# Reserve Prices, Minimum Support Prices and Farmers' Revenues: Government Grain Policy through the Prism of Rice Auctions in North India

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**Abstract**

This paper undertakes semi-nonparametric estimation of an ascending auction model for paddy (rice) auctions in a North Indian paddy market, with 2 principal objectives. First, it computes optimal reserve prices and simulates farmers' revenues from auctions at these reserve prices, and compares these to the observed reserve prices (and corresponding farmers' revenues) in the sample. While the optimal reserve prices are significantly different from the sample reserve prices, the farmers' revenues under the two sets of reserve prices are strikingly similar. Second, it undertakes a reassessment of government policy on minimum support prices. It shows that government purchases of processed rice through a levy, at an appropriately chosen levy price, can achieve the objective of providing price and farmer revenue support as effectively as direct government purchases of paddy at the minimum support price, and at a significantly lower cost[2].

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# 1 Introduction

India is the second largest producer of rice in the world, contributing more than a fifth of the world's rice output. The large government participation in the rice market is probably well known: (i) the government purchases large quantities of rice for distribution to the rural and urban poor through subsidized food outlets in its 'public distribution system' (PDS); (ii) it also announces a 'minimum support price' (MSP) for paddy (unprocessed rice) at sowing time, and attempts to buy directly from paddy markets in order to support this price and protect farmers' revenues.

Less salient perhaps is the fact of a thriving private trade in paddy purchases and milling, which is supported by government-provided market infrastructure; one of the ways in which paddy is sold is through the institution of ascending auctions run by market-appointed auctioneers in these government-organized markets.

In this paper we analyze paddy auction data from one such market in an important rice producing state in North India (district Panipat in the state of Haryana), in terms of a formal structural model of ascending auctions, and estimate millers' value distributions for paddy using a semi-nonparametric method. Our major objectives are to use these estimates to answer two sets of questions. First, how good are the reserve prices set by the auctioneer from the point of view of maximizing the expected revenue of the paddy selling farmers? We answer this by (a) estimating 'optimal reserve prices' for each paddy lot auctioned in our sample and comparing these to the actual reserve prices set by the auctioneer. (b) We also directly compare simulated ex ante expected revenues from the sale of each lot under the alternative sets of actual versus optimal reserve prices.

Our second question relates to sources of government support for farmers' revenues. The government is supposed to ensure that paddy market prices do not fall below the announced MSP; in order to ensure this, the government needs to maintain a presence as a direct buyer of paddy in many paddy markets. However, the government is also a large buyer of processed rice, doing so through the institution of a *levy*: private millers must sell a given proportion of their milled rice to the government at a levy price determined around harvest time as a markup over the MSP. Thus this levy price for rice influences millers' values for paddy in the paddy auction, and through this, influences farmers' revenues. Using our estimated auction model, we ask what level of levy price would act as a *substitute* for the government's direct interventions in paddy markets to protect the MSP.

The above questions are important for the following reasons. The choice of reserve price in an ascending auction affects the revenue that the seller expects from it; in order to determine the revenue maximizing or 'optimal' reserve price, the seller needs to know the distributions from which potential bidders draw their values for the grain. The estimation exercise helps to do precisely that, and the optimal reserve prices that we estimate thereafter may be used as a tool for policy advice to auction markets such as these. On the other hand, a finding that estimated optimal reserve prices, or more importantly expected revenues from auctions that use these reserve prices are not too different from expected revenues at reserve prices observed in the sample, can speak strongly to the good functioning of an auction market, including the informal knowledge that the auctioneer has of bidders' values. In fact, we show that this latter striking conclusion holds for the market that we study.

The second question probably has an even more important bearing on farmers' revenues and on government foodgrain policy. The government procures rice from Panipat and other markets through two routes - first, it buys paddy directly from the farmers at a pre-announced *Minimum Support Price* (MSP) and gets it milled into rice from private millers and pays them milling charges in return. Rice procured through this route is called *Custom Milled Rice* (CMR). Second, it requires the private millers to sell a pre-announced percentage of their (milled) rice to it at a pre-announced *levy price*, which is a mark-up over the MSP. Rice procured through this route is called *levy rice*. Acquiring rice through the CMR route is more expensive for the government since it requires the government to maintain a presence and purchase infrastructure at myriad primary paddy markets, and to arrange to get its paddy milled by private millers, whereas for levy rice, it simply has to accept delivery of the processed rice from millers. The main important role that the CMR route therefore serves is that it permits the government to ensure that grain sells in primary paddy markets at its announced MSP, at least.

We ask: Can the government operate mostly through the second, levy route, thereby reducing the economic cost of rice procurement, without adversely affecting farmers' incomes? Specifically, we first compute farmers' expected revenues from paddy auctions when the government is a bidder with a bid equal to the MSP. We then compute the levy price required (that, through its effect on bidders' values for paddy) to yield the same farmers' expected revenues if the government were absent from the paddy auctions. This price is only about *Rs* 14 higher than the actual levy price fixed for the season, an increase that would easily preserve the economic advantage of using the levy rather than the CMR route. We are thus able to make a strong case for the use of the levy route both for grain purchase for the PDS as well as for providing, indirectly but effectively, price and revenue support for farmers at paddy auction markets.

Structural estimation of auctions is crucial to asking policy questions of the above sort, as it enables us to simulate alternative states of the world. There is now a large and growing literature on such estimation, starting with Paarsch (1992), Laffont, Ossard and Vuong (1995), Athey and Levin (2001) among others. See Athey and Haile (2005) for a survey. One of the first papers to estimate optimal reserve prices at auctions is Paarsch (1997). Seminonparametric estimation is increasingly popular (see Chen(2007)); our implementation for auctions is similar to that by Brendstrup and Paarsch (2006). Research on agricultural markets that uses the structural auction framework is recent and relatively limited (see Meenakshi and Banerji (2005), Tostao, Chung and Brorsen (2006)).

In what follows, we describe the data in Section 2, followed by the ascending auction model, identification and estimation, and estimation results in Sections 3-5. Sections 6 and 7 report the results related to optimal reserve prices, and to considerations of levy price setting versus direct government purchases at paddy auctions as alternatives to supporting farmers' revenues in the auction context. Section 8 concludes.

# 2 Data

We use data from auctions of parmal paddy at the Panipat market, in the state of Haryana (North India) [3]. Paddy is raw harvested grain which on milling is converted into rice (grain separated from chaff and most often polished subsequently). Parmal paddies are high-yielding varieties, derived in part from the $IR - 8$ releases (vintage early Green Revolution era). The rice milled from Parmal paddy is shorter in length and thicker in width than traditional (Basmati) varieties; it has a relatively poor cooking quality. At about one-fifths the price of the traditional varieties, it is the cheapest rice in the market. The Parmal arrivals begin in October and the marketing season lasts for about a month. About 60,000 quintals of paddy arrives in the surveyed market over the entire season, of which more than 60% is concentrated in the first 3 weeks of October. The arrivals peak around the end of the first week, with about 3000 quintals arriving per day.

Panipat is a regulated wholesale grain market set up by the Government under the Market Regulation Act and run by a Market Regulation Commitee. The mode of selling the grain is through auctions. The interacting players on the ground in this market include commission agents who sell the grain on behalf of the farmers (*katcha arhtias*), and millers who purchase the grain. The government also purchases paddy at these auctions, through a commission agent (the participation of the government in this and many other markets was very limited in the given year, 1999, though). When it participates in the auction of a paddy lot, the government bids the minimum support price (MSP) that it announced for paddy during sowing season. Commission agents are registered with the Market Committee and their license is renewed annually.

The buyers side of the market is rather concentrated. Though 25 distinct buyers were recorded over the entire marketing season, the combined market share of the two largest buyers (with large mills located within 5 $km$ from the mandi) was about 45% of the total arrivals. The remaining buyers had smaller mills and picked up smaller shares of the market arrivals. It was observed that the two large buyers avoided competing with each other by alternating the days on which they made large purchases. Such collusion is expected, ceteris paribus, to depress the win price. Meenakshi and Banerji (2005) undertake parametric maximum likelihood estimation of both

[3]The data are taken from a primary survey conducted in 1999 by Meenakshi and Banerji (2005). See for example, their cited paper.

the noncooperative and the collusive models (for this market) and compare them using Vuong's test. Their results support the hypothesis of collusion, in the form of simple bid rotation by the 2 largest buyers. In the present study, therefore, we work with the maintained assumption of collusive behavior on the part of the two large buyers[4].

The sellers side of the market by contrast is far from concentrated. A *katcha artia* typically serves between 100 and 500 farmers; and earns a commission of 2% of the total value of sales from the farmer. There were 49 *katcha artias* in this market with small individual shares (none exceeding 5%).

The parmal paddy lots are sold through oral ascending auctions. The auctioneer after visual inspection of a lot announces[5] a start price for the lot, following which the bidders whose valuation for the lot is less than the start price leave. The remaining bidders are essentially the active bidders for the lot. The auctioneer then raises the price in small increments, as long as there are at least two interested bidders (active bidders keep exiting as the price goes past their valuation). The auction ends when only a single bidder is still interested. This bidder wins the object and pays an amount equal to the price at which the second-last bidder dropped out. The auctioneer receives 0.8% of the win price.

The data set was constructed using a primary survey conducted in October 1999 (See footnote (1).). This information was supplemented using market commitee records and personal interviews with millers and farmers. Based on the market shares and differences in the processing capacity, broadly two bidder-types are discernible[6]. The information recorded for each auction was the seven covariate quality vector, start (or reserve) price, win price, identity of the winner, number of potential and active bidders.

Parmal paddy is heterogeneous in several quality characteristics, variations in which affect the valuation a bidder may have for a lot. Based on information from agricultural scientists, market commitee officials and bidders at auctions, the following seven quality characteristics emerged as potentially important: moisture content, uniformity of grain size, grain luster, presence

[4]Specifically, collusion that involves simple bid rotation between them.

[5]Based on his assessment of the quality of the lot.

[6]The two large players being one type of bidder, and the small players being the other type.

of chaff, green and immature grains, broken grains and a category of other variables (encapsulating evidence of disease or pest infestation). The auctions proceed at a fast pace and so lab testing a sample for quality at the auction site is not possible. The bidders perform visual and other simple on-the-spot tests (such as breaking the grain and looking at the cross-section for evidence of brittleness). To construct the data set, a quality vector was assigned to each lot by evaluating each characteristic for a lot on a scale of either 1 to 3 (worst to best) or 1 to 2 (poor and good); the determination of quality was done using the same visual and other tests, by a trained enumerator.

The number of distinct winners on any given day was used as a proxy for the number of potential bidders for all auctions on that day[7]. The bidders who continued to participate in the auction once the start price was announced, constituted the set of active bidders for that auction.

Data for the sample are summarized in Table 1 below.

Table 1
Summary statistics of the sample

| | Mean | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|
| Start price (Rs./quintal) | 483.79 | 30.24 | 350 | 580 |
| Win price (Rs./quintal) | 505.40 | 23.80 | 400 | 611 |
| No. of potential bidders per lot | 8.51 | 0.81 | 5 | 9 |
| No. of active bidders per lot | 3.34 | 0.70 | 2 | 5 |
| Moisture content | 2.35 | 0.57 | 1 | 3 |
| Uniformity in grain size | 2.43 | 0.57 | 1 | 3 |
| Presence of chaff | 2.07 | 0.56 | 1 | 3 |
| Presence of brokens | 1.46 | 0.50 | 1 | 2 |
| Grain lustre | 1.59 | 0.49 | 1 | 2 |
| Green and immature grain | 1.17 | 0.38 | 1 | 2 |
| Others | 1.37 | 0.38 | 1 | 2 |

# 3 Theoretical Model

We study this market with oral ascending auctions as the selling mechanism within the independent private values framework. That is, we assume it is common knowl-

[7]Bidders generally stay through the bidding all day, and it is unlikely that there are bidders who don't win even a single lot.

edge that each bidder $i$'s (here miller) valuation for a given lot of grain is privately known (to him) and is an independent random variable from a distribution $F_{V_i}(.)$.

A bidder's valuation for a paddy lot depends upon the difference between the price he expects to receive from selling rice (paddy is processed into rice in mills) and the cost of processing paddy. Millers operating in this market are required to sell 75% of their rice to the government at Rs 913 per quintal[8]. The quantity and quality of rice (better quality rice fetches a higher price) that a lot of paddy produces depends on its observable quality characteristics. But the processing cost of paddy is mill-specific[9] and privately known. Thus, an IPV specification for valuations (conditional on observed quality) may be a reasonable assumption for this market.

Describing the set up more formally, based on the (observable) quality of the lot of grain being auctioned and knowledge of processing costs, a bidder places a value $v_i$ on the lot. The strategy set of each bidder consists of all (measurable) functions from the set of possible valuations to the set of possible bids; conditioning on his value, a strategy is just a bid. In an ascending auction, each bidder $i$'s bid $b_i$ is essentially the price at which he drops out. With IPV, it is a weakly dominant strategy for each bidder to drop out once the price rises past his valuation. Staying any longer would cause him to bear a negative payoff if he won. It also doesn't make sense to drop out earlier because there is always a possibility that all of the other bidders drop out by a price $w$ that is lower than $v_i$, in which case he would get a positive payoff (equal to $v_i - w$). As a result, the win price in an ascending auction is essentially the second-highest bid, which coincides with the second-highest valuation.

# 4 Nonparametric Identification and Seminonparametric Estimation of valuation distributions

In general, before attempting estimation of the bidders' value distributions from the set of observables, one needs to check whether statistically, the former can be identified from the latter; i.e., whether there exists a unique inverse for the

[8]These were the levy percentage and levy price figures for kharif 1999-2000 in the state of Haryana.

[9]With the large millers' costs typically being lower than the smaller millers' costs.

mapping from the latent distribution to the observable data. Certain economic assumptions and restrictions are typically imposed on the latent structure and the way in which that could have generated the sample data. For parametric estimation, it is sufficient to verify parametric identifiability, which is based on the premise that the functional form of the distribution from which the sample could have been drawn is known. Nonparametric estimation however, can be carried out only if nonparametric identifiability holds. Nonparametric identification results do not assume a functional form for the latent distribution and hence also have more stringent data requirements (than parametric identification).

For the independent private values framework, nonparametric identification results follow from Athey and Haile (2002)[10]. Since the lot characteristics are observed and recorded, if we also assume a functional form for the effect of these (lot-specific) covariates, the latent valuations are reduced to (or can be analyzed within) an IPV paradigm.

In the symmetric IPV model, the common distribution $F_V(.)$ from which all players draw values is identified from the win price (Athey and Haile (2002), Theorem 1)[11].

In the asymmetric IPV model, assuming that each $F_{V_i}(.)$ is continuous and that the support of the distributions $supp[F_{V_i}(.)]$ is the same for all $i$, each $F_{V_i}(.)$ is identified if the win price and identity of the winner are observed (Athey and Haile 2002, Theorem 2). In this paper, we use the asymmetric model, owing to the asymmetry in bidder values that we can infer from the market shares of the millers: recall that the 2 large millers won about 45% of the lots, while the others won uniformly small shares.

As the model is nonparametrically identified, we implement seminonparamtric estimation of the value distributions using a recently proposed strategy (Brendstrup and Paarsch (2006); see Chen (2009) for a general survey). We assume that at the $t^{th}$ auction for a lot with quality vector $z_t$, the valuation of player i of type j is given by

$$ln\ v_t^{ij} = z_t\beta\ +\ \mu\ +\ u_t^i \tag{1}$$

[10]These build on earlier results by Arnold, Balakrishnan and Nagaraja (1992) and Meilijson (1981).

[11]Adapted from Arnold, Balakrishnan and Nagaraja (1992).

The parameter vector $\beta$ that captures the marginal effect of each lot-specific characteristic, is unknown and needs to be estimated. By type or class of bidder we will refer to 2 bidder classes: 1. the 2 large bidders; 2. the rest of the bidders. Owing to bid rotation, only 1 large bidder is present at each auction, the rest being the small bidders. So, $\mu$ is the parameter that captures the asymmetry between the two bidder classes

$$\mu \begin{cases} = 0 & \text{for the large bidder} \\ \neq 0 & \text{for small bidders} \end{cases}$$

$u_t^i$ which is the idiosyncratic component of bidder i's valuation at auction t is assumed to

1. be independently and identically distributed for all bidders with distribution function $F_U(.)$,
2. have $E[u_t^i] = 0$,
3. be independent of $z_t$.

We denote the large bidders' valuation density and distribution functions by $f_{V_1}(.)$ and $F_{V_1}(.)$ and small bidders'valuation density and distribution functions by $f_{V_2}(.)$ and $F_{V_2}(.)$ respectively.

We approximate the density function $f_U(.)$ by a hermite series expansion. Gallant and Nychka (1987) show that a density with mean zero, support $(-\infty, +\infty)$ can be estimated using a hermite series. The hermite series is in the form of a polynomial squared times a normal density function (with mean zero) with the coefficients of the polynomial restricted so that the series integrates to one[12]. The rule for determining series length is data-dependent (the length of the series should be higher, the greater the sample size).

Hermite polynomials are a class of orthogonal polynomials that have support over the entire real line and the gaussian function $exp(-x^2/2)$ as the weighting function. Given the size of our sample (280 data points), a truncated Hermite series of order two is reasonable. Also, we employ as weighting function, a normal density with mean zero and standard deviation 0.4.

[12]This ensures that we have a density function.

The density function $f_U(.)$ of $u_t^i$ is approximated as

$$\hat{f}_U(s) = [\sum_{k=0}^{2} \gamma_k \; h_k^*(s)]^2 \; exp[\frac{-s^2}{2(0.4)^2}] \tag{2}$$

where

$h_k^*(.)$ is the $k^{th}$ order normalized Hermite polynomial.

$\gamma_k$ are the coefficient parameters to be estimated[13].

**Asymmetric Bidders**

Let $G(.|F_{V_1,V_2})$ be the joint distribution of the win price (second-highest order statistic) and the winner identity (the last remaining bidder). We need to estimate $F_{V_1}(.)$, $F_{V_2}(.)$ using $G(.|F_{V_1,V_2})$. This is implemented using the method of quasi-maximum likelihood.

Maximum likelihood estimation requires determination of $\hat{f}_{V_1}(.), \hat{f}_{V_2}(.)$ such that

$$(\hat{f}_{V_1}, \hat{f}_{V_2}) \quad = \quad argmax_{f_{V_1}, f_{V_2}} \frac{1}{T} \sum_{t=1}^{T} \; ln \; g(y_t|F_{V_1,V_2}) \tag{3}$$

where

$g(.)$ is the joint probability density function of the win price and the winner identity

$$\hat{f}_{V_1}(v) \quad = \quad \frac{1}{v} \; \hat{f}_U(ln \; v \; - \; z_t\hat{\beta} - \hat{\mu}) \tag{4}$$

$$\hat{f}_{V_2}(v) \quad = \quad \frac{1}{v} \; \hat{f}_U(ln \; v \; - \; z_t\hat{\beta}) \tag{5}$$

where $\hat{f}_U$ is defined in equation (2).

[13] Subject to the restriction $\sum_{k=0}^{2} \gamma_k^2 = 1$, in order that $\hat{f}_U(.)$ is actually a density function (i.e., such that it integrates to one). See the next section.

Note that the parameter space must be restricted so that $\hat{f}_{V_1}, \hat{f}_{V_2}$ are in fact densities. So we need the constraints

$$\int_0^{+\infty} \hat{f}_{V_1}(y)\ dy \quad = \quad 1 \tag{6}$$

$$\int_0^{+\infty} \hat{f}_{V_2}(y)\ dy \quad = \quad 1. \tag{7}$$

This can be implemented through the following restriction on the parameter space

$$\int_{-\infty}^{+\infty} \hat{f}_U(u)\ du \quad = \quad 1. \tag{8}$$

From equation (2), this implies the following restriction on the hermite coefficients

$$\gamma_0^2 \ + \ \gamma_1^2 \ + \ \gamma_2^2 \quad = \quad 1. \tag{9}$$

Thus to obtain $\hat{f}_{V_1}, \hat{f}_{V_2}$, we maximize $\sum_1^T \ ln\ \hat{g}(.)$ with respect to $\hat{\beta}$, $\hat{\mu}$, $\hat{\gamma_k}$ (k=0,1,2) subject to the restriction that the norm of the hermite coefficients equal one.

The number of potential bidders $p$ at an auction is assumed to be the same as the number of distinct winners on the day of that auction. But assuming there is collusion among the two large bidders, the effective number of potential bidders at an auction reduces to $p-1$.

The joint probability density of the win price and a specific small bidder winning is given by

$$\begin{pmatrix} p-3 \\ n-1 \end{pmatrix} F_{V_1}(r)(F_{V_2}(r))^{p-n-2}(1-F_{V_2}(w))(n-1)(F_{V_2}(w)-F_{V_2}(r))^{n-2}f_{V_2}(w)$$
$$+ \quad \begin{pmatrix} p-3 \\ n-2 \end{pmatrix} (F_{V_2}(r))^{p-n-1}(1-F_{V_2}(w))[(n-2)(F_{V_2}(w)-F_{V_2}(r))^{n-3}f_{V_2}(w)$$
$$(F_{V_1}(w)-F_{V_1}(r)) + (F_{V_2}(w)-F_{V_2}(r))^{n-2}f_{V_1}(w)]$$

The first term in this equation corresponds to the case where the large bidder's valuation is less than the start price $r$.

The probability that the large bidder's valuation is less than $r$ is $F_{V_1}(r)$; the probability that a specific small bidder's valuation is more than $w$ is $(1-F_{V_2}(w))$. The realized set of remaining $(n-1)$ bidders (all small) could be any one of $\left(\begin{array}{c} p-3 \\ n-1 \end{array}\right)$ different possibilities. The probability that one of these has valuation equal to $w$ while the rest have valuations between $r$ and $w$ is $(n-1)f_{V_2}(w)(F_{V_2}(w)-F_{V_2}(r))^{n-2}$. Finally, the probability that the valuations of all the (remaining) $(p-n-2)$ potential bidders are less than the reserve price is $(F_{V_2}(r))^{p-n-2}$.

The second term consists of two possibilities, the large bidder's valuation being between $r$ and $w$, and it being exactly $w$. In either case, the probability that a specific small bidder's valuation is greater than $w$ is $(1-F_{V_2}(w))$, the realized set of non-winning active small bidders can be one of $\left(\begin{array}{c} p-3 \\ n-2 \end{array}\right)$ different combinations, and the probability that the $(p-n-1)$ remaining small bidders are inactive is $(F_{V_2}(r))^{p-n-1}$. Given this, the probability that the large bidder's valuation is exactly $w$ and that the $(n-2)$ small bidders valuations are between $r$ and $w$ is $f_{V_1}(w)(F_{V_2}(w)-F_{V_2}(r))^{n-2}$; while the probability that the win price valuation belongs to one of $(n-2)$ small bidders and that the large bidder's and $(n-3)$ small bidders' valuations lie between $r$ and $w$ is $(n-2)f_{V_2}(w)(F_{V_1}(w)-F_{V_1}(r))(F_{V_2}(w)-F_{V_2}(r))^{n-3}$.

The joint probability density of the win price and a specific large bidder winning is given by

$$\left(\begin{array}{c} p-2 \\ n-1 \end{array}\right) F(r)^{p-n-1}(1-G(w))(n-1)(F(w)-F(r))^{n-2}f(w)$$

The probability that a specific large bidder's valuation is greater than the win price is $(1-F_{V_1}(w))$. The realized set of the other $(n-1)$ active bidders who are all small is akin to a random draw from the set of $(p-2)$ small potential bidders and could be one of $\left(\begin{array}{c} p-2 \\ n-1 \end{array}\right)$ different combinations. The probability that one of these $(n-1)$ small bidders has valuation equal to the win price while the rest $(n-2)$ small non-winning active bidders' valuations are between the reserve price and the win price is $(n-1)f_{V_2}(w)(F_{V_2}(w)-F_{V_2}(r))^{n-2}$. Finally, the probability that $(p-n-1)$ small bidders' valuations are less than $r$ is $(F_{V_2}(r))^{p-n-1}$.

# 5 Estimation Results

We now present the results from our constrained maximum likelihood exercise attempted using semi-nonparametric approximation to the true density functions.

We have estimated the $10 - tuple$ covariate coefficient vector $\beta$, the parameter capturing the difference in means $\mu$ and the coefficients in the hermite series expansion $\gamma_0$, $\gamma_1$, $\gamma_2$. The estimates for $\beta$ and $\mu$ are listed in Table 2. The hermite coefficients as estimated in our exercise are $\hat{\gamma}_0 = 0$, $\hat{\gamma}_1 = 0$, $\hat{\gamma}_2 = 1$.

Table 2
Semi-nonparametric maximum likelihood estimates for the asymmetric bidders specification

| | Parameter estimate | Standard error |
|---|---|---|
| Constant | 5.9464*** | 0.0601 |
| Moisture content | 0.0340*** | 0.0150 |
| Uniformity of grain | 0.0178* | 0.0157 |
| Presence of chaff | 0.0206* | 0.0156 |
| Presence of brokens | 0.0214 | 0.0191 |
| Lustre of grain | 0.0256* | 0.0189 |
| Green and immature grain | 0.0004 | 0.0188 |
| Others | 0.0047 | 0.0270 |
| Week 2 dummy | −0.0559*** | 0.0225 |
| Week 3 dummy | 0.0039 | 0.0210 |
| Difference in means | −0.1458*** | 0.0257 |
| Mean log-likelihood | -3.3096 | |

Note that *, **, *** indicate significance at 25%, 10%, 5% levels respectively.

Thus the estimated densities are

$$\hat{f}_{V_1}(v) \;=\; \frac{1}{v}\,\hat{f}_U(ln\ v \;-\; z_t\hat{\beta} - \hat{\mu})$$

$$\hat{f}_{V_2}(v) \;=\; \frac{1}{v}\,\hat{f}_U(ln\ v \;-\; z_t\hat{\beta})$$

where,

$\hat{\beta} = (5.9464, 0.0340, 0.0178, 0.0206, 0.0214, 0.0256, 0.0004, 0.0047, -0.0559, 0.0039)$

$\hat{\mu} = -0.1458$

$\hat{f_U}(s) = \frac{(s^2-1)^2}{0.76} exp[\frac{-s^2}{2(0.4)^2}].$

Since all the seven paddy characteristics are measured on a scale that is increasing in quality (either 1 to 2 or 1 to 3), they are expected to have positive signs. Our results are consistent with this expectation. Moisture content has the largest coefficient (also highly significant) suggesting that a substantial quality premium is associated with this characteristic. Three of the characteristics, viz., brokens, green and others are found to be not significant in the sample. A negative coefficient for *week* 2 dummy implies that a lot of a specific quality has a lower valuation in *week* 2 than in *week* 1. One reason for this could be that anxiety to fill up coffers is greater in *week* 1 and pumps up the valuations (the two large bidders for instance, had made 80% of their purchases by the end of *week* 1). There could be other reasons as well, such as the prices in this market get influenced by those prevailing in the other bigger markets. A negative sign on the parameter estimate (highly significant) for difference in means implies that the large bidders draw their valuations from a higher distribution than the small bidders, i.e., given a lot with a particular quality vector, the large bidders have a greater valuation for it than the small bidders.

We provide a plot of the semi-nonparametrically estimated distribution of residuals[14] in the appendix (figure 1). It can be noticed that our density is unimodal and truncated at -1 and +1[15], implying that the probability of the valuation of a bidder for a lot being far from the expected valuation for that quality is zero.

The valuation distributions of bidders in this market have previously been estimated parametrically, using a lognormal distribution[16]. Lognormal functional forms are quite popular with researchers seeking to approximate positive (or right) skewed distributions because they allow flexibility on two accounts - location and variance. We therefore test whether for the asymmetric bidders specification, the semi-nonparametrically estimated model is indeed an improvement over the log-

[14]Residuals are simply the logarithm of the valuations conditional upon the lot quality and upon the bidder type.

[15]This is unlike the lognormal approximation where the density is asymptotic on either side.

[16]See Meenakshi and Banerji (2005).

normal approximation.

It is found that the value of the Vuong's statistic for testing the lognormal model versus the semi-nonparametric model is

vstat = -10.21046

which strongly suggests that the semi-nonparametric estimates are closer to the actual data-generating process.

# 6 Optimal Reserve Prices

The choice of the reserve price (the threshold price $r$ below which the seller does not sell the object) constitutes an important instrument with the seller to increase his profits from an auction. In an ascending auction, selecting a reserve price to maximize expected profits (such a reserve price is known as an 'optimal reserve price') balances the tradeoff between not selling the object (in the event that $r > Y_1$)[17] with the possibility of a higher revenue ($= r - Y_2$) in case the reserve price lies between the highest and the second-highest valuations (i.e., in the event $Y_2 < r < Y_1$).

With collusion between the two large bidders taking the form of bid-rotation (i.e., both never together participate seriously in any one auction), the analysis and derivation of optimal reserve price follows the assumption of non-cooperative behavior among the bidders with the number of large bidders at an auction being equal to 1.

Suppose there are $N_i$ bidders of type $i, i = 1, 2$ (large and small bidders respectively). If a specific bidder of the $i^{th}$ type wins the auction, the distribution of the max of the values of all other bidders is given by $G_i(.)$ below:

$$G_1(x) = F_2(x)^{N_2} F_1(x)^{N_1-1}$$

$$G_2(x) = F_1(x)^{N_1} F_2(x)^{N_2-1}$$

The expected payment of a bidder of type $i$ with value $x \geq r$ is

[17] $Y_i$ is the $i^{th}$ highest order statistic or bid.

$$m_i(x,r) = rG_i(r) + \int_r^x y g_i(y) dy. \tag{10}$$

The first term captures the expected payment of the bidder if none of the other bidders' values is greater than $r$, the probability of which happening is $G_i(r)$. If on the other hand, there is/are other bidder(s) with values exceeding $r$, but less than $x$, the object is sold to our bidder at the highest of other values; so as the auctioneer raises the price from $r$, the probability of our bidder winning at a price $y$, is $g_i(y)$; thus, the second component of the expected payment integrates from $r$ to $x$, the product of each value with the probability of our bidder winning at that value.

The *ex-ante*[18] expected payment of a bidder of type $i$ is

$$\begin{aligned} E[m_i(X,r)] &= \int_r^w m_i(x,r) f_i(x) dx \\ &= r(1 - F_i(r))G_i(r) + \int_r^w y(1 - F_i(y))g_i(y)dy \end{aligned} \tag{11}$$

The overall expected payoff of the seller from setting a reserve price $r \geq x_0$ is

$$\Pi_0 \;=\; N_1 \; E[m_1(X,r)] \;+\; N_2 \; E[m_2(X,r)] \;+\; F_1(r)^{N_1} \; F_2(r)^{N_2} \; x_0 \tag{12}$$

Differentiating $\Pi_0$ with respect to $r$

$$\begin{aligned} \frac{d\Pi(r)}{r} \;=\; & N_1 \; \frac{d}{dr} E[m_1(X,r)] \;+\; N_2 \; \frac{d}{dr} E[m_2(X,r)] \\ & + N_1 \; F_1(r)^{N_1 - 1} \; f_1(r) \; F_2(r)^{N_2} \; x_0 \\ & + N_2 \; F_1(r)^{N_1} \; F_2(r)^{N_2 - 1} \; f_2(r) \; x_0 \end{aligned} \tag{13}$$

where

$$\frac{d}{dr} E[m_i(X,r)] \;=\; [1 \;-\; F_i(r) \;-\; r \; f_i(r)] \; G_i(r) \tag{14}$$

[18]Before the value is drawn.

Thus

$$\frac{d\Pi(r)}{dr} = N_1 \; [1 - F_1(r) - rf_1(r)] \; G_1(r) \; + \; N_2 \; [1 - F_2(r) - rf_2(r)] \; G_2(r)$$
$$+ \; N_1 \; f_1(r) \; G_1(r) \; x_0 \; + \; N_2 \; f_2(r) \; G_2(r) \; x_0 \tag{15}$$

Since,

$$f_i(r) \;=\; \lambda_i(r) \; [1 - F_i(r)] \tag{16}$$

where $\lambda_i(.)$ is the *hazard-rate* function,

we have,

$$\begin{aligned} \frac{d\Pi(r)}{dr} \;=\; & N_1 \; [1 - F_1(r) - r \; \lambda_1(r)(1 - F_1(r))] \; G_1(r) \\ & + \; N_2 \; [1 - F_2(r) - r \; \lambda_2(r)(1 - F_2(r))] \; G_2(r) \\ & + \; N_1 \; \lambda_1(r) \; [1 - F_1(r)] \; G_1(r) \; x_0 \\ & + \; N_2 \; \lambda_2(r) \; [1 - F_2(r)] \; G_2(r) \; x_0 \end{aligned}$$

$$= \; N_1[1 - (r - x_0)\lambda_1(r)] \; (1 - F_1(r)) \; F_2(r)^{N_2} \; F_1(r)^{N_1 - 1}$$
$$+ \; N_2[1 - (r - x_0)\lambda_2(r)] \; (1 - F_2(r)) \; F_1(r)^{N_1} \; F_2(r)^{N_2 - 1} \;=\; 0 \tag{17}$$

Dividing throughout by $F_1(r)^{N_1-1}F_2(r)^{N_2-1}$ we get

$$N_1 \; [1 - (r^* - x_0)\lambda_1(r^*)][1 - F_1(r^*)]F_2(r^*)$$
$$+ \; N_2 \; [1 - (r^* - x_0)\lambda_2(r^*)][1 - F_2(r^*)]F_1(r^*) \;=\; 0 \tag{18}$$

The above equation gives for a lot of a specific quality, the first order condition for profit maximization of the seller. Putting $N_1 = 1$, we get the expression (in implicit form) for the optimal reserve price ($r^*$) under simple bid rotation by the 2 large bidders in our data. Given our parameter estimates and the lot-specific covariates, Eq.(18) is numerically solved for $r^*$ for every lot in the data. These are our optimal reserve price estimates. Confidence intervals around these are constructed using the Delta Method (see Appendix).

It can be seen that the optimal reserve price for a lot is a function of its quality, competition at the auction, and how much the seller values a lot unsold at the auction, henceforth referred to as his *reservation utility* ($x_0$). While the first two variables are observed and recorded, the seller's reservation utility is unknown to us. Based upon our knowledge of the functioning of the market however, we can impute a value on $x_0$.

In the event of a lot going unsold at the formal auction, it is typically sold later through mutual negotiation with a private miller. It is useful to think of these negotiations in terms of bilateral bargaining with an outside option. Let the miller's (buyer's) valuation for the lot be ($v$), and the seller's (farmer's) be ($s$). In the absence of outside options, the subgame perfect equilibrium shares of the players in Rubinstein's model (Rubinstein (1982)) are $\frac{r_S}{r_B+r_S}$ $(v-s)$ (buyer), and $\frac{r_B}{r_B+r_S}$ $(v-s)$ (seller), where $r_B$ and $r_S$ are the buyer's and seller's respective discount rates.

The buyers (millers) can be assumed to be facing a discount rate equal to the *prime lending rate* of 15% per annum at that time, while the sellers (farmers) were able to borrow from the co-operative societies or the *katcha arhtias* at about 2% per month (i.e., 24% per annum). In the course of our interaction with them, the farmers informed us that if a lot goes unsold, then transporting it and selling it elsewhere (possibly at another market where auctions are not employed) can mean a discount of up to *Rs* 100 compared to the price obtainable in this market (through auctions). We therefore estimate the outside option of the farmer, for each lot, as the expected second-highest valuation for that quality minus a penalty amount of *Rs* 100.

In the bargaining model with an outside option for the seller, the seller's equilibrium payoff is the larger of his Rubinstein share $s + \frac{r_B}{r_B+r_S}$ $(v - s)$ and his outside option. This equilibrium payoff is the $x_0$ that we plug into Eq.(18). For a range of reasonable values for $s$ (the seller's use value for the grain), we find that this reservation utility ($x_0$) for the lot equals the farmer's payoff from the outside option.

The mean of the estimated optimal reserve prices at *Rs* 513.3 is about *Rs* 28 higher than the mean of the observed start prices of *Rs* 485.8. The mean absolute difference of *Rs* 32.3 between the two series is even higher; the confidence intervals around the optimal reserve prices are within Rs 2, so there is a significant difference between these and the observed start prices.

This significant difference between the 2 price series does not depend on our choice of $x_0$ for each lot. To see this, as well as to compare the series in a different way, we present a plot of the optimal reserve prices and start prices of lots arranged in increasing order of quality (figure 2); we use the expected second-highest valuation as proxy for quality. We notice a neat monotonically increasing relationship between quality and optimal reserve prices. This is to be expected given the theoretical relationship between the expected second-highest value and the optimal reserve price, as both vary positively with the quality of a lot. The optimal reserve price in the asymmetric bidders specification is a weighted average of the inverse hazard rates of the distributions of the two types of bidders; as the quality improves, inverse hazard rates increase, and so does the the optimal reserve price. The plot of the start prices by contrast, has a lot of noise overriding a weak upward trend; also, there appears to be crowding around certain start prices such as 480, 500, 520; (probably because these are salient start prices, perhaps corresponding to 'quality grades' in the auctioneer's mind). Finally, we note that varying the level $x_0$ of the reservation utilities of the seller leads to variation in the *levels* of the optimal reserve prices, and not the *degree of monotonicity* of the optimal reserve prices with respect to the quality and the tight relationship between the two. Irrespective of the level, the discrepancy between this close relationship and the absence of it in the case of the observed starting prices becomes obvious.

By how much would farmers' expected revenues increase if the reserve prices are optimally set? To evaluate this, we compute the expected revenue for each lot under the alternative scenarios that the reserve price equals (i) the observed start price and (ii) the optimal reserve price. The mean absolute difference between the two series of expected revenues at about *Rs* 2 is very small. Thus the non-optimality of the start prices does not make a significant difference to farmers' revenues. The takeout from this analysis indicates that the market functions well, the auctioneer is experienced and sets start prices at levels that fetch farmers' revenues close to the maximum possible. This leads us to the other instruments that have potentially large implications for farmers' revenues: government intervention in these markets.

# 7 Government intervention

In India, the government has a system of distributing subsidized rice and wheat to the poor through special food outlets in its public distribution system (PDS). To procure rice for this purpose, the government uses two channels - it buys paddy from markets such as the one described above at the MSP, and pays millers to mill the paddy for it (this is the *custom milled rice* (CMR) channel). It also buys rice directly from millers in the form of a *levy* - millers have to sell a specified proportion of their milled rice to the government at the *levy price* fixed by the government. The levy price is fixed around harvest time, as a mark-up over an estimated cost of buying paddy and processing it.

*Procuring rice for PDS through* the CMR route is much more costly than doing so through the levy route. The higher cost (including the unaccounted costs) of procuring through the CMR route arises partly because the government has to maintain purchase infrastructure in many primary markets to buy the paddy directly (unlike having levy rice delivered to it by millers). Despite this cost difference, the trend of the past years has been tilting in favour of CMR route purchases. In 1999-2000 for the state of Haryana, the government purchased about 17% of paddy arrivals whereas a decade later this had gone up to over 90%.

Since the government can procure rice through the cheaper levy route, the contribution of the CMR route is not for procurement per se, but for providing price support to farmers at the announced MSP. Using our estimated value distributions, we therefore first ask - how much difference to farmers' expected revenue would a credible, supported MSP make in this market? Then we carry this forward by asking - if the government is unable to support the MSP to an appreciable extent, what increase in the levy price would result in the same expected revenue for farmers as a credible, supported MSP? (The increase in the levy price would work by increasing millers' valuations for paddy and therefore increasing the win price of the paddy lots). If the increase required in the levy price is limited, it would be cheaper to use the levy price as an instrument to support farmers' revenues, in lieu of direct paddy purchase by the government at the MSP.

The government announces the MSP, based upon the recommendations of the Commission for Agricultural Costs and Prices (CACP), around sowing time. The CACP uses detailed calculations of production costs in order to compute the MSP. The MSP for the 1999-2000 kharif season as suggested by the CACP was *Rs* 465 for Fair Average Quality (*faq*)or 'Common' paddy and *Rs* 495 for Grade A Quality (*gaq*) (a higher quality grade). The government however, announced a bonus of

*Rs* 25 over the recommended MSP, so the effective MSP for the 1999-2000 kharif season stood at *Rs* 495 for *faq* and *Rs* 520 for *gaq*.

This kind of bonus is a political instrument for the political party in power. However, depending on the level of grain stocks and the government's fiscal situation, an unreasonably high MSP beyond the CACP recommendations can become hard to support, as was the case in the year in question. In our sample, the government participated in the market quite rarely, picking up just 23 of the 313 lots in the sample, even though many high quality lots sold for below *Rs* 520 MSP. That was simply too high a price to credibly support. In our simulations, therefore, we consider the CACP recommended prices as the ones that a government can credibly support in the market.

We therefore compute the expected revenue for each lot in our sample, under the assumption that the government is a bidder for that lot; and bids *Rs* 465 or *Rs*495 depending on whether the lot is *faq* or *gaq*. The implication for setting the optimal reserve price when the government is an additional bidder with these specific bids, is that a reserve price at or below the MSP always ensures that the lot will be sold for at least the MSP; whereas, a higher reserve price implies that the lot could go unsold, fetching the seller only his reservation utility $x_0$. So we recompute the optimal reserve prices under the assumption of the government as a bidder; we find that unless the grain is of very high quality, the optimal reserve price often equals the MSP. We compute expected revenue for each lot at these optimal reserve prices. We compare the average of these for our sample, with the (computed) average expected revenue in the absence of government as a bidder. In these computations, we are basically evaluating the right hand side of Eq.(12), using numerical integration.

The average expected revenue without government presence is *Rs* 516.74. The average expected revenue with government presence (credible MSP support of Rs 465 for *faq*, Rs 495 for *gaq*) and the original levy price is about *Rs* 524. This comparison shows that in the paddy season of the given year, direct government purchase of paddy at credible support prices would lead to only a small increase in farmers' expected revenue, of about $Rs\ 7 - Rs\ 8$ per quintal. If this is indicative of the extent to which credible price support is useful, it is natural to ask whether the expensive deep handling of grain (buying paddy across many grain markets, giving it to be milled, getting it back etc.) is really worth it, if the same level of revenue support can be accomplished by an increase in the levy price of rice.

The next part of this simulation therefore answers: What increase in levy price would increase the expected farmer's revenue by about *Rs* 8, in the absence of government support for the MSP?

An increase in the levy price shifts the bidders' value distributions to the right, raising the expected win prices and hence expected revenue from the auction. These shifts in the distributions can be captured by the shifts in their means. We first compute the mean shifts required to increase the expected revenue from an auction of an average lot by *Rs* 8.

The estimated means of the distributions of small and large bidders for the average lot of a given quality grade (*faq* or *gaq*)are respectively $e^{z\beta}$ and $e^{z\beta+\mu}$, where $z$ is the average quality vector for the grade and $\beta, \mu$ are our parameter estimates of quality and mean shifter for large bidders. Let $e^{z\beta} = m$. Then the expected revenue, as described in Eq.(12), viewed as an increasing function of the mean $m$ can be written as:

$$N_1 \; E[m_1(X, r)] \; + \; N_2 \; E[m_2(X, r)] \; + \; F_1(r)^{N_1} \; F_2(r)^{N_2} \; x_0 = H(m)$$

We first compute the mean shift $\Delta m$ required to raise the expected revenue by $Rs 8$, on average in the sample; i.e.

$$\Delta m \; s.t. \; H(m + \Delta m) - H(m) = 8. \tag{19}$$

Using numerical integration to evaluate $H(m)$, and solving this equation for $\Delta m$, we get $\Delta m = e^{6.214} - e^{6.2} = Rs499.7 - Rs\ 492.75$ or about *Rs* 6.95. Next, we compute the increase in levy price required to shift the means of the value distributions by *Rs* 6.95.

Bidder $i$'s mean or expected valuation $E[V_i]$ for a paddy lot (one quintal) equals the revenue that the milled rice is expected to fetch[19] minus the expected costs of milling

$$m \equiv E[V_i] \quad = \quad \frac{2}{3}(\frac{3}{4}L + \frac{1}{4}P - E[C_i]) \tag{20}$$

[19]Recall that the millers in this market are required to sell three-fourths of their milled rice to the government at the levy price, they can sell the remaining one-fourths in the open market, and each quintal of paddy converts to about 2/3 quintal of rice.

where

$L$ = levy price
$P$ = open market price
$E[C_i]$ = bidder $i$'s expected cost of milling one quintal of rice

Rewriting the above relation we get

$$\frac{3}{4}L \ + \ \frac{1}{4}P \ - \ E[C_i] \quad = \quad \frac{3}{2}E[V_i] \tag{21}$$

So a $\Delta L$ increase in the levy price causes the expected valuation to go up to $E[V_i'] = m + \Delta m$

$$\frac{3}{4}(L + \Delta L) \ + \ \frac{1}{4}P \ - \ E[C_i] \quad = \quad \frac{3}{2}E[V_i'] \tag{22}$$

Thus, we have

$$\frac{3}{4}(\Delta L) \quad = \quad \frac{3}{2}\ (E[V_i'] - E[V_i]) = \Delta m \tag{23}$$

$$\Delta L \quad = \quad 2(E[V_i'] - E[V_i]) = 2\Delta m \tag{24}$$

Since $\Delta m = Rs$ 6.95, an increase in the levy price to the tune of $Rs$ 13.9 per quintal of rice can substitute for direct government purchases at the CACP-determined minimum support price.

# 8 Conclusion

In this paper, we analyze a paddy auction market using the structural estimation approach to answer two important policy questions. First, how well does the auction market function in terms of maximizing the expected revenue of the paddy selling farmers? We find that although the reserve or start prices that the auctioneer chooses are not optimal, the differences from the optimal reserve prices are small enough that the expected revenues from the auctions are close to the optimum. The probable conclusion is that the auctioneers have developed a good feel for bidders' values for paddy, and act in the interest of farmers in setting their reserve or start prices.

The second question has to do with whether the government needs to handle the the grain as deeply, and in as costly a fashion, as it does, in order to enforce the minimum support price (MSP). We show that direct paddy purchases by the government in numerous paddy markets (a very expensive operation) are not needed to ensure that farmers' revenues are at levels implied by a fully enforced MSP. As the government is a large buyer of rice, a quite small increase in the levy price of rice can lead to farmers' revenues at these auctions being similar to revenues that obtain if the government buys paddy directly at the minimum support price. Since the levy route is cheaper, this strongly suggests that a rebalancing of government purchase policy, away from direct paddy purchases to purchases of levy rice from millers, can reduce the government's fiscal and managerial burden while at the same time protect farmers' revenues.

# 9 Appendix

Having derived an expression for it, we can provide an estimate and also confidence intervals for the optimal reserve price for a lot of a given quality, using our semi-nonparametrically estimated distribution of the bidders' valuations.

Recall that for a lot with quality vector $\mathbf{z}$, the valuation of player $i$ of type $j$ is given by

$$ln\ v^{ij} \ = \ \mathbf{z}\beta \ + \ \mu \ + \ u^i \tag{25}$$

The first-order condition for revenue-maximization (equation from section), which gives the optimal reserve price $r^*$ can be rewritten as an implicit function of $r^*$ and the parameter vector $\beta$

$$\gamma(r^*, \beta) \ = \ 0 \tag{26}$$

where

$$\begin{aligned} \gamma(r^*, \beta) \quad = \quad & N_1 \ \ [\, 1 - F_1(r^*, \beta) - (r^* - x_0) f_1(r^*) \,] \ \ F_2(r^*) \\ & + \ N_2 \ \ [\, 1 - F_2(r^*, \beta) - (r^* - x_0) f_2(r^*) \,] \ \ F_1(r^*) \end{aligned} \tag{27}$$

We now obtain the asymptotic distribution of the optimal reserve price based on the semi-nonparametric estimates.

Gallant and Nychka (1987) prove the consistency of SNP estimators for multivariate data. Fenton and Gallant (1996b) specialize it to the univariate case. Wong and Severini (1991) establish root-n asymptotic normality and efficiency of semi-nonparametric maximum likelihood estimators.

Consider an estimator $\hat{\beta}$ of $\beta$ that is consistent and distributed normally asymptotically. Thus,

$$T^{1/2} \ (\hat{\beta} - \beta) \ \to^d \ N(\mathbf{0}, \mathbf{V}), \tag{28}$$

where $\mathbf{V}/T$ is the variance-covariance matrix of $\hat{\beta}$. Then $\hat{r}^*$, an estimator of $r^*$ solves

$$\gamma(\hat{r}^*, \hat{\beta}) \ = \ 0. \tag{29}$$

Expanding $\gamma(\hat{r}^*, \hat{\beta})$ in a Taylor's series about $(r^*, \hat{\beta})$

$$\begin{aligned}\gamma(\hat{r}^*, \hat{\beta}) \;=\; 0 \;=\; & \gamma(r^*, \beta) \;+\; \gamma_{\hat{r}^*}(r^*, \beta)(\hat{r}^* - r^*) \\ & +\; \nabla_{\hat{\beta}}\gamma(r^*, \beta)'(\hat{\beta} - \beta) \;+\; U. \end{aligned} \tag{30}$$

Ignoring U, as it will be negligible in the neighborhood of $(r^*, \beta)$, we obtain

$$(\hat{r}^* - r^*) \;=\; \frac{-\nabla_{\hat{\beta}}\gamma(r^*, \beta)'(\hat{\beta} - \beta)}{\gamma_{\hat{r}^*}(r^*, \beta)} \;\equiv\; \mathbf{m}'(\hat{\beta} - \beta). \tag{31}$$

Thus,

$$T^{1/2}\ (\hat{r}^* - r^*) \;\to^d\; N(0, m'\mathbf{V}m). \tag{32}$$

In practice, we work with approximations, so let

$$m \;=\; \frac{-\nabla_{\hat{\beta}}\gamma(\hat{r}^*, \hat{\beta})(\hat{\beta} - \beta)}{\gamma_{\hat{r}^*}(\hat{r}^*, \hat{\beta})}. \tag{33}$$

We use the parameter estimates $(\hat{\beta})$ to compute[20] the optimal reserve price $(\hat{r}^*)$ and the value of $m$ at $\hat{r}^*$. Then we construct 95% confidence intervals around $\hat{r}^*, \hat{\beta}$ as follows.

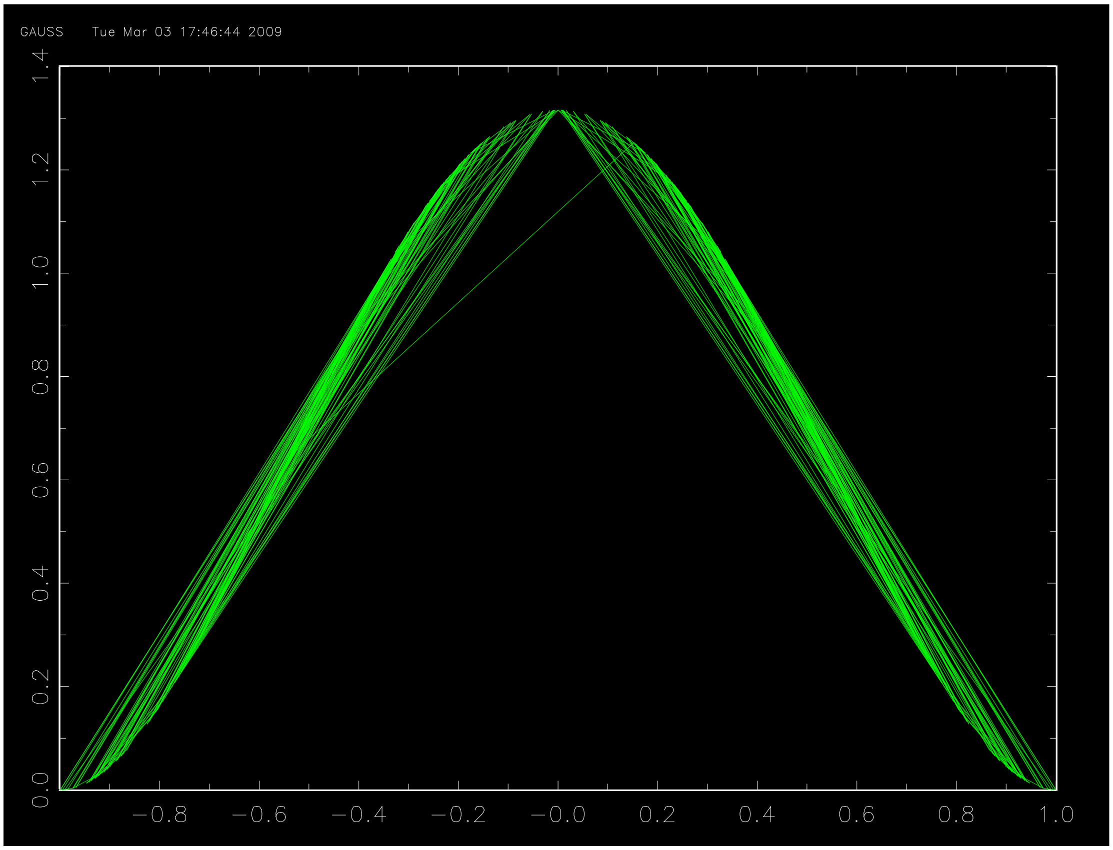
$$\left(\hat{r}^* - (1.96) * \left(\frac{m'\mathbf{V}m}{T}\right)^{1/2}\ ,\ \hat{r}^* + (1.96) * \left(\frac{m'\mathbf{V}m}{T}\right)^{1/2}\right)$$

(34)

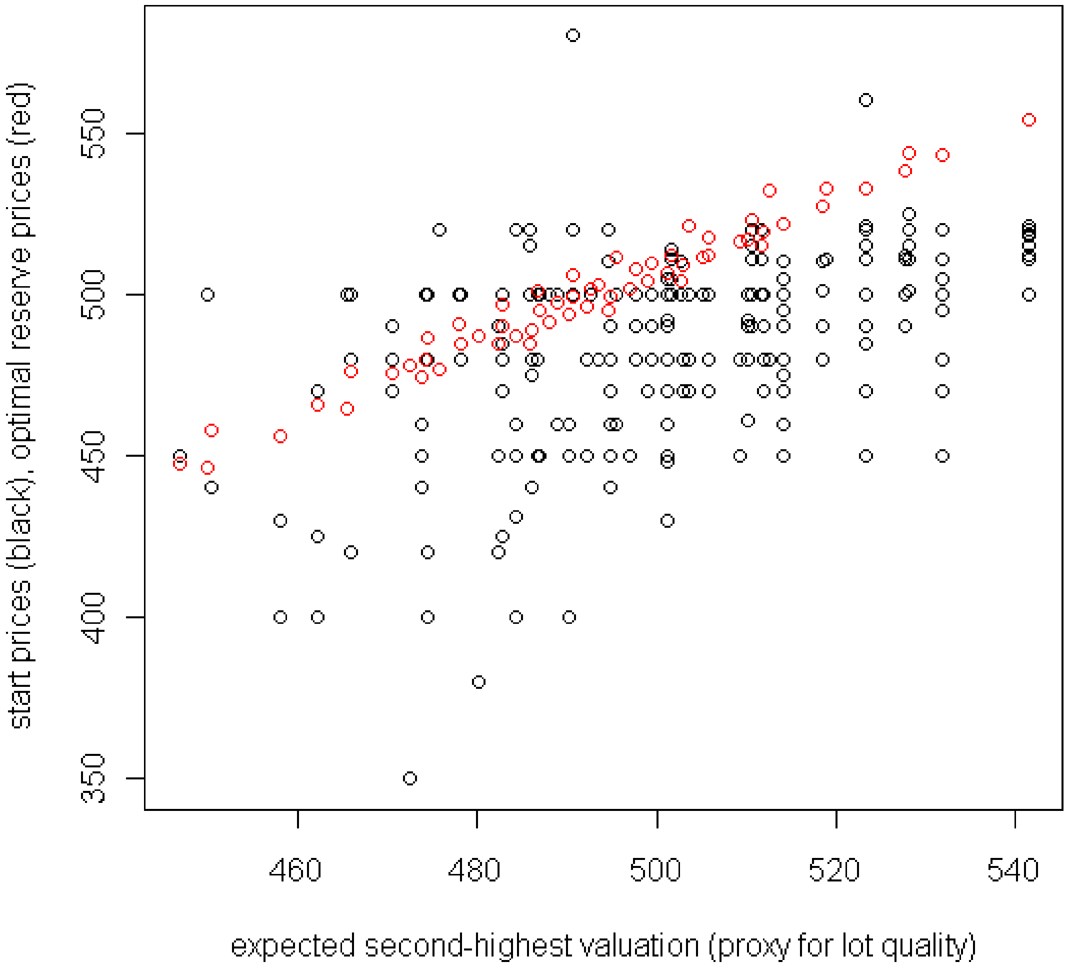
[20] for each covariate vector

**Figure 1**

Residual Density Plot



## Figure 2


start prices (black), optimal reserve prices (red)
350
400
450
500
550
460
480
500
520
540
expected second-highest valuation (proxy for lot quality)

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