic lessons.

Let V^* be the value of $V(t)$ at which the landowner would convert. This problem has boundary conditions $F^m(0) = X$, $F^m(V^*) = V^*$, and $\partial F^m(V^*)/\partial V = 1$ and thus solution $F^m(V) = X + aV^{\beta}$ with $a = (V^* - X)/V^{*\beta}$, $V^* = \beta X/\beta\text{-}1$, and $\beta > 1$ a function of r, α, and σ (Dixit and Pindyck, 1994). Together these yield $a = \beta^{-\beta}\left(X/(\beta-1)\right)^{1-\beta}$.

The market easement value, M, is the difference between $F^m(V) = F^m$ and the value of the land restricted to remain undeveloped, X:

$$\textit{Market easement value} = M = F^m - X = aV^{\beta} \qquad (2)$$

Note that M is a random variable with argument V suppressed.

Since the MALPF program is based on both the landowner's and the market's valuation of a parcel's development right, it is necessary to consider how these values may differ. There are two possible sources. First, landowners may derive utility from owning and operating the farm beyond the agricultural income it provides. This utility may lead them to own the farm beyond the cash flow optimal date to convert. We model this effect by adding a weight, ψ, to agricultural income. Thus landowner *i*'s value for his land is thus given by:

$$F^f(V) = \max_{\tau} \ \psi_i X + E[(V(\tau) - \psi_i X)e^{-\rho\tau}] \tag{3}$$

again with the expectation conditional on the current observation of V. We use superscript f to denote the farmer's valuations.

In general we expect $\psi_i > 1$, since this corresponds to landowners placing additional value on farm income. ψ_i may also be interpreted as representing the individual's private observation of agricultural income, with $\psi_i > 1$ indicating that agricultural income is higher than the market belief. We treat ψ_i as an independent private value, unobserved by the administrator and distributed independently of $V(t)$.[4,5] A higher ψ represents a greater weight on farming income (a utility effect) or a higher assessment of agricultural potential.[6] For ease of notation, we drop the *i* subscript.

Expression (3) has solution $F^f(V) = \psi X + a^f V^\beta$ with $a^f = (V^f{*} - \psi X)/V^f{*}^\beta$ and $V^f{*} = \beta\psi X/(\beta - 1)$. β is the same in both formulations since it depends only on the evolution

[4]ψ also forms the basis of the unobserved likelihood that the parcel will be developed. This likelihood is a common concern in the design of land use policies (e.g., Sánchez et al., 2006).
[5]The independence is not precise: Those farmers who have not already sold to developers are ones who have high ψ's or (temporarily) low V's.
[6]Lynch and Lovell (2003) find both agricultural income indicators and non-consumptive values affect the likelihood of enrollment. These variables include farm size, cropland use, a child planning to take over the farm, and the share of family income from the farm.

of values for developed property. When the farmer observes the same V as the market his valuation of the parcel's development right is:

$$F^f(V) - \psi X = \psi^{1-\beta} aV^\beta = \theta M \tag{4}$$

with $\theta = \psi^{1-\beta}$. When $\psi > 1$ we have $\theta < 1$, which implies that for any observation of M the landowner requires less than the market easement value for his development rights.

A second source of difference between the market (i.e., the appraiser) and an individual landowner is different observations of $V(t)$ and thus of $aV(t)^\beta$. Such disagreement about land values is a natural element of any land market although it is missing from the standard asset pricing model.

One way to incorporate this difference is to have both parties draw separate observations of $V(t)$ from some underlying distribution, which then correspond to different assessments of $aV(t)^\beta$. Let the landowner's assessment be denoted $D = aV^f(t)^\beta$, where $V^f(t)$ is his belief about $V(t)$, analogous to the (un-superscripted) $V(t)$ in (2). Then the landowner's reservation value for his development right, from (4), is:

$$\textit{Landowner easement value} = \theta D \tag{5}$$

This formulation makes clear the two elements that constitute the landowner's reservation value: the extra utility he derives from farming and his observation of the price his unconstrained property would fetch on the market.

3.2 Bidding

To participate in the MALPF auction an eligible landowner submits a bid, b_i, that represents the one-time payment he would accept in return for his parcel's development rights.

For each submitted bid, the program administrator constructs the ratio of the bid to the market easement value:

$$R_i = \frac{b_i}{M_i} \qquad (6)$$

This ratio R_i forms the basis for selecting the winning bids. Winning bidders are paid the amount of their bid, with the exceptions described in Section 2. Based on (6), the probability of acceptance at $R \leq 1$ is $\Pr(b \leq \tilde{R}^* \cdot \tilde{M})$ where R^* is the cut-off ratio.

To construct the bid, a discerning landowner must first construct the value of his development right conditional on bid acceptance and therefore conditional on the ex post report, M. There are many possible informational assumptions. We assume the landowner adopts the market easement value as his ex post valuation. The landowner's expected value of his development right conditional on winning is thus:

$$\tilde{v} = E_M(\theta \tilde{M} \mid \theta D < \tilde{R}^* \cdot \tilde{M}) \qquad (7)$$

which is above the unconditional expectation $E(\theta M) = \theta D$.[7] Landowners whose bids are selected will be those who have most underestimated M, ceteris paribus, yielding a winner's curse. They may therefore formulate their bids to hedge this risk, by bidding as if they have values above θD.

Expression (7) assumes that the landowner treats the market observation M as "correct" in forming his *ex post* valuation. Alternatively, a landowner may treat (5) as a true reservation value that need not be updated based on other parties' observation of M. In this case, there would be no common-value-type element to the auction and no winner's curse. An intermediate

[7] We do not consider the case where other bidders' information affects the ex post valuation, other than indirectly through R^*. An alternative assumption would be that M is less informative if all bidders have $D < M$ than if the D's are distributed around M. Likewise, we do not consider the case where D's are affiliated across bidders. These assumptions are obviously open to investigation.

case would be that landowners use M as informative but not definitive and therefore use Bayesian updating on D.

This expression then allows us to write the objective function for a risk neutral bidder facing a one-time auction:

$$\pi(\theta, D) = \max_{b} E_{R,M}\left[(b-\tilde{v})\big)(1-\Phi(b)\big) + \Big((1-\theta)\cdot\tilde{M}\Big)\Phi(b)\Pr(offer)\right] - k \qquad (8)$$

where Φ represents the distribution of the product $R^{*}\cdot M$ and Pr(*offer*) is the probability that an ex post offer of $M < b$ is made.[8] In a static framework this offer would always be accepted, regardless of the bid. k is a bid preparation cost.

The dynamic model, which includes when to enter the auction and the possibility of rebidding, is yet more complex. We describe the main results only heuristically. Consider bidder entry. We assume $\partial\pi/\partial\theta < 0$. Although this is a near-universal assumption, it is difficult to establish definitively given the complexity of the winner's curse. Under this assumption, for each D there exists a θ^{+} such that $\pi = 0$ and such that all $\theta_i < \theta^{+}$ enter the auction. Lower θ_i's are always more likely to enter the auction than higher θ_i's.[9] This framework further yields $\partial b/\partial\theta_i < 0$, which implies that, when D is independent of θ_i, lower θ's are more likely to win the auction. When entry is costless, D will indeed be independent of θ_i, even under more general assumptions about the winner's curse, because D contains all landowner information about M. Therefore, no landowner believes he has a "high" D relative to M. When entry is costly, D will be negatively correlated with θ_i.

These conditions together suggest that the lowest reservation price bidders enter the

[8]Equation (8) does not capture the tax benefits that accrue when development rights are sold for less than their market value. Since these tax benefits are the same for the MALPF auction and the proposed alternative take-it-or-leave-it offer, there may be little lost from this simplification.

[9]Formally, the necessary condition is that the lower is θ, the more surplus the bidder will lose from waiting for the next auction. We again argue heuristically that lower θ bidders gain more surplus π from the auction and therefore lose more surplus, $\approx\rho\pi$, from waiting for the next round.

auction earlier and win more frequently when they do enter. As these bidders leave the bidding pool, the remaining pool of potential and actual bidders contains a larger fraction of higher reservation price bidders. This shift will lead bids and ratios to rise as the number of previously accepted offers increases. The auction mechanism is essentially moving “up the supply curve”; namely, the supply curve for development rights.

4. Estimation

Analysis of auction data can use either a structural-econometric or reduced form approach. Given a tractable auction model, the structural-econometric approach is preferred because it brings economic theory (i.e., equilibrium bid functions) directly to the data, which allows researchers to estimate the underlying value distribution or to uncover the prevailing information structure (Paarsch and Hong, 2006; Athey and Haile, 2005; Hong and Shum, 2000). Conversely, many auctions are sufficiently complex that a bidding function consistent with a theoretical model cannot be derived. When this occurs, researchers are forced to use a reduced form analysis.

We use a reduced form approach in this paper for two reasons. First, the auction structure is sufficiently complex (multiple random variables, interdependent values, multiple paths for bid acceptance, possible repeat bidding, and endogenous entry) that a structural-econometric approach is essentially impossible to derive. Second, equilibrium bidding, an assumption of the structural-econometric approach, is an excessive requirement for MALPF auction bidders, both because of auction complexity and the fact that most bidders do not participate in such an auction regularly.

In most circumstances, the reduced form approach cannot be used to infer the underlying private-value distribution. Several features of the MALPF auction, however, allow us to infer this distribution using a reduced form approach.

4.1 A reduced-form model of bids

Together, equations (7) and (8) plus the dynamic entry and bid selection elements depict a complex bidding situation with multiple sources of uncertainty. We develop a simple yet rich econometric model that encompasses each of the key elements.

Bids will be above the bidder's reservation value due to the information rent that bidders accrue in a pure private values setting and to the winner's curse correction of (7). To account for these effects we specify a functional form in which individuals mark-up their bids by multiplicative γ and ω over the reservation value shown in (5). The bidding function is thus:

$$b_{it} = \gamma_{(t)}\omega\theta_i D_i \tag{9}$$

We cannot directly observe the elements of (9) but we do observe related variables that allow us to infer their values. Equation (9) includes bidder and auction-round subscripts, *i* and *t*, to make clear how components vary across observations.

4.1.1 Estimation of θ

Although we do not observe individual θ_i's, we can infer the average θ among first-bidders in each bidding-round, a sequence we denote as $\{\overline{\theta}_{(t)}\}$ where *t* indexes the bidding round. Following the discussion above, we note that as cumulative acceptances increase, there are fewer bidders left in the pool and these are bidders with higher values of θ. Bidders with high θ's, relative to the remaining pool, should sit out auction rounds until they are competitive; that is, until their θ's are in the low range of remaining θ's. Therefore, the range of θ's in a given auction round should be relatively narrowly distributed around "local mean" $\bar{\theta}_{(t)}$, which will be an increasing function of the number of previously accepted parcels, denoted CA_t for cumulative acceptances. This is our key estimation insight. This strategy relies on bidders being drawn from an otherwise invariant underlying distribution. We therefore restrict our main regressions to first-time bidders.

We adopt the general specification:

$$\ln(\bar{\theta}_{(t)}) = \zeta - \exp(\beta_1 \cdot (CA_t + 10)) \tag{10}$$

We expect bids to be increasing in cumulative acceptances, $\beta_1 < 0$. We add 10 to the number of cumulative acceptances to account for parcels that were preserved prior to the start of the MALPF program.[10] The parameter ζ measures the lower bound of θ's since $\zeta = 1 + \ln(\bar{\theta}_{(0)})$.

4.1.2 Estimation of γ

Following the standard private value auction setting, we let the information rent mark-up, γ, depend on the competitiveness of a given auction round. There are multiple possible measures of competitiveness, generically labeled $COMP_t$. These measures will be described in Section 6.1. Let $\ln(\gamma_{(t)}) = \gamma_0 + \gamma_1 COMP_t$. Greater competitiveness implies that bids will be lower, yielding the prediction $\gamma_1 < 0$. We assume that $\gamma_{(t)}$ is the same for all bidders in a given round.

[10] We were able to identify one Carroll County parcel whose development rights were donated before 1980. We suspect that there are other parcels (together accounting for 0.5 percent of rural land) with very high private values that did not participate in the MALPF auctions. This correction did not affect our results.

4.1.3 Estimation of ω

The winner's curse correction, ω, sets the bid above the unconditional estimate of the easement value to compensate for the fact that the winners will those who have most under-estimated their market easement value. Theoretically consistent specifications of the winner's curse correction are difficult to derive. Gordy (1997) notes that closed-form equilibrium bidding functions are quite rare except for the simplest of common value assumptions. Paarsch (1992) describes the assumptions that yield a multiplicative or additive winner's curse correction but these derivations assume a different information structure from the MALPF setting.

We use a multiplicative specification in (9) and define $\ln(\omega) = \omega_0$.[11] In general, we expect ω further to be (i) decreasing in θ, (ii) increasing in the number of bidders, and (iii) decreasing in the amount of information the bidder has about $\tilde{M}$. The intuition for each of these claims can be gleaned directly from (7).[12] We briefly consider each of these issues.

Relationship with θ. The winner's curse correction ω should be higher for bidders with a low θ_i because individuals with low θ_i's are more likely to have their bid accepted for a given signal F^f. Therefore, if their bid is accepted, they must have a lower *ex ante* estimate of the market easement value relative to its draw. They should shade their bids upward further to account for this greater winner's curse.

This effect applies to bidders within a round, however, not across rounds. The range of θ's within a round is much smaller than the range of θ's over the entire set of rounds. Therefore, this effect is likely to be small.

[11]An alternative specification would use an additive mark-up, of the form $\gamma(\theta D+\omega)$. An additive mark-up has the valuable feature that it is a greater percentage mark-up for low reservation values, which are the ones most susceptible to the winner's curse. Unfortunately, estimation did not converge with an additive mark-up because of collinearity with the regression constant.

[12]The full winner's curse correction comes from (8), not (7), although (7) provides useful intuition. Interactions among elements (i)-(iii) greatly complicate formal statements about the winner's curse.

Relationship with competition. The winner's curse correction should be higher as competition increases because greater competition means that the cut-off R^* will tend to be lower and therefore winning bidders will have underestimated M to a greater degree. For example, we might write $\ln(\omega) = \omega_a + \omega_b COMP_t$, with $\omega_b > 0$. In this case, the estimated parameter γ_1 in (11) might be interpreted as measuring the *net* effect of the competition and winner's curse effects, as Hong and Shum (2002) discuss, and may be positive or negative.

Relationship with bidding experience. Second-bidders should be more informed about their parcel's market easement value than first-bidders due to the appraisals that were conducted following their first bid. As a result, second-bidders should have smaller winner's curse corrections. To examine this assumption we estimated a version of (9) with only second bidders.

4.2 Estimated equation

These substitutions now allow us to specify the estimated regression. We also make use of the assumption that M is an unbiased estimate of the landowner's ex ante beliefs, yielding $E(D_i) = M_i$. Finally, we log (9) to get the estimated equation:

$$\ln(b_{it}) = \alpha_0 + \gamma_1 \cdot COMP_t + \ln(M_i) - \exp(\beta_1 \cdot (CA_t + 10)) + \varepsilon_i \tag{11}$$

where $\alpha_0 = \omega_0 + \zeta + \gamma_0$.

It is straightforward to interpret the slope coefficients in this model, γ_1 and β_1. The challenge is to identify the constant terms, γ_0, ζ, and ω_0, from α_0. An extensive set of identification procedures is necessary because each of the relevant relationships has a constant term that cannot be distinguished without such structure.

When the auction is at its most competitive we should have $\gamma \approx 1$, which implies $\gamma_0+\gamma_1 COMP_{max} \approx 0$. Thus, we specify $\gamma_0 = -\gamma_1 COMP_{max}$. When competitiveness is measured by the number of bidders we set $COMP_{max} = 60$, which is above the highest number of bidders we observed, 53. When competitiveness is measured by the budget per bidder we set $\gamma_0 = 0$, since the most competitive auction has a zero budget.[13]

In the simulations presented in Section 6.2, we assume, ω_0=0. Under this assumption, derivation of $\zeta = \alpha_0 - \gamma_0$ is then straightforward, thus yielding $\bar{\theta}_{(0)}$.

The assumption of no winner's curse correction, $\omega_0 = 0$, captures two possible scenarios. First, the assumption may be valid if there is no winner's curse. This would occur if the value the landowner places on his development right is unaffected by others' beliefs about its value; in other words, a pure private values setting. Using the notation of (7), let $\tilde{v} = E_M(\theta D \mid \theta D < \tilde{R}^* \cdot \tilde{M})$. Because D is nonrandom at the time of bidding, the conditional expectation is exactly equal to the unconditional expectation, hence no winner's curse. Second, equation (7) could be correct but individuals fail to condition their expectation in forming their bids.[14] In other words, they suffer the winner's curse. This is not an uncommon finding in the experimental literature (Kagel and Levin, 2002), although empirical analysis of high-stakes auctions usually finds at least some correction for the winner's curse (Hendricks, Pinkse, and Porter, 2003).

[13]These values for $COMP_{max}$ are out-of-sample. Kirwan et al. (2005) note in this context that predictions based on an out-of-sample regressor are typically undesirable. Such prediction is unavoidable here, however, since out-of-sample prediction is key to inferring true reservation values. A related problem is that the estimates of γ_0 are sensitive to assumptions about what level of competition will eliminate the information-rent mark-up.
[14]The implications of this second explanation are quite different from the first. Since we find at least some winner's curse correction we leave further discussion of this issue to a separate paper.

An alternative approach is to use bidder experience to provide a rough estimate of ω_0. We estimated the analog to (11) using second-bidders, who are more experienced than first-bidders.

Note that this estimation must account for the selection effect, recognizing both that second bidders were rejected in the first round and have chosen to rebid and that the timing of the second bid is endogenous. Our heuristic model of entry provides a straightforward approach. Second-bidders should re-enter precisely when they are "competitive," namely at round *t* such that their θ_i is in the range of $\overline{\theta}_{(t)}$.[15] It is therefore sufficient to treat second-bidders as equivalent to first-bidders but with a different winner's curse correction. Let $\ln(\hat{\overline{\theta}}_{(t)})$ = $\hat{\zeta} - \exp(\hat{\beta}_1 \cdot (CA_t + 10))$ with $\ln(\hat{\overline{\theta}}_t)$ derived from a separate first-bidder regression. We then estimated:

$$\ln(b_{it}) = \alpha_1 + \gamma_1 COMP_t + \ln(M_{it}) - \ln(\hat{\overline{\theta}}_{(t)}) + \varepsilon_{it} \qquad (12)$$

Let $\alpha_1 = \omega_1 + \gamma_0 + \zeta$ where ω_1 is the winner's curse correction for second-bidders. Suppose that γ_1 reflects only information-rent effects and is unaffected by the winner's curse. Since our econometric results suggest this to be the case, we feel comfortable in imposing it here. Then we can identify γ_0 as described above. If we assume that second-bidders are perfectly informed then $\omega_1 = 0$ and we can identify ζ using the same procedure as for first-bidders. Using this estimate of ζ we can then infer ω_0, the winner's curse correction for first-time bidders. Note that these assumptions yield the prediction $\alpha_1<\alpha_0$.

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[15] Our arguments further imply that second-bidders should have θ's in the upper range of the θ_t's at the time of first bid and that the greater the lag after which a second bidder enters, the higher his bidder was likely to have been in the set of θ's at the time of first bid. We do not model these effects in the current paper.

4.3 Alternative specifications

The estimated distribution of θ's depends on the functional form. We estimated two alternative specifications to (11). The first of these uses logged cumulative acceptances:

$$\ln(b_{it}) = \alpha_0 + \gamma_1 \cdot COMP_t + \ln(M_i) + \beta_2 \cdot \ln(CA_t + 10) + \varepsilon_i \tag{13}$$

We expect $\beta_2 > 0$. We then calculate $\overline{\theta}_{(t)} = (CA_t + 10)^{\beta_2} \exp(\zeta)$.

We also estimated a specification in which we replaced θM with F-ψX, from (4). This specification applies when the landowner, in forming the expected value of his development right conditional on winning, takes the market observation of $\tilde{F}^m$ as correct but does not update any market assessment of X. That is, the reservation value conditional on winning is $\tilde{v} = E(\tilde{F}^m - \psi X \mid b < \tilde{R}^*(\tilde{F}^m - X))$ with the expectation taken over $\tilde{F}^m$. This expression is identical to (7) whenever the landowner and the market share identical assessments of X.

Since $\psi \geq 1$ we use the functional form $\psi = 1+\exp(\beta_3+\beta_4(CA_t+10))$. We converted the results to θ using $\theta = \psi^{1-\beta}$ where β represents the underlying stochastic process, as in (2). The estimated equation is:

$$\ln(b_{it}) = \alpha_0 + \gamma_1 COMP_t + \ln(F_i^m - (1 + \exp(\beta_3 + \beta_4(CA_t + 10))) \cdot X_i) + \varepsilon_i \tag{14}$$

We expect bids to be increasing in cumulative acceptances, which requires $\beta_4 < 0$. There is no prediction for β_3.

5. Data

We collected a unique data set that includes all parcels that successfully applied to be eligible to bid in Carroll County starting with the program's inception in 1977. Because of the timeframe, we returned to the original parcel-level files via microfiche to track each parcel through each round of bidding. Changes of ownership presented the largest data integrity challenge. We constructed a panel dataset for each agent-parcel in each bidding round. The final data set is carefully constructed to ensure that we correctly followed each agent-parcel combination. By checking the MALPF's annual published report, which reports number of bidders and total acquisition expenditures, against the sum of accepted bids based on the parcel histories, we were able to ensure that we had as complete a record as possible of all bids. Final data include bids, parcel sizes, appraisals, agricultural values, and outcomes, as well as assorted parcel characteristics.

The MALPF auction data are affected by program events in the early 1990's. Between 1990 and 1995, in an attempt to ease the administrative pressure of conducting parcel appraisals and bid evaluations, the state decided to accept bids at two times during each fiscal year. In the first round of 1991, a state budget crisis led the state to rescind the MALPF budget after bids had been submitted and some appraisals had been conducted. No MALPF auctions were held for two years, although a few bids were submitted in the second round of 1991 and the first round of 1992. Funding was restored in 1993. In the first round of 1993, offers were made to 35 bidders on hold from the first round of 1991 bidding (those who would have been accepted had funding been available). Regular bidding recommenced in the second round of 1993.

In total, we analyze 22 auction rounds between 1980 and 1999. A second, competing preservation program became active in the County around 2000. We encountered several difficulties in acquiring sufficient post-1999 data to model the effect of this additional program on bidding behavior and therefore chose to use data only through 1999. Data summaries are provided in Tables 1 and 2. Summary statistics for the regressions are in Table 3.

There are 306 unique agent-parcels that submitted 574 unique bids. We lose data points for three reasons. (1) Some bidding parcels were deemed by the State as not likely to be accepted in that year, primarily because the bids were high relative to the budget, so no appraisal was conducted and no market easement value calculated (3 first bids lost). (2) For most of the bids in 1991 round 1 and all of the bids in 1991 round 2 and 1992, no budget was available and so no appraisals were conducted (21 first bids lost). (3) Some bids are clearly wild guesses or pure gambles. The highest ratio ever accepted was 3.31; therefore, we drop the five bids with ratios greater than this (all were first bids). None of these restrictions is likely to affect our conclusions. There were 277 usable first bids under these criteria.

The state also twice changed the formula by which agricultural values were calculated, in 1990 and 1996. To adjust agricultural values to a common formula in this model, we treated the post-1996 formula as correct, since the changes were adopted by program administrators solely to make the values closer to the true value of agricultural production on the land. We then regressed average per-acre values on dummy variables for pre-1991 and for 1991-1996 and used the coefficients to calculate a consistent agricultural formula. The formula we use is $X = \{0.263X_t,\ t \le 1991;\ 0.638X_t,\ 1991 < t \le 1996;\ X_t,\ 1996 < t \le 1999\}$ where X_t is a given parcel's agricultural value per-acre as reported by the program. We subtract this adjusted measure of X to obtain $M = F - X$.

There are several reasons why we think this solution adequately corrects for measurement error in X. First, the regression coefficients to adjust X were essentially invariant to the sample we used to estimate them. In other words, these changes in X were "across the board" and not restricted to any class of bidders, such as those with large parcels or rebidders. Second, other adjustments to X (such as no adjustment or half-adjustment) yielded results that were nonsensical, such as bids being far below the estimated reservation values, which suggests that landowners' assessment of agricultural value were closest to those computer under the post-1996 formula. Third, our estimates of equations (11) and (14) yielded quite similar results. These expressions are identical if and only if the X's are measured correctly.

In recording the number of bidders to measure auction competitiveness, we used all bids, not just first bidders or those for which full bidding data are available.

We convert all dollars to $2002 using the Northeast Housing CPI. Bids were inflated using the monthly CPI for the year and date they were submitted – July for years with one round and January and July for years with two rounds. To construct the budget-per-bidder, we use two possible budgets: (i) A statewide program budget for the given bidding round that was available as bids were being prepared. Since counties received more-or-less constant shares of this budget, this statewide figure is a good measure of budget availability in a given round. (ii) Acquisition expenditures at the county level for the previous bidding round, inflated for the previous year. Acquisition expenditures in 1985, for example, were inflated using the July 1985 CPI.

6. Results

6.1 Competition Effects

Program administrators are often eager to know the role of competition in reducing bids. Some situations might naturally have few eligible bidders, so policy-makers would like to know how successful an auction might be in driving down procurement costs. In other situations administrators may be able to increase the number of eligible bidders either by loosening the eligibility criteria or publicizing the auction more widely. They would then like to know whether the costs of these actions would likely be covered by the savings generated from lower-cost bids. Finally, administrators may want to use the effects of competition to argue to policymakers that a competition-based design is worth the increased complexity.

This section reports the effect of competition on bids. We examined several competition measures: (i) the number of bidders in that round, (ii) the State's announced budget for that round divided by the number of bidders, and (iii) the County's expenditure on parcels in the previous round divided by the number of bidders.

Endogenous competition is a problem in many empirical auction analyses. The largest potential problem arises when competition is measured by the number of bidders, since a large budget may attract more bidders but leave the budget-per-bidder unchanged, therefore yielding no change in the likelihood of a given bid being accepted and thus no change in the auction's competitiveness. Endogeneity problems are probably less severe when competition is measured in terms of budget-per-bidder. Year-to-year variation in the funds allocated to the MALPF reflects both variation in state revenues and public concerns about urban development and vanishing farmland. Although these phenomena may be correlated with bidder valuations, that correlation should be captured by the market easement value. Therefore, these budget measures are likely to be exogenous regressors.

To account for potentially endogenous numbers of bidders, we developed regressions to predict both the number of bidders and the budget-per-bidder. Much of the variation in the number of bidders depends on the State and County's promotion of the MALPF program and on publicized problems or successes. Both elements have distinct time components which we capture through period dummies. Intuition also suggests that successful bidders will beget more bidders and therefore we include as an instrument the number of bidders accepted in the previous round. Results are shown in Table 4.

We then use the predicted values from Table 4 either directly, as a predicted number of bidders, or indirectly to construct the State budget per predicted bidder, predicted State-budget-per-bidder, County expenditure (at t-1) per predicted bidder, and predicted County expenditures at t-1 per bidder at t. We refer to these latter four measures generically as budget-per-bidder.

Results are shown in Tables 5 and 6. All of the predicted competition variables show that greater competition leads to lower bids. The possible permutations to construct predicted competition are large; Table 5 represents a range of possible choices. Table 6 shows alternative specifications with two measures of competition, state budget per predicted bidder and predicted County expenditures (at t-1) per bidder (at t). These results are therefore most directly comparable to regressions 2 and 4.

To judge the magnitude of the effects and demonstrate the range of estimates, we calculated for each regression the implied mark-up at the median level of competitiveness, denoted γ_{median}. We find γ, the bid multiplier, ranging from 1.05 to 1.38, depending on our measure of competition. When we focus on the more appropriate budget-per-bidder measures of competition we find γ's ranging from 1.05 to 1.15. In other words, MALPF bids are roughly 5 to 15 percent above bidders' adjusted reservation values.

The relevant measure of competition in an auction such as the MALPF is not readily apparent, unlike for more traditional auctions with a fixed number of items for sale. The number of bidders alone (regression 1) is probably inappropriate to measure competition and so we focus on budget-per-bidder measures. Our results show that when competition is measured by the

State budget per bidder, the auctions appear less competitive than for County expenditures (in the previous year) per bidder. A regression using the total number of acres bid (not shown) yielded the correct sign for the competition measure (*i.e.*, more acres in the bidding pool led to lower bids), but this is also probably an inappropriate competition measure.

To demonstrate our findings in ways that would be more directly comparable to other auctions we also calculated the predicted percentage change in the median bid due to one additional bidder, holding the budgets fixed. This number represents, roughly speaking, the value to the auctioneer of attracting one more bidder. We found that one additional bidder on top of the median 30 bidders reduced bids by 0.1 percent to 1.4 percent, with a mode of 0.2 percent. This calculation has the advantage that it does not depend on identification of γ_0. Its interpretation does, however, rely on the additional bidder being the same as existing bidders.

6.2 Private Values Distribution

One of our key objectives is to estimate the distribution of θ, the bidder-specific parameter that captures the landowner's taste for farming and thus forms the basis for his reservation value. This private-value is the motivation for competition-based policies, which are designed to drive bids as close to the unobserved θ as possible. The distribution of θ is a key element of participation in land use policies generally, not only those that are competition-based, and thus affects enrollment in all voluntary enrollment land programs. This parameter is also a crucial factor determining the probability of land conversion, which in turn is the main variable of interest in many environmental land use policies (Sánchez et al., 2006). Finally, θ also indicates the compensation that should be awarded for eminent domain takings, since it can be used as a measure of how much a landowner values his property above the market.

We use the coefficients from the regressions in Tables 5 and 6. In all cases, the coefficients are consistent with higher cumulative acceptances leading to higher bids: $\beta_1 < 0$ (regressions 1-5), $\beta_2 > 0$ (regressions 6 and 7), and $\beta_4 < 0$ (regressions 8 and 9).

We used these results to infer the distribution of θ's, using the group-means implied by (10) and assuming that the winner's curse correction is zero. Graphs of the implied distribution functions are shown in Figure 1 for regressions 1 through 5 and Figure 2 for regressions 4 and 6 through 9; regression 4 is included in both graphs for comparison. We use $\beta = 1.54$ to convert the estimated ψ's from regression 12 to θ's, using $\theta = \psi^{1-\beta}$, where $\beta/(\beta-1)$ is the trigger between investment value and investment cost from (1).[16]

Recall that θ is less than 1 and that lower values of θ represent higher values for farm ownership and thus lower reservation easement values. Figures 1 and 2 show distributions of θ's that are far below one. Among regressions 2-7, which use the most appropriate measures of competition and do not require the additional volatility parameter β, the highest θ's at the end of the period we analyze are below 0.80. These relatively low values are perhaps not too surprising since the program is never valuable in expectation to a risk-neutral bidder with $\theta = 1$; the program is designed to attract and enroll low θ farmers. Our findings are a bit surprising since they suggest that all of the parcels could have been obtained with a take-it-or-leave-it offer of 0.80, even under a conservative assumption of no winner's curse correction. In contrast, the median ratio among accepted parcels over this period was 0.89.

Our estimates of the θ distribution are robust to functional form and competition measure. They are, however, sensitive to auxiliary assumptions about the level of competition

[16]We apply Dixit and Pindyck's notation (1994, p. 142) with parameters from Quigg's study of land development: $\rho=0.08$, $\delta=0.03$, and $\sigma=0.20$ (Quigg, 1993). We thank Charles Towe for this reference.

that would drive bids to the reservation value and, in regressions 8 and 9, the value of the volatility parameter. For example, if assume that γ = 1 when the number of bidders is 40 in regression 1, then $\hat{\hat{\theta}}_{(0)}$ = 0.39, roughly the same as the other Table 5 regressions. Likewise, if we take β=2, a typical value, then $\theta_{(0)}$ = 0.37 in regression 8, again similar to the regressions based on (9).

6.3 Winner's Curse

MALPF auction bidders would appear to be highly vulnerable to a winner's curse, since bidders bid without knowing the state's appraisal of the easement value, this market easement value should be informative to bidders, and bids that are selected are those that are lowest relative to this value. Bidders who recognize the winner's curse should bid farther above their *ex ante* reservation value.

To get a rough estimate of the winner's curse correction we estimated (12) using only second-bidders, using results from regressions 2, 3, 4, and 5 for $\hat{\hat{\theta}}_{(t)}$. There are 109 second-bidders with full data. The resulting estimates are shown in Table 7. We find substantially smaller intercepts for second-bidders in all four cases, as expected.

If bidders are concerned that greater competition enhances the winner's curse then γ_1 should be larger in magnitude for second-bidders than first-bidders. We find the opposite result, however, since the $\hat{\gamma}_1$s in Table 7 are uniformly below their counterparts in Table 5. This result leads us to suspect that the effect of competition on the winner's curse correction is essentially zero. This finding in turn leads us to focus on models with a winner's curse that is invariant to all factors except bidder information.

Our regressions provide a rough estimate of the size of the winner's curse correction by first-time bidders. If we assume that second-bidders are perfectly informed and that the winner's correction for first-time bidders is invariant to all other factors then the difference $\hat{\alpha}_0 - \hat{\alpha}_1$ is a measure of the winner's curse correction. We find winner's curse corrections of 7 to 15 percent of the unconditional reservation value.

A more sophisticated analysis of the role of information and experience would be valuable but lies beyond the scope of this paper. Joint estimation of first- and second-bidders would appear to be the most valuable approach but multiple sample selection issues would arise under this treatment, including whether offers were made to bidders at $b > M$ and whether they were accepted. We therefore leave this topic for future research.

6.4 Analysis of alternative programs

We next simulate the acquisition costs and acreage enrollments that would have occurred under a take-it-or-leave-it offer of 0.5. We use the distribution of θ's inferred from regression 4, which yields a middle-of-the-road estimates for θ's. We assume an offer ratio of 0.5 because it allows the cleanest comparison with the MALPF auction's observed outcomes. We use values of θ derived under the assumption that there is no winner's curse since this comparison is least favorable to the take-it-or-leave-it approach.

Under a take-it-or-leave-it offer of 0.5 and the regression 4 estimates, we predict that 137 first-time bidders would be accepted, 19,728 acres enrolled, and the total cost would be $32.2 million.

This prediction can be compared to the current auction, using observed ratios and an assumption that cut-off ratio was 0.98 in all years. We used observed ratios rather than simulated bids (constructed from (9)) because the observed ratios include bidders who received low drawings of *D* and thus suffered a winner's curse.[17] Any winner's curse that is experienced by bidders, even after it is corrected for, is advantageous to the auction set-up; these bidders enroll at too low a price and would not have enrolled at a take-it-or-leave-it offer equal to their bid. Under these assumptions 85 first-time bidders would have been accepted, 10,796 acres enrolled, for a total cost of $32.2 million. In other words, for the same budgetary outlay, the take-it-or-leave-it-offer would enroll 8,933 more acres, an 83 percent increase. This calculation, however, is made without any discounting and thus without any consideration for the timing of budgetary outlays. Our simulation also does not tackle the possibility that the pure take-it-or-leave-it alternative may lead either to rationing of enrollment or relaxation of the budget constraint.

Although this take-it-or-leave-it-offer appears superior to the auction approach, this comparison benefits from hindsight, which enables researchers to tailor the offer to the reservation value distribution. In contrast, auctions are valuable to policymakers precisely because they do not depend on the administrator knowing the θ distribution. Therefore, our estimated cost-saving is useful primarily where the underlying value distribution would be expected to be similar to Carroll County's. Our estimated distribution would conceivably apply, for example, to other Counties at similar stages of urban development, where similarity is measured by the number (or proportion) of preserved parcels and land price volatility.

[17]This procedure also adjusts bids so that they reflect a consistent procedure for the parcels' agricultural value. We do this by calculating the adjusted market easement value and multiplying by the observed bid ratio. In other words, we assume the bidders had the same ratio as under the current MALPF, applied to a market easement value that is consistent with the reservation value estimates.

6.5 Summary

We find that a potential winner's curse leads bidders to bid as if their values were 7 to 15 percent higher than they actually are. We then estimate a range of mark-ups above this adjusted reservation value, with a median estimate of 1.10, which implies that bids are 10 percent above the winner's-curse-compensated reservation value.[18] We cannot tell whether these mark-ups are equilibrium responses, due to the complexity of the bidding environment.

These findings were used to construct estimates of $\bar{\theta}_{(0)}$, the lower bound of the distribution of underlying reservation values, which were then combined with estimates of the distribution shape based on β_1 (or comparable coefficients estimated under alternative specifications) to provide estimates of the distribution of θ's. The unique set-up of the MALPF auction has allowed us to estimate these distributions using a reduced form bidding model rather than the more demanding structural econometric approach.

We find values for θ that are much lower than we expected, even under a conservative assumption of no winner's curse correction. These low values imply that the State could have enrolled more than 80 percent more acres under a take-it-or-leave-it offer than under the current MALPF set-up for a given expenditure.

Although evidence that corroborates or contradicts these results is scarce, some preliminary evidence is available from a similar farmland preservation program in Delaware, the Delaware Agricultural Land Preservation Foundation (DALPF) program. Under the DALPF auction, appraisals occur before the bidding and landowners then submit *ratio bids* in a sealed-bid first-price auction. The DALPF purchases the easements with the lowest ratios until the

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[18]Our breakdown of bids into a winner's curse correction and a mark-up over the adjusted reservation value is useful for intuition but is not strictly consistent with the theoretical model (8), which does not yield a clear distinction between the winner's curse correction and the bid mark-up due to information rent.

budget for that round is exhausted (DALPF, 2007). The most striking result from the DALPF auction is that the average bid to date is 0.51; in other words, quite a bit below the MALPF auction but similar to ratios that we argue should be observed.

Our estimated distribution could also be used to predict future costs and enrollment in the MALPF program. While a take-it-or-leave-it offer of 0.50 would have acquired more acreage for a similar program budget if implemented from the outset, our results suggest that a much higher offer would now be needed. At the end of our period of analysis, the offer would have had to be approximately 0.80.

There are many empirical issues that warrant further exploration. These include possible bidder collusion, asymmetric bidders, within-round distribution of θ, bidding by re-bidders, and the decision by bidders with ratios above one to accept a payment of R=1. Each of these topics would shed light on bidder behavior and thus potentially lead to better design of the MALPF auction and competition-based policies more generally. We leave these issues for future research.

Table 1. Summary statistics For MALPF Program 1980-1999: Budgets and bidders					
Bidding year and round	**Statewide budget, thousands ($2002)**	**Carroll County expenditures, thousands ($2002)**	**Number of bidders**	**Number of first-time bidders**	**First-time bids used in estimation**
1980	$5,208	$3,528	11	11	11
1981	$10,221	$4,647	32	32	32
1982	$10,933	$2,977	35	22	21
1983	$12,174	$3,048	53	38	36
1984	$8,762	$1,953	42	24	24
1985	$11,666	$1,565	29	14	13
1986	$13,627	$1,911	17	7	7
1987	$13,539	$1,096	20	17	15
1988	$12,740	$1,931	12	3	3
1989	$17,064	$3,682	27	19	19
1990	$24,794	$6,006	25	24	23
1990-2*	$17,835	$1,821	6	2	2
1991	$0	$0	29	22	22
1991-2	$0	$0	1	1	0
1992	$0	$0	4	1	0
1993	$6,795	$558	0	0	0
1993-2	$8,008	$867	22	13	4
1994	$7,120	$812	25	4	4
1994-2	$6,605	$806	30	5	3
1995	$6,535	$1,342	30	4	2
1995-2	$6,720	$795	21	1	1
1996	$12,030	$3,074	26	7	7
1997	$18,872	$3,199	22	6	4
1998	$22,986	$5,734	34	25	21
1999	$25,466	$2,522	21	4	3
Mean	**$11,188**	**$2,155**	**23**	**12**	**11**
Total	**$279,701**	**$53,875**	**574**	**306**	**277**

*In 1991 the MALPF Program funding was cut to cover a statewide budget deficit; however, the 29 bidders from 1991 were ranked and the lowest bids were funded in 1993 Round 1. All bidders in 1991 Round 2 and 1992 were summarily rejected. No bids were accepted in 1993 Round 1. Normal bidding resumed in 1993 Round 2.

Table 2. Summary statistics for MALPF program 1980-1999: Bids and ratios						
Bidding year and round	**Mean ratio, all bidders**	**Ave. bid per acre ($2002)**	**Highest accepted ratio**	**Accepte d bids**	**Cumulative acceptances (CA)**	**Ave. payment per accepted acre ($2002)**
1980	1.39	$3,407	2.10	10	10	$3,410
1981	1.15	$2,169	2.43	18	28	$1,963
1982	1.00	$1,613	0.95	16	44	$1,390
1983	1.36	$1,619	1.00	17	61	$1,332
1984	1.30	$1,528	1.00	11	72	$1,334
1985	1.20	$1,337	1.00	10	82	$1,175
1986	1.34	$1,305	1.29	12	94	$1,346
1987	1.78	$1,766	1.35	7	101	$1,591
1988	0.92	$1,662	1.20	7	108	$1,683
1989	1.29	$2,703	1.70	16	124	$2,520
1990	1.43	$3,827	1.79	20	144	$2,855
1990, 2nd round	1.16	$3,202	1.65	6	150	$3,202
1991	1.17	$3,139	1.31	6	156	$3,593
1991, 2nd round	.	$2,290	.	0	156	$0
1992	1.58	$2,676	0.00	0	156	$0
1993	.	.	.	0	156	$0
1993, 2nd round	0.86	$2,512	0.92	5	161	$2,053
1994	0.97	$2,428	0.59	1	162	$2,504
1994, 2nd round	0.83	$2,548	0.68	3	165	$1,906
1995	0.93	$2,679	0.74	3	168	$2,475
1995, 2nd round	0.92	$2,482	0.84	5	173	$1,481
1996	0.92	$2,287	0.87	10	183	$2,120
1997	0.92	$2,639	0.94	17	200	$2,197
1998	0.90	$2,980	0.87	16	216	$2,395
1999	0.87	$2,839	0.81	7	223	$2,567

Table 3. Summary Statistics for Variables Included in Regression Analysis

	Mean	Median	Std. Dev.	Min.	Max.	n
Tables 5, 6, & 7						
Bid per acre	2282	2021	1120	563	11444	277
ln(Bid per acre)	7.64	7.61	0.41	6.33	9.34	277
Number of bidders	31.7	30	10.99	6	53	277
State budget/bidder	529	402	340	208	2972	277
County exp/bidder	91.6	73.6	84.3	25.3	1001	277
Market easement value	3556	3377	1123	1432	10153	277
Cumulative acceptances	90	82	63.08	0	222	277
ln(Cumulative acceptances+10)	4.33	4.52	0.83	2.3	5.45	277
Table 4						
Number of bidders	24	25	11.88	1	53	24
State budget/bidder	604	432	600	0	2972	24
County exp./bidder	117.0	73.1	196.4	0	1001	24
Accepted last round	9.25	9	5.35	0	18	24

Table 4. Estimated Coefficients for Predicting Three Measures of Competitiveness (n = 24)

	Dependent variable		
	Number of bidders in round *t* **#A**	**State budget at *t* per bidder at *t*** **#B**	**County expenditure at *t*-1 per bidder at *t*** **#C**
County expenditure at t-1	--	0.33 (5.07)	0.12 (8.01)
State budget announced for t	-7.82×10^{-5} (0.26)	--	--
# accepted parcels at t-1	1.11 (2.59)	-53.61 (2.61)	-19.46 (4.05)
1991-1992 = 1	-15.63 (3.02)	404 (1.77)	182 (3.41)
Post-1992 = 1	1.29 (0.31)	-206 (1.13)	-49.84 (1.17)
Constant	16.64 (3.08)	400 (1.77)	22.02 (0.42)
Prob. > F	0.0076	0.0008	0.000
R^2	0.50	0.62	0.80

Table 5. Estimated Coefficients for ln(Bid per acre), first-time bidders only (equation (11), n = 277)

	#1	#2	#3	#4	#5
α_0	0.57 (6.47)	0.091 (2.46)	-0.10 (1.03)	0.033 (0.55)	-0.027 (0.35)
γ_1: Predicted Bidders (#A)	-0.014 (5.85)	--	--	--	--
γ_1: State Budget at *t* per Predicted Bidder (#A)	--	0.00031 (6.69)	--	--	--
γ_1: Predicted State-Budget-per-Bidder (#B)		--	0.00023 (3.27)	--	--
γ_1: County Exp. at *t*-1 per Predicted Bidder (#A)	--	--	--	0.00082 (2.79)	--
γ_1: Predicted County-Exp.-per-Bidder (#C)	--	--	--	--	0.00065 (3.46)
β_1	-0.0046 (6.10)	-0.0028 (4.90)	-0.0073 (4.37)	-0.0057 (5.71)	-0.0071 (4.58)
γ_{median} [b]	1.39	1.13	1.10	1.06	1.05
$\bar{\theta}_{(0)}$ [b]	0.31	0.42	0.35	0.40	0.38
R^2	0.56	0.58	0.53	0.52	0.53

[a]*t*-ratios in parentheses. [b]These estimates include Goldberger's correction (Goldberger, 1968).

Table 6. Estimated Coefficients for Alternative Specifications of ln(Bid per acre), first-time bidders only (equations (13) and (14), n= 277)

	#6 (Eqn. (13))	#7 (Eqn. (13))	#8 (Eqn. (14))	#9 (Eqn. (14))
α_0	-1.27 (13.89)	-1.55 (15.02)	-0.50 (8.53)	-0.31 (5.67)
γ_1: State Budget at *t* per Predicted Bidder (#A)	0.00035 (7.59)	--	0.00032 (7.21)	--
γ_1: County Exp. at *t*-1 per Predicted Bidder (#A)	--	0.00087 (2.83)	--	0.00087 (2.91)
β_2	0.13 (5.70)	0.23 (10.34)	--	--
β_3	--	--	0.65 (5.43)	0.97 (14.71)
β_4	--	--	-0.011 (3.38)	-0.011 (4.75)
γ_{median} [b]	1.15	1.07	1.14	1.07
$\bar{\theta}_{(0)}$ [b]	0.38	0.36	0.59[c]	0.52[c]
R^2	0.55	0.47	0.57	0.50

[a] *t*-ratios in parentheses. [b] These estimates include Goldberger's correction (Goldberger, 1968).
[c] Assumes $\theta = \psi^{-0.54}$

Table 7. Estimated Coefficients for ln(Bid per acre), second-time bidders only (equation (12), n = 109)

	#10	#11	#12	#13
α_0	-0.03 (0.56)	-0.18 (3.26)	-0.09 (2.06)	-0.17 (4.44)
γ_1: Predicted Bidders (#A)	--	--	--	--
γ_1: State Budget at *t* per Predicted Bidder (#A)	0.00026 (3.18)	--	--	--
γ_1: Predicted State-Budget-per-Bidder (#B)	--	0.00004 (0.53)	--	--
γ_1: County Exp. at *t*-1 per Predicted Bidder (#A)	--	--	0.0001 (0.37)	--
γ_1: Predicted County-Exp.-per-Bidder (#C)	--	--	--	0.00017 (0.88)
$\ln(\hat{\hat{\theta}}_{(t)})$	from #2	from #3	from #4	from #5
$\hat{\alpha}_0 - \hat{\alpha}_1$	0.12	0.08	0.12	0.14
R^2	0.44	0.49	0.48	0.50

[a] *t*-ratios in parentheses.

Figure 1. Distribution of taste parameter, regressions 1-5

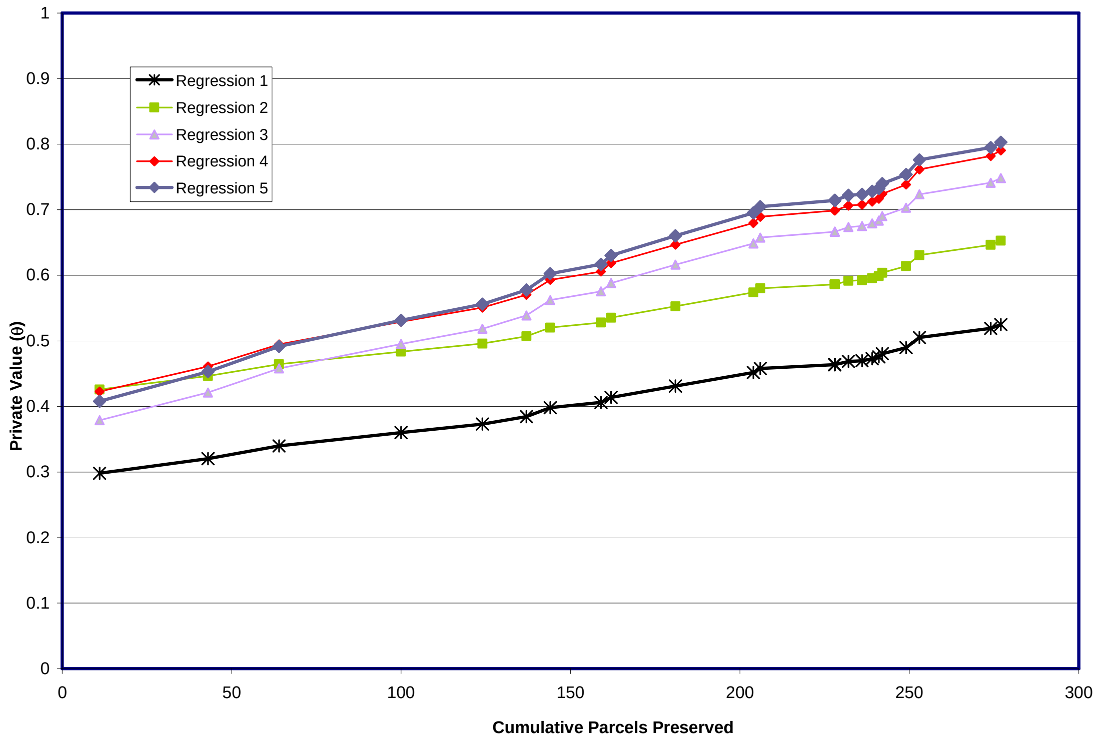
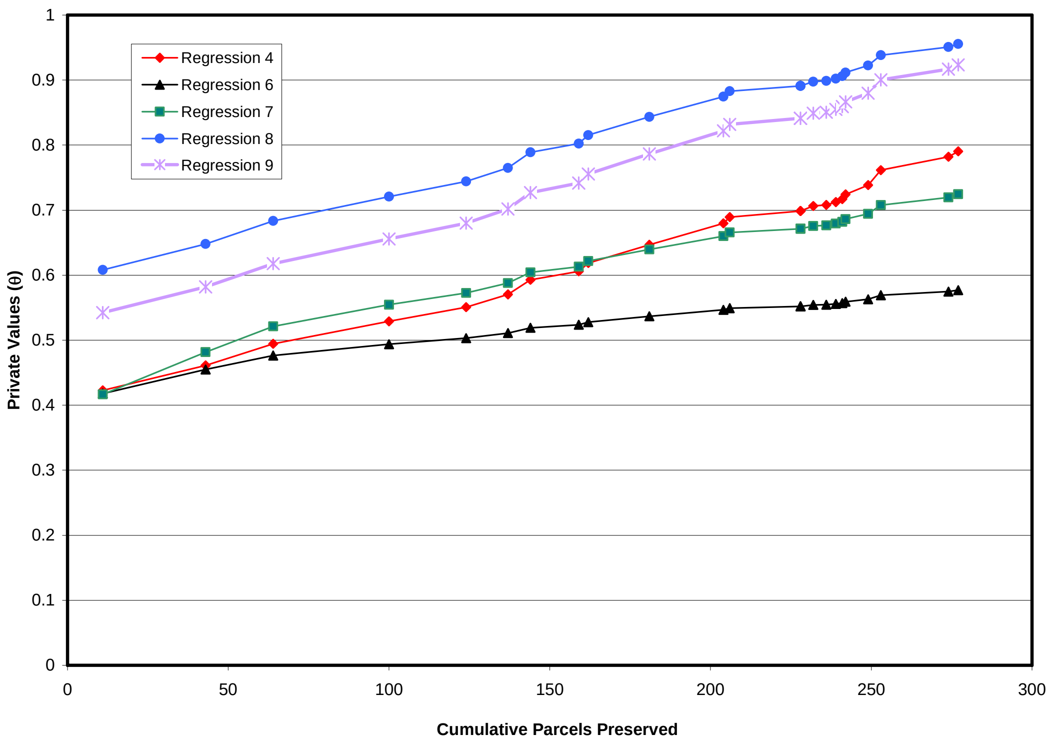


Figure 2. Distribution of taste parameter



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