Discussion Papers In Economics And Business

Detecting Collusion through Exchange of Favors in Repeated Procurement Auctions

Rieko Ishii

Discussion Paper 07-15

Graduate School of Economics and
Osaka School of International Public Policy (OSIPP)
Osaka University, Toyonaka, Osaka 560-0043, JAPAN

Detecting Collusion through Exchange of Favors in Repeated Procurement Auctions

Rieko Ishii

Discussion Paper 07-15

May 2007

この研究は「大学院経済学研究科・経済学部記念事業」
基金より援助を受けた、記して感謝する。

Graduate School of Economics and
Osaka School of International Public Policy (OSIPP)
Osaka University, Toyonaka, Osaka 560-0043, JAPAN

Detecting Collusion through Exchange of Favors in Repeated Procurement Auctions[*]

Rieko Ishii[†]

May, 2007

Abstract

It is known that bid rigging in public-work auctions in Japan often takes the form of exchanging favors. In such a scheme, the winner is designated based on the amount of favor he has given to other members of the ring. By explicitly modeling "favor" as an explanatory variable, this paper analyzes data from the public-works auctions for consulting works in Naha, Japan, to confirm that such a collusion scheme is in operation.

JEL Classification D44, H57, L44
Keywords: Bid rigging, repeated auction.

[*]I am truly indebted to Masaki Aoyagi. I am also grateful to Fumio Ohtake for extremely helpful discussions at the start of this research. I thank Koki Arai, Andreas Blume, Shigemi Izumida, Masaki Nakabayashi, Kazuo Ogawa, Martin Pesendorfer, Tatsuyoshi Saijo, Yasuo Takatsuki, Junmun Wan and seminar participants in Hitotsubashi University, Kyoto University and Micro Mini Conference at Hakone for valuable comments on earlier versions. Any errors are mine.

[†]Institute of Social and Economic Research, Osaka University, 6-1, Mihogaoka, Ibaraki-shi, Osaka, 567-0047, JAPAN; E-mail: dg009ir@mail2.econ.osaka-u.ac.jp

1 Introduction

Bid rigging is a pervasive problem in procurement auctions. According to Suzuki (2004), all antitrust cases of bid rigging between 1947 and 2000 in Japan involve a pre-auction meeting of ring members that determines the winner in their own way. As reported by Suzuki, former industry experts, and media, it is widely observed that the exchange of *favors* plays an important role in collusive negotiations in Japan. According to Hironaka (1994), a written confession by a former industry expert, it is common for a ring member to insist on his right to win the contract because he has given a favor to the others. In cases of Okinawa Prefecture and Takaraduka City, for example, each ring member kept precise record of auction results named the "balance sheet", which includes the date of auctions, the winning price, and the name of the winner, so that they can see the balance of favors among the ring (Okinawa Times June 9, 2005, Kobe District Court Decision WA810, November 7, 2001).

The objective of this paper is to hypothesize a specific collusion scheme based on the exchange of favors and show that actual bid data are consistent with the scheme. Our strategy is to test how the outcome of auctions is affected by a factor that is potentially used in the scheme, but is irrelevant when bidding is competitive. If the outcome is affected by such a factor, then it can be concluded that collusion is present. For example, if bidders choose the winner according to the well-known "phase of the moon" scheme, then we should observe a correlation between the identity of the winner and the phase of the moon.

In this paper, we propose a method to detect whether bidders collude by exchanging favors. Specifically, we define a favor to be the action of letting some other bidder win by making a phony bid. If bidder A lets bidder B win, then we say A gives B a favor. When B subsequently does the same thing for bidder A, we say B returns the favor. We say that exchange of favors takes place if B returns the favor after A gives B a favor. It should be noted that favors can be exchanged between a pair of bidders.

Favor can be measured by the value of contracts a bidder has given up by making a phony bid. We construct a measure for the exchange of favors that has taken place between every pair of bidders, and call it a score. The main objective of this paper is to analyze its effect on the winning probability of each bidder in auctions. The score at any point in time represents the net amount of favor a bidder has given to another bidder to that date: it is positive if he has given favors to her, and negative if he owes. Our result shows that the winning probability is positively related to the score. This finding suggests the presence of collusion which uses the bilateral relationship in determining the winner.

Our data show infrequent but significant drops in prices. We suppose that the ring is nearly all-inclusive in the market, and that those drops are caused by participations of a small number of non-collusive bidders. The ring bidders submit extremely high bids when the auction is all inclusive, whereas some of them lower their bid down to competitive level when they face an outsider in an auction. Therefore it is supposed that a collusive bidder's bid is higher than that of a competitive bidder on average. We classify the bidders into two groups by the average bid level. We find a tendency that a pair of bidders exchange favors when both of them submitted high bids on average, whereas bidders do not exchange favors when either of them submitted low bids on average. Our finding is consistent with the prediction that favors are exchanged only when both bidders are collusive.

Theories of collusion in auctions highlights the role of pre-auction meeting of bidders. The seminal paper by McAfee and McMillan (1992) shows that the most efficient bidder collusion in a first price auctions is that the ring member with the minimum cost bids at the reserve price while the other members bid 0 along with the monetary transfers from the winner to the losers. They also characterize an efficient collusion when no side transfer is possible. It is a static scheme in which the choice of the designed winner is independent of the history. The analysis is extended to a repeated framework by Aoyagi (2003) and Skrzypacz and Hopenhayn(2004), who analyze collusion without a side transfer in repeated auctions. In contrast to McAfee and McMillan's static bid rotation, Aoyagi constructs a dynamic bid rotation scheme in which bidders coordination is based on past history. In the scheme, play rotates among different phases that treat the bidders differently and collusion is sustained because these phases enable intertemporal transfer of bidders' payoff. Skrzypacz and Hopenhayn (2004) proposes a collusion scheme named a 'chips mechanism', in which the winner gives one chip to the loser, and when a bidder runs out of chips he is supposed to allow other bidders to win for a specific number of periods. A numerical analysis shows that this mechanism is asymptotically optimal when the distribution of bidders' values is assumed to be uniformly distributed.

It should be noted that our analysis adopts the empirical technique of Duggan and Levvit(2002), to a repeated auction environment. They analyzed match rigging in Japanese sumo wrestling and found statistical evidence of collusion: a wrestler who is on the verge of ending a tournament with a losing record wins the last bout with an unusually high frequency, but that he loses to the same opponent with an unusually high frequency when they meet the next time. Their finding suggests that a wrestler colludes with his opponent by exchanging favors: If his opponent gives him a favor today by losing intentionally, then he will return a favor in the same way in the future. The situation is more complex in bid rigging, because the value of a win varies considerably from one auction to the next, and the number of bidders is usually more than two. For example, in our data set, the largest contract is worth more than ten times than the smallest one (Figure 1). We adapt the approach of Duggan and Levvit(2002) to such a situation.

There are some empirical works on bid rigging in procurement auctions. Most of them analyze the presence of bid rigging by comparing the behavior of known or suspected colluding bidders with competitive bidders. Porter and Zona (1993) find that a winner's bidding behavior is different from that of losers even when there should be no statistical difference between them in the absence of collusion. Pesendorfer (2000) illustrates the difference in estimated bidding strategy between collusive bidder and competitive one. Bajari and Ye (2003) observe the violation of exchangeability and conditional independence, the two conditions that a competitive bidding strategy must satisfy. These approaches make full use of observable cost asymmetry among bidders measured by the distance between the office and the work site, or the amount of backlog contracts.

Our empirical approach has mainly three advantages over those mentioned above. First, it works even when the existing methods are not applicable. They are not applicable when the ring is nearly all inclusive: they require sufficient number of competitive bidders for specification or comparison purposes. Our approach is useful since all inclusive rings are common in Japan, where the regional business association is often the ring itself.

Second, unlike the previous methods, we do not require a large asymmetry across bidders in observable features such as distance from the work site and capacity utilization. Bidder asymmetry is generally small in Japanese procurement auctions because of the discretionary prescreening of potential bidders by local governments: In many cases, only those firms in a close proximity to the work site are nominated in the name of promoting the regional economy, resulting in almost identical transportation costs. Asymmetry through the presence of a backlog is also absent since some local governments avoid nominating bidders who already have a local public project in order to equalize the opportunity.

Finally, our approach discriminates the effect of backlog contracts from bid rotation. The pattern where a bidder with high capacity utilization loses and one with low capacity utilization wins under competition resembles collusive bid rotation. In competitive auctions, firms with idle capacity are more likely to win a contract than those with ongoing contracts, if bidder's cost functions exhibit decreasing returns to scale, as pointed out by Porter and Zona (1993). Meanwhile, bid rotation allocates the winning in turn and hence, the bidder with idle capacity tends to be selected. As capacity utilization is one of main factors of the cost asymmetry in their methods, it does not work in discriminating competition and collusion.

Our method deals with this difficulty by constructing proxy variables for both the favor and the backlog, separately. Both factors are obtained from the history of auctions, but irrelevant each other. A competitive result may depend on history only through the backlog, not through the favor, whereas a collusive rotation may depend on it through both of them. Therefore we can discriminate them by looking at the independence of the auction result from the score.

The paper is organized as follows. Section 2 describes the market and the data. We define the idea of favor in bid rigging and discuss how the collusion scheme which uses favors works. We also describe how variables are constructed. Section 3 presents our empirical model, and Section 4 shows the results. Section 5 concludes.

2 The Market and the Data

We first describe the bidding system of Japanese public auctions. Most local governments use a pre-screening system, in which they select the bidders themselves. In this system, the government nominates a limited number of bidders out of a list of qualified firms before each auction, and only the nominated firms can submit a bid. Basically, local governments have their own nomination policies, and some of them are made public. However, government officials can use discretion in the nomination process which is not clear to the outside observers.

The auction is the first price sealed bid procurement auction with a highest acceptable (reserve) price. Prior to the auction, governments estimate how much it will cost an average firm to complete the work, taking into account material prices and the governmental budget. The estimated price is then used as the reserve price in the auction. The bidder who submits the lowest bid wins the contract, as long as his bid is lower than the reserve price. Some local governments announce the reserve price before the auction, and others do not. However, according to the former industry experts, bidders can guess the reserve price by analogy with previous contracts, even when the reserve price is not announced (Hironaka (1994)).

We investigate the public contract auction data from a market for compensation consulting works in Naha City of Okinawa, Japan. The city planner needs to hire compensation consultants when the city relocate private buildings for its public project such as constructing a new road. The compensation consultants estimate the value of lands, buildings and plants that the city needs to purchase from their owners. The bidders are mainly real estate appraisers, architects and construction companies. Naha city uses the pre-screening system. The city chooses about 10 bidders out of 136 qualified firms for each auction. In April 2003, the middle of our data period, it started to announce the reserve price before each auction. Once the reserve price is announced, bids are valid as long as they are lower than the reserve price. Figure 2 shows the distribution of bids relative to the reserve price for 175 auctions during the data period. Bids above the reserve price were submitted until April 2003, whereas all the bids are within the reserve price after that, due to the start of the announcement of the reserve price. The bids are 101% of the reserve price on average before the start of the announcement, and 97% after that. The winning price is 93% of the reserve price on average with variance 0.72% before the start of the announcement, and 94% on average with variance 0.83% after that. We assume that the start of the announcement did not change the scheme of the ring.

The auction data are made public by Naha City through its web site, which include the results of auctions for four fiscal years (from April 2001 to March 2005). Among many procurement markets, we choose the compensation consulting market because the number of bidders relative to the frequency of auctions is small and it is appropriate to describe the market as repeated auctions.

The data include the date of auctions, the winning price, the reserve price, identity and bid of each bidder, starting and ending dates of each contract, and each bidder's number of employers, the number of years of running, and the annual sales of consulting works averaged over FY2003 and FY2004. The sales data include projects bought by Naha City, the Okinawa prefectural government, as well as other cities and public institutions.

Basic statistics are given in Table 1 to Table 4. During the data period, 1748 bids were made by 136 firms in 175 auctions. The number of contracts a firm won is 1.3 on average with the variance 2.9. 67 firms did not win a contract during the data period, while 33 firms win more than three contracts. The number of auctions a firm participated in varies from one to 43 with the average 12.9 and the variance 147.9.

Although we have no legal evidence of collusion, extreme closeness of the winning price to the reserve price in many auctions suggests the existence of bid rigging. Figure 3 shows the distribution of the winning price relative to the reserve price. In 72% of the all auctions, the winning price is within 95% of the reserve price. For a geographical reason, it is hard for firms outside Okinawa to enter the market. It is hence natural for local firms to foster a long run relationship among themselves creating an ideal environment for collusion.

At the same time, some auctions appear to be competitive, because the winning prices are considerably lower than the reserve prices. As Figure 3 shows, in 11 out of 175 auctions, the winning price is less than 80% of the reserve price. It is supposed that the ring faced some competitive bidders in the market, and that the ring and the competitive bidders were severely competing. However, since the frequency of the price wars is small, the number of competitive bidders would have been small.

2.1 The measure of favors

In this section, we give the definition of a *favor*, and present a measure of favor used in the analysis. The underlying assumption is that the collusive bidders meet prior to each auction to determine who wins the contract, and then coordinate their bids. We suppose that the likelihood that any bidder is selected as the winner depends on the history of his reciprocal relationship with other bidders.

A favor in an auction indicates the action of making a phony bid in order to let other bidder win. If bidder A makes a phony bid to let bidder B win, then we say A gives B a favor. When B makes a phony bid to let A win after that, we say B returns the favor. We say that exchange of favors takes place if B returns the favor after A gives B a favor. Therefore, if they are exchanging favors, A can expect B to help him in the future. It should be noted that, as defined in this paper, a favor between A and B is a bilateral relationship and does not involve any other bidder. In other words, the favor which was given by A to B can be returned only by B.

It is reasonable to think that the value of favors varies by contracts. A favor given by A to B in an expensive contract auction can not be fully redeemed in a single amount of a small contract, because bidder A sacrificed much for bidder B. Therefore, we suppose for simplicity that the favor given from one bidder to another in any auction is equal to the expected payoff forgone by participating in that auction. Since we consider that a favor cannot be returned completely until the same amount of sacrifice is made, we measure the balance of favors. The balance of favors is the value of the favor which was given by a bidder to another bidder, but has not been returned yet. We create a variable named "score", which represents the balance of favors between every two bidders in the ring. Bidder A's score against bidder B in period t is the net balance of favors which were given by bidder A to bidder B in all previous periods.

In the following, we illustrate how to construct the score from auction data. To see the history between every pair of bidders, we consider an ordered pair (i, j) for every $i, j = 1, 2, ..., M,\ i \neq j$, where M is the number of the ring members. Suppose, for example, there are 3 firms A,B and C in the ring. In this case we have 6 pairs, (A,B), (A,C), (B,C), (B,A), (C,A) and (C,B). Denote by x_{ijt} firm i's score against firm j at the time of auction t. It is natural to define firm j's score against i by $x_{jit} = -x_{ijt}$, for every $t = 1, 2, ..., T$, and assume all the scores equal zero at the beginning. x_{ijt} is updated after every auction which both i and j participate in. If firm i is selected by the ring and wins the contract in auction t, it implies that j gives a favor to i. Suppose v_t denotes the value of the favor that j gives i. Then $x_{ij\,t+1} = x_{ijt} - v_t$ and $x_{ji\,t+1} = x_{jit} + v_t$. If neither i nor j wins, their scores against each other remain the same: $x_{ij\,t+1} = x_{ijt}$ and $x_{ji\,t+1} = x_{jit}$.

As discussed above, it is reasonable to measure the value of favors by the expected payoff that is foregone. For simplicity, we assume the value of the contract is common to all the bidders in the auction, and is equal to the price. Therefore, $v_t = p_t/N_t$, where p_t is the winning price and N_t is the number of ring bidders in auction t. The underlying assumption is that each ring bidder has an equal chance of winning and an equal valuation on the contract.

An important assumption is that all bidders in the market belong to the ring. Therefore, N_t is assumed to be the number of bidders in the auction. The true N_t is unknown. However, as shown in Figure 3, the frequency of price wars is small. It seems that the ring was majority in the market and faced only a small number of competitive bidder.

We suppose that a bidder is likely to be selected as a winner if he has positive score against other bidders.

2.2 An inference on collusion scheme

In this section, we make an inference on how the idea of favor exchange works in bid rigging when there are more than two bidders. We present an example of possible collusion scheme which chooses the winner based on the balance of favors, and show that the scheme can be equilibrium.

We suppose that N symmetric bidders participate in infinitely repeated first price procurement auctions. I is the set of players of the game. The highest acceptable (reserve) price of each auction is $r < 1$, and the bidder's cost of delivering the work is 0. The set of possible bids in stage auction is $A_i = [0, 1]$, $i \in I$. The game begins at period 1. Action profile in period t is denoted by $b^t = (b_1^t, b_2^t, ..., b_N^t)$, $b_i^t \in A_i$. y^t represents the public randomization device in period t. h^t is history of the game, which is defined as $h^1 \equiv \emptyset$, $h^t \equiv ((b^1, y^1), ..., (b^{t-1}, y^{t-1}))$, $t = 2, 3, ...$, and H^t is the set of possible h^t.

The stage payoff $\pi_i(b_i, b_{-i})$ is b_i if b_i is strictly lower than any other bid, and 0 if b_i is not the lowest bid, and b_i/m if m bidders including b_i are tie for the first.

$x_{ij}(h^t)$ represents the score between i and j in history h^t. To make it easy to find an equilibrium, we set a ceiling on the score. It is defined that $x_{ij}(h^1) = 0$, and for $t > 1$, if j won in period $t-1$, then $x_{ij}(h^t) = \min\{x_{ij}(h^{t-1}) + 1, 1\}$ and if i won in period $t-1$, $x_{ij}(h^t) = \max\{x_{ij}(h^{t-1}) - 1, -1\}$. If neither i nor j won in period $t-1$, then $x_{ij}(h^t) = x_{ij}(h^{t-1})$. Denote $x_i(h^t) = \sum_{j \neq i} x_{ij}(h^t)$.

Consider the following scheme $\sigma_i^t : H^t \to A_i$. The scheme instructs bidder i to bid r if he is a designated winner of the auction, and 1 otherwise. The selection of the designated winner is as follows: If player i has the greatest value of $x_i(h^t)$ among I, then i is the designated winner. In the case where more than one players have the greatest $x_i(h^t)$, the designated winner is selected by public randomization. If someone deviates from the above instruction at least once during h^t, then i bids 0. This scheme assigns a contract to the bidder i whose $x_i(h^t)$, the number of bidders who were given a favor from i is the greatest.

To show that the strategy profile σ is a subgame perfect equilibrium of the game, we will say that the payoff obtained on the equilibrium path is greater than that of deviation at any information set of the game. We consider an upper bound on the number of successive periods, in which a player goes without being chosen as the winner on the path. Let L_N denote the maximum number of periods until every player wins at least once when the number of players is N. By listing all possible patterns, it can be seen that $L_2 = 3$, $L_3 = 5$. and $L_4 = 7$. All players except i win once within at most L_{N-1} periods, and win twice within at most $2L_{N-1}$ periods if i doesn't win at all. Note that in the subgame from h^t, whatever $x_{ij}(h^t)$ is, player i will win with probability 1 until after every other player wins twice, because every other player's twice wins assure that $x_i(h^t) = N - 1$. Therefore, $L_N \leq 2L_{N-1} + 1$, and then, $L_N \leq 2^{N-2}(L_2 + 1) - 1 = 2^N - 1$. It is said that when the number of player is finite, L_N is finite. Since from every on-path information set, each player will win within $L_N + 1$ periods, there exists a lower bound of payoff from t on, which is written as:

$$\underline{\mathrm{u}} = \delta^{L_N+1}r + \delta^{2(L_N+1)}r + ... = \frac{\delta^{L_N+1}r}{1 - \delta^{L_N+1}}.$$

The payoff of deviation is at most $r - \varepsilon$ for a small $\varepsilon > 0$, and $\underline{\mathrm{u}}$ exceeds this when δ is sufficiently large.

2.3 Dependent variable

The dependent variable in our analysis is an index variable which represents whether bidders won or lost in auctions. Suppose there are N_t bidders in auction t. We create $N_t - 1$ pairs of bidders, which consist of a winner i and every loser j. Henceforth, we call the pair of the winner and the loser, a "match". We then create two observations $w_{ijt} = 1$ and $w_{jit} = 0$ for a match, which mean i wins over j, and j loses to i, respectively. Therefore, $2(N_t - 1)$ observations are made for each auction t. The average of w_{ijt} is 0.5.

Consider an example where three bidders A,B, and C participated in auction t, and A won. There are two matches, (A,B) and (A,C). Then four observations are created for auction t such that $w_{ABt} = 1$, $w_{BAt} = 0$, $w_{ACt} = 1$, and $w_{CAt} = 0$.

There are two observations for a match. Since they are constrained each other, the two observations are perfectly correlated and standard errors are not correctly estimated.

Following Duggan and Levvit (2002), we correct standard errors by clustering.

3 Empirical Model

We analyze the dependence of the event that a bidder won or lost an auction, on his score between each of the other bidders and other factors that might affect win. We estimate the following binary response model by probit:

$$\begin{aligned} w_{ijt} &= \begin{cases} 1 & \text{if} \quad y_{ijt} > 0 \\ 0 & \text{if} \quad y_{ijt} \leq 0 \end{cases}, \\ \text{where} \quad y_{ijt} &\equiv a_i + b\, x_{ijt} + c_1\, \Delta backlog_{ijt} + c_2\, \Delta sales_{ij} \\ &\quad + c_3\, \Delta num\_join_{ij} + c_4\, \Delta worker_{ij} + c_5\, \Delta years_{ij} + \varepsilon_{ijt} \qquad (1) \\ &= \mathbf{z}_{ijt}\beta + \varepsilon_{ijt}, \\ &\quad i, j = 1, 2, ..., M, \;\; i \neq j, \;\; t = 1, 2, ..., T. \end{aligned}$$

We assume $\Pr(w_{ijt} = 1|\mathbf{z}_{ijt}) = \Phi(\mathbf{z}_{ijt}\beta)$, where $\Phi(\cdot)$ is the standard normal distribution function and $\mathbf{z}_{ijt}$ is the vector of explanatory variables. The log likelihood for each observation can be written as:

$$\begin{aligned} \ln L_{ijt} &= w_{ijt} \ln \Pr(y_{ijt} > 0 \mid \mathbf{z}_{ijt}) + (1 - w_{ijt}) \ln \Pr(y_{ijt} \leq 0 \mid \mathbf{z}_{ijt}) \\ &= w_{ijt} \ln \Phi(\mathbf{z}_{ijt}\beta) + (1 - w_{ijt}) \ln(1 - \Phi(\mathbf{z}_{ijt}\beta)). \end{aligned}$$

M is the number of firms and T is the number of auctions during the data period. w_{ijt} is an index variable that takes 1 if bidder i won over j in auction t and 0 otherwise.

x_{ijt} is i's score against j at t. The following variables: $\Delta backlog_{ijt}$, $\Delta sales_{ij}$, Δnum_join_{ij}, $\Delta worker_{ij}$, and $\Delta years_{ij}$ are included in order to capture the difference between bidder i and j, which might affect the result. $\Delta backlog_{ijt} \equiv backlog_{it} - backlog_{jt}$, where $backlog_{it}$ is the value of backlog projects that i has at auction t, divided by its annual sales. A backlog project is a project that bidder i has already contracted and its project period overlaps project t. $backlog_{it}$ proxies the firm's capacity utilization.[1] $\Delta sales_{ij} \equiv sales_i - sales_j$, where $sales_i$ is the annual sales of compensation consulting works of each

[1] In the present analysis, the backlog data is constructed using contract data bought by Naha City only. Though true backlog status must be affected by unobservable works such as private works, we assume it identical among bidders.

bidder averaged over FY2003 and FY2004. $\Delta num\_join_{ij} \equiv num\_join_i - num\_join_j$, where num_join_i is the number which represents how many times bidder i participated in the auction. $\Delta worker_{ij} \equiv worker_i - worker_j$, where $worker_i$ is the number of workers bidder i has. $\Delta years_{ij} \equiv years_i - years_j$, where $years_i$ represents the number of years that bidder i has been operating. Dummy variables for firms are also included in order to capture the fixed effect a_i for firm i.

ε_{ijt} is the error term which is assumed to follow a standard normal distribution given $\mathbf{z}_{ijt}$. ε_{ijt} is assumed to be independent across matches, that is, the fight between i and j in auction t is independent of that between i and other bidders. Note that ε_{ijt} and ε_{jit} are negatively correlated within the match because w_{ijt} and w_{jit} are generated by the same match where $w_{ijt} = 1$ implies $w_{jit} = 0$. However, the pooled probit estimator has a nice feature that estimated parameters will be consistent and asymptotically normal even if error terms are arbitrarily correlated within groups of observations (Wooldridge (2002)). Following Duggan and Levvit (2002) who adjusted standard errors by clustering after OLS estimation of the linear probability model, we clustered standard errors by matches.[2]

The parameter which interests us is b. If the auction is competitive, then x_{ijt} has no effect on the event, that is, b is zero. If the bidders are exchanging favors, x_{ijt} has a positive effect on the probability. We test the null hypothesis $H_0 : b = 0$, against the alternative hypothesis $H_1 : b > 0$.

4 Empirical result

Our analysis consists of two parts. In the first analysis, we estimate equation (2) and analyze the dependence of the winning probability on the score. Our result shows that

[2]Clustering robust standard error in probit model is the square root of the diagonal elements of matrix $\left[\sum_{g=1}^{G} A_g(\hat{\beta})\right]^{-1}\left[\sum_{g=1}^{G} s_g(\hat{\beta})s_g(\hat{\beta})'\right]\left[\sum_{g=1}^{G} A_g(\hat{\beta})\right]^{-1}$, where $g = 1, 2, ..., G$ are the matches and

$$A_g(\hat{\beta}) = \frac{\{\phi(\mathbf{z}_{ijt}\hat{\beta})\}^2\mathbf{z}'_{ijt}\mathbf{z}_{ijt}}{\Phi(\mathbf{z}_{ijt}\hat{\beta})\{1-\Phi(\mathbf{z}_{ijt}\hat{\beta})\}} + \frac{\{\phi(\mathbf{z}_{jit}\hat{\beta})\}^2\mathbf{z}'_{jit}\mathbf{z}_{jit}}{\Phi(\mathbf{z}_{jit}\hat{\beta})\{1-\Phi(\mathbf{z}_{jit}\hat{\beta})\}},$$

$$s_g(\hat{\beta}) = \frac{\phi(\mathbf{z}_{ijt}\hat{\beta})\mathbf{z}'_{ijt}\{w_{ijt}-\Phi(\mathbf{z}_{ijt}\hat{\beta})\}}{\Phi(\mathbf{z}_{ijt}\hat{\beta})\{1-\Phi(\mathbf{z}_{ijt}\hat{\beta})\}} + \frac{\phi(\mathbf{z}_{jit}\hat{\beta})\mathbf{z}'_{jit}\{w_{jit}-\Phi(\mathbf{z}_{jit}\hat{\beta})\}}{\Phi(\mathbf{z}_{jit}\hat{\beta})\{1-\Phi(\mathbf{z}_{jit}\hat{\beta})\}}.$$

See Wooldridge (2002) Ch.13 for details.

the winning probability is positively dependent on the score.

Favors would be exchanged between pairs of collusive bidders, and not between a pair of a collusive bidder and a competitive bidder. In the second analysis, we analyze whether the data confirm this prediction. Bidders who are colluding by favor exchange will submit passive high bids on average, whereas competitive bidders will submit aggressive low bids on average. Therefore, favors must be exchanged among a pair of passive bidders, not among a pair where either of the bidders is aggressive.

In the analysis, bidders are classified by their average bid level into two groups: "aggressive" bidders and "passive" bidders. An "aggressive" bidder is a bidder who makes low bids on average throughout the data period. A "passive" bidder is a bidder who makes high bids on average. If a bidder's average bid is lower than 95% of the reserve price, then he is "aggressive".[3] If a bidder's average bid is higher than 95%, then he is "passive". We test the dependence of winning probability on the score, when both i and j are passive, and when one of them is aggressive.

At the beginning of the data period, $x_{ijt} = 0$ for all i, j by definition. In both analyses we omitted observations such that $x_{ijt} = 0$ because these observations lower the sample variance of x_{ijt}, and standard error of its parameter may be underestimated. We also omit firms which haven't won a contract during the data period, because obviously they didn't exchange favors. Finally, we have 60 firms in which 4 are aggressive bidders and 56 are passive bidders. All firms are located within Naha City.

The analysis using early period data may be still affected by the assumption that $x_{ijt} = 0$. To see the robustness of the results, we estimate the model with several data sets sequentially eliminating early period observations. We use three data sets: (a) observations of all fiscal years, (b) observations after the second fiscal year, and (c) observations after the third fiscal year. Therefore, (a) consists of observations during FY2001-2004, and (b), (c) consist of observations during FY2002-2004, FY2003-2004, respectively. The number

[3]We used 95% of the reserve price to divide a passive bidder and an aggressive bidder. The reason is that Japan Citizen's Ombudsman Association claims that bid rigging is strongly suspected in markets where the winning price is within 95% of the reserve price on average. The association mainly consists of lawyers, and their claims are based on their nationwide research and antitrust accusations cases in the past.

of observations in each data set is 812, 736 and 518, respectively. The analysis using the latter data set is freer from the assumption, but the number of observations is smaller.

4.1 Analysis 1: Evidence of exchanging favors

We estimate model (2) to test whether the score affects the winning probability. Table 5 shows the result. The estimation results using data set (a) are in the first two columns. Next two columns shows the results using data set (b). The final two columns show the results using data set (c). For each data set we ran a couple of specifications: with and without bidder's fixed effect. The first column of every two columns corresponds to the estimation result of the model without fixed effect, and the second column corresponds to the fixed effect model. The number of observations are different between with and without fixed effect models. Since we have dummy variables for bidders in the fixed effect model, observations were lost due to perfect prediction. In data set (c), the parameter of backlog is not identified since no bidder has backlog project.

We are primarily interested in the parameter of the score shown in the first row of the table. It is positive and significant in all columns in the table. The null hypothesis that $b = 0$ is rejected in all data sets in models with and without fixed effect. This implies that the winners tend to have positive score against losers, that is, the winners have given favors to the other bidders. This supports the possibility that bidders are exchanging favors: a bidder who has given a favor tends to win.

The bidders' difference in the number of participation in the auction is significant and negative. This implies that the winners tend to submit bids less frequently than the losers. The negative sign is unexpected and remains unexplained. The difference in the number of operating years is also significant and has positive sign. This implies that the winners tend to be operating longer than the losers. It is supposed that members are not equally treated, but a firm who is operating long has relatively strong negotiation power in the pre-auction communication.

4.2 Analysis 2: Favor exchange and average bid level

We analyzed whether the score affects the winning probability when the bidder and the opponent are aggressive or passive. A modified form of model (2) is estimated, in which the term $b\,x_{ijt}$ is replaced into the sum of the following 3 terms, $b_1\,P_i\,P_j\,x_{ijt}$, $b_2\,P_i\,A_j\,x_{ijt}$, and $b_3\,A_i\,P_j\,x_{ijt}$. A_i and P_i are dummy variables which indicate whether i is aggressive or passive. P_i takes 1 if bidder i is passive and 0 otherwise. A_i takes 1 if bidder i is aggressive and 0 otherwise. $A_i\,A_j\,x_{ijt}$ is not included because there is only a match where both i and j are aggressive.

Table 6 shows the estimation result. As shown in the first row of the table, the parameter of $P_i\,P_j\,x_{ijt}$ is positive and significant in data sets (a), (b) and (c) in both specifications. Therefore the score raises the winning probability when both bidder i and bidder j are passive. On the other hand, the parameter of $P_i\,A_j\,x_{ijt}$ and $A_i\,P_j\,x_{ijt}$ is not significant with 5% significance level in any data set as shown in the second and the third rows of the table.

It can be said that when either i or j are aggressive and the other is passive, the score has no impact on winning probability. This suggests that the impact of the score on the winning probability is effective only when both i and j are passive, and invalid when one of them is aggressive. The result is consistent to the expectation that favors are exchanged only between passive bidders.

5 Conclusion

This paper provides an empirical analysis to see if bidders are colluding by exchanging favors in repeated procurement auctions. Bidding data of consulting works bought by Naha City are studied to assess if collusion by favor exchange is in operation. We constructed a virtual variable named "score", which represents the balance of favors between every pair of bidders assuming that all bidders are collusive. We then analyzed the dependence of bidders' winning probability on the score.

The result shows that the winning probability in auctions tends to be positively dependent on the score. That is, if bidder A has given a favor to another bidder B, A tends to win against B. This confirms the prediction that collusion by exchanging favors is in operation.

We next classified the bidders into two groups, supposing that the ring was not all inclusive in the market and there were some competitive firms. A bidder who submitted high bids on average was classified as a "passive" bidder and a bidder who submitted low bids on average was classified as an "aggressive" bidder. We then found that favors were exchanged within a pair of passive bidders, but not within a pair in which one was aggressive. The result is consistent with a prediction that a collusive bidder tends to bid higher than a competitive bidder.

Our analysis would be useful in detecting bidder collusion by favor exchange. However, there remains a possibility that the result is untrue. A history of auction generated through other collusion schemes can show the same characteristics as the collusion by favor exchange. For example, a simple bid rotation scheme can be seen as if they are exchanging favors when bidders are fixed throughout auctions. Further analyses using artificially generated data would be useful to know how to discriminate various collusion schemes.

References

[1] Aoyagi, M. (2003), “Bid Rotation and Collusion in Repeated Auctions,” Journal of Economic Theory, 112, pages 79-105.

[2] Bajari, P. and Ye, L. (2003), “Deciding Between Competition and Collusion,” Review of Economics and Statistics, 85.4, pages 971-989.

[3] Duggan, M. and Levitt, S. D. (2002) “Winning Isn’t Everything: Corruption in Sumo Wrestling,” American Economic Review, 92(5), pages 1594-1605.

[4] Hironaka, K. (1994), “*Dango* does exist after all (*Soredemo dango ha nakunaranai*),” Tokei Publishing (in Japanese).

[5] McAfee, R. P. and McMillan, J. (1992), “Bidding Rings,” American Economic Review, 82.3, pages 579-599.

[6] Pesendorfer, M. (2000), “A Study of Collusion in First-Price Auctions,” Review of Economic Studies, 67, pages 381-411.

[7] Porter, R. H. and Zona, J. D. (1993), “Detecting of Bid Rigging in Procurement Auctions,” Journal of Political Economy, 101.3, pages 518-538.

[8] Skrzypacz, A. and Hopenhayn, H. (2004), “Tacit collusion in repeated auctions,” Journal of Economic Theory.

[9] Suzuki, M. (2004), “A study of bid rigging (*Nyusatsu dango no kenkyu*),” Shinzansha (in Japanese).

[10] Wooldridge, J. M. (2002), “Econometric Analysis of Cross Section and Panel Data”, MIT press.

[11] Zona, J. D. (1986), “Bid-rigging and the Competitive Bidding Process: Theory and Evidence.” Ph.D. dissertation, State University of New York at Stony Brook.

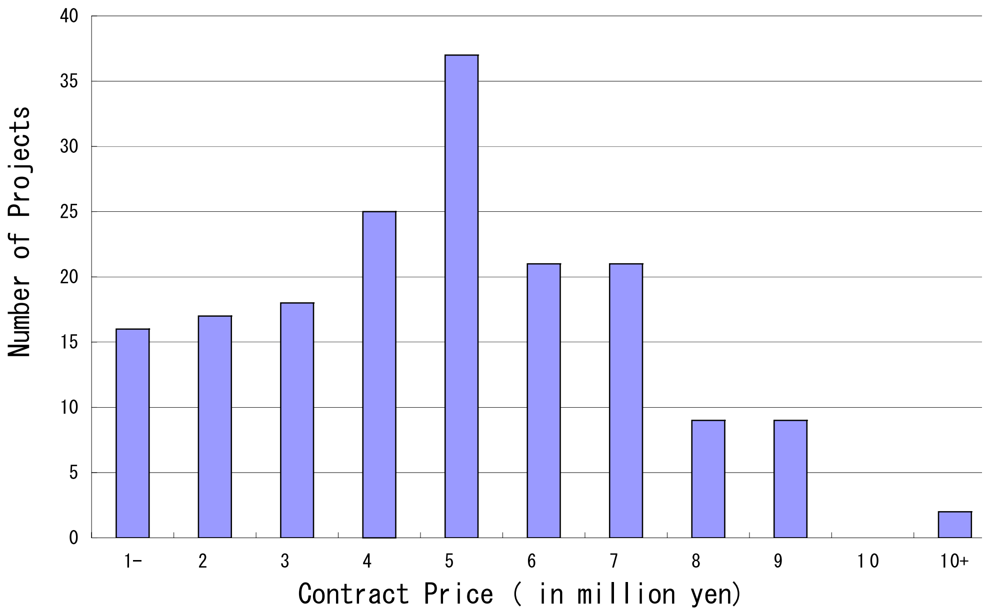

Figure 1: Compensation consulting works in Naha City

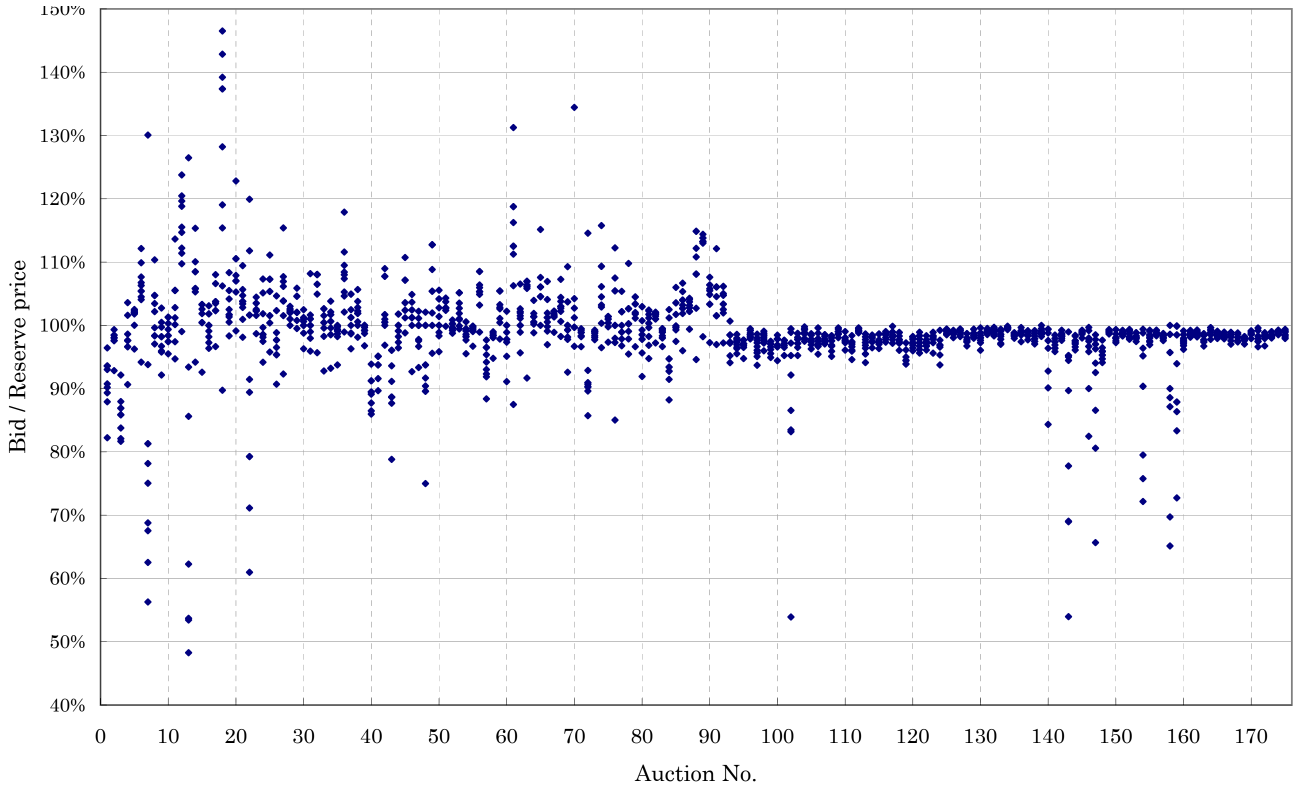

Figure 2: Distribution of bids

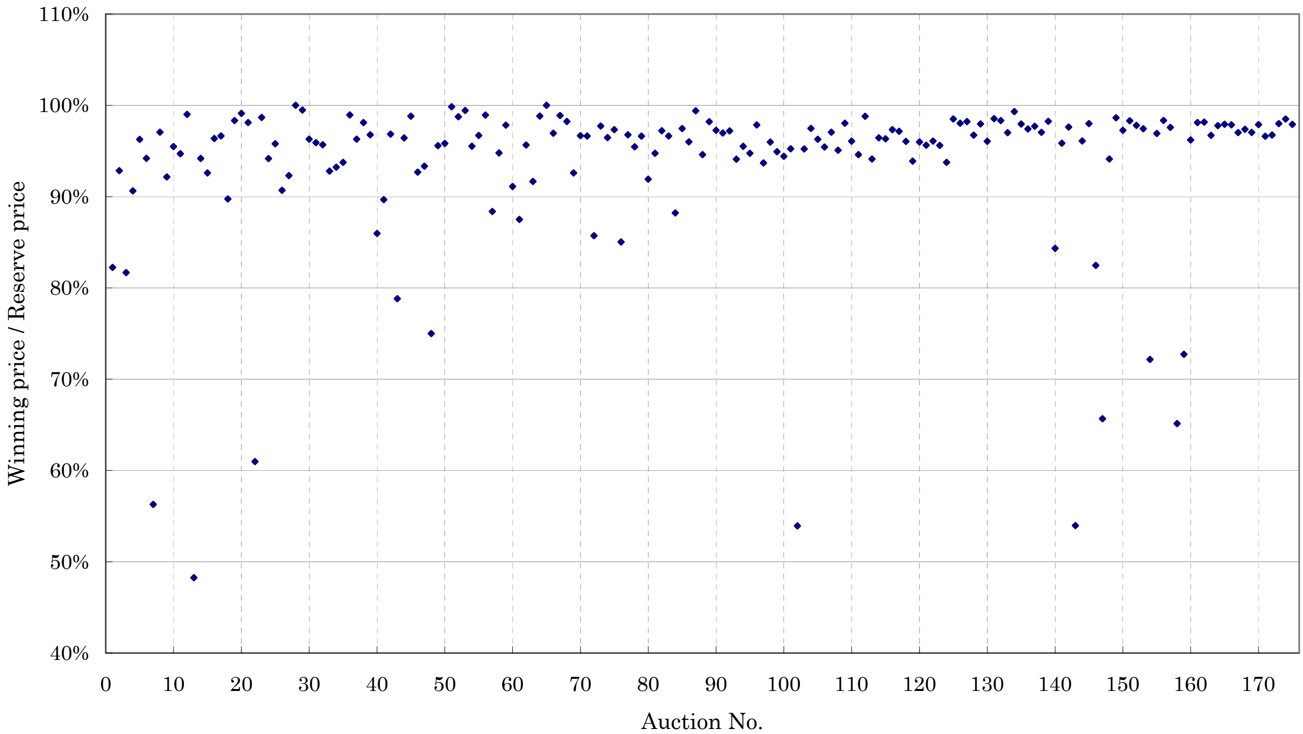

Figure 3: Distribution of winning price

Table 1: Number of land evaluation project auctions in Naha City

Fiscal year	2001	2002	2003	2004	Total
Number of auction	50	43	38	44	175

Table 2: Number of bids

Fiscal year	2001	2002	2003	2004	Total
Number of bids	498	430	380	440	1748

Table 3: Distribution of firms: frequency of participation

Number of Participation	Firms
1-10	79
11-20	27
21-30	11
31-40	16
41-	3
Total	136

Table 4: Distribution of firms: frequency of winning

Number of winning	Firms
0	67
1	22
2	15
3	14
4	11
5-	7
Total	136

Table 5: Analysis 1

Dependent Variables	Data set					
	(a)	(a)	(b)	(b)	(c)	(c)
Score	0.0398 **	0.0572 **	0.0357 *	0.0483 *	0.0439 *	0.0557 *
	(0.0127)	(0.0141)	(0.0130)	(0.0142)	(0.016)	(0.0168)
ΔNumjoin	-0.0258 **	-0.0266 **	-0.0242 **	-0.0265 **	-0.0206 *	-0.0251 *
	(0.0074)	(0.0081)	(0.0076)	(0.0084)	(0.009)	(0.0104)
ΔSales	-0.0026	-0.0028	-0.0014	-0.0006	-0.0042	-0.0059
	(0.0018)	(0.0021)	(0.002)	(0.0023)	(0.0024)	(0.0032)
ΔBacklog	-0.0019	-0.0024	0.0013	0.0005	-	-
	(0.0054)	(0.0046)	(0.0052)	(0.0042)		
ΔWorker	-0.0041	-0.009	-0.0042	-0.0101	0.0140	0.0123
	(0.0052)	(0.0055)	(0.0053)	(0.0054)	(0.0082)	(0.0098)
ΔYears	0.0212 **	0.0291 **	0.0252 **	0.0347 **	0.0230 **	0.0294 **
	(0.0064)	(0.0073)	(0.0067)	(0.0077)	(0.0085)	(0.0110)
Constant	0.0000	-	0.0000	-	0.0000	-
	(0)		(0)		(0)	
Firm dummies	No	Yes	No	Yes	No	Yes
Number of obs	812	736	736	658	516	417
Pseudo R2	0.071	0.151	0.071	0.159	0.104	0.246
Log-likelihood	-522.90	-432.93	-473.72	-383.37	-320.39	-226.47

Note: Robust standard errors are reported in parentheses. Estimation results reported in even number columns are those of fixed effect models. Bidders' dummy variables are abbreviated. **: 1% significance, *: 5% significance.

Table 6: Analysis 2

Dependent Variables	Data set (a)	(a)	(b)	(b)	(c)	(c)
Score*P*P	0.0401 **	0.0578 **	0.036 **	0.049 **	0.0447 **	0.0566 **
	(0.0131)	(0.0142)	(0.0133)	(0.0142)	(0.0158)	(0.017)
Score*P*A	0.0159	0.0808	0.0185	0.0729	-0.0104	0.0585
	(0.0622)	(0.0747)	(0.062)	(0.073)	(0.0817)	(0.105)
Score*A*P	0.0159	0.0096	0.0185	0.0157	-0.0104	-0.0075
	(0.0622)	(0.0538)	(0.062)	(0.0534)	(0.0817)	(0.0577)
ΔNumjoin	-0.0260 **	-0.0268 **	-0.0243 **	-0.0267 **	-0.021 *	-0.0253 *
	(0.0075)	(0.0081)	(0.0077)	(0.0084)	(0.009)	(0.0104)
ΔSales	-0.0027	-0.0029	-0.0014	-0.0006	-0.0042	-0.0059
	(0.0018)	(0.0021)	(0.0019)	(0.0023)	(0.0024)	(0.0032)
ΔBacklog	-0.002	-0.0025	0.0013	0.0005	-	-
	(0.0054)	(0.0046)	(0.0052)	(0.0041)		
ΔWorker	-0.0041	-0.0096	-0.0042	-0.0103	0.014	0.0119
	(0.0052)	(0.0055)	(0.0053)	(0.0054)	(0.0083)	(0.0098)
ΔYears	0.0213 **	0.0297 **	0.0252 **	0.0353 **	0.0230 **	0.0303 **
	(0.0064)	(0.0072)	(0.0067)	(0.0077)	(0.0085)	(0.0109)
Constant	0	-	0	-	0	-
	(0)		(0)		(0)	
Firm dummies	No	Yes	No	Yes	No	Yes
Number of observations	812	744	736	666	516	423
Pseudo R2	0.071	0.159	0.071	0.167	0.105	0.2141
Log likelihood	-522.98	-433.66	-473.81	-384.13	-320.27	-226.95

Note: Robust standard errors are reported in parentheses. Estimation results reported in even number columns are those of fixed effect models. Bidders' dummy variables are abbreviated. **: 1% significance, *: 5% significance.