Using Bid Rotation and Incumbency Patterns to Detect Collusion

Sylvain Chassang Kei Kawai Jun Nakabayashi Juan Ortner

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Abstract

Market division and bid rotation are two of the most commonly employed ways of allocating market under collusion. However, establishing a tight link between these allocation patterns and firm conduct has been difficult because there exist cost-based explanations that can generate these patterns under competition. Focusing on the set of auctions in which the winning bid and the losing bids are very close, we use ideas similar to regression discontinuity design to distinguish between allocation patterns that simply reflect cost differences across firms and those that are indicative of collusion. We show theoretically, that our test has correct size under the null of competition.

Applying our test to the sample of municipal auctions in Japan, we find evidence of collusion among the set of auctions whose winning bid is high reletive to the reserve price. However, we do not reject the null of competitive bidding for auctions whose winning bid is relatively low.

While the number of firms that are prosecuted for cartelization is a tiny fraction of the total number of firms, the ability of competition authorities to successfully detect and punish cartels is important for deterrence. The possibility of detection can also affect the incentives of firms in existing cartels to apply for leniency programs. Successful identifcation of cartels thus deter collusive activity and complement the effectiveness of leniency programs.

In the absence of concrete leads, screening devices that flag suspicious firm conduct may be especially useful for regulators as a first step in identifying collusion. While screens cannot substitute for direct evidence of collusion such as testimonies and records of communication, they can provide guidance on which markets or firms to focus investigation. The results from screens are also used in court to obtain warrants or authorization for a more intrusive investigation.[1] Some jurisdictions have screening programs that use algorithms to flag suspicious behavior using bidding data from public procurement auctions.[2] There have been a number of cases in which the use of screens have led to antitrust investigations and, subsequently, to successful cartel prosecution.

Screening of cartels can also be useful to those outside of antitrust authorities. For example, screening can help internal and external auditors identify collusion and help contain potential exposure from it. Screening can also help procurement offices counter suspected bidding rings by more aggressively soliciting new bidders or adopting auction mechanisms that are less susceptible to collusion (but perhaps at the cost of reduced efficiency when bidders are competitive).[3]

In this paper, we propose a way to exploit patterns of bid rotation and incumbency advantage to identify collusion. Although bidding rings often adopt internal allocation mech-

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[1] In some jurisdictions, statistical evidence from screens have been used succsefully to build a collusion case in court. See Mena-Labarthe (2012) for a collusion case in Mexico.

[2] For the U.K., the policy paper titled "UK anti-corruption strategy 2017 to 2022" published by the Department for International Development and the Home Office discusses the use of the screening tool to identify possible cartels. The Competition and Markets Authority also explains the screening tool on its webpage; https://www.gov.uk/government/publications/screening-for-cartels-tool-for-procurers.

The screening program in Korea analyzes bidding data collected from its e-procurement system. See "Cartel Enforcement Regime of Korea and Its Recent Development" by the Fair Trade Commission of Korea.

[3] Hendricks, McAfee, Williams discusses this trade-off as follows: "On the one hand, more transparent auction mechanisms can yield greater efficiency and revenues when bidders behave competitively; on the other hand, they are also more vulnerable to collusion."

anisms that result in bid rotation and incumbency patterns, it has been hard to establish a formal link between these allocation patterns and firm conduct. As is well known, this is because there are non-collusive cost-based explanations for these allocation patterns. In particular, bid rotation patterns can arise under competition with increasing marginal costs and incumbency advantage can be explained by cost asymmetries among competitive firms. As Porter (2005) describes, "*An empirical challenge is to develop tests that can discriminate between collusive and non-cooperative explanations for rotation or incumbency patterns.*"

In this paper, we propose a way of overcoming this challenge by applying ideas from regression discontinuity design (Lee, 2008, Thistlewaite and Campbell, 1960). In particular, we compare the backlog and incumbency status between a bidder who wins the auction by a small margin and a bidder who loses by a small margin. Under fairly mild assumptions, we show that the standard identification assumption invoked in regression discontinuity is met when bidders bid competitively, i.e., whether a bidder wins or loses is as-if-random conditional on its bid being very close to the most competitive rival bid. This implies that under competition, even if backlog or incumbency status affect bidder costs, the differences in these variables between the winner and the loser should vanish as the bid difference between them approaches zero. If, on the other hand, bids are generated by collusive bidding, the differences in these variables between the winner and the loser may not disappear depending on the manner in which the bidding ring allocates projects. For example, if the bidding ring always allocates projects to the incumbent bidder, there will necessarily be a stark difference in the extent to which the winner is an incumbent even conditional on auctions in which the winner and the loser bid very close to each other. We use these results to construct our empirical test.

We apply our test to a dataset of public procurement auctions from the Tohoku region of Japan. Our baseline sample consists of about 7,000 auctions from 11 municipalities between 2004 to 2017. The format of the auctions is first-price sealed bid. While none of the firms in our data have been implicated by the antitrust authorities, there is some reason to suspect that bidding rings may have been active in the municipalities that we study. In one of our previous work, we find evidence of collusive bidding in public works auctions let by the Ministry of Land Infrastructure and Transportation.[4] Some of the bidders that we found to be bidding non-competitively in our earlier work are also active participants of the municipal auctions that we study in this paper.

We find that there are significant differences in the backlog, incumbency status, and geographical proximity between marginal winners and marginal losers when we focus on the subset of auctions in which the winning bid, as measured by the fraction of the reserve price, is above the median of the sample. We do not find statistically significant differences among the subset of auctions in which the winning bid is below the median. Because collusive bidding tends to elevate prices, the fact that we find significant difference for auctions with a high winning bid and not for auctions with a low winning bid suggests that the tests based on backlog and incumbency have reasonable size and power in practice.

One of the benefits of the screening method that we propose is its simplicity. In particular, we do not need much data on project characteristics or bidder characteristics to implement the test. This is because the regression discontinuity design makes it less important to control for auction and bidder heterogeneity. This is a feature that is different from more structural approaches to detecting collusion that rely on specifying bidder costs accurately. Another feature of our test is that it is valid under relatively mild assumptions on the primitives of the model. In particular, the consistency of the test does not rely on whether bidders are risk averse, have private values, or correlated signals.

More generally, we think that comparing the characteristics of the marginal winner and the marginal loser provides a useful way of turning many informal arguments about sus-

[4]See Kawai and Nakabayashi (2017).

picious bidding behavior into formal tests of competition. For example, subcontracting is sometimes9 considered to facilitate collusion. geographic segmentation is often considered to be a sign of collusion (Porter and Zona 1999).[5] One can easily construct a test that compares whether marginal winners are more likely to be local firms than marginal losers. Extent of subcotracting,[6] joint bidding (Porter Zona 1993, OECD 2013), etc. can be also be compared between marginal winners and losers.

Literature The paper is most closely related to papers that propose ways to differentiate between competitive and non-competitive bidding in auctions. Some of the pioneering work include Baldwin, Marshall and Richard (1997), Hendricks and Porter (1998), and Porter and Zona (1999, 2002). The paper that is closest to ours is Porter and Zona (1999) who study how cost variables such as backlog and proximity to construction sites affect the level of bids and the ranking of bids in auctions for road pavement projects. They find that the losing bids of suspected ring members do not respond to cost shifters which suggests that those bids are likely to be phantom bids. They also find that the lowest bid among the suspected members *does* respond to cost variables presumably to compete against rival bidders that were not part of the cartel. The obvious similarity between Porter and Zona (1999) and our paper is that they both use the relationship between bids and cost shifters such as backlog to screen for collusion. There is a difference in the basic idea behind the

[5] For example, the Department of Justice maintains a document called “Price Fixing, Bid Rigging, and Market Allocation Schemes: What They Are and What to Look For”, in which they state “Subcontracting arrangements are often part of a bid-rigging scheme.” Similar statements are found in a report by the OECD (2013). See also Conley and Decarolis (2016) for a discussion that links subcontracting to collusion.

[6] Many procuring agencies require the list of subcontractors to be specified in the initial proposal. For example, “Subletting and Subcontracting Fair Practices Act” (Public Contract Code 4100 et seq.) of California requires that “any person making a bid or offer to perform the work, shall, in his or her bid or offer, set forth ... (T)he name, the location of the place of business, ... of each subcontractor who will perform work or labor or render service to the prime contractor.” As another example, the state of Hawii’s public procurement code includes a section called “Construction contracts; requirement to list subcontractors”, where it is stated that, “If the invitation for bids is for construction, the invitation shall specify that all bids include the name of each person/firm to be engaged by the bidder as a joint contractor or subcontractor in the performance of the contract and the nature and scope of the work to be performed by each.”

two papers, however. Porter and Zona (1999) focus on the differential incentives of the designated cartel bidder and the non-designated cartel bidders to submit serious bids. Our idea is to exploit bidding paterns that reflect commonly used cartel allocation mechanisms, such as rotation and incumbency patterns, to detect collusion.

Some of the more recent papers that distinguish between competition and collusion include Pesendorfer (2002), Bajari and Ye (2006), Ishii (2009), Athey, Levin and Seira (2011), Conley and Decarolis (2013), Kawai and Nakabayashi (2017), Andreyanov (2017) and Schurter (2017). Other related work that study collusion in auctions include Asker (2010) who studies the internal organization of a known bidding ring. Ohashi (2009) and Chassang and Ortner (2018) document how changes in the details of the auction can affect the ability of bidders to maintain collusion. Clark et. al analyze the breakdown of a cartel and its implications on prices.[7]

Institutional Details and Data We use bidding data from public works auctions in 11 municipalities from the Tohoku region of Japan. There are about 7,000 auctions and about 52,000 unique bids. The most common types of projects include civil engineering, architecture, and road improvement. The auction format for all of the municipalities is first-price sealed bid with a reserve price. The reserve price is public in 2 cities and secret in the others.[8]

In more than 60% of auctions, participation in the auctions is restricted to invited bidders only. Even for auctions in which participation is not by invitation, eligibility is often limited to firms with some physical presense in the municipality. The participation restrictions make new entry difficult, often resulting in the same set of firms facing each other repeatedly over time.

[7] For a survey of the literature up to the mid 2000s, see Harrington (2005) and Porter (2005).

[8] For municipalities with a secret reserve price, there are reauctions for lettings in which none of the bids meet the secret reserve price.

	Mean	Std. Dev.	Min	Max	Obs
Winbid/Reserve	93.2%	0.083	35%	100%	7,024
No. bidders	7.38	5.51	1	47	7,024
Reserve Price (Mil. Yen)	23.2	143.0	0.016	7,890	7,024

Table 1:

We have data on all of the bids, the reserve price, the name of the project, and some information about the type of project, i.e., maintenance, repair, civil engineering etc. We also have data on the location of firms.

1 Theory

Pending...

2 Analysis

2.0.1 Analysis Using Backlog

Our first analysis compares the backlog of marginal winners and marginal losers. We define the forcing variable as the difference between bidder i's bid and its most competitive rival bid:

$$\Delta_{it} = b_{it} - \min_{j \neq i} b_{jt},$$

where b_{it} is the normalized bid of firm i in auction t. If firm i is the lowest bidder in auction t, Δ_{it} is negative, and it is the difference between the lowest bid and the second lowest bid. If firm i is not the lowest bidder, Δ_{it} is positive and it is the difference between the lowest bid and bidder i's bid.

We measure bidder i's backlog at the time of bidding in auction t by taking the one-year cumulative sum of the projects won by bidder i and standardizing this sum by the (within-firm) standard deviation.[9] In particular, if we denote the raw one-year backlog of bidder i as bl_{it}^{raw}, our measure of backlog, bl_{it}, is computed by subtracting the within-firm mean of bl_{it}^{raw} and dividing by the within-firm standard deviation, $\sigma_{bl_i^{rqw}}$, as follows;

$$bl_{it} = \frac{bl_{it}^{raw} - \overline{bl_i^{raw}}}{\sigma_{bl_i^{rqw}}}.$$

The standadized backlog measure allows us to compare firms of different sizes on the same scale. Because the backlog of each firm is measured relative to the firm's own historical average, bl_{it}^{norm} is zero if firm i's raw backlog is equal to its time-series average at the time of auction t.

The discontinuity in the backlog that we wish to estimate is the following:

$$\beta = \lim_{\Delta_{it} \searrow +0} \mathbf{E}[bl_{it}|\Delta_{it}] - \lim_{\Delta_{it} \nearrow -0} \mathbf{E}[bl_{it}|\Delta_{it}].$$

The first term of the expression is the expected backlog of the marginal losers and the second term is the expected backlog of the marginal winners.

We estimate β using a local linear regression as follows:

$$\begin{aligned}
\widehat{\beta} &= \widehat{b_0^+} - \widehat{b_0^-}, &(1)\\
(\widehat{b_0^+}, \widehat{b_1^+}) &= \texttt{argmin} \sum_{i,t}^{T} 1\{\Delta_{it} > 0\}(bl_{it} - b_0^+ - b_1^+ \Delta_{it})^2 K\left(\frac{\Delta_{it}}{h_n}\right) &(2)\\
(\widehat{b_0^-}, \widehat{b_1^-}) &= \texttt{argmin} \sum_{i,t}^{T} 1\{\Delta_{it} < 0\}(bl_{it} - b_0^- - b_1^- \Delta_{it})^2 K\left(\frac{\Delta_{it}}{h_n}\right) &(3)
\end{aligned}$$

[9]One-year cumulative sum of the projects is computed by adding up the winning bid of auctions won by bidder i during the period starting 365 days before auction t and ending right before auction t.

	Marginally Lowest		Marginally 2nd Lowest	
	Below Median	Above Median	Below Median	Above Median
	(1)	(2)	(3)	(4)
Δ_{it}	0.108	0.167^{***}	0.067	0.032
	$(-0.0281, 0.258)$	$(0.074, 0.280)$	$(-0.035, 0.180)$	$(-0.079, 0.144)$
Obs.	$16,545$	$14,014$	$18,106$	$14,249$

95% confidence interval in parentheses.

*p<0.10, **p<0.05, ***p<0.01

Table 2:

where h_n is the bandwidth and $K(\cdot)$ is the kernel. For our baseline estimates, we use a mean square error optimal bandwidth and a triangular kernel. The heteroskedasticity-robust standard error of the estimate is computed using the bias correction method proposed in Calonico et. al (2014). We estimate the coefficients separately for the set of auctions in which the lowest bid is below the municipality median and above the median. We expect the former sample to have less collusive bidding and the estimated coefficient to be close to zero. To the extent that the latter sample contains collusive bidding, the coefficient estimate for this sample may be statistically different from zero.

Table 2 reports the estimation results. In column (1), we report the results for the sample of auctions in which the winning bid is below the median. We find that the estimate of β is 0.108, implying that marginal winners have about 0.108 standard deviation more backlog than marginal losers on average. The bandwidth of the triangular kernel that we use is 0.027. The estimate is not statistically significant from zero. In column (2), we report the results for the sample of auctions with a winning bid above the median. We find that the estimate of β is 0.167 and that it is statistically significant at the 1% level. The estimate implies that marginal winners have about 0.167 standard deviation more backlog than marginal losers. The bandwidth that we use is 0.023. The bin plots of bl_{it} against Δ_{it}

that correspond to these results are illustrated in the left panels of Figure 1.

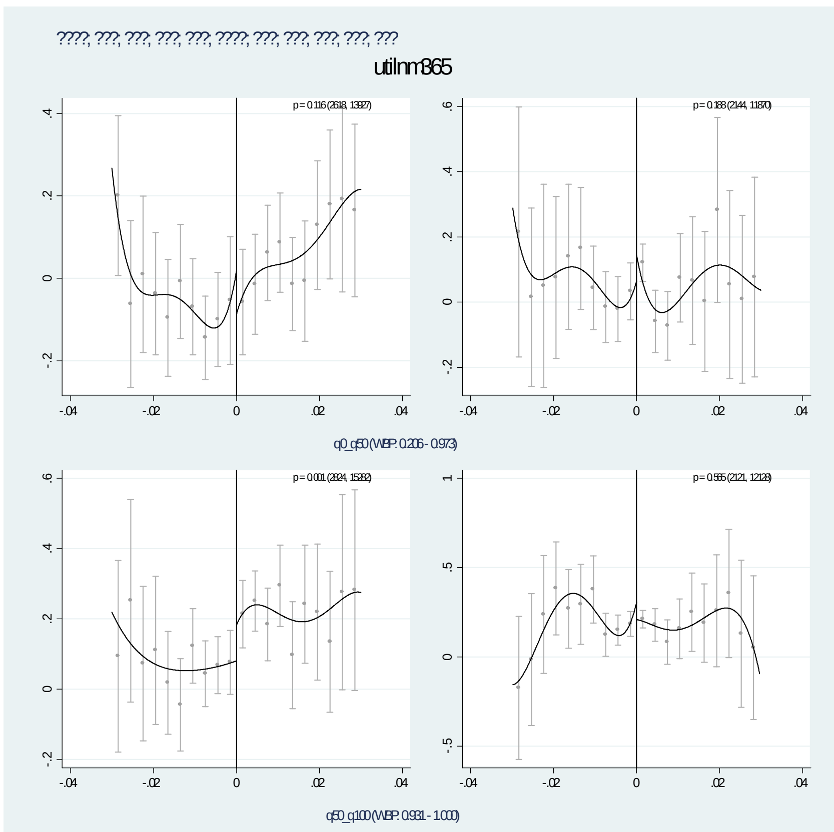
The fact that β is statistically significant in column (2), but not in column (1), is consistent with firms bidding non-competitively in the sample of auctions in which the winning bid is above the median. The fact that marginal winners have smaller backlog than marginal losers for auctions with high winning bids is consistent with presence of collusion among these auctions.

In column (3) and (4), we compare the backlog of marginal second place bidders to those who are ranked lower than second. Unlike between winners and non-winners, there are no compelling reasons to expect bidder backlog to differ between marginal second place bidders and those who are lower ranked even under collusion. For exmaple, if the losing bids are submitted randomly, then the differences in backlog between marginal second place bidders and those who are lower ranked should be zero. The coefficients reported in columns (3) and (4) are both statistically indistinguishable from zero, suggesting that the ranking of losing bids are not systematically related to backlog. The binplots that correspond to the results in columns (3) and (4) are illustrated in the right panels of Figure 1.

2.1 Analysis Using Incumbency Status

A common allocation mechanism used in cartels is market division. One consequence of market division is that incumbents win with high probability. Of course, the mere fact that incumbents win more frequently may simply reflect cost heterogeneity across firms. In order to distinguish between incumbency patterns generated by cost heterogeneity and that generated by non-competitive bidding, we compare whether or not a marginal winner is more likely to be an incumbent than a marginal non-winner.

In order to define incumbency status, we determine, for each auction, whether or not


????; ???; ???; ???; ???; ????; ???; ???; ???; ???; ???
utilnm365
p= 0.116 (26.18, 139.27)
p= 0.188 (21.44, 118.70)
q0_q50 (WBP: 0.206 - 0.973)
p= 0.001 (28.24, 152.82)
p= 0.565 (21.21, 121.28)
q50_q100 (WBP: 0.931 - 1.000)

there exists another auction in the past with the same project name. If bidder i in the auction is the winner of the most recent previous auction with the same name, we set incumbency, I_{it}, to be equal to one for bidder i, and zero, otherwise. For most auctions, there is no incumbent as there are no other auctions with the same project name. There are a total of 330 auctions for which there is an incumbent.

The estimating equation is as follows:

$$\beta = \lim_{\Delta_{it} \searrow +0} \mathbf{E}[inc_{it}|\Delta_{it}] - \lim_{\Delta_{it} \nearrow -0} \mathbf{E}[inc_{it}|\Delta_{it}].$$

where inc_{it} is a dummy variable that is equal to 1 if firm i is an incumbent in auction t and Δ_{it} is the difference between the bid of firm i and the bid of its most competitive rival, defined as before. We estimate equation (**??**) on the sample in which there exists an incumbent, using the same estimator as before.

Table 2 reports the estimation results. Column (1) and (2) correspond to the sample of auctions in which the winning bid is below the median and above the median, respectively. We find that the estimate of β is -0.177 in column (1) and it is not statistically significant. In column (2), we find that the estiamte is -0.390 and it is statistically significant. The estimate implies that that marginal winners are 39 percentage points more likely to be an incumbent compared to marginal losers. The fact that we estimate a coefficient that is statistically different from zero in column (2) suggests that bidding behavior is inconsistent with competitive bidding in the sample of auctions with a winning bid that is above the median. In columns (3) and (4) we report the estimates of a regression model in which we replace Δ_{it} with Δ_{it}^2, but otherwise identical as equation (**??**). We find that our estimates are not statistically significant, implying that marginal second place bidders are no more likely to be an incumbent than bidders who are lower ranked. The bin plots that correspond to the regressions are given in panels (1) through (4) of Figure 2.

	Marginally Lowest		Marginally 2nd Lowest	
	Below Median	Above Median	Below Median	Above Median
	(1)	(2)	(3)	(4)
Δ_{it}	-0.177 $(-0.505, 0.152)$	-0.390^{***} $(-0.643, -0.141)$	-0.082 $(-0.231, 0.074)$	0.002 $(-0.120, 0.121)$
Obs.	$1,139$	$1,076$	932	807

95% confidence interval in parentheses.

*p<0.10, **p<0.05, ***p<0.01

Table 3: