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THE IDENTIFICATION OF COLLUSIVE BIDDING IN THE HIGHWAY CONSTRUCTION INDUSTRY

by

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Executive Summary

This report presents our research on methods for identifying when bidders on highway construction projects are colluding. We have focused our analysis on those indicators of collusive bidding which are manifestations of the objectives or operational needs of collusive groups. While in general it is possible to develop and provide apparent empirical support for ad hoc indicators by sifting through data, such indicators are unlikely to have efficacy outside of the data set on which they were developed.

The approach we have taken is to develop a theoretical framework which considers the objectives of the colluders and the institutional framework in which they operate. We then derive aspects of the bidding behavior of collusive groups which differentiate them from contractors entering competitive bids. Next we develop empirical analogs of these aspects of behavior as indicators of collusive bidding and, using a sample of bid situations, calibrate models to determine the practical importance of these indicators. Finally, we use these models to forecast which of an independent sample of bid situations involves collusion.

These steps essentially describe a scientific program for the development of indicators of collusion. The results are good. Based on our sample state (North Carolina), this method correctly classifies 85 percent of bids let between 1975 and 1981. The next step in developing this methodology is application of the techniques to diverse data sets. Such testing will identify shortcomings and lead to improvements in the methods we have developed for identifying collusive behavior in bidding.

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Introduction

In 1980 the Antitrust Division of the Department of Justice began an intensive effort to convict bid-riggers in the paving and highway construction industry. In fact, more antitrust cases were filed against highway contractors in 1980 than in all previous years combined.[1/] This concentration of effort by the Antitrust Division led us to consider systems for identifying collusive bids on highway contracts.[2/]

A method for identifying collusive bids would serve three main purposes:

1) aiding investigation of suspected collusion and helping to direct investigative resources;
2) screening current and future bid responses for collusive behavior; and
3) deterring bidders from collusive behavior.

To be particularly useful, this method should rely only on information easily available to state and federal investigators. It must also be reasonably accurate, difficult to thwart, and detect aspects of collusive behavior which are difficult for the colluders to alter.

1/ Most cases involve bids let for segments of the Interstate System where substantial sums of federal funds are involved. In all, 62 of 83 antitrust cases filed by the DOJ in 1980 involved paving and highway construction.

2/ Part of our motivation for developing methods for identifying colluders grew out of our need to produce reliable measures of the presence of collusion for our deterrence research. Developing indicators of when bidding is collusive is the obverse side of producing measures of the prevalence of collusion. Our research on the deterrent effect of enforcing antitrust laws in the breadbaking, ready-mix concrete, and highway construction industries has been supported by grants from the National Institute of Justice.

The identification method we have developed is composed of three discrete tests based on data from one or more contracts. Each test is, by itself, a useful indicator of collusion. The accuracy of each is enhanced by the addition of the others. This report discusses the development of our methodology.

In the next section of this paper we discuss the behavior of firms that submit collusive bids. Aspects of the behavior of these firms which differentiate them from firms bidding competitively provide the motivation for our tests for the presence of collusive bidding. This is followed by an empirical section where we determine the efficacy of these indicators. We use the three tests to predict which of an independent set of bid situations involved collusion. A final section presents conclusions.

The Theory of Collusive Behavior and Its Application to Bid Rigging

Theoretical and empirical investigations of collusion abound in the economic literature.[3/] A cartel of price-fixers is usually assumed to pursue the objective of raising the profits of its members above the normal level. As part of this effort they must also monitor individual cartel members to be sure none breaks his agreement and avoid detection by outside agencies responsible for enforcing anti-trust laws. Since it must simultaneously monitor, avoid detection, and enhance profits, the cartel is bound to take some actions which will allow detection. Our approach has been to isolate those characteristics of a bidding system which can differentiate a cartel's behavior from competitive behavior when the cartel seeks extra-ordinary profits.

Consider a bidding market of n bidders, bidding on a large number of contracts sequentially. On any contract let b_1 denote the low bid, b_2 the second lowest, and so on. For a cartel to form there must be some set of contractors who can exert monopoly power in the bidding market. Often it is supposed that this is achieved by admitting all contractors into the cartel, but our investigations indicate that this is not a reasonable assumption. Paving contracting cartels form not out of all potential bidders, but rather out of a subset who possess a cost advantage on certain types of jobs. That is, there are p contractors who find that they are consistently the p lowest bidders (they account for bids $b_1,\ldots,b_p$) on many jobs. There is then a strong incentive for these p firms to form a cartel.

[3/]See, for example, Milgrom and Weber in "A Theory of Auctions and Competitive Bidding," Econometrica, 50, September 1982, 1089-1122.

Suppose the cartel does indeed form, and consider a representative contract on which the cartel's members have a cost advantage and in the competitive case would be the p low bidders. The cartel would like to win the contract, achieve extra-ordinary profits, monitor its members, and avoid detection. We note that the cartel need expend little energy on monitoring its members since the results of the bid letting are usually publicly available.

Formally, the cartel's maximization problem for a single contract[4/] is:

$$(1) \qquad \max_{(b_1,\ldots,b_p)} \; b_1 - b_1^c - d(b_1,\ldots,b_p)$$

where b_1^c = competitive low bid, and $d(\vec{b})$ is a loss function associated with detection.

Call the solution to this problem $(b_1^*,\ldots,b_p^*)$. Under standard continuity conditions there will be an interior solution to equation (1), so that $b_1^* > b_1^c$ will hold. Thus, regardless of the loss due to the risk of detection, $d(\vec{b})$, the cartel will mark up the low bid to b_1^*. When states let highway construction jobs they normally have an engineer estimate the cost of the job. Call this estimate e. If the engineer's estimate is reasonably accurate and

[4/]We believe that Cartel behavior over time is an important but relatively undeveloped area of inquiry. Problems which a construction cartel might have to face over time include decision about who should be asked to join, how members can be kept efficient so that entry or expansion of existing competitors can be thwarted, how the risk of apprehension and statute of limitation operate to generate an optimal level of collusion that might depend on previous cartel profits, and how profits are to be divided amongst members over time.

unbiased,[5] then the comparison of the low bid to e should reveal the cartel's presence. This is the basis of our first test.

We have developed a two stage procedure for estimating the profit level on a contract let. The procedure is as follows:

(1) Define the simple measure of profit rates as the ratio of the low bid to the engineer's estimate.[6] Formally we define:

$$\text{MARKUP} = \text{low bid/engineer's estimate} = b_1/e \quad .$$

(2) Next, correct MARKUP for economic conditions in the paving industry. It has often been observed that the markup of price over costs tends to rise when demand is strong (especially in construction, a particularly cyclical industry). Several different series could be used as measures of activity, but the most reasonable series available is employment in

[5] In highway construction cost is a function of locale, technique, input prices, and scale of production, all of which are commonly known to the engineer.

[6] Note that since we are interested only in differentiating collusive contracts from non-collusive contracts, and not in obtaining an absolute measure of profit rates, this measure of profit rates is not sensitive to systematic differences in the level of the engineer's estimate versus the low bid.

the construction industry by state.[7] This variable is denoted CYCLE. Other corrections could be included, such as dummy variables to measure special jobs (eg. airport construction). The corrected MARKUP variable is the residual of the ordinary least squares regression of MARKUP on this variable. This corrected measure of markup is denoted RESID.

In the empirical section we investigate the relationship between RESID and the incidence of collusion on contracts. Our method of estimating excess profits uses the engineer's estimate rather than an estimate of a cost function for the low bid contractor.[8]

Once the cartel has increased the low bid, it will turn its attention to the avoidance of detection. In most states the department of transportation checks to see if a let contract "looks

[7] This series is a compilation of several Bureau of Labor Statistics Publications, and is monthly employed (by state and industry) divided by the annual average labor force (state and industry).

[8] We have adopted this cost function approach in studies of antitrust enforcement in bread and concrete industries. See M. Block, F. Nold and J. Sidak, "The Deterrent Effect of Antitrust Enforcement," Journal of Political Economy, June 1981. In the case of highway construction, estimation of costs requires a detailed listing of the line items on each contract let. Not only is such a listing often large (over 100 items) and hence unmanageabe and expensive to work with, but the presence of unbalanced bidding makes the relationship between cost estimates and actual costs on particular items problematic. There are also serious empirical problem in trying to estimate cost function for markets where collusion is common. Consequently, we have decided not to attempt direct estimation of cost functions for highway construction, although using the engineer's estimate could be deficient if continued exposure to rigged bids caused the engineers to inflate their estimates.

competitive" by (1) checking to see whether there are other bidders in the vicinity of the low bid (that is, whether b_2, b_3, etc... are near b_1), and (2) demanding a minimum number of bidders on the contract.

To "look competitive" the cartel will have some of its members submit complementary bids: bids which are quite near b_1^*, though slightly higher.[9/] We can model this behavior by having $\alpha(p - 1)$ of the cartel's members bid very near b_1^*. The remaining $(1 - \alpha)(p - 1)$ members then bid somewhat higher than b_1^*. Although this cartel policy may make the bid "look competitive", it allows detection of the cartel's presence by means of a test of the variance of all bids submitted on the contract. Define the mean of the bids:

$$\bar{b} = \frac{1}{n}\sum_{i=1}^{n} b_i \quad , \text{ where } n \text{ is the number of bidders} \quad .$$

The square of the coefficient of variation of the bids on the contract is

$$\text{(2)} \qquad \text{CVBID} = \frac{1}{n-1}\sum_{i=1}^{n}\left(\frac{b_i}{\bar{b}} - 1\right)^2 \quad .$$

Now compare the variances of the competitive and collusive cases. In the collusive case the $n - p$ bidders who are not a part of the cartel will submit the same bids as in the competitive case. The

9/The cartel may use its bidding pattern to try to educate the state's engineer. Cartel bids which are relatively high but close together may be submitted as a way of convincing the engineer that he misestimated costs and should revise his procedures upward on future projects. We will develop this conjecture further in a later technical report.

cartel will raise its low bid from b_1^c to b_1^*, will have $\alpha(p - 1)$ other bids also near but above b_1^*, and the remaining $(1-\alpha)(p-1)$ bids even higher. It can be shown that under mild conditions this implies that dispersion will be lower in the collusive case. Checking the dispersion of bids on a contract is then a second way of detecting collusion.

As mentioned above, states commonly require a minimum number of bidders on a contract. Recall that on the bids on which the cartel operates its p members have a cost advantage on the remainder of the contractors. We expect that fewer of these contractors will bid on the potentially collusive contracts than usual, since they suffer a cost disadvantage and are unlikely to win the job. Thus, to insure that the contract will be awarded the cartel must have several of its members other than the one designated to win (the low-bidder who bids b_1^*) bid on the contract. Following this strategy of requiring several members to bid on any individual contract will increase the cartel's chances of successful collusion on that contract. But should the strategy be utilized on many contracts the cartel will leave itself open to yet another avenue of detection. Cartel members will be found to bid with one another a higher proportion of the time than specific pairs of contractors normally are expected to bid together.[10/]

10/One can define a two-dimensional array $K(i,j)$ which contains as its $(i,j)^{th}$ entry the number of times the i and j contractors have bid together. K will then tend to be larger whenever i and j are both members of the cartel. In fact, the function K can be used in many ways to investigate collusion in a bidding market, one of which we have adopted as our third test of collusive activity.

A measure of this effect can be constructed as follows:

(1) Each contractor is assigned a number which represents the degree to which he tends to bid relatively intensely with a few other contractors. For contractor j, let I(j) be the ratio of the number of different contractors whom contractor j has bid with to the total number of other bidders on contracts j has bid on. For example, if two contracts were let and contractors A, B, C, and D bid on the first contract, and contractors A, B, C, and E on the second, then I(A) would = 4/6. Formally, let H_j be the set of contracts which contractor j has bid on, and C be the set of all contractors. Then

$$I(j) = \frac{\sum_{c \in C} v_j(c)}{\sum_{h \in H_j} N_h}$$

where $v_j(c)$ is 1 if contractor j has ever bid with contractor c and 0 otherwise, and N_h is the number of bidders (other than j) on contract h.

(2) Each contract is then assigned a number which represents the sum of the values of I(j) for all contractors who have bid on that contract. We define

$$\text{GROUP }(h) = \sum_{j \in J_h} I(j) \quad .$$

where J_h = the set of contractors who have bid on contract h.

A low value of GROUP on contract h indicates that the bidders on h have a tendency to bid intensively with a small group of other contractors.[11]

We use GROUP as an indicator of whether particular contracts reflect collusion.[12] Note that GROUP does not directly measure whether the contractors who are bidding on a job bid more often with each other, but rather whether they are contractors who in general exhibit this aspect of collusive behavior.

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[11] Note that the variable GROUP can be normalized by dividing by the number of bidders on contract h. Analysis with this normalized variable gave results similar to those for GROUP.

[12] A more elaborate variable could be developed indicating how often specific groups of contractors have bid together. Group has performed adequately so we have not taken this approach any further. We discuss the possibility that GROUP may be a proxy for the type of project being bid in the next section.

Empirical Results

Our empirical work has been carried out with two distinct data sets. The first was provided by the Federal Highway Administration and contains information on the winning contractor, his low bid, the engineer's estimate, data on the project, the state, as well as some other facets of the contract for all 50 states over the years 1975-81. However, since this source does not identify bidders other than the low bidder on the contract, or their bids, we cannot use our variance and group tests with it. Our second data set is from the North Carolina Department of Transportation. This data set provides information only for the state of North Carolina, covers the years 1975-81, and includes all bidders on a contract and their bids, as well as much additional information. Nearly all states keep such records, but we chose North Carolina for three reasons. First, there have been a large number of bid-rigging cases in North Carolina, so finding ways to discriminate between collusive and noncollusive contracts presents an interesting problem. Second, North Carolina was able to provide us with detailed data on highway contracts on computer tape.[13/] Finally, the North Carolina Department of Transportation has identified whether a contract represented collusive bidding on the basis of discussions conducted

[13/]Few states have made this data readily accessible on computer tape, though many are in the process of doing so. Since cartels probably do not recognize state boundaries, calculation of our group variable using North Carolina data alone may be somewhat inaccurate.

with apprehended bid riggers; this is a substantial improvement over our national collusion variable which we discuss below.

Tests Based on the Markup

We begin the analysis by developing a profit indicator. Our first step is to correct MARKUP, the ratio of low bid to engineer's estimate, for the level of economic activity. The indicator for economic activity which we use is the percentage of the construction labor force employed, denoted CYCLE. As an example of the volatility of this series we present a plot of CYCLE over the years 1975-81 for our test state of North Carolina in Figure 1. Using the national FHWA data set we obtained the results in Table I which show a statistically significant relationship between CYCLE and MARKUP. Apparently, the higher the level of activity in construction _vis a vis_ the recent past the higher the markup on highway construction jobs.[14/] Also, we have included dummy variables for each state to account for any systematic differences between states in the way engineers' estimates are constructed.

The adjustment of MARKUP for these systematic differences and the level of economic activity is accomplished by calculating the residuals from the regression. For each contract we have created the variable RESID, which represents that part of MARKUP which cannot be explained by the systematic state differences or variations in CYCLE, our indicator of general construction activity. RESID provides

[14/]We used several other specifications which considered lagged as well as contemporaneous values of CYCLE. The results were essentially the same.

EMPLØYMENT IN NC CØNSTRUCTIØN

FIGURE 1

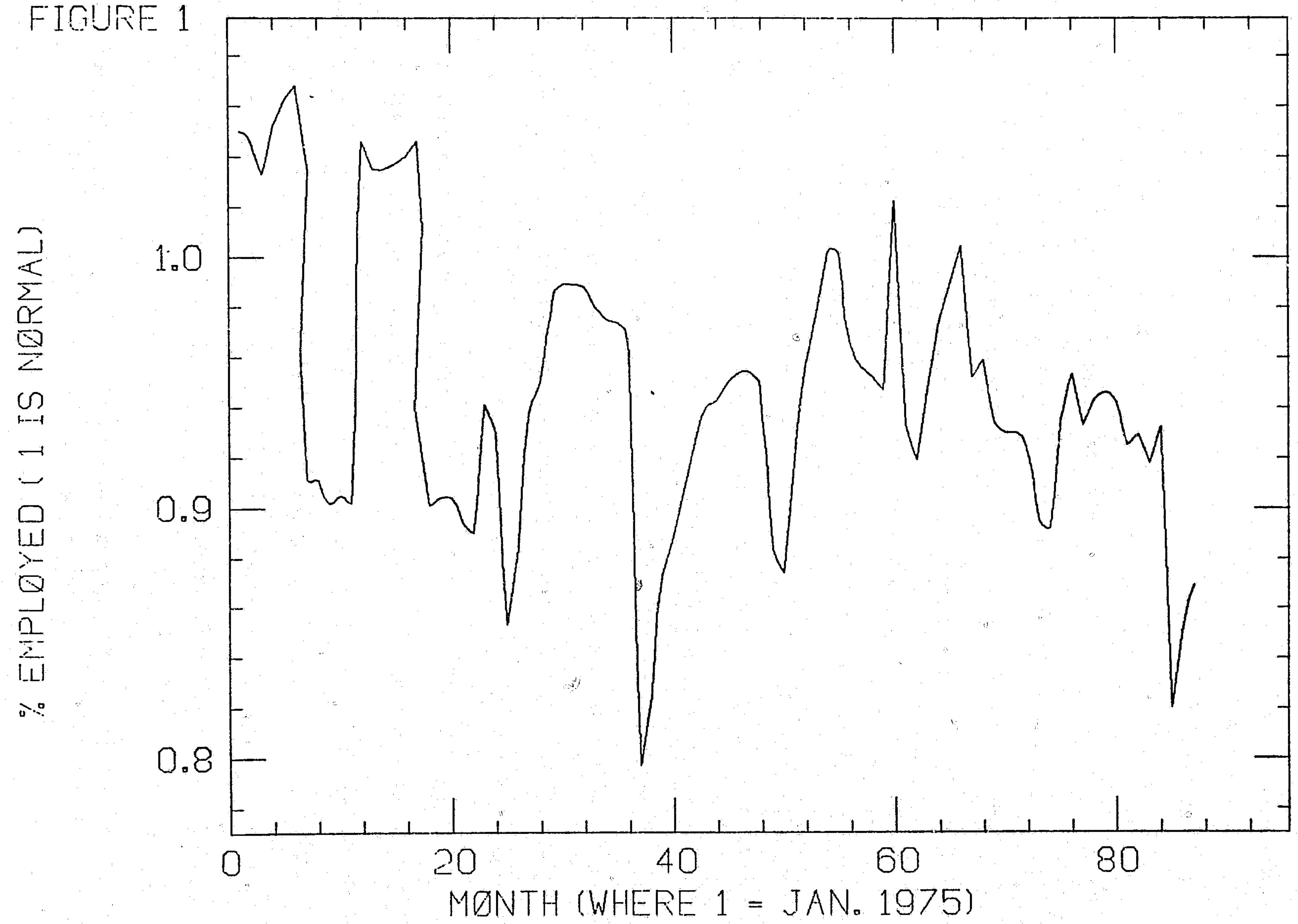

TABLE 1

Regression of MARKUP on Activity

Estimate of CYCLE Test Statistic	.138 (5.57)
Estimates of State Dummies	Alaska .778; Connecticut .685; Delaware .729; Florida .826; Georgia .856; Illinois .818; Indiana .737; Kentucky .800; Louisiana .818; Maine .820; Maryland .742; Massachusetts .776; Michigan .774; Mississippi .898; New Hampshire .743; New Jersey .791; New York .750; North Carolina .775; Ohio .713; Pennsylvania .841; Rhode Island .750; South Carolina .851; Vermont .824; Tennessee .814; Virginia .790; Wisconsin .704; West Virginia .804; Washington, DC .688; Alaska .729; Arizona .766; Arkansas .889; Hawaii .756; California .817; Colorado .799; Iowa .807; Idaho .750; Kansas .754; Minnesota .806; Montana .804; Missouri .796; Nebraska .776; New Mexico .797; Oregon .739; South Dakota .834; Utah .824; Texas .854; Washington .777; Wyoming .777; North Dakota .862; Oklahoma .833.
Sum of Squares	3399.9
R^2	.075
MARKUP Mean	.928
Number of Observations	3940

us with a way of assessing the extent that the low bid on the contract reflects extra-ordinary profits for the winning contractor.

Results on the ability of RESID to serve as an indicator of collusion are presented in Table II for a random sample of our national data. Roughly 4000 observations were selected from the more than 13000 available to us.[15/] We chose to use a LOGIT model to estimate RESID's explanatory power, both because of LOGIT's similarity to more traditional discriminate analysis, and because we wanted to have an easy method for generating the probability that a given contract was collusive.[16/] As expected, there exists a positive relationship between RESID and the indicator of collusion, COLLUDE. The COLLUDE variable was constructed by comparing the list of firms named in DOJ bid-rigging cases and assuming that the contract involved collusion whenever the low bidder was on the list of indicted colluders. The relationship with RESID came through despite the biases inherent in our COLLUDE variable towards

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[15/] In fact we could enhance the statistical significance of any of the results we present for RESID by merely drawing a larger random sample from the FHWA data.

[16/] See J. A. Anderson in Discriminant Analysis and Application, T. Cacoullos, ed., Academic Press, 1977.

TABLE II

LOGIT Regression of COLLUDE on RESID

Independent Variable	Dependent Variable COLLUDE
RESID	.765 (1.66)*
Intercept	-2.83 (40.6)
Number of Observations	3940

*The number in parenthesis is the t-statistic, which is the coefficient divided by the standard error. The t-statistic is signed identically to its coefficient.

masking the relationship.[17/]

Table III contains results of a similar LOGIT analysis which uses only the North Carolina data.[18/] The variable RESID is calculated using the coefficients presented in Table I (the North Carolina dummy and the coefficient for CYCLE). We test RESID against both COLLUDE and a separate measure of collusion included by contract on the North Carolina tape, which we call NCCOLLUDE.[19/] As the

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17/The procedure used to define COLLUDE would tend to bias our results in two ways. First, it is quite unlikely that firms collude on all contracts, especially since they cannot control who will bid. In addition, a group of firms might collude but accidentally lose the contract to a non-colluding bidder. Consequently, our procedure will incorrectly indicate collusion on occasions where the bid was actually competitive and erroneously indicate competition when the collusive group misjudge the level of bids entered by non-cartel members. Second, not all collusive groups have been uncovered by DOJ investigations. Furthermore, not all members of uncovered groups are mentioned on indictments. Therefore, some contracts placed in the non-collusive category may in fact be collusive. All of these effects bias our results towards finding no relationship between COLLUDE and RESID.

18/There is an important point that concerns the utility of the simple estimated model presented in Table II as a way of predicting collusion. There have been no bid rigging cases in a large number of states so the nationwide incidence of highway collusion appears low. This is a reflection of the weakness of COLLUDE as a variable which results in a large negative intercept in the LOGIT model and, vis a vis the results presented in Table III, a low coefficient for RESID. Consequently, forecasts from the national model will give estimates of the probability of a contract being collusive which are misscaled for North Carolina. The results of Table II should be viewed as a summary of all states which understates the power of RESID to identify collusive contracts and the incidence of collusion in general.

19/NCCOLLUDE is the indicator of collusion compiled by the North Carolina DOT and is based on interviews with apprehended bid riggers. COLLUDE and NCCOLLUDE differ on approximately one-third of the North Carolina contracts.

TABLE III

LOGIT Results

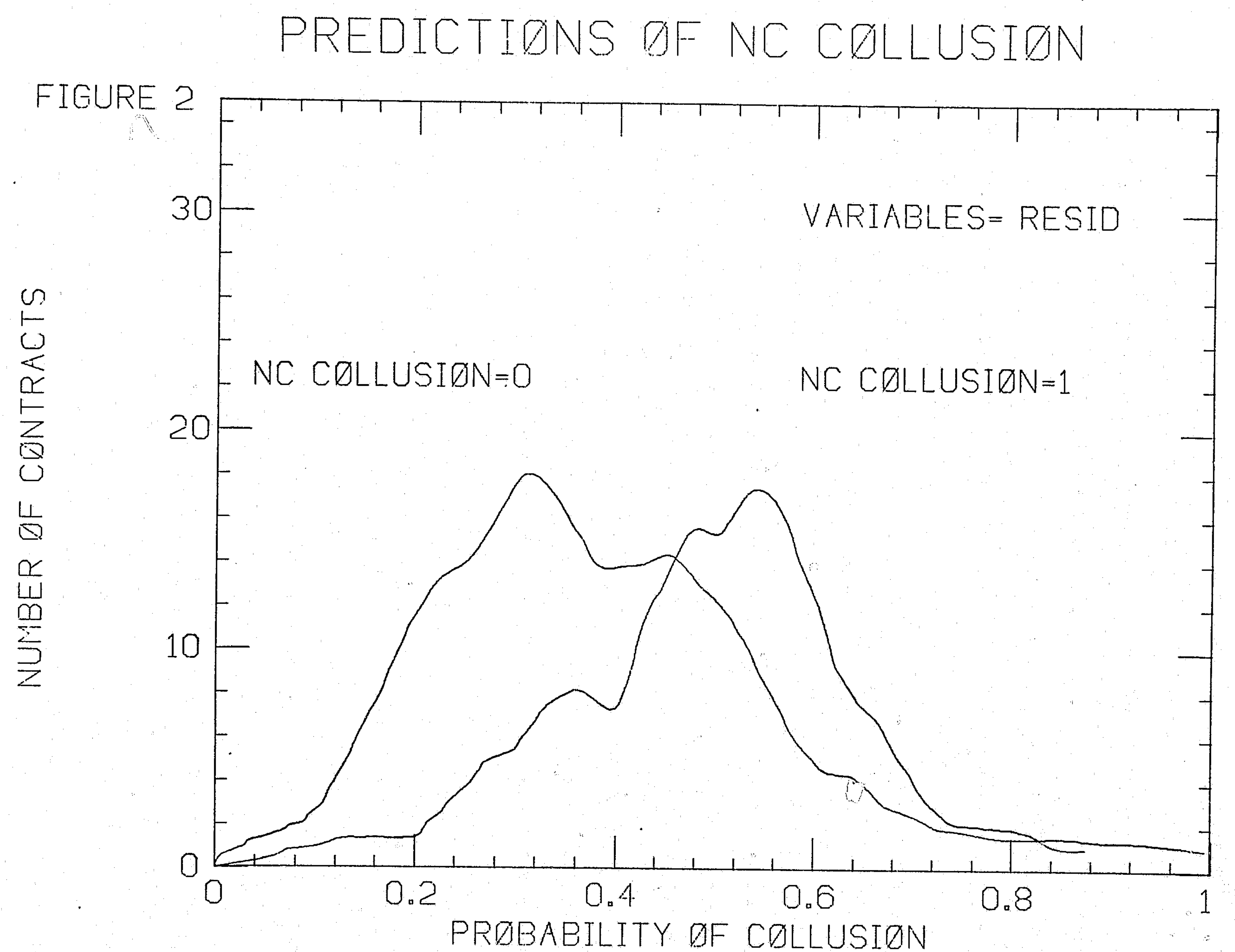
State of North Carolina

Independent Variable	Dependent Variable: COLLUDE	Dependent Variable: NCCOLLUDE
RESID	1.09 (3.01)*	4.77 (10.4)
Intercept	-.203 (3.32)	-.531 (7.78)
Sample Size	1237	1237

*The t-statistic for each coefficient is given in parenthesis and is signed identically.

next step in our analysis of the North Carolina data we assign each contract a probability of being collusive based on the results of Table III for NCCOLLUDE. We then calculate two probability densities, one for those contracts known to be collusive (according to NCCOLLUDE), and one for those not suspected of being collusive. The two densities are presented in Figure 2. Note that the two densities do differ, indicating that the RESID test by itself can be used to detect collusion.

FIGURE 2


PREDICTIØNS ØF NC CØLLUSIØN
VARIABLES= RESID
NC CØLLUSIØN=0
NC CØLLUSIØN=1
NUMBER ØF CØNTRACTS
PRØBABILITY ØF CØLLUSIØN
0
10
20
30
0
0.2
0.4
0.6
0.8
1

The Coefficient of Variation and Group Tests

We are able to investigate the efficacy of our coefficient of variation and group indicators only on the North Carolina data set. The variable CVBID is a measure of the dispersion of bids received on a particular contract relative to the mean bid. The variable GROUP measures the intensity with which the bidders on a contract tend to bid with a limited number of other contractors.

Table IV gives estimated LOGIT models similar to those given in Table III for CVBID and GROUP. Both CVBID and GROUP appear useful in distinguishing competitive from collusive bid situations. Again, results are stronger for the more accurate dependent variable, NCCOLLUDE. Table V presents the results of two separate LOGIT models designed to test the discriminatory power of these variables in combination with RESID. The first LOGIT model uses RESID and CVBID, while the second LOGIT model uses all three indicators. The results get progressively stronger, particularly with the collusion variable NCCOLLUDE. For each estimated model we calculate a probability of collusion for each contract, and aggregate the estimates into two groups, one representing known collusive contracts (according to NCCOLLUDE) and one representing contracts not suspected of collusion. Figure 3 presents sample densities for the (RESID, CVBID model and Figure 4 for the (RESID, CVBID, GROUP) model. Note that each pair of densities (NCCOLLUDE = 0 and NCCOLLUDE = 1) becomes more and more distinguishable. Our ability to detect collusion is clearly improved by the addition of CVBID and then GROUP to the analysis.

Table IV

LOGIT Results

State of North Carolina

Independent Variable	Dependent Variable	
	COLLUDE	NCCOLLUDE
CVBID	-14.6 (4.95)	-80.3 (9.82)
Intercept	1.44	.397
Sample Size	1212	1212
GROUP	-.711 (7.58)	-2.90 (13.5)
Intercept	.410	1.40
Sample Size	1237	1237

TABLE V

LOGIT Results

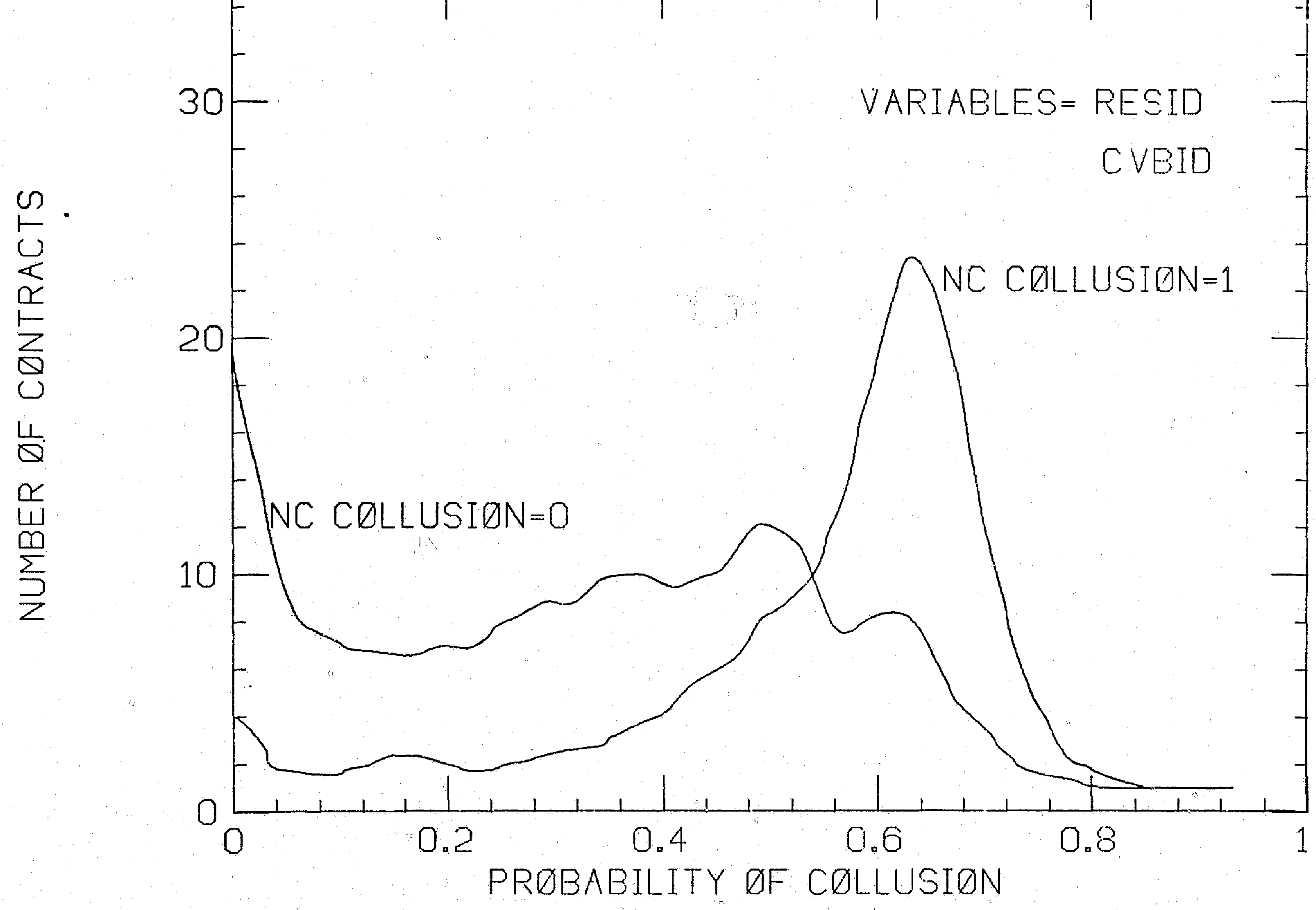
State of North Carolina

Independent Variable	Dependent Variable	
Model 1:	COLLUDE	NCCOLLUDE
RESID	.357 (.922)	3.20 (6.72)
CVBID	-13.2 (4.29)	-64.0 (8.19)
Intercept	.044 (.583)	.175 (1.84)
Model 2:		
RESID	-.126 (.313)	3.21 (5.80)
CVBID	-10.3 (3.56)	-43.4 (5.68)
GROUP	-.671 (6.80)	-2.98 (12.2)
Intercept	.550 (5.31)	1.83 (11.6)

*The t-statistic for each ceofficient is given in parenthesis, and is assumed to signed identically.

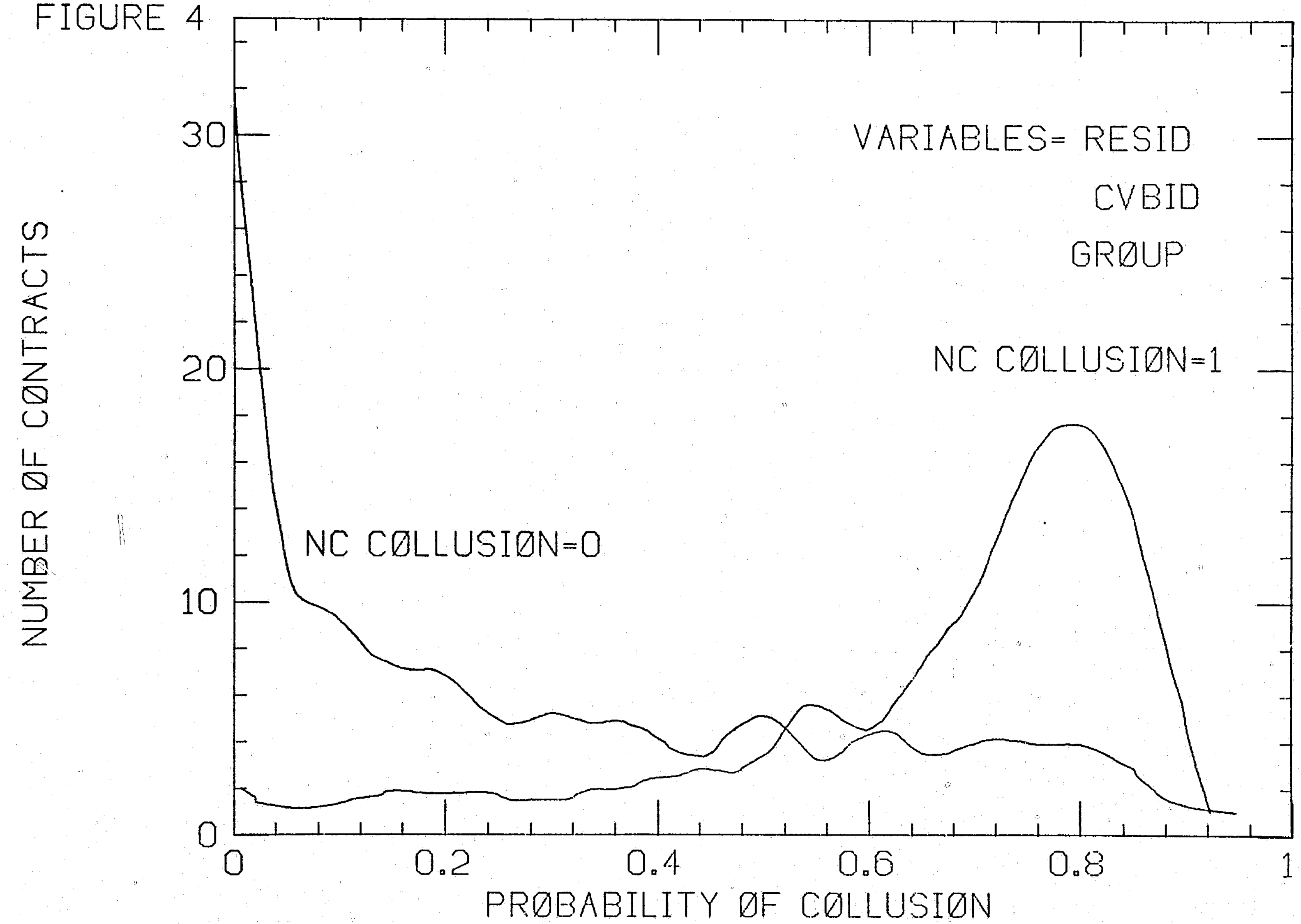
PREDICTIONS OF NC COLLUSION

FIGURE 3



PREDICTIØNS ØF NC CØLLUSIØN

FIGURE 4



The Identification of Bid-Rigging

The estimated LOGIT models can be used to predict the probability that a given contract is collusive. For this purpose we re-estimated the North Carolina models presented in Table V for 80 percent of the North Carolina contracts drawn at random from the data. We then applied these re-estimated coefficients to predict the probability of collusion on each of the contracts in the remaining 20 percent of the data.[20/]

As a simple decision rule we consider the contract to be identified as collusive if the estimated probability of collusion exceeded 50 percent.[21/] Using this criterion, the estimated LOGIT model based on RESID[22/] and CVBID correctly classified 76 percent

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[20/] Perhaps a simple example of how we are using the estimate model is in order. Suppose our objective is to identify a single leg bone as to whether the animal was male or female. Assume also that we know the species and have a sample in which the sex of the animal and the width of the bone are known. Letting the dependent variable be 1 if the bone is from a male, we calibrate a LOGIT model which uses width to discriminate between the sexes. We can then use this model estimated on the sample (where we know sex and width) to forecast the sex of the animal from which a leg bone of unknown origin comes. In the present application, collusion parallels sex and width our measures RESID, CVBID and GROUP.

[21/] A logical approach to this problem would involve selecting a cut-off value in such a way that the resources used by those investigating the contracts is balanced by the cost savings, including any deterrent effects, associated with apprehending colluders.

[22/] We have explored whether the adjustment of the simple MARKUP variable, low bid over engineer's estimate, for economic conditions was useful. We have determined that it is an important step. For example, in 25 percent of the sample withheld for forecasting, RESID is greater than 1 while MARKUP is less than 1. In 41 percent of those situations, the NCCOLLUDE variable indicated collusive bidding.

of the contracts while the model based on those variables plus GROUP correctly classified 85 percent. We have taken the information given by NCCOLLUDE as the standard to which our classification schemes should be compared. Without any detection scheme one could achieve the highest degree of correct classification simply by guessing all contracts to be non-collusive, for 55 percent of the contracts fall in that category. But then one would never classify any contract as collusive and so would not identify any bid-riggers. In comparison, our LOGIT detection scheme correctly classifies 81 out of the 103 North Carolina bid-rigged contracts (as determined by NCCOLLUDE) with the variables RESID and CVBID, and 92 out of the 103 when using the variables RESID, CVBID, and GROUP.[23/] Although these results are preliminary and need extension, they suggest the approach we have taken provides a viable method for identifying bid-riggers.[24/]

[23/] Our definition of the variable GROUP would have to be changed if forecasting was to be conducted over a long time period or covered situations where some firms had a history of bidding with one another and had been identified as colluders. One modification would be to calculate GROUP over a particular time period and a second would be to further standardize that variable for the number of bids contractor j had entered. While GROUP has proven adequate for our purposes, clearly the notion of firms bidding together can generate more refined and perhaps more useful indicator variables.

[24/] An alternative way to use the indicators in combination is to use estimated models like those in Tables III and IV as separate tests. For example, suppose we predicted the probability that a particular contract reflected collusive bidding using those models and found that each probability exceeded .5. We could assign a score of 3 to that contract, a contract with two imputed probabilities greater than .5 would have a score of 2. Repeating the procedure of withholding 20 percent of the sample, estimating the models and predicting the incidence of collusion for the withheld data we obtained interesting results. Suppose we used the rule that only those contracts with a score of 3 would be called collusive. There were 32 such contracts with scores of 3; 31 of these were, in fact, collusive according to the NCCOLLUDE variable. If we called contracts collusive if they had a score of 2 or 3 we would identify 102 bid situations as collusive. Of these, 79 of these bid situations (77 percent) reflected collusive bidding according to the NCCOLLUDE variable.

Conclusions

There are, of course, a variety of issues which may be important to the detection of collusion which have been dealt with only summarily. Many of these issues concern the type and location of the work to be let. Whether the work is to be performed in rural or urban districts seems important, since rural jobs are more difficult for the state's transportation department to observe and generally have fewer cost-effective bidders. We therefore suspect that rural jobs may be more susceptible to collusion. Interstate and primary jobs may be more or less likely to be colluded on (there are arguments in both directions) than secondary paving jobs, but we believe the distinction may be worth investigating. Also, analysis of contractors who trade-off jobs with other contractors across state lines requires analysis of all states involved. Finally, jobs for paving where the majority of the costs are for grading and leveling roads may be easier to analyze than more complicated jobs.

Also, we have left virtually untouched an avenue of analysis which could significantly improve our understanding of and ability to identify colluders. This approach centers on the analysis of the data organized by contractor rather than contract. While we have been successful in identifying contracts as collusive, we do not know whether all bidders participated in the collusion. However, reorganizing the data to yield the bidding history of each contractor, with special attention placed on the estimated probabilities of collusion by contract from our models, offers a realistic opportunity to develop classification schemes for contractors.

Finally, there are significant theoretical and statistical issues which must be addressed before more progress with cartel identification schemes can be made. Only the indicator of extra-ordinary profits on a contract has a firm rationale in the existing theories of collusive behavior. We believe that it is possible to gain deeper insights into cartel behavior which will rationalize other reliable indicators of collusive behavior. *Ad hoc* indicators of collusive behavior are unlikely to be very useful since we can expect collusive groups to alter behaviors which are not central to their efforts in order to mask their operations. Similarly, the presence of collusive bids in auction data has implications about the appropriateness of standard statistical techniques. These problems are not intractable and the success of this research is encouraging, but much more works needs to be done.

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