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Buyer Collusion and Efficiency of Government Intervention in Wheat Markets in Northern India: An Asymmetric Structural Auctions Analysis

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Abstract

This paper uses auction theory to analyze wholesale markets for wheat in Northern India. This approach enables us not only to characterize the market in terms of buyer asymmetries, but also to detect the existence of collusion and to quantify its impact on market prices. We show that buyer asymmetries exacerbate the downward impact of collusion on prices. The paper also demonstrates the use of auction theory to analyze questions of government efficiency. It considers whether the government paid too much for the wheat it procured at the minimum support price, and shows that for our sample it did not. The paper is based on a primary survey of two wholesale markets in North India.

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1. Introduction

The use of auctions to effect sales of foodgrains in wholesale markets has a long history in India. Descriptions of the marketing of grain dating back at least to the 1930's (Government of India, 1937) indicate that grain was often sold through an oral, ascending auction. Over the years, this process was institutionalized through the setting up of regulated markets.[1] However, studies analyzing the *process* of price formation in these markets do not exist, although there is a large literature on studying the market outcomes themselves (such as the literature on market integration in Indian agriculture; e.g., Wilson and Swami (1999), Palaskas and Harriss-White (1993)).

Some studies (such as Palaskas and Harriss-White (1993)) suggest that regulated markets in India do not in fact serve the function of maximizing farmers' revenue, because of the lack of transparency in the price formation process, and the widespread existence of collusion. But these studies have not analyzed the *behavior* of agents in grain markets in any substantively formal way. As a result, they are silent on the forms that collusion may take, and have obviously not quantified the effect of such collusion on market prices.

The theory of auctions provides a powerful tool to analyze such questions. It not only enables a precise theoretical description of the market, but can be employed to quantify the effects of collusion amongst a subset of buyers. It is relatively unused in the analysis of grain markets in developing countries.

Most grain markets in developing countries are characterized by buyer concentration, with relatively few buyers dominating the market. This feature implies that there are systematic differences in willingness to pay (arising out of asymmetries in mill size, technology, as well from distinctive markets they may face for the processed grain). Auction theory also permits us to characterize such buyer asymmetry in the market, and to analyze its influence on auction outcomes, both in the presence and absence of collusion.

The first of our objectives is to characterize the behavior of buyers in a wholesale wheat auction market in North India. Specifically, we analyze asymmetries across buyers, detect whether collusion exists, and the form it takes.

A second objective of our paper is to analyze questions of the efficiency of the government's procurement, in the specific sense of whether the government is paying too much for the quality of grain it purchases. Other studies have asked related questions on the efficiency of government procurement: for instance, it is widely believed that government grain is of inferior quality (either because of poor purchase or storage decisions—see for example Balakrishnan and Ramaswami (1997)). An equally pertinent question is the one we ask: given the quality of grain that the government purchases, does it pay too much?

We focus on rural wheat markets in Delhi and Haryana in North India. For nearly four decades, government intervention in these markets has been substantial. Each year, the Government of India announces a minimum support price (MSP) at the time of sowing which provides a floor below which market prices cannot fall. The government is committed to purchasing all 'fair average quality'[2] grain at the MSP, in case market prices are not higher than this. This wheat is later sold at subsidized prices through the Public Distribution System (see Appendix A).

The paper is based on a primary survey of two regulated wheat markets: one in Narela (a large market in the state of Delhi) and one in Panipat (a comparatively small market in the state of Haryana) and conducted in 1999. In Narela, all the wheat was bought by private millers and traders, and prices were inevitably higher than the MSP. In Panipat (about 100 kilometers away from Delhi), on the other hand, the procuring arms of the state government bought virtually all the grain that arrived at the MSP, which was Rupees 550 per quintal. In fact, for the state of Haryana as a whole, the government procured nearly 45 percent of wheat production in 1999.[3]

A principal advantage to estimating a structural model using auction theory is that it enables simulation of alternative states of the world. Having detected collusion and estimated a collusive model, we are able to quantify its impact on market prices by simulating environments in the presence and absence of collusion. In the market that we study, it is the presence of buyer asymmetry that exacerbates the downward impact of collusion on market prices.

Similarly, using this framework, we are able to analyze the question of the efficiency of government intervention by posing the following question: if the lots of grain that we observe in Panipat were to be sold on the Narela market instead, what prices would we expect them to sell at? And, how do these prices compare with the price that the government actually paid in Panipat? By modeling buyer behavior in the Narela market, we are able to take any lot of grain from Panipat (with given quality characteristics), and simulate an auction with a given number of players to derive the counterfactual win price.

As noted earlier, the use of auction theory to analyze markets in developing countries has been limited, although there is now a substantial empirical literature for various commodities in North America and Europe. This empirical literature may be categorized broadly in two groups. One estimates *reduced forms*, testing relationships implied by auction theory (e.g. Hendricks and Porter (1988), Porter and Zona (1999)). A second and relatively more recent group of studies estimates *structural* auction models. Early contributions include Paarsch (1992) and Laffont, Ossard and Vuong (1995).

Still more recent is the literature estimating *asymmetric* structural auctions models. Important contributions include Bajari (1997), and Campo, Perrigne and Vuong (2001) on first-price sealed-bid auctions, and Athey and Haile (forthcoming) and Hong and Shum (2000) on ascending auctions. Work on collusion in auctions that uses structural models includes Baldwin, Marshall and Richard (1997) and Bajari and Ye (2001(a) and (b)). Sareen (forthcoming) is one of several recent surveys of the fast expanding literature. The present paper estimates asymmetric structural auctions models.

It is important to note here that the literature that uses the hedonic framework to analyze agricultural prices is not directly relevant. In this approach, prices are characterized as a function of the quality of grain (the earliest examples of this are perhaps Waugh's (1928) famous study of asparagus; other examples include Mercier, Lyford and Oliveira (1994), Uri and Hyberg (1996) and McConnell and Strand (2000)). But for the kind of auction markets for grain that we study in this paper, the hedonic approach is not appropriate. These markets display a degree of buyer concentration and collusion, and hence cannot be characterized as competitive in the sense of the hedonic model.

We set out in the next section a description of the wheat markets that we surveyed, along with summary statistics of the main variables. In Section 3, we describe models of collusive and of non-cooperative behavior in the auctions at the Narela market. Estimation results are in Section 4. As reported there, the data support the collusive model. We proceed then to use the parameter estimates from the collusive model for several sets of simulations with the objectives of performing a validation exercise (4.2), measuring the impact of collusion on sale prices (4.3), and evaluating the efficiency of government procurement in the Panipat market (4.4). Section 5 concludes; some details of government intervention in grain markets, models estimated and auxiliary results are provided in appendices.

2. The Wheat Market in Narela and Panipat

The peak marketing season in Narela lasts approximately a month starting in the second week of April. In 1999, over this period, nearly 176,000 quintals of grain arrived in the market. Grain arrivals were heaviest in the third week of April, with over 10,000 quintals of grain arriving each day. By the end of April, arrivals were much lower: between 5,000 and 8,000 quintals, and finally tapered down to 2,000 to 3,000 quintals a day by the middle of May. Thus nearly 80 percent of the total market arrivals for the season took place by the end of April. Panipat is a much smaller market–over the season about 16,000 quintals of wheat arrived, and arrivals virtually stopped by early May 1999.

In these regulated markets, each farmer contracts with a commission agent, known as *katcha arhtia*, who arranges to display the wheat in lots, store it overnight if it is unsold on a particular day, weigh the grain, and so on, in return for a commission of 2 percent of the sale price of the grain. In Narela, the grain is sold to both private millers, and traders who represent mills (frequently located some distance away in southern India). In Panipat, no auctions took place; government agencies bought up virtually the entire market at the MSP.

2.1. The Auction Process in Narela

Once the grain brought by the farmer is displayed in lots in the market yard, the *katcha arhtia* starts the process of auctioning. Several players compete for the lot, and each makes independent assessments of quality by examining the grain. The auction starts at the MSP, bidding proceeds as the seller then begins to raise the price; as the price rises, bidders 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 have dropped out; this bidder wins the lot at the price last announced.[4] The auction then proceeds to another lot and the process begins again.[5] Since the *katcha arhtia* receives a commission on the sale price value of the lot sold, he has an incentive to raise the price.

2.2. The Players in the Narela Auctions.

Over the peak marketing season, there were about 50 purchasers of wheat, most of whom had small market shares. The three largest buyers however accounted for about 45 percent of the market. Among these, one, whom we refer to as H, is a large local miller (19%), one, SM, is a trader who buys on behalf of mills located in South and Southwest India (14%), and the third, SR, is a trader who buys for mills located near Delhi[6] (12%).

The Narela market also appeared to be characterized by collusion between the two traders and the miller. Casual observation suggested that when one of them bid, the other two did not. The players bought wheat of approximately similar quality (see Section 2.3), so it is not the case that we were observing tacit coordination across different levels of quality. Since we do not have a record of bidder identities per auction, we can only hope to gather statistical evidence of this bid rotation, which we present in Sections 3 and 4. In the empirical literature on collusion in auctions, it is assumed that the form of bid rotation is "efficient", that is, the cartel player who bids is the one having the highest valuation amongst all cartel players. This does not fit the wheat auction market in Narela. In order for a cartel to determine who the highest valuation player within the cartel is, there would have to be a mechanism by which the cartel players reveal their valuations within the group. In the wheat market, the players assess the quality of a given lot on the spot, while the auction is on. This determines their valuations or willingness to pay. The rapidity of the auction and the open space in which it is conducted does not afford players an environment in which they may exchange information. It is likely that bid rotation is therefore either predetermined, or determined through signals such as eye contact, but is not conditional upon an intra-cartel revelation of valuations at each auction.

2.3 Data collection

The data set is based on a primary survey that we conducted in April and May 1999, which is the marketing season for wheat. This was supplemented with information from market committee records[7], and personal interviews. In this paper we focus on peak part of the season, which consisted of the latter half of April and the first week of May.

For each lot auctioned, a market committee official records the identities of the farmer whose lot is being auctioned, and the buyer, as well as the sale price. This information is inadequate to conduct a study of the auction. Therefore, we tracked a random sample of wheat auctions on ten days spread over three weeks from mid April to early May (totaling 421 auctions, or about 14% of the population of auctions).

We had a team of two investigators. One noted the starting price (per quintal of grain; in Narela, the starting price was invariably the MSP), winning price, the number of active bidders after the starting price was announced, and the name of the winner of each lot. The other noted down particulars of quality of the lot of grain being sold. Auctions are conducted at a rapid rate; typically, there is a crowd of farmers and commission agents watching each auction. In this atmosphere, given our resources and unfamiliarity with many of the players, it was not possible to observe and record the identities of all bidders, or the prices at which they dropped out of the bidding. Thus we have no record of participation rates of different players. It is reasonable to assume, though, that if a player is present at some auctions on a given day, then participation at other auctions is costless.

As noted earlier, Panipat is a much smaller market; no auctions took place here. Therefore, in this market, we only recorded quality characteristics of the grain or each lot in our sample over a two-week period. We thus collected over 100 observations; by early May, there were virtually no wheat arrivals at Panipat.

For recording information on the quality of grain in the lot, we held interviews with market committee and Food Corporation of India (the procurement arm of the central government) officials, buyers and agricultural scientists. These discussions indicated that the following quality characteristics influence wheat prices: moisture content, uniformity in grain size, the presence of foreign matter, and the presence of other foodgrain in the lot. These quality characteristics translate after milling to different quality grades of wheat flour. Through pre-testing, we determined a consistent pattern of visually evaluating these on a scale of 1 to 3 (worst to best quality). In doing so, we mimicked the quality assessment process undertaken by the bidders. An alternative would have been to collect samples from each lot and have them laboratory tested; we did not take this route in order to avoid undue attention and suspicion. As it transpired, the season was exceptionally hot and dry that year; therefore the moisture content of virtually all lots was ideal. Consequently, we drop this variable from our analysis.

2.4. Summary Statistics

The above three quality variables constitute the major variables in the vector x_t of observables in lot *t* of grain in the sample and the data on them are summarized along with price and bidder information in Table 1.

Table 1A. Some summary statistics of the Narela sample (sample size=421)

	Mean	Std. Dev	Min	Max
Winning price (Rs per quintal)	562.60	6.37	550.5	602.50
Number of bidders	2.95	1.10	2	6
Uniformity in grain size	2.19	0.50	1	3
Absence of o ther foodgrains	2.74	0.46	1	3
Absence of foreign matter	2.49	0.60	1	3

Market committee records show that during the peak marketing period, there were at least 90 buyers who won auctions. In our sample, we recorded 50 such buyers. However, as mentioned above, the three top players (H, SR and SM) accounted for 45 percent of all purchases. A few other buyers have shares less than 5%, and yet many others' shares are less than 1% each.

The fact that H and SR cater to local mills, while SM's clientele is located in relatively distant South and Southwest India indicates that transport costs differ significantly between SM on the one hand, and the other two. Other things being equal, one would expect SM's willingness to pay for a lot to be less than that of H or SR.

Two to four bidders actively bid in most auctions. This number is small relative to the total number of purchasers of grain on any given day (between 6 and 13 in the peak marketing days), for primarily two reasons. Potential bidders with valuations less than the minimum support price are not observed. Second, millers with low capacity mills participate in relatively few auctions through the day. Given the heterogeneity of the grain, it is also possible that different buyers are interested in grain of different qualities.

The top two players bought approximately similar qualities of wheat. For simplicity, we construct an aggregate quality variable which is the unweighted sum of the three quality characteristics, and therefore ranges from 3 to 9. The average quality bought by SM was 7.03, while that bought by H was 7.27. The quality of wheat bought by SR was somewhat higher, at 7.77; other purchasers' average quality was 7.58. A similar exercise conducted with individual quality characteristics yields qualitatively the same results; in particular, there is no sharp distinction in any quality attribute of grain in the purchases of the top three buyers.

Table 1B below provides similar features of the wheat procured by the government at Panipat. Here, too, moisture content was ideal—95% of the lots sold had ‘ideal’ moisture content—and is therefore not included in the analysis. While the average quality of wheat in Panipat (in terms of uniformity, presence of other foodgrains and foreign matter) was somewhat lower than that in Narela, the differences are not meaningful.

Table 1B. Summary statistics of the Panipat Sample

	Mean	Std. Dev	Min	Max
Uniformity in grain size	2.08	0.45	1	3
Absence of Other foodgrains	2.67	0.59	1	3
Absence of foreign matter	2.55	0.55	1	3
Aggregate quality	7.30	0.98	3	9

As a further aid to describing the auction market for wheat in Narela, we regress the win price on several factors that affect it, which include the three quality variables, and the number of active bidders for each lot. In each case, one would expect the coefficients to be positive. We also include dummy variables for two of the three weeks in our sample to capture the impact of conditions in other markets, and a dummy variable for each for the three large buyers.
The results, set out in Table 2 below, highlight several features of our data set.

Table 2. OLS Regression Results
(Dependent variable: Win Price in Rs. per quintal; number of observations = 421)

	Coefficient	Standard Error
Uniformity in grain size	3.2	0.4
Presence of foreign matter	1.0	0.4
Presence of other foodgrains	2.4	0.5
Number of bidders	0.5	0.2
Week 2 dummy	6.4	0.5
Week 3 dummy	10.8	0.7
Dummy for SM	-2.7	0.7
Dummy for H	-0.8	0.6
Dummy for SR	0.2	0.7
Constant	540.4	2.2
R-squared	0.46	

First, all the quality variables have the expected positive sign and are statistically significant; of these uniformity in grain size would appear to be the most important. Further, factors other than quality also have a significant impact on the winning price. In particular, the number of bidders has the expected sign and is statistically significant. Therefore, while quality of grain is an important determinant of the price at which it is eventually sold, the role played by auctions and the competition amongst buyers it engenders, as captured by the number of bidders variable, cannot be ignored either. We note also that the relatively small coefficient (approximately 50 paise) associated with the number of bidders is a consequence of the regression not taking into account bidder identities; as we show in section 4.3, the positive impact of an additional *large*, cartel bidder on the winprice is substantial.

What is also interesting is that after controlling for quality and the number of bidders, it is only SM who is able to buy grain at significantly lower prices than his competitors.[8] The coefficients associated with the other two of the large buyers are *not* statistically different from zero. A possible reason for this is explored in Section 4.2 below.

3. Models of Collusion and Non-cooperation

3.1. The Auction Framework

The auction models that we estimate are 'independent private values' (IPV) models that display asymmetries across bidders. Suppose there are *p* potential buyers for a given lot. The IPV assumption implies (a) the *valuation* v_i (or *willingness to pay* for the lot) of bidder *i*, is privately known to the bidder; (b) the bidders' valuations $v_1,...,v_p$ are drawn independently from some underlying distribution or distributions that are common knowledge.

It is well known that for ascending auctions in the IPV setting (see for example Klemperer (2000)), in Bayesian equilibrium a player's bid (or price at which he quits the auction) equals his valuation. The winning bid or sale price is therefore equal to the second highest valuation out of $(v_1,...,v_p)$. If we assume that the bidders' strategies in our data set are not dynamic but lot-specific as in the above description, it then follows that the winning prices are realizations of the second (that is, second-highest) order statistic.

Besides the simplicity that the IPV assumption lends to the ensuing analysis, its other virtue is its reasonableness in our context. The valuation of a miller depends upon the difference between the price he receives for selling wheat flour and the cost of processing wheat[9]. Open market (retail and wholesale) prices of wheat vary substantially across the country and by grade. To the extent that a miller's markets are privately known, this is an IPV component. The processing cost of wheat is mill-specific and privately known; there can be significant cost differences across firms.[10] This lends support to an IPV, rather than a common-values, specification.[11] The traders SM and SR are known to purchase grain on orders from millers. One can therefore interpret, say, SM's valuation for a lot as the price at which a client miller has agreed to buy the grain.

The specific characteristics of each of the three large buyers are suggestive of a pattern of differences in their willingness to pay for wheat. SR, and H, who buy for mills at or near Delhi would have the highest willingness to pay. In contrast, SM, whose grain is transported to mills nearly 2000 kilometers away, would have a lower willingness to pay. The mode of transport of grain—whether by road or rail—may also be private information, and adds a further IPV component to valuations. One would expect that the willingness to pay of the small buyers is lower still.

We therefore assume four different distributions of valuations – one each for the three large buyers—HM, SR and SM, and one for the rest of the buyers, who are 'small'. We club together buyers other than the 3 large buyers because their market shares are individually small; moreover, distinguishing them satisfactorily would require that we observe all bidder identities and bids of players who drop out, which is not the case with our data.

We use the notation that the small players draw their valuations from a distribution F (with corresponding density f), while SM, H and SR draw from G_i

(i=1,2,3, respectively), with corresponding densities g_i. All distributions have common left and right supports a and b, respectively. Since we observe, for any given lot, the MSP (which is also the starting price of the auction), and the number of bidders n that are subsequently involved in the bidding, this number n corresponds to those bidders whose valuations are greater than the MSP.

3.2. The Collusive Model

Our first model presumes a simple form of bid rotation between the three large buyers, whereby only one of them bids at a given lot. Thus of the n bidders observed at each lot, $m = n - 1$ are 'small' and one is large (the cartel bidder). This accords well with casual observation during fieldwork that the large bidders would not bid against each other. As we elaborate later in Section 4.2, this arrangement also explains the OLS regression result in Table 2 above that SM's win prices are lower than that of the others. We argued in Section 2.2 that efficient bid rotation does not fit the context of this auction. We therefore assume that at each auction, the three cartel bidders use a randomization to assign the lot to one cartel member to bid on.[12]

In our sample, we observe both the win price and the identity of the winner. Suppose that for a given lot the designated large bidder is player i, whose valuation for the lot is a draw from the distribution G_i; suppose that the number of small bidders at the lot is m, and each of them draws a valuation independently from F. The probability that the winprice (which equals the second highest of these n=m+1 valuations) is less than or equal to v and the winner is the large bidder, i, is given by[13]:

$$H_{g_i}(v) \equiv \Pr(V^{(n-1:n)} \leq v \;\&\; i\ wins) =$$
$$\int_a^v [F(t)]^m \, dG_i(t) + [F(v)]^m (1 - G_i(v)) \qquad (1)$$

where a is the common left support of all the distributions and $V^{(n-1:n)}$ denotes the second-highest (or (n-1)th out of a sample of size n) order statistic. The first term in

Eq. (1) corresponds to events in which all bidders have valuations less than v, and the second, to the event in which only the winner, i, has a valuation strictly greater than v.[14]

On the other hand, with the same large bidder being present in the auction, the probability of the winprice being less than or equal to v and the winner being a specific *small* player j is

$$H_{f,g_i}(v) \equiv \Pr(V^{(n-1:n)} \leq v \,\&\, j\ wins) =$$
$$\int_a^v [F(t)]^{m-1} G_i(t) dF(t) \;+\; [F(v)]^{m-1} G_i(v)[1-F(v)] \qquad (2)$$

The corresponding densities $h_{g_i}, h_{f,g_i}, i=1,2,3$ are provided in Appendix B (equations (B1) & (B2)). With the valuation distributions truncated at Rs.550, the densities are $\overline{h}_{g_i}, \overline{h}_{f,g_i}, i=1,2,3$. These form the basis of the likelihood function used in the estimation (see Appendix B).

The sample observations are thus partitioned into four subsets, by winner. The density $\overline{h}_{g_i}$ is used whenever the winner is the large buyer $i, i=1,2,3$. When a small bidder wins, however, we do not know which of the large bidders was assigned to bid on the lot. Therefore, the density we use is a weighted average: $\sum_{i=1}^{3} \alpha_i \overline{h}_{f,g_i}(v)$ where the weights sum to one. α_i may be interpreted as the probability that the large player i was the designated large bidder, given that a specific small player j is observed to have won the lot. (see Appendix B for details).

This estimation using the joint density above is possible because of a recent identification result (Athey and Haile (forthcoming), Theorem 2 (a), and Meilijson (1981)). The theorem states that under the IPV assumption, and assuming that the 'latent' distributions from which different bidders draw valuations are continuous and have a common support, the joint distribution H of the second highest order statistic and the identity of the winner uniquely identifies all the latent distributions. The present paper is perhaps one of the early applications of this powerful result.

3.3. The Non-cooperative Model

Under non-cooperative behavior, we assume that each of the three large bidders would participate at every lot auctioned. As noted in Section 2.3, if a bidder is present on a given day, participation at each auction has no additional cost. Our records show that the cartel bidders were present on practically all days. Even so, if a bidder's participation at an auction depends on the quality characteristics of the lot, this need not be the case. However, we have seen that there are no substantial differences in the quality characteristics of the lots bought by the large players; thus non-cooperation implying participation at each lot is a reasonable approximation. A more complete characterization would require information on bidder identities at each auction, which is absent in our data set for reasons outlined earlier.

With three large bidders drawing valuations from G_i, i =1,2,3, and m small bidders from F, the probability of the winprice being less than or equal to v and the winner being a specific large player i, is (indexing the other two large players by k and l)

$$H_{g_i}^N(v) \equiv \Pr(V^{(n-1:n)} \leq v \;\&\; i\ wins) = \int_a^v [F(t)]^m G_k(t)\, G_l(t)\, dG_i(t) \; + \\ [F(v)]^m G_k(v)\, G_l(v)[1-G_i(v)] \qquad (3)$$

As in Eq. (1) and (2), the first term relates to events in which all players' valuations are less than or equal to v, and the second to the event that i's valuation exceeds v while others' valuations are less than or equal to v.

On the other hand, the probability that the winprice is less than or equal to v and the winner is a specific *small* player j, with all three large players bidding is

$$H_f^N(v) \equiv \Pr(V^{(n-1:n)} \leq v \,\&\, j\,wins) = \int_a^v [F(t)]^{m-1} G_1(t)\, G_2(t)\, G_3(t) dF(t) +$$

$$[F(v)]^{m-1} G_1(v)\, G_2(v)\, G_3(t)[1 - F(v)] \qquad (4)$$

The corresponding densities and truncated densities are set out in Appendix B, which also spells out their use in the maximum likelihood procedure used for estimating the non-cooperative model. Once again, Theorem 2 of Athey and Haile (forthcoming) is invoked to ensure identification of the four underlying distributions.

4. Model Estimation and Results

To estimate the collusive and non-cooperative models, we parameterize *F* and G_i by assuming that all four latent distributions are distributed as truncated normal; with the left truncation at the MSP of Rs. 550. The mean of each distribution is assumed to be a linear function of quality characteristics, and weekly dummies. Thus, the mean of *F* is specified as $x_t'\beta$, where the vector x_t consists of the three quality variables for lot *t* and two weekly dummies, and a '1' to capture a constant term. Further, given that quality premia do not appear to vary by bidder (see endnote 8), we assume that the means of the four groups of bidders vary only up to a constant. Thus the mean of G_i is given by $x_t'\beta + \mu_i$, $i = 1,2,3$. For simplicity, we assume that the variances of the large players' distributions are the same, but different from the variance of *F*.

We estimate the collusive and non-cooperative models using maximum likelihood. The two models are non-nested. To choose between them, we first compare the log likelihood values, and the sum of squared differences between the observed and predicted win prices. We then formally use Vuong's (1989) model selection test. We use STATA and GAUSS for the estimation and simulations below.

4.1 Deciding between the Collusive and the Non-Cooperative Models

The log likelihood value for the collusive model at –1574.01 is higher than that of the non-cooperative model of –1841.18. Also, the mean residual sum of squares for the collusive model at 28.04 is much lower than the corresponding 62.65 for the non-cooperative model. Finally, Vuong's test statistic at 11.60 also favors the collusive model.

The collusive model thus characterizes our data set better than the non-cooperative model. To verify that the truncated normal distribution accurately characterizes the latent distribution of valuations, we perform the Kolmogorov-Smirnov (KS) test for the collusive model. While the details of this are presented in Appendix C, we simply note here that the KS test validates the distributional assumptions. The rest of this section therefore focuses on the collusive model, and illustrates its implications.

The estimated parameters of the collusive model are presented in Table 3 below.

Table 3. Maximum likelihood parameter estimates of the collusive model

	Coefficient	Standard error
Uniformity in grain size	3.35	0.44
Absence of foreign matter	0.47	1.23
Absence of Other foodgrains	2.83	0.55
Week 2 dummy	6.95	0.55
Week 3 dummy	11.73	0.86
Constant	538.69	2.16

The quality parameters all have the expected sign, although the coefficient associated with foreign matter is statistically insignificant.

Furthermore, the estimated μ_1 for the latent distribution for SM, at Rupees 1.30 per quintal, implies that the mean of SM's distribution for a given lot of grain is only slightly higher than that of the small players. μ_2 and μ_3 (the 'mean differences' of H and SR respectively) are estimated at Rupees 25 and 35. These much larger numbers accord well with locational advantages of local mills (served by

H and SR) as compared to the distant mills served by SM. Although the mills served by SR are somewhat farther away compared to H's mill, casual empiricism suggests that they are larger – thus the difference in the means of the distributions between SR and H probably reflects economies of scale. The standard deviations of the distributions of valuations of three large players are smaller at Rupees 3.93, in contrast to that of the small players, whose standard deviation is Rupees 8.35.

The estimates of $\alpha_i, i = 1,2,3$ are respectively 0.99, 0.005, 0.005. Recall the interpretation that α_i is the probability that large player *i* was the large bidder on a lot, conditional upon any specific small player winning it. The estimates are consistent with the mean differences in the latent distributions; if SR or H bid on a lot, it is almost certain that no small player will have a higher valuation (given the observed low numbers of small bidders). By implication, observing that the winner is a small player means that the large bidder was almost certainly SM.

Given that the estimated latent distributions of SR and H stochastically dominate SM's, the fact of his large market share is consistent with their not bidding when he bids on a lot. Moreover, SM's valuations are not too much higher than those of small players (although their variance is much lower). Thus his large market share may be explained by a high frequency of participation, something that we noticed during the field work.

4.2. A Validation Exercise for the Collusive Model:

As a check on the estimated model, we conduct a simulation experiment to determine whether we are able to replicate the lower prices paid by SM when he wins, indicated by the OLS in Section 2.2. Under bid-rotation, small players would bid against exactly one of the three large buyers. We simulate *m* draws from *F* and one draw from G_1, all truncated at Rupees 550, and compute win prices. For the purposes of simulation, the mean of *F*, and G_1 are evaluated at average quality, and Week 2, using the coefficients in Table 3 above. The simulation is replicated 10,000 times, and an extract from the results, outlined in Table 4 below indicates that when the number of draws m from F is relatively small, SM does indeed win at prices more than Rs. 2 lower than when small players win. This price advantage disappears as m increases.

Table 4. Simulated win prices for SM and SR (10,000 replications) (Rupees per quintal)

Small players bid against SM (m draws from F and one draw from G_1)		
M	Win price for SM	Win price for small buyers
1	556.4	558.8
2	558.9	559.4
3	560.4	559.7

The result that SM's winprices are lower than average is not unexpected, given that there are often only 1 or 2 small bidders bidding against him, and the higher mean and lower variance of the distribution from which his valuation is drawn. The intuition is best understood when SM bids against exactly one small bidder. Whenever the small bidder wins, the win price is equal to SM's draw; whenever SM wins, on the other hand, the win price is a draw from F; being from a 'lower' distribution, this draw tends to be lower in magnitude.[15]

4.3. Impact of Collusion on Win Prices

Bid rotation, by lowering the number of bidders in an auction, naturally results in lower win prices. Its impact is heightened under asymmetry, because the two absent bidders draw valuations from distributions that stochastically dominate that of the small players. Since H and SR, the buyers with the largest valuations, never bid against each other; this is quantitatively the most important factor in lowering win prices in the presence of collusion.

In Table 5 below, we report expected win prices under collusion, and compare them with prices that would have prevailed had all three large bidders been present at each auction. In computing these predicted win prices, we do not truncate the players' valuation distributions, so as to allow for the possibility that the win price is actually below the MSP in the absence of the government enforcing it. The expected winprice is the expectation of the second order statistic (whose density is z under

collusion and z^N under non-cooperative play; these expressions are Eq.(B7) and (B9) respectively in Appendix B). We vary the total number of (potential) bidders from 6 to 13. This variable is not the same as the number of active bidders that we record at each lot; active bidders have valuations that are higher than the starting price of Rupees 550. The range of between 6 and 13 of potential bidders corresponds to the total number of buyers who won one or more auctions on the days in our sample. This is a reasonable approximation, since it was hard to observe buyers who did not win even a single lot on any given day, and because for a buyer who is present on a given day, the additional cost of participating in any auction is zero. Note that for the collusive model, $p = m + 1$, where m is the number of small (and here, potential), bidders. For the non-cooperative model,
$p = m + 3$.

Table 5. Quantifying the impact of bid rotation in Narela
Expected win prices (Rupees per quintal)

Number of small potential bidders	Small players (mean of F is Rupees 560) bid against:			Non-cooperative
	SM (mean of G_1 is Rs. 561.3)	H (mean of G_2 is Rs. 585)	SR (mean of is G_3 Rs. 595)	All three large players are present at every auction*
6	566.0	570.5	570.6	585.0
7	566.8	571.2	571.3	585.0
8	567.4	571.8	571.9	585.0
9	568.0	572.3	572.4	585.0
10	568.5	572.8	572.8	585.0
11	569.0	573.1	573.2	585.0
12	569.4	573.5	573.6	585.0
13	569.8	573.8	573.9	585.0

Note: * Win prices vary in the second decimal place, and increase with m.

These results indicate that the presence of all three large bidders would inflate win prices by between Rs. 10 and 20; far higher than what is implied by the OLS regression reported in Table 2.

We compute similar expected win prices for various other means; qualitatively the results remain unchanged and hence are not reported above.

4.4. Is Government Procurement in Panipat Inefficient?

The procurement arms of the government purchased all wheat arrivals in Panipat at the MSP. In order to assess whether the government thereby paid too much given the quality of grain, we estimate what prices the grain in our Panipat sample would have fetched, had it sold in Narela. As noted in Section 2.3, we recorded quality information for over 100 lots of grain sold in Panipat to the government. These translate into approximately 20 distinct quality vectors. For each of these twenty quality vectors x, a small buyer in Narela would have a valuation drawn from the distribution F (as in the above sections) with mean $x\beta$, and a large player *i* would draw his valuation from the distribution G_i with mean $x\beta + \mu_i$; where all the coefficients are the ML estimates of the collusive model (given in Table 3 and the subsequent paragraph). For our counterfactual, we assume that valuations are drawn from untruncated distributions, in order to allow for possibility that the (counterfactual) win price is MSP. We compute the expected winprice of the Panipat grain in Narela, (under the estimated collusive model representing bidder behavior in Narela), using the density z of the second highest order statistic (Eq. (B7), Appendix B). We do this varying the number of small potential bidders from 6 to 13, and under scenarios where the large bidder is either SM, or H, or SR. An extract of the results is presented in Table 6, for eight of the twenty distinct quality vectors in our Panipat sample. The expected win prices represent what the government would have expected to pay in Narela for the grain it bought in Panipat at the MSP. (Transportation costs are not germane as the government has warehouses next to the market yard in both markets).

Table 6. Expected win prices for Panipat wheat if sold in Narela, various scenarios (Rupees per quintal)

	Expected win prices when SR participates with m small potential bidders		*Expected win prices when SM participates with m small potential bidders*	
	m=6	*m*=13	*m*=6	*m*=13
Quality vector 1	559.3	562.6	554.7	558.5
Quality vector 2	562.0	565.4	557.5	561.3
Quality vector 3	563.0	566.4	558.5	562.3
Quality vector 4	565.4	568.7	560.8	564.6
Quality vector 5	569.2	572.6	564.6	568.4
Quality vector 6	571.9	575.2	567.3	571.1
Quality vector 7	572.8	576.2	568.2	572.0
Quality vector 8	575.7	579.0	571.1	574.9

It is clear that Panipat wheat would have sold in Narela for Rs. 5 to 20 *more* than the MSP of Rs. 550 per quintal at which the government procured wheat in Panipat. Clearly, at least during this season, the government did not pay an excessive price for its grain.

These figures also provide an indication for why there are no private players in Panipat. In principle, millers and traders could have bought grain in Panipat for one rupee more than the support price, which is lower than what prevailed in Narela. However, unlike the case with the government, transport costs do matter here. Price differences of the range indicated in this table would not have covered transport costs, (which was about Rs. 15 quintal).

5. Conclusions

This is perhaps one of the first papers to study grain markets in developing countries using the theory of auctions. We have tested structural models of behavior at these auctions. This approach enables us to identify significant asymmetries between buyers, and a simple, yet effective, form of collusion amongst a set of large buyers. The structural modeling helps uncover and underscore the fact that collusion depresses market prices appreciably, precisely because the two players with the highest valuations for the grain are part of a cartel which disallows their bidding simultaneously at any lot. Incidentally, this collusion also keeps prices relatively close to the MSP.

These results required the explicit modeling of buyer asymmetry, in itself recent to the empirical literature on structural estimation. In particular, an identification result in Athey and Haile (forthcoming) and Meilijson (1981) permits the modeling of asymmetry by using the joint distribution of the win price and the identity of the winner, rather than the marginal densities traditionally employed in the literature.

We are also able to use these results to evaluate the efficiency of government procurement, even when only a single price (the MSP) prevails as is the case in the small Panipat market. For the season during which we did our fieldwork, we find government operations were not inefficient, in the sense that similar quality grain would have commanded a higher price in the larger Narela market. This result may however be specific to this season. The reason is that a significant determinant of quality is moisture content which was excellent in 1999 due to the unseasonal dry heat. In a season which displayed more variation in the moisture content of grain, it is possible that at least some of the grain procured by the government might have commanded a lower price at markets such as Narela. This would be exacerbated given the pattern of picking up all arrivals at certain markets, as is the case in Haryana. It is also the case that in years when the quality of grain is rendered worse by factors such as bad weather or disease, the government, under pressure from lobbies, is known to relax norms for acceptable quality grain.

The approach in this paper can be extended in several directions. First, data on bidder identities at each auction can enable us to model participation in auctions, and thus lead to a richer analysis of the market. Second, it would be worthwhile to assess whether our conclusion of efficient government purchases would also hold in a more normal year (with greater variation in moisture content, for example), or whether in such years the government picks up significantly poorer quality grain than private players. There is anecdotal evidence that the government's policy of purchasing almost all the grain that arrives in selected markets results in adverse selection across markets. Farmers with better quality grain would go to markets such as Narela (with auctions determining the above-MSP sale price), and those with worse quality grain to markets like Panipat (where they are guaranteed the MSP). Our analysis of the efficiency of government purchases can easily be extended to address this question, provided there is data for more than one season.

Auction theory has a still wider applicability in developing country markets, as market institutions are increasingly replacing more traditional forms of exchange. The sale of produce through an open auction assures the farmer of the highest possible price, and has the added advantage of providing transparency and market information. This is not to suggest that collusion cannot occur—indeed it does in most small markets, but that it can be detected and analyzed quite easily. The importance of this needs scarcely to be underscored, given that market regulatory authorities do have the power to penalize agents who engage in ‘unfair’ practices.

Appendix A

Government intervention in grain (wheat) markets in India

The present form of government intervention in grain markets in general, and in the wheat market in particular, dates back to the beginning of the green revolution in the mid-1960's, with the setting up of two parallel institutions: the Agricultural Prices Commission (APC) and the Food Corporation of India (FCI). The former has the responsibility for determining and announcing minimum support prices for various commodities, while the latter is entrusted with procuring grain from producers and distributing it through the subsidized public distribution system (PDS).

Both these institutions were designed at a time when India faced food shortages, and was dependent on PL 480 supplies to meet its domestic needs. The green revolution was seen as a way to reduce dependence on food imports, the implied conditionalities associated with which were seen as politically unacceptable. The minimum support price announced by the APC—later renamed as the Commission on Agricultural Costs and Prices—was meant to ensure that farmers' incomes did not suffer from a fall in prices in the event of a large harvest that was expected as a result of the adoption of the new technology package. Initially, a separate procurement price was also determined; this was the price at which the FCI, or designated state agencies would procure grain. The procurement price was typically higher than the MSP and 'close to' the market price for the grain. Thus while the MSP would be announced at the time of sowing of the crop, the procurement price would be announced closer to the harvest. Various methods of procurement of grain—involving varying degrees of compulsion—were adopted to meet the needs of the public distribution system. As the green revolution gathered momentum and supply constraints eased, so did the element of compulsion.

For the past several years, there has been no distinction between support and procurement prices; in the 1990's in particular, government procurement has been driven by the need to enforce the MSP, rather than to meet its obligations under the public distribution system. It is widely acknowledged that the MSP is too high, resulting in accumulation of stocks by the government. In what can only be described as a curse of plenty, food stocks held by the government are today the same order of magnitude as the entire cereal production of the country during the crisis drought years in the mid-1960s.

Appendix B

1. Densities used in the Likelihood function for the Collusive Model

Differentiating Equations 1 and 2 (Section 3) with respect to v we get the corresponding densities (B1) and (B2) below.

$$h_{g_i}(v) = m(1 - G_i(v))[F(v)]^{m-1} f(v) \qquad (B1)$$

$$h_f(v) = (1 - F(v))[F(v)]^{m-2}\{(m-1) f(v) G_i(v) + F(v) g_i(v)\} \qquad (B2)$$

Let $\overline{F}$ and $\overline{G_i}$ be the probabilities that valuations drawn from F and G_i respectively are less than Rs. 550. If valuations are drawn from F and G_i and *truncated* at Rs.550, the densities corresponding to equations (B1) and (B2) are respectively: (we drop the argument v for the sake of visual tidiness)

$$\overline{h}_{g_i} = m\left(\frac{1-G_i}{1-\overline{G_i}}\right)\left(\frac{F-\overline{F}}{1-\overline{F}}\right)^{m-1}\left(\frac{f}{1-\overline{F}}\right) \qquad (B1)'$$

$$\overline{h}_{f,g_i} = \left(\frac{1-F}{1-\overline{F}}\right)\left(\frac{F-\overline{F}}{1-\overline{F}}\right)^{m-2} \times \left\{(m-1)\left(\frac{f.(G_i-\overline{G_i})}{(1-\overline{F})(1-\overline{G_i})}\right)+\left(\frac{g_i.(F-\overline{F})}{(1-\overline{F})(1-\overline{G_i})}\right)\right\} \qquad (B2)'$$

Assuming independence across observations, the likelihood function is multiplicative. For lots won by large player $i,\ i = 1,2,3$, the corresponding expression in the (log) likelihood is given by (the log of) Eq.(B1)'. The players' distributions for a given lot t depend on lot-specific quality characteristics (and week dummies) encapsulated in a vector x_t. Specifically, the distributions are normal, with mean of F being $x_t\beta$ (x_t also includes a constant term), and the mean of G_i being $X_t\beta + \mu_i$, $i = 1,2,3$. The variances are assumed to be constant across lots, although not necessarily the same across players.

On the other hand, if a lot is won by a small player, then we do not observe which large player was designated by the cartel to bid for the lot. The corresponding term in the likelihood is taken to be $\sum_{i=1}^{3}\alpha_i\overline{h}_{f,g_i}(v)$, where $\sum_{i=1}^{3}\alpha_i = 1$. That is, the term is a weighted average of densities given in Eq. (B2)'. We may interpret α_i as the probability that the large player who bid was player i, conditional upon a small player winning the lot. This probability may in general depend upon the number m of small bidders. Therefore we also tried a specification using weights α_{im} depending on the number of small bidders m, but this made practically no difference.

The parameters estimated by the ML method are the vector $\beta, \mu_1, \mu_2, \mu_3, \alpha_1, \alpha_2, \alpha_3$. We also make the simplifying assumption that the large players' variances are identical, but different from that of the small players. Thus in addition, we estimate σ_1, σ_2, where the first is the standard deviation of F, while the latter is the standard deviation of G_1, G_2 and G_3.

2. Densities used in the Likelihood function for the Non-cooperative Model

Differentiating Eq.(3) and (4) we get the corresponding densities (B3) and (B4):

$$\begin{aligned} h_{g_i}^{N}(v) = (1 - G_i(v))[F(v)]^{m-1}\{&F(v)G_j(v)g_k(v) + F(v)g_j(v)G_k(v) \\ &+ mG_j(v)G_k(v)f(v)\} \end{aligned} \qquad (B3)$$

$$h_f^N(v) = (1-F(v))[F(v)]^{m-2}\{F(v)G_1(v)G_2(v)g_3(v) + F(v)G_1(v)g_2(v)G_3(v) + F(v)g_1(v)G_2(v)G_3(v) + (m-1)G_1(v)G_2(v)G_3(v)f(v)\} \qquad (B4)$$

The corresponding expressions when the players' valuations are from truncated distributions are (dropping the argument v for neatness):

$$\overline{h}_{g_i}^N = \left(\frac{1-G_i}{1-\overline{G}_i}\right)\left(\frac{F-\overline{F}}{1-\overline{F}}\right)^{m-1} \times \left\{\frac{(F-\overline{F})(G_j-\overline{G}_j)g_k + (F-\overline{F})g_j(G_k-\overline{G}_k) + m(G_j-\overline{G}_j)(G_k-\overline{G}_k)f}{(1-\overline{F})(1-\overline{G}_j)(1-\overline{G}_k)}\right\} \quad (B3)'$$

$$\overline{h}_f^N = \left(\frac{1-F}{1-\overline{F}}\right)\left(\frac{F-\overline{F}}{1-\overline{F}}\right)^{m-2}\Bigg[\left\{\frac{(F-\overline{F})(G_1-\overline{G}_1)(G_2-\overline{G}_2)g_3}{(1-\overline{F})(1-\overline{G}_1)(1-\overline{G}_2)(1-\overline{G}_3)}\right\} + \left\{\frac{(F-\overline{F})(G_1-\overline{G}_1)(G_3-\overline{G}_3)g_2}{(1-\overline{F})(1-\overline{G}_1)(1-\overline{G}_2)(1-\overline{G}_3)}\right\} + \left\{\frac{(F-\overline{F})(G_2-\overline{G}_2)(G_3-\overline{G}_3)g_1}{(1-\overline{F})(1-\overline{G}_1)(1-\overline{G}_2)(1-\overline{G}_3)}\right\} + (m-1)\left\{\frac{(G_2-\overline{G}_2)(G_3-\overline{G}_3)(G_1-\overline{G}_1)f}{(1-\overline{F})(1-\overline{G}_1)(1-\overline{G}_2)(1-\overline{G}_3)}\right\}\Bigg] \quad (B4)'$$

As in the collusive model, lot-specific covariates determine the means of the valuation distributions. The parameters estimated by ML are $\beta, \mu_1, \mu_2, \mu_3$ and the player specific standard deviations σ_1, σ_2 and are reported in Appendix C. A comparison of Eq. (B1)' with (B3)', and Eq. (B2)' with (B4)' shows that one is not necessarily greater than the other, viz., the likelihoods of the two models cannot be ordered.

3. Distribution and Density of Second Order Statistic under Alternative Assumptions

The distribution and density, under various alternative assumptions, used in Sections 4.1 (for the Kolmogorov-Smirnov test), 4.3 and 4.4 are set out below. We first collect all the expressions and then point out which one is used where.

Under collusion, with *m* small players drawing valuations from *F* and 1 large player, player *i*, drawing his valuation from G_i, ($n = m + 1$), the distribution *Z* of the second highest order statistic is given by

$$Z(v) \equiv \Pr(V^{(n-1:n)} \leq v) = [F(v)]^m G_i(v) + m[F(v)]^{m-1} G_i(v)(1-F(v)) + [F(v)]^m (1-G_i(v)) \qquad (B5)$$

The first term on the right hand side corresponds to the event that all the players' valuations are less than or equal to *v*; the second term to events in which one small player's valuation exceeds *v* and everyone else has valuations less than or equal to *v* (there are *m* such events); the third term corresponds to the event in which all small players' valuations are less than or equal to *v* and the large player's valuation exceeds *v*. Note that here we are considering the marginal distribution (and density) of the win price; in the estimation of the two models we use the joint density of win price and identity of the winner. After a cancellation, the expression simplifies to

$$Z(v) = m[F(v)]^{m-1} G_i(v)(1-F(v)) + [F(v)]^m$$

If players were to draw valuations from distributions truncated at Rupees 550, the corresponding distribution is

$$\overline{Z}(v) = m\left(\frac{F-\overline{F}}{1-\overline{F}}\right)^{m-1}\left(\frac{G_i-\overline{G_i}}{1-\overline{G_i}}\right)\left(\frac{1-F}{1-\overline{F}}\right) + \left(\frac{F-\overline{F}}{1-\overline{F}}\right)^m \qquad (B6)$$

where $\overline{F} = F(550)$ and $\overline{G_i} = G_i(550)$.

The density z corresponding to Z is obtained by differentiating Eq. (B5) with respect to v. Suppressing the argument v from the right hand side for notational simplicity, we have

$$z(v) = mF^{m-1} f(1-G_i) + m(1-F)F^{m-2}\{Fg_i + (m-1) f\, G_i\} \qquad (B7)$$

The non-cooperative model (Section 4.3) assumes that all three large players bid at each lot. With *m* small bidders drawing valuations from *F*, and the three large bidders from G_1, G_2, G_3, the distribution Z^N of the second highest order statistic (with *n* = *m*+3) is given by

$$\begin{aligned} Z^N(v) = \Pr(V^{(n-1:n)} \le v) = F^m G_1 G_2 G_3 + mF^{m-1} G_1 G_2 G_3 (1-F) + \\ F^m G_1 G_2 (1-G_3) + F^m G_1 G_3 (1-G_2) + F^m G_2 G_3 (1-G_1) \end{aligned} \qquad (B8)$$

where for simplicity we have dropped the argument v from the right hand side. The first term on the right hand corresponds to the event in which all players' valuations are less than or equal to *v*, the second term to events in which all players barring one small player have valuations less than or equal to *v*, and the three other terms to events in which exactly one of the large players' valuations exceeds *v*. After cancellations, we rewrite as follows.

$$Z^N(v) = F^{m-1} G_1 G_2 G_3 (m - mF - 2F) + F^m (G_1 G_2 + G_1 G_3 + G_2 G_3)$$

The density z^N is obtained by differentiating the above with respect to v. Thus

$$z^N(v) = z_1^N(v) + z_2^N(v) \qquad (B9)$$, where

$$\begin{aligned} z_1^N(v) = -(m+2)F^{m-1} G_1 G_2 G_3 f + \{m(1-F) - 2F\}\{F^{m-1} G_1 G_2 g_3 + \\ F^{m-1} G_1 g_2 G_3 + F^{m-1} g_1 G_2 G_3 + (m-1)F^{m-2} G_1 G_2 G_3 f\} \end{aligned}$$

$$z_2^N(v) = F^m(G_1 g_2 + g_1 G_2 + G_1 g_3 + g_1 G_3 + G_2 g_3 + g_2 G_3) + \\ mF^{m-1} f(G_1 G_2 + G_1 G_3 + G_2 G_3)$$

Eq. (B6) gives the theoretical distribution for the Kolmogorov-Smirnov test (Appendix C). Eq. (B7) and (B9) are densities with respect to which we compute expected winprices for Section 4.3. Eq. (B7) is used again to compute expected win prices for Panipat grain, if it were sold in Narela (Section 4.4).

Appendix C

1. Maximum likelihood parameter estimates of the non-cooperative model (Section 4.1)

	Coefficient	Standard error
Uniformity in grain size	4.23	0.62
Presence of foreign matter	1.28	0.54
Presence of Other foodgrains	3.78	0.76
Week 2 dummy	10.58	1.06
Week 3 dummy	15.99	1.43
Constant	517.60	3.86

Log likelihood = -1841.18

The estimated 'mean differences' (μ_1, μ_2, μ_3) of SM, H and SR are respectively 7.7, 7.8, 7.9. The standard deviation of the small players' distribution *F* is 14.72, and that of the large players' distributions is 7.13.

2. The Kolmogorov-Smirnov Test

We compare the theoretical distribution of the winprice under collusion and under the assumption that the players' valuations are drawn from truncated normal distributions, with its empirical distribution. The theoretical distribution is given in expression (B6) – it is the distribution of the second highest order statistic under collusion. It is clear that it depends on the number *m* of small players, the identity of the large bidder at the lot, and the vector x_t of quality and week dummies specific to the lot. We make subsets of the data for which these variables take the same value (and thus give the same theoretical distribution). In particular, lots with different quality vectors x_t fall into different subsets. This cannot be circumvented by looking instead at the distribution of winprice minus its expectation, because the truncated values $\overline{F}, \overline{G_i}$ are still quality vector specific.

We provide an extract of the results. The subsets presented have SM as the large player. This corresponds to lots which either SM won or small players won. (We assume, under collusion, that when a small player wins, SM must have been the large bidder. See Section 4.1 for the reason).

# of obser-vations	# of small bidders	Unifo r-mity	Foreign matter	Other Food-grains	Week2 Dummy	Week3 dummy	KS test Statistic	5% cutoff	1% cutoff
6	1	1	3	3	1	0	0.42	0.519	0.617
6	1	3	3	3	1	0	0.22	0.519	0.617
6	2	3	2	3	1	0	0.16	0.519	0.617
6	3	2	2	3	1	0	0.24	0.519	0.617
6	2	2	2	3	0	0	0.19	0.519	0.617
6	3	2	3	3	0	0	0.20	0.519	0.617
7	2	2	3	2	1	0	0.09	0.483	0.576
8	2	2	2	3	1	0	0.19	0.454	0.542
8	2	3	3	3	1	0	0.11	0.454	0.542
9	1	2	2	3	1	0	0.50	0.430	0.513
10	1	2	3	3	0	0	0.27	0.409	0.489
15	2	2	3	3	1	0	0.18	0.338	0.404
17	1	2	3	3	1	0	0.37	0.318	0.381
19	1	2	2	3	0	0	0.11	0.301	0.361

The assumption of normality is to be rejected (at 5% or 1% significance level) if the value of the test statistic (column 8) exceeds the relevant cutoffs (columns 9 and 10). Observe that the hypothesis is never rejected at the 1% level. It is rejected at the 5% level for two subsets, both having just 1 small bidder. For the reported subsets as well as the unreported ones (which are similar), the hypothesis does very well when the number of small bidders is 2,3 or 4; the occasional higher values of the KS statistic, as in the above table, occur for extremes in the number of small bidders. The good fit in subsets obviates the need for a meta-analysis.

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[1] Regulated markets are set up under the Agricultural Produce Acts of each state. They are managed by a Market Committee, which consists of farmers, commission agents, and government representatives. The responsibilities of the Committee include maintaining the physical infrastructure of the market yard, issuing licenses to commission agents who sell and buy produce, appointing auctioneers and record keepers, mediating disputes and so on.

[2] Fair Average Quality wheat is that which has no more than 12% moisture content (with price discounts up to 14%), and containing less than: 0.75% foreign matter, 2% of other foodgrains; 2% damaged kernels; 6% of slightly damaged grains; and 7% shriveled and broken grains.

[3] There is of course an extensive literature on issues relating to the impact of the procurement policy. Some examples include Balakrishnan and Ramaswami (2000, 1995), Gulati and Sharma (1990), Jha et al. (1999, 1998), Krishna and Raychaudhuri (1980), Krishnaji (1990), Storm (1994).

[4] 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 (although such incidents are rare). The auctioneer's starting price is not necessarily the same as the farmer's reservation price. The auctions proceed too quickly for the auctioneer to take time to determine the farmer's reservation price at each lot.

[5] Most lots are approximately equal in size (about 3.5 tons), and it is rare for multiple lots to be sold in any auction.

[6] We use these abbreviations H, SM and SR in order not to reveal players' identities.

[7] A market committee official records the following details of each sale: the name of the farmer and of the commission agent representing him, the winning bid (in Rs./quintal), the name of the winner, and the approximate quantity of the lot. Thus information on the quantum of daily arrivals can also be obtained by aggregation. The records do not record any explicit quality variables.

[8] We try an alternative formulation of the regression, where quality premia are allowed to vary for each of the large buyers. The results indicate that there are no significant differences in quality premia paid by these purchasers.

[9] Most of the bidders in our market are millers, and resale of unprocessed grain is seldom considered; such resale, if significant, could add a common-value component to the valuation. Widespread resale would bring in the kind of signaling considerations examined by Haile (2000, 2001).

[10] See for example evidence in Malik, Niwas and Gangwar (1998).

[11] Since we observe only the winprice, and not any other bid, statistical evidence in support of the IPV hypothesis is not easy to provide.

[12] Efficient collusion by a cartel can be designed, in a given auction, by a 'pre-auction knockout', for instance (e.g. Baldwin, Marshall and Richard (1997)). The wheat market auctions we study have a 'repeated' nature. The bid rotation that we suggest keeps winprices down, and can be sustained by the threat of reversion to non-cooperative behavior.

[13] From hereon, m will denote the total number of small bidders. In different contexts, this will be the total number of small potential bidders, or the total number of small bidders with valuations greater than the auction starting price.

[14] The second-highest valuation can be less than or equal to v in one of two mutually exclusive ways: (i) either all n valuations are $\leq v$, or (ii) the $(n-1)$ lowest valuations are $\leq v$ and the highest is $> v$. In the former case, the probability of the highest valuation being t is given by $[F(t)]^m dG_i(t)$ due to independence, where $t \in [a, v]$; in the latter, the probability that the highest bidder has a valuation $> v$ is given by $(1-G_i(v))$, and the probability that the remaining bidders have valuations $\leq v$ is given by $[F(v)]^m$.

[15] Other possible explanations exist in a common-values framework (see Bikhchandani (1989) and Nelson (1995)).