1. Introduction

Many small wholesale grain markets in India are characterized by large numbers of sellers and a relatively small number of buyers, thereby lending the price formation process open to manipulation through collusion. Government intervention limits the extent of such manipulation through the institution of regulated markets, where the rules of exchange are clearly spelled out and the price formation process is transparent. Unfortunately, recent studies that document how agricultural markets operate—especially in Northern India—and the extent to which they hinder or serve farmers, are rare. In this paper we attempt to fill this gap by studying the functioning of a regulated basmati paddy market in the state of Haryana in North India.[1]

In contrast to earlier studies of agricultural markets, which focus on market outcomes, this paper examines the *process* by which prices are determined. We focus on the method of sale, the *open ascending auction*, which is of overarching significance in characterizing the market. Surprisingly, no previous work in India has made use of this approach in any serious way. Furthermore, we explicitly analyze the strategic behavior of the various agents in the market. In particular, we examine whether[2] the existence of a small number of buyers relative to the number of sellers results in collusion by buyers, and its consequences therefore for prices and for efficiency.

Basmati is an aromatic, long-grain rice variety,[3] grown only in Northern India and Pakistan. It is the most expensive variety of rice; with its distinctive cooking characteristics, high-end basmati sells at ten times the price of the cheapest rice varieties. A large proportion of the basmati produced in North India is exported. Government procurement operations exclude basmati, and support prices for “Grade-A” varieties of paddy are too low to be relevant. Therefore, only private players participate in basmati paddy markets; the government’s role is limited to regulating the open auction.

The rest of this section contextualises this paper in the literature on Indian agricultural markets and the empirical literature on auctions. Section 2 describes the characteristics of the basmati market in Panipat, Haryana. Sections 3 and 4 set up a non-cooperative and a collusive model, respectively. This is followed by a description of the database in Section 5. Section 6 adduces the empirical results. We conclude, and discuss extensions, in Section 7.

There is an extensive literature on agricultural markets in India. Earlier work suggests that the "ideal perfectly competitive environment...is not prevalent." (Subbarao (1978)). This is corroborated by studies of marketing margins (for example, Jha et. al (1998, 1999)) as well as those of spatial integration (for example, Lele (1971), Wilson and Swami (1999)). [4] Other studies, notably Palaskas and Harriss-White (1993), find evidence of barriers to entry in the short run, and skewed control over storage facilities that serve to facilitate collusive behaviour on the part of buyers in West Bengal, although in Southern India, "structural conditions for competitive behaviour are propitious" (Harriss-White, 1996).

There is a separate and rich body of literature on auctions. Apart from theoretical analyses of various kinds of auctions in a game theoretic framework (see McAfee and McMillan (1987) and Klemperer (1999) for extensive reviews), recent years have seen a mushrooming of empirical work. In applied work, two approaches to the analysis of auctions have been followed. The first and perhaps more popular approach is to test econometrically the *implications* of auction theory (such as, contrasting the implications of non-cooperative versus collusive bidding behaviour), referred to in the literature as testing the 'reduced form' (see for example Nelson (1995), Porter and Zona (1999), Hendricks and Porter (1988), Hendricks, Porter and Boudreau (1987)). An alternative, more recent approach is to estimate *structural* models (for example, Paarsch (1992), Laffont, Ossard and Vuong (1995), Baldwin, Marshall and Richard (BMR) (1997), Hong and Shum (2000), Donald, Paarsch and Robert (1997), and Sareen (1999). Laffont (1997) and Sareen (forthcoming) are surveys of some of this literature).

In the present paper, we estimate simple, structural models of 'independent private values' auctions. The principal difference from earlier empirical work with such models is that the incentives governing a subset of players in our study are non-standard; we motivate this in Section 2. Furthermore, a distinction is drawn between 'large' and 'small' players; we model this as large players' 'valuations' or 'willingness to pay' being drawn from a distribution that first-order stochastically dominates that from which valuations of the small players are drawn. With this framework, we set out in Section 3 a simple non-cooperative model, followed by an alternative collusive model in the next section. Collusion takes the form of assigning "bidding rights" amongst the colluding players; the rules of assignment are simple, and exploit the Principal-Agent slack that exists between distant millers (Principals) and their purchasing agents (Agents). The collusion is sustained by the threat of non-cooperative play if any one player deviates from the collusive scheme. We estimate both these models through maximum likelihood, and find that the collusive model better describes our data. However, unlike standard implications of collusion for prices, our results suggest that prices are not necessarily suppressed by collusion.

2. The Institutional Setting: the Basmati Market in Panipat[5]

Panipat *mandi* is a small (in terms of volume of transactions) regulated market situated in Panipat district in Haryana. The peak arrivals of basmati take place during eight weeks—from late October to late December. Arrival patterns seem to mimic those of the harvest: farmers bring their grain to the market soon after cutting the crop. Over the 1999 harvest season, basmati arrivals totaled approximately 127,000 quintals, over 75 percent of which arrived by the end of November.

2.1. The Players in the Market

The Sellers:

Farmers do not directly sell their produce at the *mandi*, instead, a commission agent, or *katcha artia* undertakes to sell the grain. *Katcha artias* earn a commission of 3 percent of the total value of sales, which is paid by the buyer. [6]

The Buyers:

Pakka artias work as commission agents for the mills, undertaking to represent them at grain auctions and buy grain for them. Once a lot of grain is auctioned, the *pakka artia* with the winning bid has the responsibility to store the grain purchased from the market until it is transported to the mill. A mill typically picks up grain from several mandis, and usually appoints only one *pakka artia* as its agent at any mandi. However, it is possible for a *pakka artia* to act as the agent for more than one mill. *Pakka artia*s earn a commission of two percent on the value of sales.[7]

As commission agents for mills, *pakka artia*s are generally given price ranges in which to buy grain of a given variety and quality. Some of them are in constant touch with their mills on cellular phones, even as auctioning takes place. Others also communicate with mills regularly over the course of the day; since mill owners pick up grain from several *mandi*s, this enables them to fine tune their purchase decisions across *mandi*s. Constant communication between mill-owner and *pakka artia*, and the fact that details of each auction including quantity sold, variety, and price get recorded in several places, enable the mill-owner to monitor prices quite closely. Checks on quality, however, can only occur upon delivery. Given the multidimensional nature of quality and wide variation along each of these dimensions (see Section 5), some differences of perception between millers and their agents, about price-quality correspondence can occur.

Buyers of basmati in Panipat may be categorized into three groups. The first group (Group A) of purchasers consists of representatives of local mills, who buy on their own account. Indeed, frequently, the owners themselves participate in the bidding. The second are *pakka artia*s (Group B) who buy on behalf of one or more large mills which are located relatively far away, and earn a commission on the value of the transaction. These mills buy in several markets (in 50-100 markets in Haryana and the neighboring states). The final group (Group C) consists of a large number of commission agents who buy primarily on their own account. We label players in Groups A and B as 'large' and those in Group C as 'small' players. As described in Section 5, in our setting, there is only one miller in Group A; and three *pakka artias* in Group B. Together they command a market share of 60 percent.

The significance of this classification of buyers lies in the *incentives* governing purchase decisions. Agents who represent mills and buy on commission (Group B), which depends on the *sale value*, have an incentive to try and raise the price so as to maximize their commission. However, the daily monitoring of purchase decisions means that too high a price may cause the millers to stop all purchases from this mandi. In contrast, local millers (Group A) clearly try to purchase grain at as low a price as they are able. As we will see later, these differences in buyers have important consequences for price determination.

The Auctioneer:

The market committee appoints an auctioneer who formally conducts the auction. The auctioneer receives 0.8 percent of the sale value of the lots sold; he thus has an incentive to raise the price as well.

2.2 The Auction Process

Grains brought by the farmer are displayed in lots by the *katcha artia*. The auctioneer starts the process of auctioning a lot by announcing a starting price which he determines by reaching into the middle of a pile of grain, and inspecting a fistful for quality. Once assessed, it is rare for the lot to be unsold at this price. Several players compete for the lot, and each makes independent assessments of quality by similarly examining the grain. Bidding proceeds as the auctioneer then begins to raise the price; as the price rises, bidders may indicate that they have dropped out of the race by throwing down the fistful of grain that they drew out to examine. This process continues until all but one bidder has dropped out. The remaining bidder wins the lot at the price last announced.[8] In this manner, the auctioneer proceeds from lot to lot until all the grain is sold.

3. The Non-cooperative Model

Although many lots of basmati are auctioned each day, they are extremely heterogeneous in quality. On any given day, it is hard to observe many lots of identical quality. Given this, the theory of auctions of a single object may be utilized as a framework for analysis.[9]

Consider the case then of a single lot to be auctioned. Suppose there are n potential buyers for this good. Denote their "*valuations*", or *willingness to pay* for the commodity by $(v_1,...,v_n)$. The valuations are privately known to the bidders. We employ the “independent private values” (IPV) setting. We believe this assumption is reasonable for the following reasons: first, a significant determinant of a miller's valuation or willingness to pay is the miller's privately known, mill-specific processing costs. Second, the millers' export markets are not identical—they range from countries in the Middle East, Europe, North America, and Japan. While the possibility of resale of grain is a common-value component, it is likely that the first two IPV components overwhelm this, and are responsible for most of the residual uncertainty about players' valuations.

We assume that the 'large' buyers (Groups A and B) draw their valuations from a higher distribution, *G*, than the 'small' buyers (Group C), most of whom buy for resale, and all of whom draw their valuations from a lower distribution ***F*.** There are two reasons behind this assumption: (a) millers have the *option* of processing the grain and selling rice, or reselling the paddy, whereas non-millers can only resell the paddy; (b) large millers can exploit economies of scale in processing. The two distributions, and 'who draws from what distribution', are common knowledge.

As is well known for ascending auctions in the IPV setting, in Bayesian equilibrium a player's bid (or price at which he quits the auction) equals his valuation. This holds also for players in group B (*pakka artia*s), even though they have non-standard payoffs. We assume that a group B player's valuation v is a ceiling set by his miller. Therefore, if he wins a lot at a price $p \leq v$ he gets a payoff equal to kp, where k is the percentage earned on the purchase price. Clearly, it is optimal for the player to stay with the bidding until the price equals v, and to drop out thereafter.[10] The winning bid or sale price is thus equal to the second highest valuation out of $(v_1,...,v_n)$. In a data set where the objects are sold by English auction, and players' strategies are not dynamic but object specific, the winning prices would therefore be realisations of the second order statistic.

In our model, suppose *m* (small) of the *n* potential bidders randomly draw their valuations from the lower distribution, *F*, and the rest (*n*-*m*) large bidders randomly draw their valuations from a higher distribution, ***G*.** The distribution $H_{(2)(n,m)}$ of the second order statistic is then given by

$$H_{(2)(n-m,m)}(v) = m[F(v)]^{m-1}[G(v)]^{n-m}(1-F(v)) + (n-m)[F(v)]^{m}[G(v)]^{n-m-1}(1-G(v))$$

$$+[F(v)]^{m}[G(v)]^{n-m} \qquad (1)$$

We assume the mean of valuations drawn from F is given by $z\beta$, where z is a vector of quality variables and other distribution-shifters. If this static game is played many times, with this formulation, it is easy to see that the *(n-m)* large buyers would win more often and would have larger market shares. Furthermore, there is a positive probability that the *m* small buyers also win; when they do, however, on average, the win price is lower than when one of the large buyers wins a lot.

4. The Collusive Model

Collusion between Group A and Group B players takes the form of allocating bidding rights on individual lots. Buyer A (in our data set Group A has a single buyer) benefits greatly by excluding bidders from Group B (thereby getting a substantial drop in the win price); however, buyers in Group B do not similarly benefit from exclusion as they prefer *higher* prices. Thus in return for an arrangement which permits Buyer A to exclude others from bidding, buyers in Group B must benefit in some way. We propose that a beneficial market share scheme is worked out as follows:

Buyer A is assigned the "right" to bid at proportion α of the lots (with buyers in Group B keeping out of the bidding), and buyers in B bid at the remaining proportion (1 -α) of the lots (with Buyer A keeping out of the bidding). It is not obvious that Group B players would want to exclude competitors by a further allocation of rights amongst themselves, as they benefit from higher prices. The small players (Group C) are not part of this arrangement. This bid rotation scheme is a minimal form of collusion, but proves adequate for our empirical purpose.[11] We retain the static nature of bidding: at lot *t*, player *i c*hooses his bid as a function of his valuation v_{it} for that lot; he does not condition on past play. Buyer A benefits significantly if buyers in group B do not bid, as A is then the only player drawing a valuation from *G*. The win price is therefore likely to be a draw from the lower distribution F. In return, Buyer A trades off market share to Group B, by agreeing to an α that is lower than his expected market share under non-cooperative play.

The simplest way to enforce collusion is to consider the auction of an infinite number of lots; deviation from collusive behaviour at any auction is then deterred by the threat of all players reverting to non-cooperative play, thus wiping out all future gains from collusion (Friedman (1971)).[12]

For simplicity, we assume that players in Groups A and B observe the outcome of a randomization before each auction such that bidding rights to the auction are assigned to Buyer A with probability α and to Group B with probability 1-α. At each auction t, buyers observe the quality vector z_t and draw valuations from $F(v \mid z_t)$ and $G(v \mid z_t)$; (z_t is drawn from a sample space S with probability measure μ). If a player i is in Group C, his bid is a function of his valuation v_{it} alone (and is independent of past play). If player i is in group A or B, his decision to bid or not at the auction depends on the outcome of the current randomization, and on whether players in the past have obeyed the assignment of bidding rights. If he decides to bid, his bid depends only on his valuation v_{it}, and is independent of past play. We now provide conditions under which the following strategy profile is a (subgame perfect) equilibrium:

For all players i in group C, i's bid at an auction equals his valuation v_{it}. For all i in groups A and B, (a) i obeys the bidding rights assignment determined by the outcome of the current randomization, provided all players have done so in the past. Otherwise, i bids at each auction; (b) if i decides to bid at an auction, his bid equals his valuation v_{it}.

If the discount factor δ used by the players to discount the future is sufficiently high, then this strategy profile is an equilibrium provided the per-period payoff from collusion exceeds that from non-cooperative play (as is evident, 'Nash threats' (Friedman (1971)) are used to sustain collusion). For buyer A, this translates into the condition

$$\alpha \pi_A - \bar{\pi}_A > 0 \qquad (2),\ \text{where}$$

$$\pi_A = \mathrm{E}_\mu \ \{ \ \mathrm{E}_G \ \{[F(v \mid z_t)]^m \ \{v - \mathrm{E}_{H_{(2),(1,m)}} (\ \mid z_t, v = v_{(1)})\}\}\} ;$$

This is A's expected payoff under collusion, if A gets to bid: if A has valuation v when the lot is of quality z_t, his expected payoff is $[F(v \mid z_t)]^m \ \{v - \mathrm{E}_{H_{(2),(1,m)}} (\ \mid z_t, v = v_{(1)})\}$, where the first term equals his probability of winning, and the second term is his expected payoff given that his valuation is the highest. We then take expectations with respect to G for his valuation, and with respect to μ for quality z_t.

$$\bar{\pi}_A = \mathrm{E}_\mu \ \{ \ \mathrm{E}_G \ \{[F(v \mid z_t)]^m \ [G(v \mid z_t)]^{n-m-1} \{v - \mathrm{E}_{H_{(2),(n-m,m)}} (\ \mid z_t, v = v_{(1)})\}\}\} ;$$

(A's expected payoff under non-cooperative play)

Let $\mathrm{E}_{H_{(2),(1,m)}} (\ \mid z_t, v = v_{(1)}) \equiv r(z_t, v = v_{(1)})$ and $\mathrm{E}_{H_{(2),(n-m,m)}} (\ \mid z_t, v = v_{(1)}) \equiv p(z_t, v = v_{(1)})$; these are the expectations of the second order statistic conditioned on A's valuation v being the highest. Since $r(z_t, v = v_{(1)})$ < $p(z_t, v = v_{(1)})$, it follows that

$$v - r(z_t, v = v_{(1)}) > [G(x \mid z_t)]^{n-m-1} \ (v - p(z_t, v = v_{(1)})) .$$

Therefore, $\pi_A - \bar{\pi}_A > 0$ (3). Since $r(z_t, v = v_{(1)})$ < $p(z_t, v = v_{(1)})$ significantly, (as the expected win price on the left is a draw from a lower distribution), we expect $\pi_A - \bar{\pi}_A$ to be far greater than zero.

Consider now any buyer in group B. The condition analogous to (2) is:

$(1-\alpha)\pi_B - \bar{\pi}_B > 0$ (4), where

$$\pi_B = k \ \mathrm{E}_\mu \ \{ \ \mathrm{E}_G \{[F(v \mid z_t)]^m [G(v \mid z_t)]^{n-m-2} \ \ \mathrm{E}_{H_{(2),(n-m-1,m)}} (\ \mid z_t, v = v_{(1)})\}\} ;$$

(expected payoff under collusion, if group B gets to bid; k denotes the commission percentage of the win price that the buyer gets), and

$$\bar{\pi}_B = k \ \mathrm{E}_\mu \ \{ \ \mathrm{E}_G \{[F(v \mid z_t)]^m [G(v \mid z_t)]^{n-m-1} \ \mathrm{E}_{H_{(2),(n-m,m)}} (\ \mid z_t, v = v_{(1)})\}\} ;$$

(expected payoff under non-cooperative play).

Let $\mathrm{E}_{H_{(2),(n-m-1,m)}} (\ \mid z_t, v = v_{(1)}) \equiv q(z_t, v = v_{(1)})$. A necessary condition for (4) to hold is $\pi_B - \bar{\pi}_B > 0$ (5). If

$[q(z_t, v = v_{(1)}) / \ p(z_t, v = v_{(1)})] \ > \ G(v \mid z_t), \ \forall \ (z_t, v)$ (6), then (5) obviously holds. (Eq.(6) represents the trade-off of buyers in group B between a lower expected win price ($q(\ ) \ < \ p(\ )$), and a higher probability of winning, when buyer A does not bid). For reasonable values of (z_t, v) in our data, the left-hand-side of (6) is very close to 1. Therefore (6) holds for most values of (z_t, v), and we make the reasonable assumption that (5) holds. Note that in order for (2) and (3) to hold simultaneously for some $0 < \alpha < 1$, we need $(\bar{\pi}_A / \pi_A) + (\bar{\pi}_B / \pi_B) \ < \ 1$ (7). We assume Eq.(7) holds.

5. Database

To construct our database, we exploit the seasonality in basmati paddy market arrivals in northern India. Our data collection efforts thus focussed on these few months. We conducted our own survey, and supplemented this data base with information from market committee records,[13] and personal interviews.

To obtain information on the starting price, the number of bidders, and the quality of the lot, we tracked a random sample of auctions on two-to-three days a week during the peak marketing season. For each auction, we had a team of two investigators. One noted down particulars of the starting price, winning price, number of bidders and the name of the winner; the other noted down particulars of quality.

Prior interviews with market committee officials, the FCI, buyers and agricultural scientists indicated that there are several characteristics of paddy that influence paddy prices. These are: moisture content, uniformity in grain size, the presence of chaff, grain lustre, the presence of green and immature grain (indicative of a premature harvest), the percentage of broken grains, and a catch all category of other quality variables that might influence price (such as fungal disease, pest infestation etc[14]). Through pre-testing, we determined a consistent pattern of evaluating these on a scale of 1 to 3; with a rank of 1 indicating the worst quality and a rank of 3 the best. For some quality variables, only two ranks were assigned: poor (1) and good (2).[15] These constitute the major variables in *z* noted above. Over eight weeks, we were thus able to track 1080 auctions.

6. Results:

To estimate the non-cooperative and collusive models, we make the usual assumption that F, G are lognormal. Denote the respective densities f, g and let $h_{(2)(n,m)}$ be the density of the second order statistic. $h_{(2)(n,m)}$ is used for maximum likelihood estimation; the expression for $h_{(2)(n,m)}$ is given in Appendix A.

We assume that *F* and *G* have the same variance. The expectation of F equals $z\beta$, where β is a vector of parameters and z is the corresponding vector of the variables that act as distribution shifters (*G* has a higher mean; Section 6.2 describes the procedure used to fix the difference between the means of *F* and *G*). The parameter vector β can be estimated by the method of maximum likelihood using the distribution of the second-order statistics derived above.

In our estimation, we have not incorporated information on the auctioneer's first price. In principle, this could be used to truncate the *F* and *G* distributions (as BMR (1997) have done with one distribution), given information on the number of bidders whose valuations lie above this starting price. Although we record in our data the number of 'active' bidders, given the speed at which the auctioning proceeds, it is likely that this was measured with error.[16] Instead, our analysis uses the number of 'potential' bidders at each auction (see below), and as such, does not incorporate the starting price in deriving the likelihood expressions. We don't examine the important question of whether the auctioneer's first price is 'optimally' set, either.

6.1. Some Summary Statistics

We begin by describing the particulars of buyers in the market. Although in principle the total number of buyers of basmati is large, the first two groups of purchasers dominate the market in Panipat. Over the eight week period beginning in October, there were 54 distinct purchasers. Of these, most purchased relatively small amounts. There were four buyers[17] who each had a market share in excess of ten percent (Gupta and Sons—19%, Gaurav Trading Company—15%, Anand Trading Company—17% & India International Rice—11%); collectively, their market share was a little over 60 percent. Four other buyers had shares higher than five percent: the top eight purchasers commanded over 80 percent of the sales of Basmati in

Panipat Mandi. Among these four largest purchasers, three represented mills (usually more than one mill). All these mills were some distance away from the mandi. The fourth large purchaser (India International Rice) was a representative of a local mill; the mill owner was almost invariably present at the auction as well.

The number of active bidders in our data set was for most auctions either two (38 percent) or three (36 percent), although the potential number of bidders was much larger. We use the total number of winning pakka artias on any given day as an indicator of the number of potential bidders.[18] The number of potential bidders on any given day in the peak marketing months was at least ten, and was often higher.

While the auctioneer's starting price captured the quality of grain reasonably, there is a substantial difference between the winning price and the auctioneer's starting price, which averaged Rs. 97 per quintal, or approximately 11 percent of the average start price, and ranged from zero (no sale) to nearly 40 percent. This is a large difference, in relation to the bid increments, which were as small as Re 1, and rarely exceeded Rs. 5 per quintal.

A useful way of summarizing the data is to employ ordinary least squares, regressing the win price on the number of bidders, grain prices in other markets (captured through weekly dummy variables), the quality characteristics of the lot, quantum of previous day's arrivals (to capture supply effects), a within day time trend, and dummy variables corresponding to the purchases (wins) of the four major players. Grain prices in other markets, and quality act as distribution shifters of F and G, (thereby affecting the win price); the within day trend is used to probe into the existence of patterns of prices/arrival of information during the course of the day.

It is evident (Table 1) that the quality of a lot has an important bearing on the win price, with each of the quality characteristics contributing independently to the variation in prices. It appears that supply does not influence price; but the number of bidders does. The addition of another bidder causes, *cet. par*, the winning price to rise by Rs. 23.

The coefficients associated with the large buyers are all positive, but are statistically significant only for the large pakka artias (the buyers in Group B). The price premia they pay range between Rs. 7 and Rs. 35, which are not, however, statistically different from each other. It is only Buyer A, the local miller, who appears to be winning at the same price as buyers in Group C. This strongly suggests that Buyer A wins *in the absence of* serious bidding by Group B buyers, and that when he bids, he is the only player to draw his valuation from the higher distribution.

We turn now to a formal test of the two models.

6.1 Testing the noncooperative and collusive models:

Using the models set up in sections 3 and 4, we estimate the parameters of the β vector, confining our attention to the seven quality characteristics, the previous day's arrivals, and the seven weekly dummy variables. We specify the total number of potential bidders (*n* in section 3 above) and the number of small purchasers (*m* in section 3) on a day-to-day basis. The number of potential bidders was taken to be the sum total of all winners on a given day, and the small bidders were identified as the appropriate subset of these.

Further, as noted earlier, we specify *F* and *G* to be lognormal, and that the expected value of the valuations drawn from *G* is greater than the expected value of valuations drawn from *F*. This number[19] was derived from simulation exercises, in which the difference in the mean of the distributions that would translate into the average difference in winning bids between large and small buyers was estimated. In doing this simulation exercise, we not only controlled for quality, but also excluded those lots which were won by India International Rice.

The likelihood in the collusive model is specified as follows: Whenever IIR wins, we infer that he was assigned the bidding rights over the lot, and employ the density $h_{(2),(1,m)}$, as there is only one bidder who draws from the higher distribution *G*. Similarly, whenever buyers from Group B win, we employ the density $h_{(2),(n-m-1,m)}$; (since IIR does not bid, there are only (*n*-*m*-1) bidders who draw from *G*). We do not observe which group is assigned bidding rights on a lot won by a member of Group C.

The bidding rights allocation parameter, say, $\hat{\alpha}$ is thus not observed, but may be recovered from the data making use of the Theorem of Total Probabilities (see Appendix A for details). On such lots, we use the density $\hat{\alpha}\, h_{(2),(1,m)} + (1-\hat{\alpha})h_{(2),(n-m-1,m)}$.

The results of the ML estimation of the noncooperative and collusive models using STATA is set out in Table 2:

The parameter estimates of both models have the correct signs. However, clearly, *the log likelihood value of the collusive model is much higher than that of the non-cooperative model.* Furthermore, note that despite the similar coefficient values, the computed residual sum of squares for the collusive model, at 19.9, is much lower than that of the non-cooperative model, at 29.1. These results are thus consistent with a collusive arrangement that permits India International Rice to purchase large quantities of grain at prices less than India International Rice's highest valuation. As argued earlier, the lower limit to the price paid by India International Rice for a given lot is set by the highest willingness to pay among the small buyers. This is indeed consistent with the results of the OLS regression reported above. At the same time, it is not in the interest of the other large buyers to pay lower prices, simply because their commission would then be adversely affected.

7. Conclusions

There are three striking characteristics of the regulated market in Panipat which drive our results. The first is inherent in the design of rules governing the regulated market: the contract between the principals and their agents is determined by the market committee to the extent that a commission must be paid on the value of purchases. The second feature is that the distance between mills and markets, as well as the wide variation in the quality of grain, translate into monitoring costs for the miller which in turn can be exploited by commission agents opportunistically. These features become manifest in the form of an aligning of interests of a subset (in Panipat, a large subset) of buyers and sellers. Finally, 'large' buyers draw their valuations from a higher distribution than the 'small' buyers in Panipat (this is likely to characterize many small markets).

These three features together facilitate a particularly simple form of collusion (that does not require revelation of valuations or transfer payments within the bidding ring), allocating bidding rights amongst large buyers. As other large buyers are excluded, the differences between the local miller's valuations and his winning prices are substantial (as the two are drawn from different distributions). These differences are clearly being traded off against a smaller market share.

To the extent that bidding rights are not conditioned upon which group (A or B) contains the highest valuation, the allocation of lots to buyers is not necessarily efficient. However, despite the presence of collusion, prices need not be driven down appreciably. Indeed, in relation to other studies of the impact of collusion on prices (for example, BMR(1997)), the impact on market prices need not be adverse. A successful k-player bidding ring in that paper may be able to drive prices down to the $(k+1)^{st}$ highest valuation. In our case, however, the incentives of the large commission agents militate against this form of collusion. In fact, the greater the presence of such Group B buyers in a market, the better off farmers are.

Our findings are of wider significance than the one market we study here. The features of the Panipat market noted above are typical of grain markets in North India and hence our approach, we believe, is more widely applicable. Our analysis also highlights the importance of contextualising auction mechanisms within a specific institutional framework. For instance, the received literature does not usually study auctions in which purchasers are agents. Whenever buyers are agents, the nature of the contract with their principals has a crucial bearing on market behaviour and therefore on outcomes. The present study illustrates this amply.

The simple framework we have used has yielded rich insights into competition and collusion in grain markets. However, certain issues, such as the movement of prices during the course of the day, the impact of information revelation on prices, and the impact on prices of the reputation of various buyers, and their opportunities for reputation formation across the season, may be fruitfully studied in a separate exercise.

Table 1: OLS estimates of the determinants of win-prices at basmati auctions:

(the dependent variable is the winning price of basmati):

Independent variable	**Coefficient**	**t-ratio**
Previous day's arrivals	-0.0001	-0.03
Number of bidders	23.40	10.84
Moisture Content	37.14	8.76
Uniformity in grain size	45.28	12.77
Presence of chaff	35.00	10.38
Presence of brokens	32.73	8.29
Lustre of grain	28.83	6.00
Presence of green and immature grain	36.37	7.80
Other factors	39.93	9.84
Dummy for Gupta and Sons	26.43	4.13
Dummy for Anand Trading Company	18.92	3.24
Dummy for Gaurav Trading Company	6.68	1.95
Dummy for India International Rice	0.27	0.04
Week 1 dummy	57.53	3.02
Week 2 dummy	-11.74	-1.02
Week 3 dummy	32.58	3.35
Week 4 dummy	-12.13	-0.69
Week 5 dummy	6.93	0.48
Week 6 dummy	20.66	1.66
Week 7 dummy	-34.29	-3.18
Within day trend	0.14	1.76
Constant	396.22	21.62
R^2 =0.63, n=1080		

Table 2: Maximum likelihood estimation of non-cooperative and collusive models:

(The dependent variable is the log of the winning price)

	Noncooperative	Collusive
Distribution shifter	Coefficient (std error)	Coefficient (std error)
Moisture Content	0.04 (0.005)	0.05 (0.004)
Uniformity in grain size	0.06 (0.004)	0.05 (0.003)
Presence of chaff	0.05 (0.004)	0.04 (0.003)
Presence of brokens	0.04 (0.004)	0.04 (0.004)
Lustre of grain	0.04 (0.005)	0.04 (0.004)
Presence of green and immature grain	0.05 (0.005)	0.05 (0.004)
Other factors	0.05 (0.004)	0.05 (0.004)
Week 1 dummy	0.08 (0.026)	0.07 (0.0240
Week 2 dummy	-0.10 (0.013)	-0.06 (0.112)
Week 3 dummy	-0.04 (0.011)	-0.01 (0.010)
Week 4 dummy	-0.08 (0.019)	0.004 (0.165)
Week 5 dummy	-0.04 (0.016)	-0.01 (0.014)
Week 6 dummy	-0.05 (0.014)	-0.01 (0.013)
Week 7 dummy	-0.09 (0.012)	-0.07 (0.011)
Previous day's arrivals	Neg (neg)	Neg (neg)
Constant	6.14 (0.021)	6.18 (0.018)
Log Likelihood value	*1450.68*	*1641.10*

Appendix A

1. Density corresponding to the distribution of the second order statistic $H_{(2),(n-m,m)}$ under noncooperative behaviour

Given that a random sample of size m is drawn from a distribution F and another random sample of size (n-m) is drawn from a distribution *G*, the distribution of the second-order statistic $H_{(2)}$ is as given in expression (1) in the text. The corresponding probability density function is given by:

$$h_{(2)(n-m,m)}(v) = m[F(v)]^{m-2}[G(v)]^{n-m-1}\{-F(v)G(v)f(v) + (n-m)[1-F(v)]F(v)g(v) + (m-1)[1-F(v)]f(v)g(v)\}$$

$$+(n-m)[F(v)]^{m-1}[G(v)]^{n-m-2}\{-F(v)G(v)g(v) + (n-m-1)[1-G(v)]F(v)g(v) + m[1-G(v)]f(v)G(v)\}$$

$$+[F(v)]^{m-1}[G(v)]^{n-m-1}\{(n-m)F(v)g(v) + m f(v)G(v)\}$$

2. Density corresponding to the distribution of the second order statistic under collusive behaviour is given by

$h_{(2),(1,m)}$ -- if Buyer A wins the lot

$h_{(2),(n-m-1,m)}$ -- if a buyer in Group B wins

$\hat{\alpha}\, h_{(2),(1,m)} + (1-\hat{\alpha})\, h_{(2),(n-m-1,m)}$ -- if a buyer in Group C wins

Appendix B

Computing the bidding rights allocation parameter $\hat{\alpha}$:

The realized market share s of buyer A (IIR) relative to group B, is approximately equal to the product of $\hat{\alpha}$ and the probability that A wins the lot, given that he was assigned the bidding rights for it, P[A wins | A is assigned the lot]. We take the view that the allocation parameter is determined on a daily basis.[20] We compute P[A wins|A is assigned the lot] (P(A wins|A) for brevity), and similarly P[B wins| B] for each day of our sample from simulation exercises of 1000 runs each. Given this and the daily market shares s and $(1 – s)$, $\hat{\alpha}$ is computed from:

$s = [\hat{\alpha}\ P(A\ wins\ |\ A\ )]/[\hat{\alpha}\ P(A\ wins\ |\ A\ ) + (1-\hat{\alpha})P(B\ wins\ |\ B\ )]$, so that

$\hat{\alpha}\ = [s\ P(B\ wins\ |\ B)]\ /\ [s\ P(B\ wins\ |\ B) + (1-s)\ P(A\ wins\ |\ A)]$

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[1] To the best of our knowledge, this is the first ever study of this variety of grain.

[2] This paper is part of a larger study of paddy and wheat markets. In addition to analysing questions related to efficiency, the larger project studies the following interrelated issues:

- the impact of government intervention on the price formation mechanism;
- whether there is any evidence of interlinking of credit advances to farmers by commission.

[3] 'Paddy' refers to the harvested grain whereas 'rice' refers to the milled grain.

[4] The Second ICSSR Survey of Research in Economics: *Agricultural Marketing and Credit* (1989) reviews the earlier and other related work.

[5] Set up under the Market Regulation Act, regulated markets are run by market regulatory committees. The functions of a market committee include: maintaining the physical infrastructure of the market place; supervise weighment; settle disputes; appoint auctioneers; provide transparency to the price formation process; maintain market records (on arrivals and auction prices), and to ensure that no unauthorized costs are passed on to the farmer.

[6] The responsibilities of the agent include cleaning the grain brought to the market, providing display space for the grain, procuring bags, and making the final payments. The commission agent does not charge the farmer anything for these services, but earns interest income from him by financing working capital loans during cultivation, as well as consumption loans, which are repaid post-harvest at interest rates ranging from 2 to 3 percent per month (we do not study this interlinkage here). Of course, where farmers come from a distance (such as those who come from the neighbouring state) there is no exclusivity to the contract between the katcha artia and the farmer; the contract is negotiated on a day-to-day basis.

[7] The distinction between the katcha and pakka artias is thus primarily one of function: katcha artias *sell* grain on behalf of farmers; pakka artias *purchase* grain on their own account, or on behalf of mills. Both kinds of artias must be registered with the market committee; registration fees are nominal, and must be renewed on an annual basis. The license to trade is not transferable. There are no visible barriers to entry. The cost of acquiring shops at the Panipat market for example, at between Rs. 60,000 and Rs. 100,000, is a very small fraction of the annual turnover of katcha artias (of about Rs. 10 million).

[8] There is a caveat to this: the farmer has the right to opt out of the transaction if the final price is not satisfactory for any reason. Such incidents are rare; we did not observe many during our field work. In principle, therefore, the auctioneer's first price is not the same as the farmer's reservation price. The auction proceeds too quickly for the auctioneer to take time to determine the farmer's reservation price at each lot.

[9] Recent literature on sequential auctions of multiple objects (Donald, Paarsch and Robert (1997)) assumes homogeneity of objects. The major difference vis-à-vis single-object auctions is that players bids may not be equal to their valuations; multiple (Perfect-Bayesian) equilibria exist, and empirical implementation must exclude all but one of them. There is little by way of theoretical and empirical work in this dynamic setting when the objects are heterogeneous, and is an area of future research.

[10] The difference in the payoffs of Group A and Group B players is more starkly brought out if we consider a sealed-bid, first price, auction. Then, a Group A player with valuation v would shade his bid below v whereas a Group B player with valuation v would bid v.

[11] Skrzypacz and Hopenhayn (1999) have recently studied the possibility of collusive schemes better than bid rotation in infinitely repeated 'standard auctions'. Earlier theoretical work, mostly on single object auctions, includes McAfee and McMillan (1992), Mailath and Zemsky (1991), Ungern-Stenberg (1988), Graham and Marshall (1987).

[12] Since millers operate in several markets, collusion may in fact be easier than in the single market setup that we consider. This idea can be traced to the "multi-market contact" literature starting with Bernheim and Whinston (1990).

[13] Each sale is recorded by a market committee official. Details on the name of the farmer, the name of *katcha artia*, approximate quantity in the lot, the winning bid, and the name of the winner are thus available for each auction. Also, information on daily market arrivals can be obtained from these records. The market committee records do not, unfortunately distinguish between variety. And as noted earlier, varietal differences can be substantial in this crop. However, it is possible to cull variety-specific information from these records by (a) noting the different harvest and marketing periods for each of the varieties, (b) taking advantage of the fact that each variety is sold in distinct price bands which by and large do not overlap, and (c) using our sample data as well as the trends in prices over the season to determine these price bands. As a result, we were able to isolate over 9250 transactions pertaining to basmati in Panipat. This data set was used to identify the major buyers and sellers, and to calculate the associated market shares.

[14] It is also important to note that quality assessment in the case of paddy is difficult: for example the relationship between moisture content and quality of grain is distinctly non-linear, with both too-low as well as too-high moisture adversely affecting milling ratios.

[15] Although we were told that some of these quality variables were correlated, for example in paddy green and immature grain is associated with high moisture content, it turned out that in our sample, the pairwise correlations were all low.

[16] It is possible that a bidder has a valuation higher than the starting price, but does not participate vocally in the bidding. We observed that much of the signaling between the auctioneer and bidder is through eye contact. Such a bidder is likely to go unrecorded.

[17] The names have been changed in order to protect the identities of the buyers.

[18] We make the reasonable assumption that all serious bidders won at least one lot a day.

[19] This translates into a difference in means of about Rs. 30.

[20] The allocation parameter can be taken as sensitive to the distribution of quality across lots on a given day.