Testing for Cheating Between Bidders and Auctioneers in Sealed-Bid Auctions

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Abstract

This paper proposes a method of bidder-auctioneer cheating in sealed bid auctions. Based on statistical properties of the bids, I develop a regression method for analyzing potential cheating of this particular type. I apply this regression specification to data from the New York City School Construction Authority auctions, an approximate $1 billion per year auction market in which an auctioneer was charged with bid rigging. Comparing auction lots before the cheating scandal with those after the scandal, I find significant differences in bidding. Additionally, there exists evidence that cheating was not limited to the one auctioneer charged with bid rigging. Applying the regression analysis to lots where bid rigging occurred with certainty, I find that this regression method is effective in identifying these lots.

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I. Introduction

Much has been written on the topic of bidder collusion, often called bidding rings or cartels, in auction markets. Robinson (1985), and Graham and Marshall (1987) are examples of theoretical works on this subject. Porter and Zona (1993) and Brannman (1996), among others, offer statistical evidence for the presence of bidding rings in auction data. The possibility of cheating between a bidder and an auction official, however, has received little attention in the literature.[2] Yet, given the willingness of bidders to cheat in auctions[3], bidder-official cheating could be a problem, as many large auctions (particularly government auctions) hire officials who presumably make small salaries relative to the prices of the items they auction off. It is therefore reasonable to think that some of these auction officials might be willing to enter a bid rigging scheme in exchange for kickbacks from dishonest bidders. Another reason to be concerned with bidder-official cheating is that in sealed bid auctions equilibrium involving bidding rings may not exist, since ring members may not be informed of each other's bids, and therefore cannot punish those who break the ring (Robinson, 1985). Thus, if bidders in a sealed bid auction wish to profit from bid rigging, they may find it difficult to do so through a cartel.

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[2] Burguet and Perry (2000) have a working paper on bidder-auctioneer cheating in first-price sealed bid auctions, developed separately and roughly simultaneously from this paper. Other than this work, I am unaware of any other formal work on the subject of bidder-auctioneer cheating. I note, however, that Rothkopf and Harstad (1995) model auctioneer-only cheating in a Vickrey auction context. Their paper is discussed below.

[3] According to Porter and Zona (1993), more than 50% of the criminal cases filed between 1982 and 1988 by the Antitrust Division of the Department of Justice involved cheating in auction markets.

While these may be convincing reasons to be concerned with bidder-official cheating in auctions, an even more convincing reason is that such cheating has already occurred in a major auction market. The New York City School Construction Authority (SCA hereafter) uses a sealed bid auction mechanism to distribute approximately one billion dollars in contracts each year. In the summer of 1992, the SCA became aware of a bid rigging scam involving two SCA employees and eleven members of seven construction firms. The scam was seen as an embarrassment to the SCA, which had been created four years earlier in part to deal with corruption in the industry. For this reason, many of the details of the scam were never made public, although the major pieces of information, such as the names of those involved, and a description of the nature of cheating are available[4]. With this information, I attempt to contribute to the existing bid rigging literature. I start by introducing a mechanism through which a bidder and auctioneer might cheat in a sealed bid auction. Modeling bidder-auctioneer cheating as a distortion of the distribution of the distance between the 1st and 2nd bids, I develop a regression method for detecting bidder-official cheating in auction data. The regression specification is generated using the fact that if bids are iid draws, then the ordered bids from a Markov chain. Given the above, I show that conditioning the distance between the first two log bids on bids higher than the 3rd bid, is unnecessary after conditioning on the 3rd bid. Furthermore, I show that assumptions of iid producer costs, and the dishonest bidder being the low cost bidder are enough to ensure a proper regression specification. Finally, I apply this specification to data generated in the New York City SCA auctions,

[4] See Olmstead (1993), Raab (1993), and Fried (1994) for a complete account of the scandal.

in order to test for previously undiscovered bidder-auctioneer cheating, and to analyze lots where cheating was known to have occurred.

The contents of this paper are as follows: Section II introduces the mechanism through which a bidder and auctioneer can cheat in a sealed bid auction. Section III reviews the relevant theoretical work on auctioneer cheating, and Section IV discusses the existing empirical auction literature. Section V introduces the empirical model used to test for bidder official cheating, Section VI details the history of the SCA auctions and the cheating scam, and Section VII discusses the data. Section VIII, section IX, and section X contain empirical results, and section XI concludes.

II. Bidder-Auctioneer Cheating: The "Magic Number"

In this section, I present informal descriptions of a possible form of bidder-official cheating. A brief model of this cheating, and a comparison of cheating to honest bidding is presented in Appendix A. The reader is also referred to Ingraham (2000) for a more complete treatment of the model.

To begin discussion, I note that the SCA auctions are procurement auctions. Thus, this paper considers bidder-auctioneer cheating in a procurement auction framework. With trivial modifications, however, the model can be transformed to a value auction setting[5].

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[5]In moving from a procurement auction to a value auction, the only real change in notation is that the probability of winning the auction is determined by the probability of bidding above other bidders rather than below them.

A procurement auction is an auction for a contract to perform a service for the auctioning body. In the case of SCA, the item up for auction is a contract to repair or build a school building. For this reason, the winning bid is the lowest bid received rather than the highest bid received, as is the case in auctions for art, wine, or various collectibles. Additionally, the mechanism I consider is a first-price, sealed bid auction. Thus, contractors view their own private costs, and submit bids based on those costs. An auctioneer opens bids at a public ceremony, reading and recording bids. The lowest bid wins the contract, and the winning producer receives her bid as payment for completed work.

Now suppose that in a specific auction lot, there exists a dishonest producer. This producer wishes to increase her expected profits through the bribery of the auctioneer. The dishonest producer persuades an auctioneer to falsify a bid in the auction on her behalf, in exchange for a kickback. The producer reveals her private costs to this auctioneer. The auctioneer agrees to view all legal bids, and if the lowest legal bid is above the dishonest producer's cost, the auctioneer submits a fake bid just below the lowest legal bid. Not only has the dishonest bidder increased her probability of winning the auction lot, but she has also secured the contract at the highest possible price. This form of cheating will be referred to as "magic number" cheating (MNC hereafter). The magic number (MN hereafter) is the artificial bid the auctioneer submits on behalf of the dishonest bidder. In order for this type of cheating to be successful, it is necessary for the auctioneer to have complete control over the submitted bids long enough to doctor one bid, before any honest persons can view them. If the auction is private, in that the auctioneer runs the market almost exclusively, the opportunity for this type of cheating should be readily available. If the auction is public, however, and the auctioneer is a government employee, then the opportunity for MNC will depend upon how well the agency monitors its auctioneers.

III. Existing Theoretical Literature

As stated in the introduction, the concept of a bid rigging scam between an auctioneer and a bidder is, to my knowledge, a new concept in the auction literature. Rothkopf and Harstad (1995) (RH hereafter), however, develop a model of auctioneer only cheating, where the cheating mechanism is in some ways similar to that put forth in section II. In their model, RH state that in the context of a Vickrey auction, the auctioneer may artificially distort the second highest bid in order to increase her revenues[6]. Specifically, the authors propose a scenario where before each auction, the auctioneer has the option of choosing either a Vickrey or first-price mechanism. If the auctioneer chooses a Vickrey auction, then with some secret probability she will falsely inflate the second highest bid in order to increase her revenues. Bidders estimate the probability of cheating, and shade their bids in the Vickrey scenario based on this probability estimate. In a static setting, only auctioneers with the highest probability of cheating will hold Vickrey auctions. Furthermore, their expected revenues from holding dishonest Vickrey, or honest first-price auctions, will be equal.

[6] The simplest form of a Vickrey auction is a second price auction, where only one item is auctioned in a given lot, and the winning bidder pays the second high bid.

Additionally, the authors consider a dynamic model where the above form of bid rigging can occur over a stream of auctions, and cheating is discovered with a positive probability. In equilibrium, if cheating is discovered, the guilty auctioneer holds only first-price auctions in the future, and pays some form of penalty. In this manner, the frequency of Vickrey auctions diminishes over time. While this model does not consider cheating between a bidder and auction official, it does involve an auctioneer distorting a bid distribution, and therefore deserves mention.

Ingraham (2000) develops a model of competitive bidding in the presence of MNC for first-price, sealed bid auctions. The results of this model compared to bidding without MNC are detailed in Appendix A. For the purpose of this paper, however, the model need only be discussed briefly. First, make the following two assumptions:

(1) Producer costs are iid draws from a continuous density, and are private information for each producer.

(2) If MNC occurs, the MN bid submitted on behalf of the dishonest bidder, is purely exogenous.

Given the above assumptions, one can show that honest bidders will modify their equilibrium bid functions if they suspect MNC. These modified bids, however, are still iid random variables. Given the above information, it is clear that testing for MNC is complicated by the fact that honest bidders' equilibrium strategies are structurally different when they believe that MNC is present. We will return to this idea in section V,[7] as we must consider how all strategies might be affected by MNC.

IV. Existing Empirical Literature

Since we are unaware of any empirical work in the area of bidder-official cheating, it is difficult to identify any statistical model that directly applies to this topic. However, general information on the econometrics of auctions can be gained from previous work. We now discuss this work.

Porter and Zona (1993), offer statistical tests for the detection of bidding rings. The authors use auction data for state highway contracts in Nassau and Suffolk counties, New York to analyze bidding of known ring members and competitive firms. Specifically, the authors have a-priori knowledge of a bidding ring, and know the identities of all cartel members. They first test for cartel existence by regressing log bids on a set of bidder characteristics, competitive bids, and cartel bids. The results show great numeric contrasts in estimated parameters between the cartel sample and the competitive sample. In the cartel sample, parameters are sometimes insignificant, and often have the opposite expected sign. Additionally, Chow tests reveal statistical differences in the estimated

[7] To conclude this section, I acknowledge the presence of Burguet and Perry (2000), but will not discuss any elements of their paper, as I have yet to receive a response from the authors regarding their work. For the reader's information, I assume that copies of, or information regarding, "Bribery and Favoritism by Auctioneers in Sealed Bid Auctions" can be attained through either Roberto Burguet, Institute for Economic Analysis, Campus UAB, Bellaterra, Barcelona, Spain 08193; or from Martin K. Perry, Department of Economics, Rutgers University, New Brunswick, NJ, 08901.

parameters between the cartel and competitive samples. The authors then estimate a multinomial logit model of bid rankings for both samples. They find statistical differences in the low ranking versus high ranking bids for the cartel sample, and therefore reject the null hypothesis that low and high ranking bids are generated by a similar process. For the competitive sample, however, they are unable to reject this null hypothesis. These results are expected under cartel bidding, since in a cartel the low bidder must compete with non-cartel bids, but losing cartel bids are, as the authors say, "phantom bids". Under competitive bidding, however, there are no such phantom bids, and therefore the result of not rejecting the null hypothesis of similar high and low ranking bid processes, is expected. Based on the above results, the authors conclude that the bidding ring did in fact distort the auction from a competitive market. Thus, from Porter and Zona (1993) we extract the need to use information imbedded in non-collusive auction lots as a benchmark to test for cheating in other lots. If statistically significant differences in bidding are found where cheating is suspected, then this is convincing evidence that bid rigging has occurred.

Brannman (1996) uses Forest Service timber auction data to estimate the effects of potential and expected competition on observed bidding. His data is generated from both sealed bid and English auctions, and his sample sizes are small (only 93 sealed bid auctions and 51 English auctions). Brannman defines a potential bidder as one whose timber mill is within 115 miles of the auction lot and has submitted at least one previous bid. He calculates the expected number of bidders for an auction lot by estimating a probit model of bid submission, distances between the lot and the bidder's mill. Brannman then regresses a vector of explanatory variables, the number of bidders in the auction, and either the expected or potential number of bidders in the auction on the winning bid relative to board feet of timber. This is done separately for sealed bid and oral auctions. He finds, that only the actual number of bidders is significant in oral auctions, where both actual and potential bidders are significant in sealed bid auctions (the p-value for potential bidders is .11). Brannman states that because the expected number of bidders is significant in sealed bid auctions, this may be preliminary evidence of a bidding ring. The logic behind this statement is that ring members were able to preclude potential competition from entering a sealed bid auction and therefore entered the auction with knowledge of the actual number of bidders. A problem with this type of analysis is that Brannman constructs his potential bidder variable in an ad-hoc manner. It could be the case that bidders simply have better knowledge of the potential bidders in a lot than what Brannman gives them credit for knowing. Thus, the actual number of bidders could be related to the true potential number of bidders, which the author is unable to capture in his regression.

Brannman then makes a more convincing argument for the presence of bidding rings by constructing a weighted index of relative bid frequencies. Specifically, for all bidders, indexed by i, Brannman creates a variable H_i. H_i is the number of firms who bid in the same auction as i, divided by the total number of bids a firm other than i submitted in all auctions where i was active. Higher values of H_i indicate a lower likelihood of bidder i being involved in a bidding ring. Then, the author takes a weighted average of H_i for each bidder, the weights being the number bids that i ever submitted in a sample. Brannman then adds this average H variable to winning bid regressions described above. The results are that the average H variable is significant at the 95% level, and the estimated coefficient is a large positive number for the sealed bid sample. In the English auction sample, the same coefficient is significant at the 82% level and a large positive number. Thus, Brannman concludes that the best evidence for bidding rings appears in the sealed bid auctions. This evidence is certainly not as convincing as that presented in Porter and Zona, where the authors had actual information on ring members, and were able to test for differences in bidding based on ring membership. In the very least, however, Brannman's paper is an effort to detect cheating in an auction, when no a-priori knowledge of the identities of ring members is available. Thus, we should take from this article an understanding of the difficulty that may be involved in convincingly showing that cheating has occurred in an auction.

Hendricks and Porter (1988) develop a method of testing for the presence of bidding under asymmetric information. The premise of the model is that within an affiliated[8] values auction, one bidder, or set of bidders, has superior knowledge of the true value of the auctioned item. All other bidders share publicly provided information on the item, this public information being less accurate than that of the informed bidder(s). The model is designed to examine bidding in auctions for offshore oil leases. An Information advantage could be present in that some of the bidders already own leases on neighboring tracts, and therefore can better estimate profits. One of the key implications of the theory is that the highest neighbor and non-neighbor bids should have the same distribution. Furthermore, the number of non-neighbor bidders in an auction lot should not affect the neighbor bid, and ex-post profits should be correlated with neighbor bids only, signifying asymmetric information. To test these and other implications of the theory, the authors

[8] See Milgrom and Webber (1982) for a definition and thorough treatment of auctions under affiliation.

estimate maximum likelihood models of the joint distributions of the highest neighbor and non-neighbor bid. Results are quite encouraging. At the 5% level of significance, the authors cannot reject the null hypothesis that the parameters of the two equations are equal. Additionally, they find that the number of bidders in the auction affects only non-neighbor bids with any statistical and empirical significance. Finally, when conditioning on ex-post profitability of the tract, the estimated equations are statistically different and profitability is significant only in the case of neighbor bids. Thus, the neighbor bidders appear to have an information advantage.

Of the above papers, Porter and Zona (1993) and Hendricks and Porter (1988) could be referred to as structural estimations of auction data, in that they attempt to estimate specific equations and/or results generated from auction theory[9]. This is a particularly attractive quality to have in one's estimation, since auction theory offers a researcher specific results she can test within her data. Recently, attention has been given to nonparametric estimation of auctions, in which some characteristic of the auction model, generally a bid function, is estimated while applying minimal assumptions to the data.

Examples of work on nonparametric estimation of auctions are Elyakime, Laffont, Loisel, and Vuong (1994), abbreviated ELLV henceforth, and Guerre, Perrigne, and Vuong (1999), abbreviated GPV henceforth. Either of these papers can be consulted for a thorough explanation of this estimation for first-price auctions[10]. In words, nonparametric estimation assumes that costs are iid draws from a well-behaved

[9] I use the term "structural estimation" a bit loosely here. A stricter, and probably more widely accepted, definition of the term is an estimation attempting to uncover underlying costs (values) from observed bids by applying assumptions such as iid costs (values) or common costs (values) to the data.

[10] ELLV include a secret reserve price in their estimation. GPV include the asymptotic theory behind this type of estimator.

distribution. Given this assumption, the equilibrium bids are iid, and the inverse bid function depends only on the realized bids, and the density and distribution of those bids. Employing the use of a kernel technique (a standard statistical technique to estimate an underlying density), an estimate of the bid distribution is attained, and estimates of the costs can be recovered. In Monte Carlo simulations, GPV show that kernel estimation works very well in uncovering the underlying costs when bids are generated using the equilibrium bid function. Note, however, that kernel estimation, at least in its current form, will not work in testing for MNC. The reason for this assertion is the fact that in auction lots where cheating has occurred, some bidding rule other than the equilibrium bid function has generated at least one of the observed bids. Thus, applying the inverse bid function to these bids is inappropriate. Furthermore, Ingraham (2000) shows that if honest bidders suspect MNC, they change their equilibrium bid function. The new bid function depends on the distribution of costs as well as the distribution of bids. Thus, nonparametric estimation is impossible due to identification problems in the inverse bid function.[11] Given the above discussion, it seems necessary to develop a statistical test that accounts for the specific nature of bid distortion occurring in cases of MNC.

V. A Test for Magic Number Cheating

This section proposes a test for uncovering MNC in sealed bid auctions. Before diving into the specifics of the test, a bit of intuition might help in motivating its

[11] To see the identification problem, consult the inverse bid function in ELLV, but substitute the cost distribution in place of the distribution of the secret reserve. It should now be evident that kernel estimation is impossible unless the researcher knows the distribution of the variable she is trying to estimate.

construction. Recall from section III that successful MNC should distort the difference between the second and first bid, leaving higher order bids unchanged[12]. Thus, an effective way to test for this type of cheating would be to use the information available in the bid distribution, and test its relationship to the lower part of the bid distribution.

Proceeding formally, we assume that for any given auction lot, log bids[13], $B_i=\{B_1, B_2,\ldots, B_N\}$, are a random sample of size N from continuous density function g(B) on (b_{min},b_{max}), with associated distribution G(B). Note, however, that we analyze bids in order, not at random.[14] Therefore, we must call upon the rich order statistics literature to complete our analysis. Define the *ordered* log bids as $S_i = \{S_1, S_2,\ldots, S_N\}$, where S_1 is the smallest B_1, S_2 the second smallest, and so forth. The density and distribution functions of S_i, call them $f_i(s)$ and $F_i(s)$ respectively, are given in (David 1981, 8-9)

$$f_i(s) = [N!/(i-1)!(N-i)!]G(s)^{i-1}[1-G(s)]^{N-i}g(s) \qquad (5.1)$$

$$F_i(s) = \sum_{k=i}^{N} \binom{N}{k} G(s)^k[1 - G(s)]^{N-k} \qquad (5.2)$$

An interesting property of order statistics that will prove quite useful in testing for magic number cheating, is that order statistics form a Markov process (David 1981, 20).

[12] When we say "unchanged" here, we mean unchanged with respect to honest, equilibrium bidding conditioned on the information that bidders are incorporating into their bid functions. If bidders suspect MNC in a given lot, then they bid that way regardless of whether or not it actually occurs. If they do not suspect MNC, then the same statement holds.

[13] It does not matter whether we consider log bids or bids, because draws from a random sample can undergo any monotonic transformation and still maintain all their properties. Thus, from this point on the analysis employs log bids only.

[14] In our cheating model we are interested in distortion of the difference between the second low bid and the winning bid. The winning bid is the first order statistic, which has an associated distribution of $1-[1-G(b)]^N$

To see this interesting characteristic, consider the following example: suppose the researcher is interested in the density of the ith ordered log bid given a particular realization of S_{i+1}. This conditional density is evident by taking the realization, call it y, of S_{i+1} as given, and then understanding that the remaining i draws must fall below y. Thus, the draws $S_1, S_2, \ldots, S_i$ can be seen as order statistics drawn from the density g(s) truncated on the right at the value y. Thus, given $S_{i+1} = y$, S_i has a conditional density of

$$f_i(s|S_{i+1}=y) = [i!/(i-1)!][G(s)^{i-1}g(s)]/G(y)^i \qquad (5.3)$$

We should also note the fact that because of the Markovian nature of order statistics, it will be the case that

$f_i(s|S_{i+1}=s_1, S_{i+2}=s_{2,\ldots,} S_{N+1}=s_N) = f_i(s|S_{i+1}=y)$, because a truncation at an order statistic higher than i+1 is meaningless if you have already truncated the density at i+1.

Applying the above information toward a test for MNC is straightforward. Recall that MNC results in a distortion of the difference between the first and second log bid realizations. This difference, however, is bounded above by the third bid. Thus, we can model the first and second log bids as ordered draws from a sample of 2 from the density g(b) truncated at the third log bid. Additionally, due to the Markov property that the ordered bids exhibit, information regarding ordered log bids above the 3rd is superfluous. To see this, define $D = S_2 – S_1$. Now, note that the density function of d conditioned on a value of S_3, call it $f_{21}(D|S_3=y)$, can be written as

$$f_{21}(D|S_3=y) = [2/G(y)^2] \int_0^y g(s)g(D+s)ds \qquad (5.4)$$

Equation 5.4 is obtained from the transformation of the joint distribution of two order statistics (David 1981, 9-10). Obviously, conditioning on other log bids in addition to the 3rd log bid will not change equation 5.4 at all, as the density is already truncated at the 3rd log bid. Hence, the 3rd log bid is a sufficient statistic for the log difference of the 2nd and 1st log bids[15].

Now we must consider auction lots in which MNC has occurred. Here we must assume that if MNC occurs, the dishonest bidder would have won the lot regardless. This is not necessarily a realistic assumption, but is necessary to proceed. If we do not make this assumption, then the observed bid ordering is not the true bid ordering, and our model is not specified correctly. Finally, we introduce MNC to the model as a further truncation of the distribution of the first spacing. Specifically, after viewing $S_3 = y$, the auctioneer chooses a function ?(y), where 0 < ?(y) < y, and truncates the density of the first spacing at ?(y) rather than y. Thus, the density of this first spacing, when MNC is present, can be written as

$$f_{21}(D|S_3=y, MNC) = f_{21}(D|S_3=?(y)) \quad (5.5)$$

This will be the case for values between the ranges 0 and ?(y). In words, equation 5.5 simply means that the auctioneer maintains the random nature of the spacing between the lowest log bids, but reduces the range under which this spacing is drawn.

The first item to note in equation 5.5 is that bids higher than the 3rd bid are superfluous if you have already conditioned on the third bid. Thus, our regression

[15] Additionally, we should note that this sufficiency property allows for maximal use of our sample data. If we condition on the 4th log bid as well, we must naturally omit lots with only three submitted bids, and will therefore lose efficiency.

presented below is correctly specified under all possible states of the world[16]. These states of the world are the four combinations of the occurrence/nonoccurrence of MNC, and honest bidder's expectation/non-expectation of MNC.

Secondly, note that the expected value of the first spacing conditioned on y is smaller when MNC is present.[17] Thus, we expect that on average the first spacing should take on smaller values in instances of MNC, which makes perfect sense. Next, consider the marginal effect of y on the conditional expectation of the first spacing in lots with MNC as opposed to lots without MNC. These marginals are easily derived by appealing to Leibniz's rule for differentiation, but their relative values prove allusive without assumptions on the derivative of ?(.) with respect to y. For the purposes of completeness, the partial derivatives are provided below.

$$dE(D|S3=y)/dy = yf_{21}(y|S_3=y) + ?_0^{y} D\ df_{21}(D|S_3=y)/dy\ dD, \quad \text{where}$$

$$df_{21}(D|S_3=y)/dy = 2g(y)g(y+D)/G(y)^2 - ?_0^{y} 4g(x)g(x+D)/G(y)^3 dx$$

$$dE(D|S3=?(y))/dy = ?(y)f_{21}(?(y)|S_3=?(y))?'(y) + ?_0^{?(y)} D\ df_{21}(D|S_3=?(y))/dy\ dD$$

[16] Another way to model MNC would be to consider it a distortion of the draw of the first bid relative to the second, instead of a draw of the spacing of the first two bids. This will make the theory a bit cleaner, but will make empirical interpretations of regressions more difficult, as our regression model involves regressing the second bid on the first. I have performed all analysis presented in the paper using this very specification, and the results are virtually identical to that presented below, changing none of the conclusions in this paper. Thus, I prefer to use the spacing model in order to make empirical interpretations cleaner, while creating more work on the theory end.

[17] This is easily verified. See for example Chapter 20 in Greene (1997).

$$df_{21}(D|S_3=?(y))/dy = 2?'(y)H(y,D) + \int_0^{?(y)} ?'(y)J(y,D,x)dx$$

In the above, J(.) and H(.) are functions based on the differentiation $f_{21}(.)$. Now, note that every term of dE(D|S3=?(y))/dy contains a multiple of ?'(y). Thus, as ?'(y) tends to zero, so to will dE(D|S3=?(y))/dy. Furthermore, note that the dishonest bidder, and therefore the auctioneer, will find cheating most profitable if ?'(y) is close to zero. Therefore it would make sense that the marginal effect of the 3rd bid on the first spacing be smaller in instances of MNC than in honest auctions.

With the above discussion in place, we now proceed in defining a regression specification. Define Y as an Lx1 vector of log differences between the second and first observed bids, where L is the total number of auction lots with at least 3 submitted bids. Define X as a LxK matrix of explanatory variables, including moments of the log of the third bid, moments of the number of bidders, and various lot characteristics. Since we are interested in testing for cheating, we may also include indicator variables for particular auctioneers or bidders. Furthermore, we include indicators of when news of the cheating scheme became public. The logic behind the inclusion of these dummies is that significant and small (or negative) coefficients on auctioneer dummies would be a sign of MNC. Additionally, a structural difference in the relationship between Y and X, before, as opposed to after, news of the scandal became public, would indicate that cheating could have been a serious issue prior to news of the scandal. Specifically, the frequency of cheating could have been high pre-scandal, or bidders may have suspected cheating pre-scandal and therefore adjusted their bid functions in the fashion discussed in appendix A, and detailed in Ingraham (2000).

Finalizing our specification, we can use least squares to estimate the equation

$$Y_{21} = X\beta + e \qquad 5.6$$

In 5.6, e is the standard Lx1 iid disturbance vector with zero mean[18]. We now proceed with a discussion of SCA and the MNC scandal.

VI. The SCA Bidding System, and 1992 Magic Number Scandal

Prior to 1987, many problems existed within the school construction industry in New York City. The main problem in the industry was job quality, and job assignment time. According to individuals within SCA[19] it sometimes took as long as six months to assign a particular job to a contractor. Additionally, job quality was a concern. Jobs were often in an unsatisfactory manner, leading to longer than necessary times for completion. Finally, industry corruption has long been a problem. Contractors are often charged with wage violation scams[20], and in some cases entire sectors are over-run with organized

[18] Asymptotic properties of order statistics are discussed in Chapter 9 of David (1981), and Pyke (1965) discusses the asymptotic theory of spacings. Basic results are that an order statistic "of the extreme" has a nonnormal limiting distribution as the number of draws becomes infinite. Simply, the extreme can be thought of as either tail of the parent distribution. The limiting distribution of a quantile, or value not in the tail of this distribution, has a normal limiting distribution. The limiting distribution of spacings, however, are exponential as shown in section 5 of Pyke (1965).

[19] I spoke to a high-ranking person within SCA, who has worked at SCA almost since its inception, and was present when news of the cheating scandal broke.

[20] A wage violation scam is the act of paying workers less than the going wage on construction labor (around $22 per hour), while billing out labor at that price. In extreme cases these scams involve billing labor at the going rate, while hiring illegal aliens and paying them $6 per hour. In this manner, large profits are made on units of labor.

crime[21]. In December of 1988 SCA was created to remove the backlog in school construction jobs, and to address the problem of contractor integrity. SCA was given almost complete autonomy from all other offices in NYC, and with the exception of two top ranking individuals appointed by the mayor and governor, SCA leadership is internal[22].

In order to allocate contracts, SCA uses a “bidding system”, which is nothing more than a first-price, sealed bid procurement auction. Auctioned contracts range in scale from the installation of a handicap sink (an estimated $6,700 job) to the construction of a new school (an estimated $85,000,000 job). Job sites are spread over all five New York City boroughs[23]. Most jobs are located at a single building, although some jobs require service at multiple buildings throughout a single borough, a combination of boroughs, or the entire city.[24]

The main players in the auction scheme are the bidders, the contract specialists, and the project officers.

The bidders are simply construction firms bidding on various projects. In order to bid on a project, you must first "prequalify", which involves filling out a 22 page form detailing information about individuals in your firm, previous work completed for the city, past

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[21] In 1998 it was discovered that the interior office construction job assignments industry in New York City were run through bid rigging and organized crime (Bagli, 1998). Additionally, in 1991 SCA disallowed 52 contractors from bidding on its jobs, stating that they had ties to organized crime (Raab, 1991).

[22] Information regarding all aspects of current SCA practice and mission is available at http://www.nycsca.org/sca/home.html.

[23] Bronx, Brooklyn, Queens, Manhattan, and Staten Island.

[24] For example, most asbestos abatement jobs were contracted out for buildings across multiple boroughs.

work experience, and a history of the ownership of your firm.[25] Bids submitted by firms that are not yet prequalified, are immediately rejected. If the prequalification form is filled out incorrectly, all bids from that firm are rejected until the prequalification form is properly completed. In addition, prequalification is not guaranteed. Firms will be denied prequalification status if key members within the firm have recent criminal convictions, are under criminal investigation, or even are suspected of “integrity problems”.

The first main auction official is the contract specialist, an employee of SCA. Contract specialists serve as auctioneers, opening sealed bids, recording those bids, making sure forms are completed properly, and ultimately assigning the job to a contractor. Contract specialists are not necessarily assigned auctions based on job type (as will be the case with project officers). Specialists are generally assigned between 10 and 40 contracts per fiscal year. Their main duty is to assign contracts quickly, and to the firm best suited to perform that work. When we say “best suited” here, we mean the prequalified firm that submitted the lowest bid on a particular job, and filled out all bid information correctly. Thus, if the lowest submitted bid was from a prequalified firm that correctly completed all paperwork, and listed registered or prequalified subcontractors when necessary, then that firm is awarded the job. Otherwise, the specialist looks at the second lowest bid. If that firm has satisfactorily completed all paperwork, then she is awarded the job. Otherwise, the process continues until a contractor is able to secure the

[25] Subcontractors completing more than an estimated $10,000 worth of work on the project must be registered with SCA. If the value of their work is under $500,000 they may be only “sub-registered”, and must fill out less paperwork than if they are to perform more than $500,000 worth of work, which requires prequalification status, and the 22 page form that accompanies said status.

job. As a final note, although there are occasions when contract specialists work together on a single auction, these instances are very rare.

The second type of official employed at SCA is the project officer. Project officers visit the site of a project, and estimate its scale (often with the help of design plans from the engineering office) across all dimensions that would affect the cost of project completion. These measurements, and any design plans, are then made public to all firms wishing to submit a bid in the auction. The firms can either visit SCA to view the plans, or they can order their own copies at a cost[26]. Additionally, the project officer calculates a "project estimate". This project estimate is the estimated cost of completing the job, and is recorded at SCA, but *not* made public. Once a contractor has been assigned the job in question, it is the project officer's duty to frequent the job site, making sure that construction is completed in a satisfactory fashion. Because of the nature of the project officer's job, she is assigned to sites based on job type. For example, only a few project officers may be responsible for all plumbing jobs. These officers would have particular expertise in assessing the cost and quality of such a job.

On their web site, SCA states that Contract Specialists and Project Officers are required to have a four-year degree at an accredited institution, and at least four years of experience in the industry. Hiring is also possible if the individual possesses a sufficient amount of industry experience to perform her job. Starting salary for entry level employees is in the vicinity of $40,000. These hiring qualifications and salaries reflect SCA standards in the year 2000 (Conversation with SCA official). In 1992, the employees charged with accepting bribes were making salaries of between $60,000 and

[26] Costs range from about $50 to $250.

$70,000 a year. As an interesting aside, and a nice introduction to the 1992 cheating scam, John Dransfield, a project officer charged with bid rigging, was convicted of third-degree burglary prior to his hiring at SCA. On his SCA application he left blank the question asking, “Have you ever been convicted of a misdemeanor/felony?” At the time of Parker’s hire, New York law prevented SCA from investigating his record on its own. Thus, SCA hired him without any knowledge of his criminal past. Since 1992, however, SCA has been allowed to run background checks on all of its potential hires (Olmstead, 1993).

During the summer of 1992, Elias Meris, the principal owner of the Meris Construction Corporation of Brooklyn, New York, was under investigation by the Internal Revenue Service. Seeking leniency with IRS agents, Meris offered information on an SCA bid rigging scam involving SCA employees and other contractors. Meris, working undercover for prosecutors, taped conversations with senior project officer John Dransfield, leading prosecutors to charge both Parker and Dransfield with bid rigging. When confronted by authorities, Parker secretly pleaded guilty to charges of accepting bribes, and began working undercover to weed out contractors guilty of this act. Dransfield, however, pleaded not guilty to charges of accepting bribes until January 21, 1994 when he finally pleaded guilty to this charges (Raab, 1993). The Inspector General’s office at SCA estimated that Dransfield accepted $100,000 in bribes from the cheating scam, and laundered the money through his Long Island construction firm (Fried, 1994). In addition to Parker and Dransfield, Samuel Manoharan--a project officer with SCA for only a few months, was criminally charged with accepting bribes. Manoharan was charged with accepting between $3,000 and $4,000 in bribes for allowing a change order[27], and for passing electrical work he should have failed (Olmstead, 1993). The nature of the cheating was MNC. The strict details of the scam are somewhat cloudy, but what is certain is that out of the three SCA employees charged, Parker was clearly the ring leader, bringing in Dransfield at a later time. Dransfield seemed to serve as somewhat of an industry connection, arranging for contracts to be rigged, and Parker, being the contract specialist, submitted MN bids at the auction. Specifically, at the public bid openings, Parker would save the dishonest contractor's bid for last, and knowing the current low bid, he would submit a false bid just below this price. In this manner, the dishonest contractor is almost certain to win the contract, and will win the contract at the highest possible price (Olmstead, 1993).

Along with the three SCA employees discussed above, eleven individuals within seven contracting firms were implicated in the scam. These firms were Christ Gatzonis Electrical Contractor Inc., GTS Contracting Corp., Batex Contracting Corp., American Construction Management Corp., Wolff & Munier Inc., Simins Falotico Group, and CZK Construction Corp (Olmstead, 1993) and (Raab, 1993). These seven firms won 43 SCA auctions with winning bids totaling over $23 million[28]. Interestingly enough, Elias Meris was never charged in the bid rigging scam, even though one would think that his knowledge of the cheating scam and his income tax evasion would indicate possible involvement. In addition, Meris Construction was allowed to submit bids in SCA

[27] A change order is a classic contractor scam, where the contractor bribes a government official into agreeing that initial government estimates on unit costs or production needs were too low, and more money is therefore needed to complete a job. In the SCA auctions, project officers are responsible for allowing all change orders.

[28] Some of these contracts were cancelled after criminal charges were made. In addition to the 43 winning contracts, these firms no doubt served as subcontractors on many more projects. The subcontractor data is not available to us.

auctions after the bid rigging scam was broken, and proceeded to win $10 million worth of contracts after becoming an informant (Raab, 1993).

Given the above information on the bid rigging scam and its surrounding details, we must consider the possibility that cheating was not limited to the eight auction lots in which bidders and officials were charged with bribery and bid rigging. First, we must consider that specialists other than Parker engaged in MNC. Second, we must consider that Parker may have engaged in MNC outside of the eight lots where he was implicated. We explore these ideas in sections VIII and IX respectively. In section X, we focus on regression analysis of the eight lots where we know cheating occurred.[29]

VII. The Data

The complete data set (including all auctions) represents 1,789 auctions held from May 1990 to January 1997. In these 1,789 auctions, just over $3 billion in contracts were awarded. Eliminating auctions where the lowest bid did not win the project, and auctions with only 1 bidder, we cut our sample to 969 auctions with a total of $2.29 billion in winning bids. Since in our tests for cheating we include the 3rd lowest bid as an explanatory variable, we must limit ourselves to lots with at least three bidders. This will cut our sample to 890 observations with a sum of $2.24 billion in winning bids. If we omit the seven lots where we know MNC occurred, the sample then falls to 883 lots with

[29] In actuality, we will only be able to analyze seven of the eight magic number lots, as I am unable to identify the eighth in the data.

a total of $2.23 billion in winning bids[30]. Table 1 contains a list of variable names used in the empirical portion of this paper. Table 2 includes a summary of the non specialist dummy variables listed in Table 1, and the value of the winning bid for the sample of 883 lots. Finally, in Table 3 we give summary statistics on the number of auction lots that contract specialists presided over in each of the three relevant samples. Here, it makes sense to briefly discuss the variable "x" in Table 1. This variable equals 1 for all auction lots prior to April 21, 1993, when the MNC scandal became public. We will use this indicator variable to control for possible differences in bidding before or after the scandal.

VIII. Analysis of Pre vs. Post Scandal Bidding

We begin this section with the estimation of the basic empirical model discussed in section V. These results are presented in table 4. The first item to mention regarding table 4 is the serious multicolinearity problem between moments of lbid3 and moments of lnpest. The problem is so severe in fact that the correlation coefficient between these two variables is .98 within the sample of 883 useable auction lots. Recall, however, that moments of lbid3 are included in the regression model because of a specific theory result regarding the conditional density of ldev21 given lbid3. While the variable lnpest is included for intuitive reasons only. Additionally, the variable lbid3 has the advantage of

[30] We should note here that in terms of auction data sets, 900+ observations is quite large. Guerre, Perrigne and Vuong (1999) use samples of 200 in their Monte Carlo study explaining that this is a typical sample size for auction data.

always being at least as big as ldev21. Therefore, the relationship between ldev21 and lbid3 has a specific meaning in terms of cheating. This is not the case with lnpest, a variable which proxies only for the variance of the parent distribution, and therefore has less meaning than ordered realizations within a distribution. For these reasons, we will restrict future analysis to estimations involving moments of lbid3 only, and exclude moments of lnpest from the regressions. Obviously, we now face the problem of omitted variable bias in future regressions, because we exclude variables that are jointly significant in the first specification[31]. This bias will not affect our analysis, however, because we are not interested in the value of the coefficient on lbid3, so much as changes in this coefficient that might occur after news of the cheating scandal is announced. For completeness sake, however, results generated when specification I or specification III is used as the base regression are described throughout the remainder of the paper.

Next, we interpret the signs on estimated coefficients in Table 4. Note that in all three regressions, n and nsq have the expected signs. The coefficient on n can be seen in two lights. First, increases in n denote more competition in an auction, and therefore competitive bidding should force bids closer to true costs, tightening the bid distribution. Second, more draws from a fixed distribution means that the probability of realizing a third order statistic toward the tail of the distribution has increased[32]. Thus, the parent density is truncated further to the left, and the remaining distribution where realizations of the second and first log bid can fall is reduced. Hence, ldev21 is smaller with increased probability. Additionally, we see that the sign on nsq is positive, indicating

[31] In Spec I, the variables lnpest and lnpsq are jointly significant at a p-value of less than .01. The same is true for the joint significance of lbid3 and lbid3sq.

[32] This can easily be verified from the general CDF for an order statistic presented in Section V.

that increases in the number of bidders leads to decreases in ldev21, but at a decreasing rate. This is to be expected if the underlying pdf, g(s) in Section V, is well behaved with no sudden increasing jumps in probability when moving further into the distribution tail.

Next, note that lbid3 has the expected positive sign in the first and second regressions. Statistically, this result means that increases in lbid3 lead to less of a truncation in the underlying density from which ldev21 is drawn. As a result, the conditional expectation of ldev21 has increased. Finally, note the signs on lnpest and lnpsq, which are negative and positive respectively. If these variables proxy for the spread of the underlying bid distribution as average project size grows, then this indicates one of two possibilities: (1) in larger projects, SCA prequalified only the more efficient firms, and therefore spread in g(s) is reduced, or (2) larger projects were more conducive to MNC. Given the rather obscure nature of MNC, and the fact that in theory it would be relatively easy to eliminate one would have to reject (2) in favor of (1) simply on the grounds of common sense.[33] The fact that MNC occurred in this data, however, would make one believe that rejecting (2) altogether is not prudent until more evidence is presented. With the above analysis in place, we now proceed to Table 5, where we test for a structural difference in bidding before versus after news of the MNC scandal.

Table 5 should be read as follows: the first column applies specification II from table 4 on auction lots occurring prior to April 21, 1993. The second column applies that same specification to all lots after April 21, 1993, and the third column is the absolute value of

[33] One could also argue that larger projects are more profitable, and will therefore attract more bidders. In this fashion ldev21 would be smaller as an indirect effect of the relationship between lnpest and n. While it is true that a regression of n and nsq on lnpest yeilds a positive, concave relationship with statistically significant variables, the correlation coefficient between lnpest and nsq is only .17, and not enough to affect the coefficients on lnpest and lnpsq in a largely noticeable fashion.

the differences in estimated coefficients between the two samples. The t-statistics below the differences in the third column are those generated from a *one parameter* test of significance in the pooled sample.[34] Thus, we see that structural differences in bidding occur separately in the relationship between ldev21 and the moments of lbid3, and the relationship between ldev21 and the intercept term. Additionally, a Chow test for all parameters, pre versus post scandal, yields an F-statistic of 2.11, which is significant at a 6.2% level of confidence. Note, however, that a test of joint significance of the variables x, x*lbid3, and x*lb3sq, in the pooled sample, will yield and F-statistic of 2.96, which is significant at the 5% level. Furthermore, a test of joint significance of the interaction terms x*n and x*nsq yields an F-statistic of 2.90 which is significant at the 5.5% level. One might argue that the difference in moments of lbid3 across the two samples is meaningless, since neither parameter is statistically significant in either sample. Note, however, that these parameters are jointly significant at the 1% level in both samples. In addition, we can see from table 5A that if we exclude, lbid3 from the regression, that the estimated coefficient on lbid3 is significant in both samples. Furthermore, the difference in the coefficient on lbid3 between samples is significant. Finally, a Chow test of all parameters in table 5A, yields an F-statistic of 2.76, rejecting the null hypothesis of equal parameters at the 5% level. Hence, the result of structural difference between lbid3 and ldev21 in the two samples is robust.

[34] To give a specific example, if one runs a regression using specification II on the entire sample, but includes the dummy variable x, and no other additional variables, one would find x significant at the .01 level with an estimated t-statistic of 2.71.

Given the above discussion, we can conclude that a structural difference in bidding was present between the samples[35]. That difference is strongest, both empirically and statistically, in the moments of lbid3, and the constant term. Across the two samples, we see large differences in estimated coefficients on the intercept and moments of lbid3. These differences are significant at the 5% level. The difference in moments of the number of bidders, however, is empirically much smaller between the two samples, and not jointly significant at the 5% level.

Now that the statistical nature of the difference in coefficients has been discussed, consider the empirical differences in the estimated coefficients. First, note that the sign on lbid3 is negative for the pre-scandal pool, but positive for the post-scandal pool. In words, this result indicates that before the scandal, increases in lbid3 lead to decreases in ldev21. This result is contrary to established theory of competitive bidding under private iid costs[36]. If MNC occurred in any significant sense, then this could lead to a negative sign on lbid3, because for larger auction lots the benefits from MNC are increased. Therefore, firms would increase their likelihood of cheating in these lots, and ldev21

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[35] Here we note that strikingly similar results are obtained if the basic regression specification employed is specification III in table 4. Following similar methodology as described immediately above, one finds that the relationship between lnpest and ldev21 was negative and concave pre-scandal, but positive and concave post scandal. Interactions between x and the moments of lnpest, and the dummy x are jointly significant at the 5% level. Interactions between x and moments of n are jointly significant at the 10% level. This is not surprising, given the close relation between lbid3 and lnpest, but is reassuring nonetheless. Finally, we note that if specification I in table 4 is employed, then the multicollinearity problem washes out any movement in moments of lbid3 or lnpest across the two samples, and no structural difference is found at a 10% level of confidence. This problem appears to be one of small sample sizes, however, considering that controlling for the two variables separately yields similar results.

[36] Recall that even if honest bidders expect MNC, their bids are still iid random variables, and therefore the coefficient on lbid3 should still be postive, assuming that only honest bidders were bidding in the auction.

would be artificially reduced with greater frequency[37]. Next, note that the differences between moments of n are rather small between the two samples. This indicates that on an empirical level, the relationship between ldev21 and n was roughly the same between samples. In an intuitive context, recall that if MNC is present in a given lot, the only way for an honest bidder to win that lot is to underbid the dishonest bidder's cost. As n gets large, two things occur. First, more bidders are being drawn from a fixed distribution. Thus, the likelihood that one of these honest bidders has an equilibrium bid below the dishonest bidder's cost will increase. Second, as n increases the auction becomes more competitive, and therefore bidders will submit bids closer to their costs. Even if MNC does occur, it is less obvious since bids are already compressed rather tightly[38]. Hence, a structural difference in bidding exists when comparing bids prior to news of the MNC scandal to bids submitted after the scandal. In addition, the structural difference occurs in a manner leading us to conclude that MNC did occur outside of the lots in which bidders were indicted. This is a very powerful result, but is still rather vague in that we have not attempted to control for the identities of auctioneers in our samples. We present this analysis next.

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[37] Note that even in the post scandal regression from table 5, that the marginal of lbid3 on ldev21 is negative for lbid3 higher than roughly 10. This would correspond to bids of about $20,000 or almost our entire sample. Thus, to be precise we should think of this marginal being more negative pre-scandal rather than just the sign on lbid3 being negative pre-scandal and positive post-scandal.

[38] See Appendix B for a comparison of two auction lots were MNC is known to have occurred. It becomes evident that MNC can be less obvious in lots with more bids.

IX. Analyzing Particular Specialists

In the previous section, evidence was presented suggesting that MNC occurred outside of the auction lots where individuals were charged with criminal activity. In this section we attempt to narrow our search, focusing on particular contract specialists who might be guilty of MNC. To proceed, we first note that only nine specialists can be considered as potentially dishonest. The reason for this assertion is that only these nine specialists oversaw auctions prior to April 21, 1993[39]. Additionally, only four of these nine specialists worked at SCA after April 21, 1993. This fact will further limit the scope of require analysis[40]. Before proceeding, we list CS dummies and relevant lot summaries. This information is presented in table 6. Table 6 should be read as follows: the first column lists a randomly generated ID. Numbers of lots auctioned off are broken down in the second and third columns for pre and post scandal samples respectively. The approximate date of exit from SCA is listed in the final column[41].

Regarding table 6, note that four specialists left during the Summer of 1992, when Meris first became a court's informant. This may be purely circumstantial, but is

[39] To be perfectly accurate, there were 15 specialists prior to April 21, 1993, but 5 of these specialists only worked on one to five lots, and therefore their actions cannot be analyzed with any meaningful results expected. Additionally, one of the 15 specialists is Mark Parker, who we already know to be guilty. Thus, we have only 9 specialists we need concern ourselves with in thorough analysis.

[40] In a conversation with an SCA employee, it was stated that SCA took measures to ensure that this type of cheating would never again occur. Thus, we feel it safe to assume that MNC could only have occurred prior to April 21, 1993.

[41] We do have exact dates of the last auction presided over for specialists, although we withhold this information. Additionally, the exact data of Parker's dismissal from SCA is somewhat uncertain. The last lots Parker auctioned off were sometime around March or April of 1993, but many of these lots were subsequently canceled, as they were procured at auction by firms indicted for MNC.

certainly worth noting. Finally, the “unknowns” in column four, presided over auctions until the end of the data set. Therefore, little is known of their employment at SCA beyond those dates, with the exception of one individual who is still employed at SCA (as of November, 2000)[42].

To begin our statistical analysis of the above contract specialists, we first run a regression controlling only for average affects. For specialists 14, 17, 22, and 32 we also include interactions between those indicators and the dummy variable x. These results are presented in table 7.

Note in table 7, that the estimated coefficient on “Park”, the dummy variable for Parker auctions, is positive. Thus, Parker auctions yielded, on average, larger values for ldev21, which would indicate no cheating. Thus, it appears (at least on the surface) that Parker’s MNC did not occur outside of the auction lots in which he was indicted[43]. Next, note that some estimated coefficients on CS dummies switch signs if we control for structural differences in the slope coefficients. Thus, it appears that in the first specification, negative signs on some CS dummies are absorbing omitted information on structural differences in the slopes. Finally, note that estimated coefficients on xCS17 and xCS32 remain negative even after controlling for interactions between x and the slope terms. These intercepts, however, are not statistically significant at any reasonable level of confidence, however. Thus, results in table 7 have offered little information as to who may have been cheating in SCA auctions prior to April 21, 1993, and might indicate

[42] I ascertained this information by checking names of specialists for recently auctioned jobs. This information is available on SCA’s web.

[43] We return to this idea in Section X. Note that in table 7 we are controlling for all Parker lots, not Parker/Dransfield lots, and are therefore not using all the information at our disposal.

that no cheating occurred outside of the eight rigged lots. This analysis tests only for differences in intercepts, relative to other lots. A more meaningful test would be to compare bidding before versus after news of the scandal within a particular CS sample. We now do this comparison for the four specialists (CS14, CS17, CS22, CS32) with lots both before and after the scandal. These results are presented in tables 8 and 9.

Regarding tables 8 and 9, I first note that we are certainly cutting samples to rather small sizes, and therefore skepticism of results presented in these tables may be well grounded. It is for this reason that we limit our analysis to looking simply for average (intercept) differences within a specialist for before versus after April 1993[44]. Note that the dummy variable x is statistically significant for both samples in table 8. For CS32, x is significant at 5% level, and for CS17, x is significant at the 6% level. Additionally, the estimated parameter on x is negative for both these auctioneers, indicating that auctions prior to April 1993 realized smaller average values of ldev21. Thus, we find evidence that specialists 17 and 32 may have been guilty of MNC prior to April 21, 1993. In table 9, the estimated coefficient on the indicator x is negative for both CS14 and CS22, but that coefficient is not statistically significant for either sample. Thus, there is no evidence to suggest MNC for CS14 or CS22 based on this analysis.

[44] If one includes interactions between x and the moments of lbid3 in these four regressions, one finds these variables are separately significant at the 5% level for the CS32 regression and separately significant at the 6% level for the CS17 sample. Tests of joint significance of x, xlbid3 and xlb3sq yield statistics above the 10% critical value for the CS32 sample and above the 5% critical value for the CS17 sample. These coefficients are never significant, either separately or jointly, for the CS14 or CS22 samples. Thus, the slope coefficients pick up a structural difference in bidding much the same as the intercept term for the CS17 and CS32 samples. Note, however, that estimated coefficients on intercepts change significantly with the inclusion of these terms, as the small sample problem of deciding exactly where the difference in bidding lies is evident. For this reason we prefer to focus analysis on differences in average affects only.

Naturally, the question arises as to how much weight the researcher should put on results in table 8, and therefore how useful this analysis is in detecting MNC. Part of the answer will be deferred to Section X, where we run regressions controlling for lots with known MNC. To give a general answer to the question, we must proceed very carefully when using statistical analyses to test for bid rigging. This analysis is probably best served to test the null hypothesis, H_o: CS# was guilty of MNC. Based on table 9, we reject H_o for CS14 and CS22. Based on table 8, we are unable to reject H_o for CS17 and CS32. Therefore, this form of analysis is best used to get a sense of who might be engaging in MNC. One can then effectively focus monitoring efforts on these specific individuals.

X. A More Thorough Analysis of Parker Lots

We begin our analysis of Parker auction lots by focusing on lots where Dransfield served as project officer. We control for the Parker/Dransfield lots both within the entire sample of 883 lots, and within the sample of 92 Parker lots where MNC did not occur with certainty. Surprisingly enough, no statistically significant results are obtained[45]. Thus, we find no evidence to indicate that Parker rigged bids outside of the lots where cheating was discovered. For the sake of completeness, table 10 contains results controlling for slope and intercept differences in the full sample, and intercept differences

[45] Controlling for both differences in intercepts, and slope coefficients in both the large sample and the Parker only sample, there is no statistically significant difference between Parker/Dransfield lots and other lots. This analysis is performed using the same regression specification of sections IIIV and IX.

in the Parker only sample. Note that while the "pd" indicator variable is negative for the Parker only sample, it is nowhere near significant. Based on these results, we have no grounds to conclude that Parker engaged in MNC other than in the lots where he was implicated.

We finalize our statistical analysis of the SCA auctions with a regression including the auction lots where MNC was discovered. Recall that only 7 of the 8 lots are identified in our data set. We identify these 7 lots with a dummy "MN" and include this dummy in regressions using both the entire sample (now of 890 lots) and the sample of Parker only lots (now 99 lots). These results are included in table 11.

Obviously, the main result from table 11 is the negative and significant dummy MN. Thus, this regression analysis is sensitive to actual cases of MNC, even if it occurs in only 7 lots. We also note that interactions between MN and the moments of lbid3 are separately significant at the 5% level in both samples. Additionally, the interaction between MN and n is significant at a 5% confidence level in both samples, whereas an interaction between MN and nsq is never significant at the 5% level. Finally, these slopes are never jointly significant in either sample, either with one another or with the MN indicator. This fact can be attributed more to a sample size issue than anything else. Clearly, the regression is picking up a difference in bidding in the MN lots relative to others, but with only 7 lots structural differences cannot simultaneously be attributed to multiple RHS variables.

The above results may not be overwhelming proof that our regression analysis is an effective tool in uncovering MNC. It is, however, a good first step in assessing its sensitivity toward distortions of the bid distribution.

XI. Conclusion

This paper develops a regression model specifically aimed at analyzing cheating of the “magic number” variety. The model is applied to the SCA data for years 1990 through January, 1997, and analysis suggests that two auctioneers (other than the auctioneer already convicted) may have been guilty of bid rigging. We find no results to indicate that the guilty auctioneer, Mark Parker, engaged in MNC outside the auction lots in which he was charged with accepting bribes. The regression method does appear to effectively determine MNC, but we have only 7 auction lots where this form of cheating is known to have occurred. Therefore, conclusive evidence that this test is effective in unearthing guilty auctioneers is not yet available. The next step in assessing the regression model’s sensitivity to MNC is probably a Monte Carlo study aimed at the specific form of cheating described in this paper.

Table 1. Definition of Variables

ldev21	= log(2nd low bid) – log(winning bid)
lbid3	= log(3rd low bid)
lb3sq	= log(3rd low bid)^2
n	= number of bidders
nsq	= number of bidders squared
lnp	= log(project estimate)
lnpsq	= lnp^2
CS#	= 1 if lot was auctioned by a particular CS. The CS indicator number is random.
x	= 1 if lot was auctioned prior to April 21, 1993.

Table 2. Summary Statistics, Sample: n = 3, MNC Uncertain

	Mean	Std	Min	Max
bid	2458000	6425000	3500	6.67e+07
ldev21	0.105	0.102	0	0.699
lbid3	13.302	1.709	8.7	18.05
lb3sq	179.867	46.298	75.72	325.79
n	6.929	4.131	3.0	28.0
nsq	65.07	89.77	9.0	784.0
lnpest	13.293	1.72	8.52	18.26
lnpsq	179.636	46.75	72.54	333.36
x	0.617	0.486	0.0	1.0

Table 3. Summary of CS Dummies

	Total	x = 1	x = 0
# officers	22	16	14
ave # lots	38.45	31.81	24.07
std # lots	37.13	27.12	20.92
min # lots	1	1	1
max #	119	92	63
officer missing	37	36	1

Table 4. OLS Results, Dependent Variable: ldev21.
* represents significance at 10%, ** at 5%.

	Estimated Parameters & t-Statistics		
	Spec I	Spec II	Spec III
lbid3	0.18**	0.015	----
	(2.02)	(0.69)	
lb3sq	-0.0005	-0.001	----
	(1.57)	(1.28)	
n	-0.009**	-0.013**	-.023**
	(3.27)	(4.80)	(7.72)
nsq	0.0003**	0.0004**	0.0008**
	(2.34)	(3.25)	(5.74)
lnpest	-0.17*	----	-0.055**
	(1.95)		(2.30)
lnpsq	0.004	----	0.001
	(1.34)		(1.53)
Const	0.15	0.154	0.70**
	(1.07)	(1.06)	(4.42)
Obs	883	883	956
R^2	0.13	0.10	0.17
Adj R^2	0.12	0.10	0.16

Table 5. OLS Results, Dependent Variable: ldev21.
* represents significance at 10%, ** at 5%.

	Pre-Scandal	Post-Scandal	|Pre-Post|
lbid3	-0.01	0.043	0.053**
	(0.41)	(0.76)	(2.62)
lbid3sq	-0.0001	-0.0021	0.002**
	(0.12)	(1.06)	(2.49)
n	-0.011**	-0.017**	0.006*
	(3.49)	(3.33)	(1.70)
nsq	0.0004**	0.0005**	0.0001
	(2.50)	(2.11)	(0.75)
Const	0.31*	0.006	0.304**
	(1.88)	(0.02)	(2.71)
Obs	545	338	
R^2	0.10	0.11	
Adj R^2	0.10	0.11	

Table 5A. OLS Results, Dependent Variable: ldev21.
* represents significance at 10%, ** at 5%.

	Pre-Scandal	Post-Scandal	|Pre-Post|
lbid3	-0.013**	-0.016**	0.003**
	(5.73)	(4.35)	(2.76)
n	-0.011**	-0.017**	0.006*
	(3.50)	(3.41)	(1.81)
nsq	0.0004**	0.0005**	0.0001
	(2.50)	(2.14)	(0.77)
Const	0.33**	0.42**	0.09**
	(10.32)	(7.49)	(2.87)
Obs	545	338	
R^2	0.10	0.11	
Adj R^2	0.10	0.11	

Table 6. CS Dummies of Interest in Testing MNC, Lots where n = 3

ID	Pre-Scandal	Post-Scandal	Last Auction
CS8	54	0	Summer, 1992
CS12	37	0	Summer, 1992
CS14	60	59	Unknown
CS17	55	22	1995
CS22	41	36	Unknown
CS27	16	0	Winter, 1991
CS30	47	0	Summer, 1992
CS32	55	63	Unknown
CS37	42	0	Summer, 1992
Parker	92	0	Around March 1993

Table 7. Controlling for Average Affects, Dep. Var.: ldev21
* represents significance at 10%, ** at 5%.

	Coef	|t-stat|	Coef	|t-stat|
lbid3	0.0038	0.170	0.003	0.134
lb3sq	-.0006	0.781	-.0007	0.847
n	-.013**	4.892	-.017**	3.563
nsq	0.0004**	3.416	0.0006**	2.268
CS8	-.016	1.061	0.003	0.161
CS12	0.0006	0.033	0.021	0.945
CS14	0.018	1.259	0.012	0.830
CS17	0.022	1.021	0.019	0.864
CS22	0.023	1.313	0.018	1.023
CS27	-.017	0.661	0.035*	0.145
CS30	0.010	0.573	0.004	1.428
CS32	0.026*	1.871	0.029	1.309
CS37	-.002	0.113	0.019	0.839
Park	0.014	1.141	0.018*	1.920
xCS14	-.020	1.131	0.006	0.254
xCS17	-.036	1.477	-.013	0.435
xCS22	-.011	0.495	0.012	0.439
xCS32	-.049**	2.682	-.021	0.862
x*lbid3	----	----	-.011*	1.836
x*lb3sq	----	----	0.0005	1.483
x*n	----	----	0.005	0.806
x*nsq	----	----	-.0001	0.486
cons	0.23	1.536	0.28	1.791
obs	883		883	
R^2	0.12		0.12	
Adj R^2	0.10		0.10	

Table 8. CS32 and CS17 Samples, Dep. Var.: ldev21
* represents significance at 10%, ** at 5%.

	CS32 Sample		CS17 Sample	
	Coef	|t-stat|	Coef	|t-stat|
lbid3	0.048	0.71	-.09	1.36
lbid3sq	-.002	0.91	-.002	1.06
numbid	-.009	0.98	-.011	1.20
numbsq	0.0002	0.40	0.0003	0.64
x	-.042**	2.18	-.042*	1.92
cons	-.062	0.13	0.96**	2.03
Obs	118		77	
R^2	0.13		0.22	
Adj R^2	0.09		0.16	

Table 9. CS22 and CS14 Samples, Dep. Var.: ldev21
* represents significance at 10%, ** at 5%.

	CS22 Sample		CS14 Sample	
	Coef	|t-stat|	Coef	|t-stat|
lbid3	-.053	0.77	0.016	0.19
lbid3sq	0.001	0.49	-.0009	0.31
numbed	-.032**	4.00	-.027**	2.30
numbsq	0.0012**	3.45	0.001*	1.94
x	-.016	0.75	-.02	0.98
cons	0.77	1.61	0.19	0.34
obs	77		119	
R^2	0.37		0.09	
Adj R^2	0.32		0.06	

Table 10. Parker Analysis, Dep. Var.: ldev21
* represents significance at 10%, ** at 5%.

	Full Sample		Parker Only	
	Coef	|t-stat|	Coef	|t-stat|
lbid3	0.015	0.68	-.003	0.04
lbid3sq	-.001	1.27	-.0005	0.16
numbid	-.013**	4.78	-.020**	2.41
numbsq	0.0004**	3.25	0.0006*	1.97
pd	0.61	0.25	-.024	0.69
pdlbid3	-.12	0.29	-----	-----
pdlb3sq	0.005	0.29	-----	-----
pdn	0.021	0.66	-----	-----
pdnsq	-.0008	0.65	-----	-----
cons	0.15	1.04	0.36	0.68
Obs	883		92	
R^2	0.10		0.14	
Adj R^2	0.09		0.10	

Table 11. Analysis of MN Lots, Dep. Var.: ldev21
* represents significance at 10%, ** at 5%.

	Full Sample	Parker Only		
	Coef	|t-stat|	Coef	|t-stat|
lbid3	0.015	0.69	-.005	0.06
lbid3sq	-.001	1.28	-.0004	0.14
numbid	-.013**	4.80	-.022**	2.75
numbsq	0.0004**	3.24	0.0007**	2.20
MN	-.09**	2.44	-.11**	2.55
cons	0.15	1.06	0.36	0.71
Obs	890		99	
R^2	0.10		0.18	
Adj R^2	0.10		0.13	

Appendix A. Equilibrium Strategy when Bidders Suspect MNC

Here we briefly review existing auction theory as it applies to first-price, sealed bid procurement auctions. We then show that even if honest bidders suspect MNC, the iid nature of bids is maintained, and therefore the empirical model in section V still applies. We begin with the assumption that bidder costs are iid draws from a continuous density, f(C), on $[C_{min}, C_{max}]$ with associated distribution function F(C). Let i index the bidder in a given lot, and let N represent the number of bidders in that lot. Bidders view their own cost draws, but have no information on other bidder's costs other than the functions f(C) and F(C), which are common knowledge. A player's strategy is then her bid function, which we denote as $B_i(.)$, and is found by choosing bids, b_i, to maximize expected profit, $?_i$. Thus, we write the maximization problem for bidder i as:

$$\max_{\{b_i\}} ?_i = [b_i - C_i] \text{ Prob}\{i \text{ wins}|b_i\}$$

The standard method of solving the above problem, is to posit a monotonic increasing bid function, $B(C_i)$, that is symmetric for all bidders. One can then prove that bidder i will in fact

choose $B(C_i)$ in equilibrium. In this manner, one can show that the equilibrium strategy for i is given by[46]:

$$B(C_i) = C_i + ?_{C_i}^{C_{max}}[1 - F(u)]^{N-1}du/[1 - F(C_i)]^{N-1} \qquad \text{(A.1)}$$

[46] The formal solution to the problem is given in, among others, Paarsch (1994).

Additionally, bidder i will have an equilibrium expected profit of

$$? _i = [B(C_i) – C_i] [1 – F(C_i)]^{N-1} \qquad (A.2)$$

Our next step is to add one assumption to the above model. Specifically, assume that honest bidders expect that MNC will occur in an auction lot. We will now derive honest bidders' symmetric, equilibrium strategy under the addition of this new assumption. We keep all notation identical to that above, but will posit a symmetric, equilibrium strategy, ß(.). To proceed, we write the maximization problem for i in the presence of MNC as

$$\underset{\{b_i\}}{\text{Max}}\ ? _i = [b_i – C_i] \text{ Prob}\{\text{i wins}|b_i \text{ and suspect MNC}\}$$

In an auction lot with N bidder where only one bidder is engaging in MNC, this same problem can be rewritten as

$$\underset{\{b_i\}}{\text{Max}}\ ? _i = [b_i – C_i] \text{ Prob}\{b_i < b_j | \text{j honest}\}^{N-2} \text{ Prob}\{b_i < C^* | \text{* dishonest}\}$$

Note that the above maximization problem is written only after positing a symmetric, monotonic bid function[47]. To interpret the probability of winning, we see that in order to win the lot, i must submit a bid below all of the honest N-2 bidders. In order to outbid the dishonest bidder, however, i must submit a bid below the dishonest bidder's cost, as explained in section II.

To solve the above problem, we could simply derive and solve the first order condition resulting from the above maximization problem. There is, however, a much simpler solution. The above problem can be thought of as a first price auction with N-1 total bidders and a secret reserve price. The secret reserve is C^* which has a density function f(.) on [C_{min}, C_{max}]. Given this knowledge, we can simply appeal to the

[47] Otherwise bids are iid draws for honest bidders.

equilibrium bid function for first price auction with secret reserve that ELLV (1994) have already solved. Modifying the ELLV bid function to accommodate the distribution of the "secret reserve" in our setting, we find that the equilibrium strategy for honest bidder i when MNC is expected can be written as

$$ß(C_i) = C_i + \frac{\int_{C_i}^{C_{max}} [1-F(u)]^{N-2}[1-F(ß(u))]du}{[1-F(C_i)]^{N-2}[1-F(ß(C_i))]} \quad \text{(A.3)}$$

For the purposes of this paper, the main result regarding ß(.) is that because honest bidders' equilibrium strategy is still characterized through a symmetric, monotonic bid function, honest bids will still be iid random variables in a given auction lot. Therefore the empirical model discussed in section V will still hold even if honest bidders suspect MNC.

Appendix B. A Comparison of Two MNC Lots

To put the idea that increased bid submission can hide the effects of MNC into a more obvious light, consider two auction lots where cheating occurred with certainty. The first, we call lot A, the second lot B. The bid distributions for lots A and B are presented in Table B.1. Note that in Lot A, the difference between the first and second log bid is only .05%. The third bid, however, is just .081% higher than the winner. Thus, it would appear that increased competition lead to a tighter distribution of ordered bids. Now, consider lot B. Here, the winning bid is only .011% below the second lowest bid, and in addition the winning bid is .082% below the third lowest bid. The cheating is more obvious in this case, at least in part due to fewer bidders crowding the lower end of the bid distribution.

Table B.1 Two MNC Auction Lots

Lot A		Lot B	
Bid($)	log(Bid)	Bid($)	log(Bid)
506000	13.13429	2290000	14.64406
536000	13.19189	2317000	14.65578
547000	13.2122	2488000	14.72699
565990	13.24633	2645000	14.78818
667000	13.41055		
757500	13.53778		
788000	13.57725		

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