Kawai, Nakabayashi, Ortner and Chassang (2023, REStud)

Student Presentation in Empirical Industrial Organization

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https://yasu0704xx.github.io

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- Consider first-price sealed-bid auctions.
- Cartels participating in procurement auctions frequently use bid rotation or prioritize incumbents to allocate contracts.
- However, establishing a link between observed allocation patterns and firm conduct has been difficult: Cartels? Cost-based competition?
- Kawai et al. (2023)
  - Focus on auctions in which the winning and losing bids are very close
  - Discriminate between competition and non-competitive bid rotation and incumbency patterns, relying on RD-type analysis
- Empirical examples
  1. Ohio milk auctions (Porter and Zona, 1999)
  2. Auctions for construction projects let by municipalities in Tohuku, Japan

Contents

Empirical Strategy

How to Detect Cartels?

- For distinguishing between competition and collusion, Kawai et al. (2023) compare the backlog and incumbency status of a bidder who wins the auction by a small margin to those of a bidder who loses by a small margin.
- Their tests of non-competitive behavior seek to detect discontinuities in the distribution of backlog, incumbency status, or other economically relevant covariates around close winners and close losers.

Key Ideas

- Competition $\Rightarrow$ Local Randomization $\Rightarrow$ No Discontinuity
- Cartel $\Rightarrow$ Collusive Bidding $\Rightarrow$ Discontinuity

Local Randomization under Competition

- Under competition, bids are, of course, endogenous.
- That is, bidders' characteristics such as size of backlog or incumbency status will surely affect both bidders' choice and an auction result.
- Local randomization: Focusing only on winners and losers whose bids are close, characteristics of such bidders' should be almost balanced JUST BELOW and AT the winning bid price, respectively.
- Thus, under competition, differences in backlog or incumbency status between close winners and close losers should vanish.

Collusive Bidding under Cartel

- Under cartel, on the other hand, bids are generated by collusive bidding.
  - Bid rotations
  - Incumbents
- The above local randomization does not hold here anymore, and the differences in backlog or incumbency status between close winners and close losers need not disappear.

Regression Discontinuity Approach

- Let $\Delta_{i,t} \equiv b_{i,t} - \wedge b_{-i,t}$ denote the difference between the bid of firm i, and the most competitive (second lowest) alternative bid at time t.
  - If $\Delta_{i,t} < 0$, bidder i wins the auction; if $\Delta_{i,t} > 0$, bidder i loses.
- Let $x_{i,t}$ be a measure of firm i's backlog before bidding at time t.
- Define β as the difference in average backlog/incumbency status between close losers and close winners:

$$\beta = \lim_{\epsilon \downarrow 0^+} \mathbb{E}[x_{i,t} | \Delta_{i,t} = \epsilon] - \lim_{\epsilon \uparrow 0^-} \mathbb{E}[x_{i,t} | \Delta_{i,t} = \epsilon] \tag{1}$$

  - They pool across bidder i and acution t when computing $\widehat{\beta}$.
- Test the null $\mathbb{H}_0 : \beta = 0$.
  - When x denotes backlog, β should satisfy $\beta > 0$ under bid rotation
  - When x denotes incumbency status, β should satisfy $\beta < 0$ under prioritized incumbents
- Reject $\mathbb{H}_0 \implies$ Reject "competition" (some evidence of collusion)

Ohio School Milk Auctions

Ohio School Milk Auctions: Porter and Zona (1999)

- Porter and Zona (1999) study bidding on school milk auctions using data collected by the state of Ohio as part of its efforts to sue dairies for bid rigging.
- School districts hold auctions every year, typically between May and August to determine the supplier of milk for the following school year.
- The dataset includes bids from three bidders located around Cincinnati that were charged for collusion.

Summary Statistics of Auctions

TABLE 1

Summary statistics of auctions: Ohio school milk auctions

	(1) All	(2) Non-competitive		(3) Control	
	All years	All years	Excl 83,89	All years	Excl 83,89
No. of bidders	1.866	1.983	2.058	1.763	1.770
	(0.909)	(0.891)	(0.882)	(0.838)	(0.846)
Winning bid	0.131	0.136	0.138	0.131	0.131
	(0.013)	(0.015)	(0.015)	(0.013)	(0.013)
2nd lowest bid	0.135	0.142	0.144	0.135	0.135
	(0.013)	(0.015)	(0.014)	(0.012)	(0.013)
3rd lowest bid	0.138	0.147	0.149	0.138	0.137
	(0.013)	(0.016)	(0.014)	(0.012)	(0.012)
Obs.	3,754	235	189	3,267	2,658

Notes: The first column corresponds to the set of all auctions, the second column corresponds to the set of auctions in which only the defendant firms bid, and the last column corresponds to those in which no defendant firm bid.

Summary Statistics on Incumbency

TABLE 2

Summary statistics on incumbency: Ohio school milk auctions

	(1) All			(2) Non-Competitive			(3) Control		
	Win/Inc	Ratio	Total	Win/Inc	Ratio	Total	Win/Inc	Ratio	Total
1980	.	.	249	.	.	4	.	.	230
1981	136/185	0.74	273	6/7	0.86	12	123/162	0.76	235
1982	148/188	0.79	287	9/10	0.90	13	131/161	0.81	252
1983	162/214	0.76	318	7/10	0.70	16	150/187	0.80	274
1984	199/249	0.80	339	18/20	0.90	24	174/215	0.81	293
1985	205/260	0.79	357	18/18	1.00	22	177/226	0.78	314
1986	242/293	0.83	378	16/19	0.84	25	216/255	0.85	332
1987	236/287	0.82	411	18/20	0.90	27	211/255	0.83	358
1988	253/304	0.83	419	18/20	0.90	28	227/263	0.86	359
1989	257/332	0.77	392	13/19	0.68	30	236/289	0.82	335
1990	185/247	0.75	331	17/29	0.59	34	165/211	0.78	285
Obs.		3,754			235			3,267	

Notes: Column (1) corresponds to the set of all auctions, Column (2) corresponds to the set of auctions in which only the defendant firms bid, and the Column (3) corresponds to those in which no defendant firm bid.

Histogram of $\Delta_{i,t}$

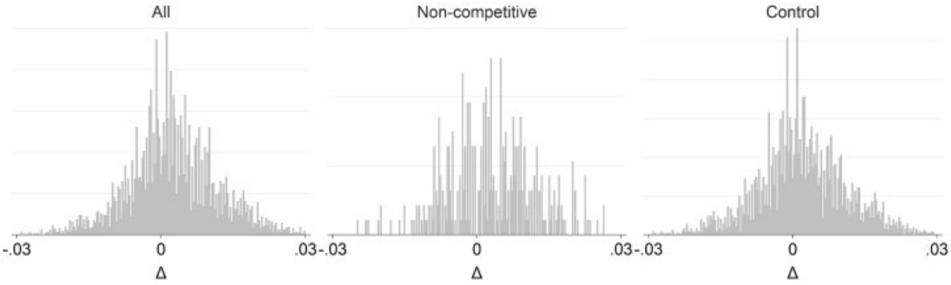

FIGURE 2

Histogram of $\Delta_{i,t}$: Ohio school milk auctions

Notes: The left panel corresponds to the sample of all auctions, the middle corresponds to the sample of non-competitive auctions and the right panel corresponds to the set of competitive auctions. The horizontal axis is units of dollars.

RD Estimates

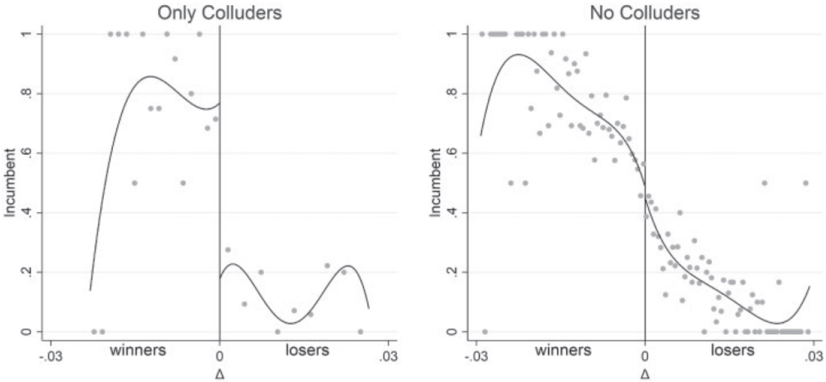

FIGURE 3

Binned scatter plot for incumbency: Ohio school milk auctions

Notes: Left panel corresponds to Column (2) Panel (A) of Table 3 and right panel corresponds to Column (1), Panel (B) of Table 3. The curves in the figure correspond to fourth order (global) polynomial approximations of the conditional means.

RD Estimates

TABLE 3
Regression discontinuity estimates: Ohio school milk auctions

	(1)	(2)
	Incumbency	
	All years	Exclude 1983 and 1989
Panel (A)		
Non-competitive auctions		
$\hat{\beta}$	−0.312*	−0.379**
	(0.177)	(0.181)
h	0.004	0.005
Obs.	309	266
Panel (B)		
Control		
$\hat{\beta}$	−0.031	−0.068
	(0.063)	(0.062)
h	0.004	0.005
Obs.	3,053	2,455

Panel (A) corresponds to the sample of auctions in which only the defendant bidders bid. Panel (B) corresponds to the sample of control auctions in which none of the defendant bidders bid. Standard errors are clustered at the level of the school district and reported in parenthesis. The table also reports the bandwidth h used for the estimation. *, **, and ***, respectively denote significance at the 10%, 5%, and 1% levels.

Procurement Auctions in Japan

Public Procurement Auctions in Japan

- Data: Bids submitted by construction firms participating in auctions for construction projects let by municipalities in the Tohoku region of Japan
- Roughly 11,000 procurement auctions let by 16 municipalities between 2004-2018
- No firm has been charged for colluding in any of the auctions in their sample.
- However, Kawai and Nakabayashi (2022) and Chassang et al. (2022) suggest that some of these auctions are collusive.

Summary Statistics of Auctions and Bidders

TABLE 4

Summary statistics of auctions and bidders: municipal auctions from Japan

	(1) Auctions		(2) Bidders	
	Mean	Std. Dev.	Mean	Std. Dev.
Reserve (Mil. Yen)	22.26	77.14		
Winning bid (Mil. Yen)	20.71	71.78		
Win bid/reserve	0.926	0.083		
No.# of bidders	6.80	4.21		
Incumbent participates (0/1)	0.044	0.204		
No.# of auctions participated			22.56	45.93
No. of wins			3.32	6.97
Raw backlog (90-day)			4.11	17.16
Raw backlog (180-day)			6.45	22.85
Obs.	11,207		3,377	

Notes: The reserve price, winning bid, and backlog measures are reported in units of millions of yen.

Histogram of $\Delta_{i,t}$

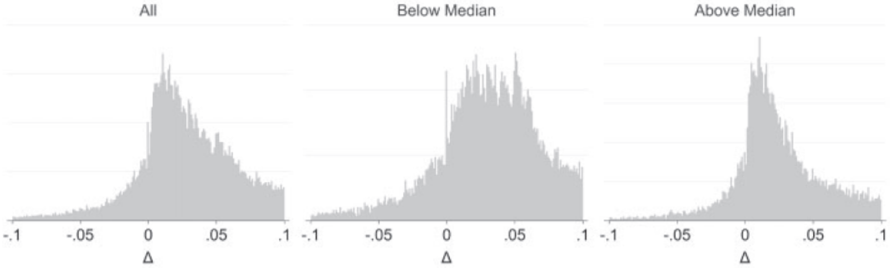

FIGURE 4

Histogram of $\Delta_{i,t}$: municipal auctions from Japan

Notes: The left panel corresponds to the histogram of $\Delta_{i,t}$ for the entire sample. The middle panel corresponds to the sample of bids below the median winning bid of the relevant municipality. The right panel corresponds to the sample of bids above the median. The histogram is truncated at $\Delta_{i,t} = -0.1$ and $\Delta_{i,t} = 0.1$ for readability.

RD Estimates

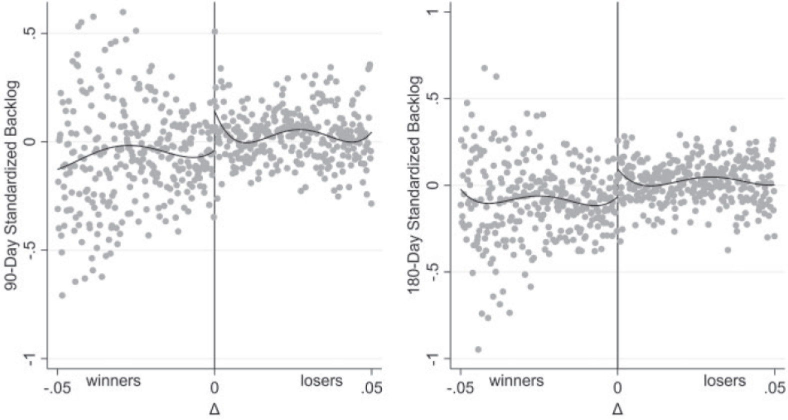

FIGURE 5

Binned scatter plot for 90-day and 180-day standardized backlog: municipal auctions from Japan

Notes: The curves in the figure correspond to fourth-order (global) polynomial approximations of the conditional means.

RD Estimates

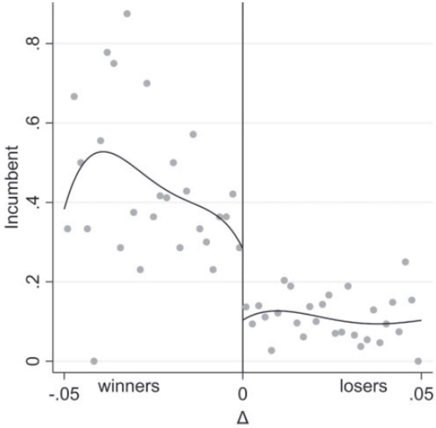

FIGURE 6

Binned scatter plot for incumbency: municipal auctions from Japan

Notes: The curves in the figure correspond to fourth-order (global) polynomial approximations of the conditional means.

RD Estimates

TABLE 5
Regression discontinuity estimates: municipal auctions from Japan

	(1)	(2)	(3)	(4)	(5)
	90-day backlog		180-day backlog		Incumbent
	Standardized	Raw	Standardized	Raw	
$\hat{\beta}$	0.136***	3.782*	0.147***	6.747**	−0.184**
	(0.038)	(2.250)	(0.038)	(3.157)	(0.078)
h	0.020	0.016	0.022	0.015	0.026
Obs.	59,367	63,742	59,413	63,742	2,517

Notes: Standard errors are clustered at the auction level and reported in parenthesis. The table also reports the bandwidth h used for the estimation. *, **, and ***, respectively denote significance at the 10%, 5%, and 1% levels.

Conclusion

Conclusion

- It has been difficult to identify allocation patterns that reflect agreements among cartels from those that simply reflect bidder cost heterogeneity.
- Kawai et al. (2023) make this possible by conditioning on auctions that are determined by a close margin.
- Their approach is fairly robust to model mis-specification, since they rely on nonparametric LPR.
- Any observed covariate suspected to reflect collusive strategies can be exploited.
    - e.g., geographic segmentation, sub-contracting, joint bidding

Appendix:
Game Theoretic Explanations

Theoretical Foundations (Sections 2 and 4)

- For all histories $h_{i,t} = (\theta_t, z_{i,t})$ and bids $b \in [0,1]$, define bidder i's residual demand as

$$D_i(b \mid h_{i,t}) \equiv \mathbb{P}\left(\wedge b_{-i} \succ b\right).$$

  $D_i(b \mid h_{i,t})$ is the probability with which firm i expects to win the auction at history $h_{i,t}$ if she places bid b.

- The probability that bidder i wins conditional on submitting a close bid satisfies

$$\mathbb{P}\left(\{i \text{ wins} \mid h_{i,t}\} \text{ and } \{|b_{i,t} - \wedge b_{-i,t}| \le \epsilon\}\right) = \frac{D_i(b_{i,t}|h_{i,t}) - D_i(b_{i,t}+\epsilon|h_{i,t})}{D_i(b_{i,t}-\epsilon|h_{i,t}) - D_i(b_{i,t}+\epsilon|h_{i,t})} \tag{2}$$

- It follows that whenever D_i is strictly decreasing and continuously differentiable, then, for a bid-difference ϵ small, the probability of winning conditional on close winning and losing bids is approximately $\frac{1}{2}$, regardless of history $h_{i,t}$.

Lemma 1 (Smooth Demand)

Assume that $D_i(\cdot \mid h_{i,t})$ is differentiable, with $D_i'(b_i \mid h_{i,t})$ strictly negative and continuous in bids $b_i \in [0,1]$. For all $\eta > 0$, there exists $\epsilon > 0$ small enough such that, for all histories $h_{i,t}$,

$$\left|\mathbb{P}\left(\{i \text{ wins} \mid h_{i,t}\} \text{ and } \{|b_{i,t} - \wedge b_{-i,t}| \leq \epsilon\}\right) - \frac{1}{2}\right| \leq \eta. \tag{3}$$

- Lemma 1 implies the following corollary.

Corollary 1

For all $\eta > 0$, there exists $\epsilon > 0$ small enough such that, for all $x \in X$,

$$|\mathbb{P}\left(x_{i,t} = x | \Delta_{i,t} \in (0, \epsilon)\right) - \mathbb{P}\left(x_{i,t} = x | \Delta_{i,t} \in (-\epsilon, 0)\right)| < \eta.$$

- In words, the distribution of covariates $x_{i,t}$ observable to the econometrician has to be the same for marginal winners and marginal losers.
- Whenever X is finite, Corollary 1 implies that the expectation of xi,t conditional on Δ must be continuous around $\Delta = 0$.

Remark 1

Conditional on winning, bidder i's continuation value $V_i(1, b_i \mid h_i)$ does not depend on her own bid b_i.

Definition 1

We say that bidding behavior is sensitive if there exists h_i such that expected continuation value $v_i(0, b, b' \mid h_i)$ is not Lipschitz continuous in b, b'.

Definition 2

We say that a Markov perfect equilibrium σ is competitively enforced if bidding behavior under σ is not sensitive.

Proposition 1 (Equilibrium Beliefs Conditional on Close Bids)

Consider an environment ε *and an MPE* σ *that is competitively enforced. For all* $\eta > 0$, *there exists* $\epsilon > 0$ *small enough such that, for all histories* $h_{i,t} = (\theta_t, z_{i,t})$ *and bid* $b_{i,t} \in (\epsilon, 1-\epsilon)$,

$$\mathbb{P}_\sigma \left(\{i \textit{ wins} \mid h_{i,t}\} \textit{ and } \{|b_{i,t} - \wedge b_{-i,t}| < \epsilon\}\right) \geq \frac{1}{2} - \eta.$$

Corollary 2 (As-if Random Bids)

Consider an environment ε *and MPE* σ *that is competitively enforced. For all* $\eta > 0$, *there exists* $\epsilon > 0$ *small enough such that*

$$\mathbb{E}_{\varepsilon,\sigma}\left[\left|\mathbb{P}_\sigma(\{i \textit{ wins} \mid h_{i,t}\} \textit{ and } \{|b_{i,t} - \wedge b_{-i,t}| < \epsilon\}) - \frac{1}{2}\right| \Big| \epsilon\textit{-close}\right] \leq \eta. \tag{4}$$

Appendix:
Robust Bias-Corrected RD

Estimation and Inference

- Kawai et al. (2023) estimate β in (1) by local polynomial regressions (LPRs).
- For inference, they rely on a bias-correction procedure developed by Calonico, Cattaneo and Titiunik (2014).

Estimation

- Let $b_0^+ = \lim_{\epsilon \downarrow 0^+} \mathbb{E}[x_{i,t} | \Delta_{i,t} = \epsilon]$ and $b_0^- = \lim_{\epsilon \uparrow 0^-} \mathbb{E}[x_{i,t} | \Delta_{i,t} = \epsilon]$. For estimating β in (1), it suffices to estimate b_0^+ and b_0^-.
- Consider the following LPRs with polynomial order $p = 1$ (i.e., local linear regressions):

$$\left(\widehat{b_0^+}, \widehat{b_1^+}\right) = \arg\min \sum_{i,t}^{T} \left(X_{i,t} - b_0^+ - b_1^+ \Delta_{i,t}\right)^2 K\left(\frac{\Delta_{i,t}}{h_n}\right) 1(\Delta_{i,t} > 0),$$

$$\left(\widehat{b_0^-}, \widehat{b_1^-}\right) = \arg\min \sum_{i,t}^{T} \left(X_{i,t} - b_0^- - b_1^- \Delta_{i,t}\right)^2 K\left(\frac{\Delta_{i,t}}{h_n}\right) 1(\Delta_{i,t} < 0),$$

  where h_n is the bandwidth and $K(\cdot)$ is the kernel.
- Then, β can be estimated by $\widehat{\beta} = \widehat{b_0^+} - \widehat{b_0^-}$.
- The (asymptotic) MSE optimal bandwidth satisfies $h_n \propto n^{-\frac{1}{5}}$.

Inference

- For inference, the (asymptotic) MSE optimal bandwidth should be avoided: The (A)MSE optimal bandwidth does not address the asymptotic bias $\mathcal{B}$ appearing in

$$\sqrt{nh_n}\left(\widehat{\beta} - \beta - {h_n}^2\mathcal{B}\right) \xrightarrow{d} \text{Normal}(0, \mathcal{V}).$$

- Calonico, Cattaneo and Titiunik (2014) propose to correct asymptotic bias for valid inference, not to eliminate the bias (e.g., by undersmoothing).
- Let $\hat{\mathcal{B}}$ denote the estimator of $\mathcal{B}$ based on LPRs using bandwidth b_n, which can differ from h_n. The bias-corrected estimator of β is given by

$$\widehat{\beta^{\text{bc}}} \equiv \widehat{\beta} - {h_n}^2\widehat{\mathcal{B}}.$$

- Under certain conditions on h_n and b_n and regularity conditions, Calonico, Cattaneo and Titiunik (2014) show that the robust bias-corrected t statistic satisfies

$$T^{\mathsf{bc}} \equiv \frac{\sqrt{nh_n}\left(\widehat{\beta}^{\mathsf{bc}} - \beta\right)}{\sqrt{\mathcal{V}^{\mathsf{bc}}}} \xrightarrow{d} \text{Normal}(0, 1),$$

where $\mathcal{V}^{\mathsf{bc}} \equiv \mathcal{V} + \mathcal{C}^{\mathsf{bc}}$ and $\mathcal{C}^{\mathsf{bc}}$ is a correction term.

- Using an estimator of $\mathcal{V}^{\mathsf{bc}}$, the $1-\alpha$ confidence interval of β based on T^{bc} is given by

$$\left[\widehat{\beta}^{\mathsf{bc}} - z_{1-\frac{\alpha}{2}}\sqrt{\frac{\widehat{\mathcal{V}}^{\mathsf{bc}}}{nh_n}}, \quad \widehat{\beta}^{\mathsf{bc}} + z_{1-\frac{\alpha}{2}}\sqrt{\frac{\widehat{\mathcal{V}}^{\mathsf{bc}}}{nh_n}}\right].$$