A Study of Bid-rigging in Procurement Auctions: Evidence from Indonesia, Georgia, Mongolia, Malta, and State of California*

Kei Kawai[†], Jun Nakabayashi[‡], and Daichi Shimamoto[§]

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Abstract

We apply a Regression Discontinuity based approach to screen for collusion developed in Kawai et al. (2022) to public procurement data from five countries. We find that bidders who win by a very small margin have significantly lower backlog than those who lose by a very small margin in the sample of procurement auctions from Indonesia, suggesting that bidders collude by bid rotation. Our results suggest that the proportion of noncompetitive auctions is at least about 5% for all E-procurement auctions and about 3% for all auctions in Indonesia. We cannot reject the null of competition in other countries.

KEYWORDS: collusion, antitrust, procurement.

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†U.C. Berkeley, kei@berkeley.edu

‡Kyoto University, nakabayashi.jun.8x@kyoto-u.ac.jp

§Kindai University, d.shimamoto@eco.kindai.ac.jp

1 Introduction

Both developed and developing countries spend substantial sums of money on public procurement, averaging about 12% of the national GDP across countries in the world (Bosio et al., 2022). Competitive tendering, in particular auctions, is the preferred method of procurement for many governments and aid organizations.[1] Hence, the efficiency of public spending is often closely tied to the efficiency of public procurement auctions. To the extent that efficiency of public procurement auctions varies across countries, these differences may account for a significant proportion of productivity differences across countries.

One major challenge in achieving efficiency in competitive tendering is collusion amongst bidders. Collusive agreements often distort allocation away from the efficient outcome (McAfee and McMillan, 1992, Athey and Bagwell, 2008) and increase prices leading to wasted tax dollars or, in the case of developing countries, foreign aid. For developing countries, relatively little emphasis has been placed on eliminating collusion until now, however. Much of the effort at improving the efficiency of competitive tendering has been channeled towards reducing corruption.[2]

In this paper, we study bidding in public procurement auctions from three developing countries, Indonesia, Georgia, and Mongolia as well as from Malta and the U.S. (California). The set of countries that we analyze are determined by ease of access to bidding data. For Indonesia, we analyze an existing dataset studied previously by Lewis-Faupel et al. (2016). The data for other countries were collected by ourselves from the web pages of the respective public procurement agencies. Using a strategy for detecting collusion proposed in Kawai et al. (2022b), we find evidence of wide-spread bid-rigging in Indonesia. We cannot reject

[1]For example, the United Nations Commission on International Trade Law has adopted a model law on public procurement aimed at helping developing countries revise existing procurement laws or formulate new ones. Article 28 of the model law stipulates that "Except as otherwise provided for in articles 29 to 31 of this Law, a procuring entity shall conduct procurement by means of open tendering."

[2]Several aid organizations including the Millennium Challenge Corporation make fighting corruption a precondition for providing aid. See Olken and Pande (2012), for a survey of corruption in developing countries.

the null of competition for other datasets.

Because collusion is illegal in all of the countries that we study,[3] identifying collusion from bidding data is not straightforward. In this paper, we detect collusion by identifying collusive bid rotation patterns using ideas based on regression discontinuity (RD) design. Bidding rings often allocate projects by rotation in which ring members take turns winning the auction, an implication of which is that the winner often has lower backlog (amount of recently awarded contracts) than the losers. In order to distinguish collusive bid rotation patterns from similar patterns that may arise under competition (say, due to capacity constraints), our detection method focuses on sharp differences in the backlog between winners and losers who submit nearly identical bids. Our focus on marginal winners and marginal losers allows us to distinguish rotation patterns that arise under competition from those that arise as a result of collusion.

In order to understand the logic of our test, suppose that bidders are bidding competitively. Even for relatively simple public works projects, estimating the cost of projects typically consists of determining the costs for hundreds of components including various materials, labor and equipment use. As long as we condition on auctions in which the bids are almost tied, it is intuitive to imagine that small idiosyncrasies in the process of estimating each of these cost components could have resulted in either firm to win the auction. In other words, winning or losing is as-if random conditional on close bids. Hence, under the null of competition, a high-backlog bidder is just as likely to be a winner as a loser, and similarly for a low-backlog bidder *conditional on the bids being very close*. Systematic differences in the backlog between the marginal winner and the marginal loser are unlikely to result under the null of competition, suggesting coordinated bidding. Kawai et al. (2022b) formalize these ideas in the context of a dynamic game setting in which bidders repeatedly participate in auctions.

[3]Article 22 of the Law of the Republic of Indonesia No 5 of 1999, Article 7 of the Law of Georgia No 2159 of 21 March 2014, Article 7.1.4 of Law on Prohibiting Unfair Competition, for Mongolia, The Maltese Competition Act, Chapter 379 of the Laws of Malta, and Section 1 of the Sherman Act for the U.S.

We implement our test in the form of a RD test. In particular, we take the backlog of firm i at time t as the outcome variable and take the running variable to be the margin of victory or defeat, i.e., $\Delta_{i,t} \equiv b_{i,t} - \wedge \mathbf{b}_{-i,t}$, where $b_{i,t}$ is firm i's bid in auction t and $\wedge \mathbf{b}_{-i,t}$ is the lowest bid among its competitors. We then test whether or not the expected backlog when $\Delta_{i,t}$ converges to 0 from the right equals the expected backlog when $\Delta_{i,t}$ converges to 0 from the left. Discontinuity in the outcome variable at $\Delta_{i,t} = 0$ is evidence against competition.

Based on our test, we find that there is wide-spread collusion in Indonesia, suggesting that large amounts of government taxes and foreign aid were wasted in the country to collusion. Our results suggest that, among the set of almost-tied auctions let by the Indonesian Ministry of Public Works, the proportion of noncompetitive auctions is at least about 5% for E-procurement auctions and at least about 3% for all auctions. The true extent of collusion is probably even much higher since our test is conservative and has power only against cartels that allocate projects based on a rotation scheme. Our findings highlight the importance of reducing collusion for efficient provision of public goods.

As for countries other than Indonesia, we do not find evidence of bid rigging with our screen although this should not be interpreted as implying that auctions are necessarily competitive. Our test has power only against bidding rings that use rotation schemes, and moreover, the power of our test is limited against bidding rings that allocate both public and private projects given that our backlog measures are constructed from public procurement data alone. Our screen should best be thought of as a diagnostic tool that can flag noncompetitive behavior in some settings but not in others.

Related Literature There is a large literature on collusion in public procurement auctions, primarily focused on developed countries (e.g., Hendricks and Porter (1988), Porter and Zona (1993, 1999), Abrantes-Metz et al. (2006), Conley and Decarolis (2016), Schurter

(2017), Chassang and Ortner (2019), Kawai and Nakabayashi (2022)).[4] Outside of developed countries, recent work by Baránek et al. (2021) document evidence of collusion in Ukraine and Silveira et al. (2022) in Brazil, but there is still not a lot of work.[5] Our findings from Indonesia provide support to the view that preventing collusion should be an important focus for improving public procurement in developing countries.

For developing countries, there is a much larger literature that studies corruption in public procurement (see, e.g., Olken (2007), Zamboni and Litschig (2018), Mironov and Zhuravskaya (2016), Andreyanov et al. (2016), Bosio et al. (2022)). There is also a closely related literature that documents distortions in the allocation of government contracts toward politically connected firms (e.g., Burgess et al. (2015), Lehne et al. (2018)).[6] Corruption can sometimes strengthen collusion and vice versa (Lambert-Mogiliansky, 2011).

More specific to the Indonesian context, the fact that we find evidence of collusion in Indonesia helps interpret the results of Lewis-Faupel et al. (2016) who study the impact of introducing electronic procurement (E-procurement) in Indonesia. Somewhat surprisingly, Lewis-Faupel et al. (2016) find "no systematic evidence that electronic procurement lowers prices paid by the government" (p.260).[7] The results of our paper suggest that the lack of any systematic price effect is likely due to collusion. We find evidence of widespread collusion even after the introduction of E-procurement in Indonesia, suggesting that the introduction of E-procurement did not diminish the ability of contractors to collude. Widespread collusion among firms in Indonesia is likely to have eliminated any possible gains from

[4]Other related work include Bajari and Ye (2003) who find evidence of collusion in auctions for seal-coat contracts, Athey et al. (2011), who find collusion in forest timber auctions, Ishii (2009) and Chassang et al. (2022), who find evidence of collusion in Japanese procurement auctions. There are recent papers that utilize machine learning, such as Huber and Imhof (2019) and Imhof and Wallimann (2021). There are also papers that study the internal organization of cartels such as Asker (2010), Pesendorfer (2000), Clark et al. (2020), Kawai et al. (2022a). See Harrington (2008) and Asker and Nocke (2021) for a survey.

[5]This is not to say that there aren't any reports of bid rigging in developing countries. A document titled "Ex officio cartel investigations and the use of screens to detect cartels" published by the OECD summarizes the efforts and experience of various governments, both developed and developing, to screen for cartels.

[6]See Bandiera et al. (2009) and Decarolis et al. (2020) for evidence of passive waste in government procurement.

[7]Lewis-Faupel et al. (2016) find evidence that E-procurement results in quality improvements.

reduction in corruption associated with E-procurement auctions.

2 Framework for Detecting Collusion

In this section, we briefly discuss the detection method developed in Kawai et al. (2022b) which we apply to our setting.[8] The basic idea in Kawai et al. (2022b) is that under the null of competition, any bidder, regardless of its characteristic, is just as likely to be the winner as the loser *conditional on being one of the two lowest bidders in a very close auction*. This implies that a firm with a high level of backlog will be the marginal winner half of the time and the marginal loser in the other half, and similarly for a firm with a low level of backlog. Winning and losing are "as-if-random" conditional on close bids.

This idea can be used to construct a test based on the logic of regression discontinuity that has correct size under the null of competition. Consider a test statistic β_ϵ equal to the difference in the average backlog between winners who win by less than ϵ and the average backlog of losers who lose by less than ϵ. Under the null, β_ϵ should converge to zero as ϵ approaches zero even if the level of backlog affects costs. If instead, bids are generated by collusive bidding, the differences in backlog between close winners and close losers need not disappear. For example, if bidding rings always allocate projects using a bid rotation scheme, marginal winners will always have lower backlog than close losers.[9] Our test of collusive behavior seeks to detect discontinuities in the amount of backlog between close winners and close losers.

To formalize the foregoing discussion, define the T-day backlog of firm i at auction t by

[8]In Kawai et al. (2022b), we apply the detection method to bidding data from a well-known cartel case in Ohio and to procurement data from public works contracts in Japan.

[9]Optimal bidding by a cartel often requires the bid difference between the winner and the loser to be close to zero in order to incentivize the winning bidder not to deviate, see e.g., Marshall and Marx (2007, 2012) and Chassang and Ortner (2019).

adding together the value of the auctions won by firm i in the T days prior to auction t:

$$B_{i,t}^{T}=\sum_{\tau\in A_{i,t}^{T}} b_{i,\tau}\mathbf{1}_{\{i \text{ wins auction } \tau\}},$$

where $b_{i,\tau}$ is bidder i's bid in auction τ, $\mathbf{1}_{\{\cdot\}}$ is an indicator function, and $A_{i,t}^{T}$ denotes the set of auctions in which bidder i participates that take place within the T day window leading up to, but not including, the day of auction t.[10]

As for the running variable, for each auction t and each bidder i, we define $\Delta_{i,t}$ to be the margin (as a percentage of the reserve price) by which bidder i won or lost:

$$\Delta_{i,t}=\frac{b_{i,t}-\min_{j\neq i} b_{j,t}}{r_t}, \tag{1}$$

where r_t is the reserve price of auction t. Note that $\Delta_{i,t}$ is negative for the lowest bidder and positive for all other bidders. Values of $\Delta_{i,t}$ close to zero imply that bidder i was a close winner or a close loser. The rationale for normalizing the bid difference by r_t is to scale all observations in terms of percentages.

The test statistic that we use to detect collusion is as follows:

$$\beta=\lim_{\Delta_{i,t}\searrow 0^{+}}\mathbf{E}[Y_{i,t}|\Delta_{i,t}]-\lim_{\Delta_{i,t}\nearrow 0^{-}}\mathbf{E}[Y_{i,t}|\Delta_{i,t}],$$

where $Y_{i,t}$ is equal to log backlog, $\log(1+B_{i,t}^{T})$, for T equals to 30, 60, 90, or 120 days.[11] If a cartel allocates contracts using a rotation scheme, we expect β to be strictly positive.

[10]We acknowledge that our measure of backlog misses work completed for private buyers. To the extent that cartel allocates projects for public and private buyers, our measure of backlog is going to capture only a subset of the backlog relevant for allocation. Note that this measurement error affects the power of the test but not its consistency.

[11]The rationale for using log backlog as the outcome variable is to give weight to observations from small firms. Backlog has a very skewed distribution, which means that if we use raw backlog as the outcome measure, our results will be driven mostly by observations from very large firms.

We estimate β using a local linear regression as follows:

$$\widehat{\beta} = \widehat{b_0^+} - \widehat{b_0^-}, \text{ with}$$
$$(\widehat{b_0^+}, \widehat{b_1^+}) = \arg\min \textstyle\sum_{i,t}^{T} (Y_{i,t} - b_0^+ - b_1^+ \Delta_{i,t})^2 K\left(\frac{\Delta_{i,t}}{h_n}\right) \mathbf{1}_{\Delta_{i,t}>0},$$
$$(\widehat{b_0^-}, \widehat{b_1^-}) = \arg\min \textstyle\sum_{i,t}^{T} (Y_{it} - b_0^- - b_1^- \Delta_{i,t})^2 K\left(\frac{\Delta_{i,t}}{h_n}\right) \mathbf{1}_{\Delta_{i,t}<0},$$

where h_n is the bandwidth and $K(\cdot)$ is the kernel. Note that we pool across bidders i and auction t when computing $\widehat{\beta}$. We use a coverage error rate optimal bandwidth and a triangular kernel with a bias correction procedure as proposed in Calonico et al. (2014). We test the null $H_0 : \beta = 0$, against the alternative $H_1 : \beta \neq 0$.

3 Results

We apply our test to data sets from five countries, Indonesia, Georgia, Mongolia, Malta, and the U.S. (California). Table 1 summarizes the key features of the data from each country. We also report the ranking of the countries that we study with respect to the competition law index, a measure of the stringency of competition regulation for 116 countries constructed by Bradford and Chilton (2018).[12]

3.1 Indonesia

We study bidding in public works auctions let by the Ministry of Public Works (MPW) between 2004 and 2008. Our sample corresponds to the subset of auctions studied by Lewis-Faupel et al. (2016) that excludes consulting contracts.[13] The auction format is first-price

[12] We use the exception-adjusted competition law index for 2010, the most recent available year.

[13] Lewis-Faupel et al. (2016) study both public works contracts and consulting contracts let by the MPW. Consulting contracts are awarded using a scoring auction in which the score consists of a combination of a technical score and the price. We do not study consulting contracts in this paper because we do not have access to the data on the technical scores.

	Period	Project Type	Auction Format	Comp. Law Index
Indonesia	2004-2008	Public Works	FPSB, Paper, then Electronic	115th/116
Georgia	2016-2019	Public Works Services, Goods	FPSB, Electronic	NA
Mongolia	2018-2022	Public Works Services, Goods	FPSB, Electronic	82nd/116
Malta	2011-2020	Public Works Services, Goods	FPSB, Electronic	30th/116
California (USA)	2014-2020	Public Works	Both Electronic and Non-electronic	66th/116

Note: Indonesia switches from Paper-based to Electronic in the middle of the sample. Comp. Law Index is a measure of the stringency of competition regulation constructed for 116 countries by Bradford and Chilton (2018).

Table 1: Summary of the Data Sets

sealed bid in which the lowest bidder is awarded the contract subject to meeting minimum administrative and technical qualifications. Indonesia started rolling out electronic procurement auctions during the sample period, replacing manual handling of paper-based bidding documents with online processing.[14] Most auctions at the beginning of the sample are paper based while most auctions towards the end are E-procurement auctions.

Table 2 reports the summary statistics of the auctions and the bidders in the sample. The first column of the top panel corresponds to the summary statistics for the set of all public works auctions in the sample. The second and third columns of the top panel correspond to paper-based and E-procurement auctions, respectively. The bottom panel reports the summary statistics of the bidders.

Focusing on the first column of the top panel, we find that the average lowest bid in the sample is about 2.88 billion rupiahs, or about $21,000 US dollars. There are about 7.3 bidders on average, and the ratio between the lowest bid and the reserve price is about 84%.

[14] The actual bidding takes place in person for both paper-based and E-procurement auctions. See section I.B of Lewis-Faupel et al. (2016) for a detailed discussion.

Table 2: Summary Statistics: Public Works Auctions in Indonesia

	By Auctions					
	All		Electronic		Paper Based	
	Mean	Obs.	Mean	Obs.	Mean	Obs.
Low bid (Million)	2,882 (7,745)	9,382	3,546 (10,182)	4,038	2,380 (5,139)	5,344
# Bids	7.298 (5.083)	9,414	7.705 (5.087)	4,006	6.997 (5.060)	5,408
Reserve (Million)	3,393 (11,892)	9,502	4,317 (16,883)	4,099	2,692 (5,599)	5,403
Low Bid / Reserve	0.844 (0.286)	9,382	0.810 (0.166)	4,038	0.870 (0.347)	5,344

	By Bidders	
	Mean	Obs.
# Participation	11.888 (28.52)	28,077
# Winning	0.338 (1.23)	28,077
30-Day Backlog	61.867 (660.85)	24,191
60-Day Backlog	92.763 (1,032.35)	24,191
90-Day Backlog	111.447 (1,335.47)	24,191
120-Day Backlog	128.049 (1,633.41)	24,191

	30 Days	60 Days	90 Days	120 Days
$\hat{\beta}$	0.522**	0.675**	0.613**	0.665**
	(0.240)	(0.267)	(0.276)	(0.289)
p-value	[0.029]	[0.011]	[0.027]	[0.021]
h	0.023	0.022	0.022	0.022
Obs.	55,506	55,506	55,506	55,506

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

Table 3: RD Estimates for Log Backlog: Public Works Auctions in Indonesia

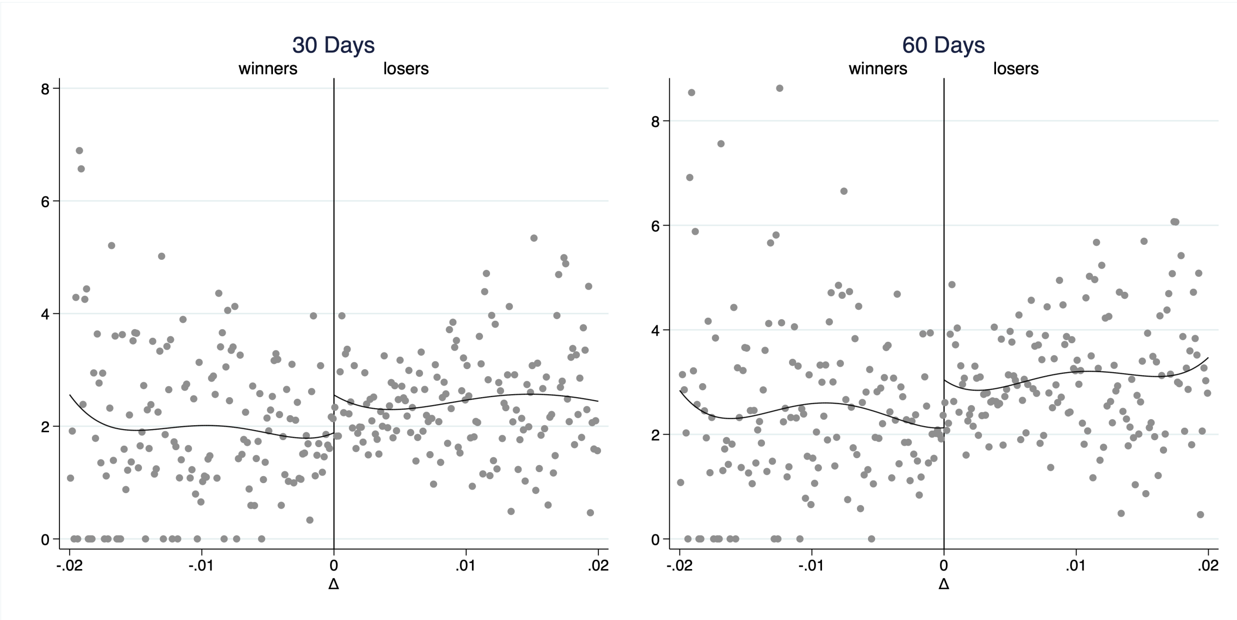
Comparing E-procurement auctions (second column) and paper-based auctions (third column), we find that E-procurement auctions have more bidders, a higher reserve price, and lower lowest bid to reserve ratio, on average. Although the means are quite different between the two sets of auctions, Lewis-Faupel et al. (2016) find that these differences disappear once province and time fixed effects are controlled for.

The bottom panel reports the summary statistics of the bidders. The average bidder participates in about 11.9 auctions during our sample and wins about 0.34 auctions.

We now report the RD estimates that we discussed in Section 2. Table 3 reports the RD estimates for log backlog, $\log(1 + B_{i,t}^T)$, with T equal to 30, 60, 90 and 120 days, for the full sample. The running variable is the margin by which firm i won or lost, $\Delta_{i,t}$, defined in expression (1).[15] We find that our RD estimates are 0.522, 0.675, 0.613 and 0.665, respectively. Our estimates imply, for example, that the 30-day and 60-day log backlog are lower for the marginal winner than for the marginal loser by about 0.522 and 0.675 points. All of these estimates are statistically significant at the 5% level.[16] These results suggest that a significant fraction of the auctions are allocated to members of bidding rings that employ a rotation scheme. Table 3 also reports the coverage-error-rate optimal bandwidth,

[15]Figure OA.1 of the Online Appendix plots the histogram of the running variable.

[16]We conduct the RD tests for 5 countries. The p-values that account for the multiple hypothesis tests are 0.138, 0.056, 0.126, 0.101.



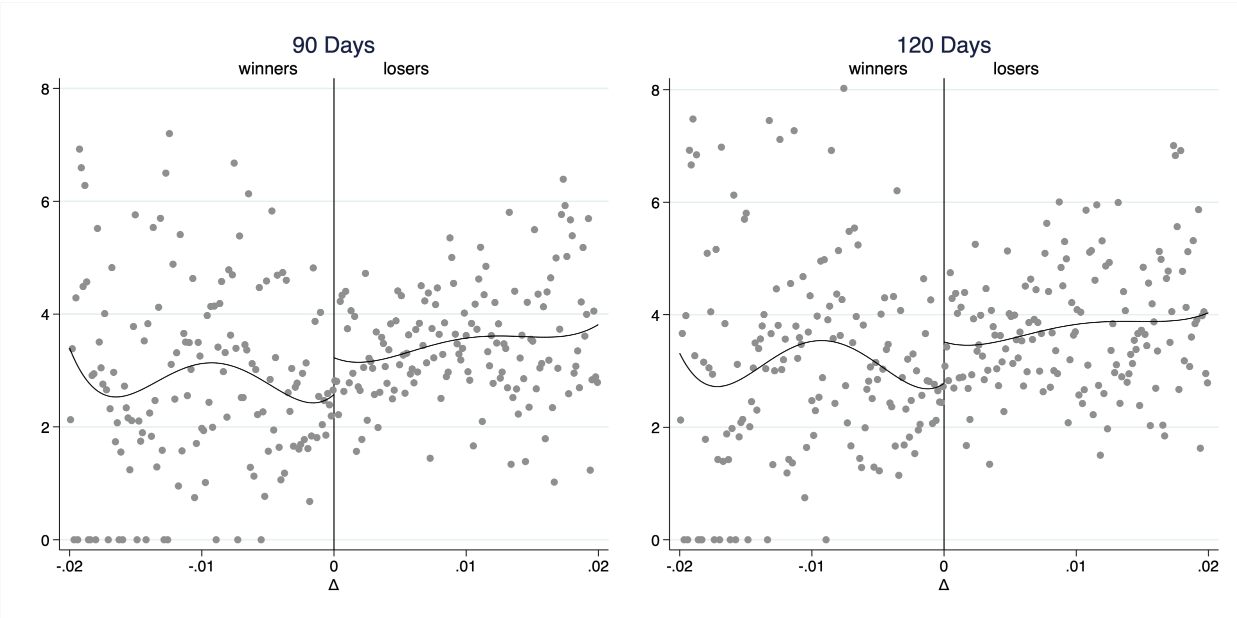
Note: Left panel corresponds to the first column of Table 3. Right panel corresponds to the second column. The curves correspond to 4th order (global) polynomial approximations of the conditional means.

Figure 1: Binned Scatter Plot for 30-Day and 60-Day Log Backlog: Public Works Auctions from Indonesia.

h, used to compute the RD estimates.

Figure 1 corresponds to the binned scatter plot for the first two columns of Table 3. Figure 2 corresponds to the last two columns. For both figures, the horizontal axis is $\Delta_{i,t}$, the margin of victory or defeat. Since $\Delta_{i,t}$ is negative if bidder i wins, and positive if bidder i loses, the negative part of the horizontal axis corresponds to winners and the positive part corresponds to the losers. The vertical axis of Figure 1 corresponds to the 30-day log backlog in the left panel and the 60-day log backlog in the right. For Figure 2, the vertical axis corresponds to the 90-day log backlog in the left panel and 120-day log backlog in the right. Each dot in the figure corresponds to the bin average. The discontinuity in the outcome variable at $\Delta = 0$ is visible in all of the graphs.

As we discussed above, the sample of auctions in Indonesia consists of E-procurement auctions and paper-based auctions. Table 4 reports the results by type of auction. The top



Note: Left panel corresponds to the third column of Table 3. Right panel corresponds to the last column. The curves correspond to 4th order (global) polynomial approximations of the conditional means.

Figure 2: Binned Scatter Plot for 90-Day and 120-Day Log Backlog: Public Works Auctions from Indonesia.

panel corresponds to the results for E-procurement auctions and the bottom panel corresponds to those for paper-based auctions. We find that our RD estimates are positive and statistically significant, at around 0.9 to 1.1, for E-procurement auctions. The estimates are all statistically significant at the 1% level.[17] These results suggest that bid rigging is pervasive among E-procurement auctions. On the other hand, the estimates for paper-based auction are smaller in magnitude and not statistically significant. The binned scatter plots corresponding to E-procurement auctions are given by Figures 3 and 4. The binned scatter plots for paper-based auctions are given in Online Appendix OA.

The fact that we find evidence of collusion in E-procurement auctions sheds light on why Lewis-Faupel et al. (2016) do not find a price decrease after the introduction of E-

[17]The adjusted p-values that account for the fact that we conduct the tests for 5 countries are 0.025, 0.005, 0.015, and 0.025.

	E-Procurement			
	30 Days	60 Days	90 Days	120 Days
$\hat{\beta}$	0.930***	1.136***	1.106***	1.116***
	(0.331)	(0.352)	(0.376)	(0.398)
p-value	[0.005]	[0.001]	[0.003]	[0.005]
h	0.032	0.038	0.038	0.039
Obs.	30,719	30,719	30,719	30,719
	Paper Based			
	30 Days	60 Days	90 Days	120 Days
$\hat{\beta}$	0.304	0.465	0.389	0.435
	(0.308)	(0.340)	(0.351)	(0.355)
p-value	[0.324]	[0.172]	[0.267]	[0.221]
h	0.022	0.021	0.021	0.021
Obs.	24,929	24,929	24,929	24,929

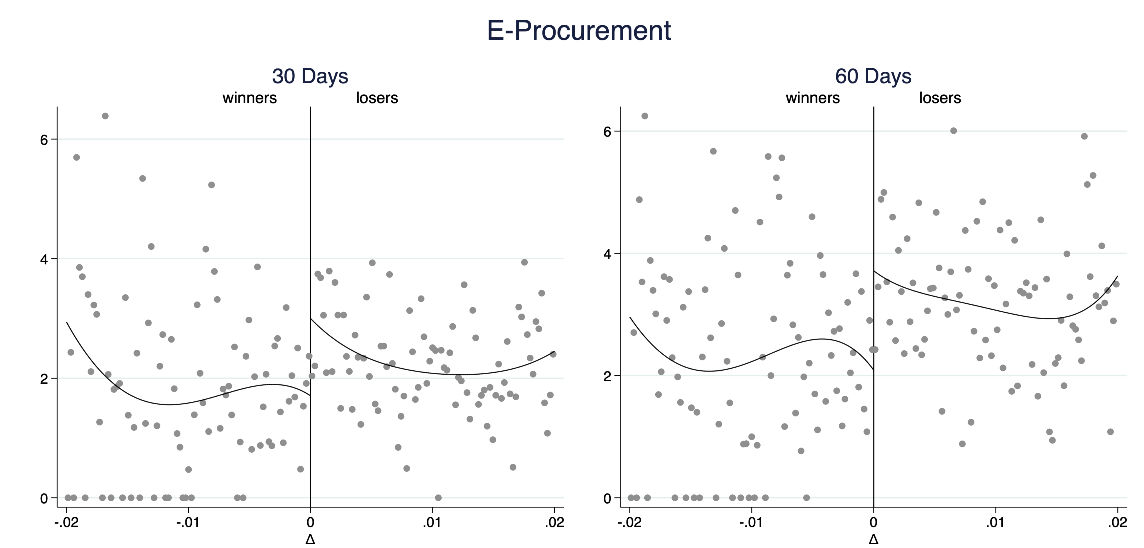
Note: Standard errors are clustered at the auction level and reported in parenthesis. The table also reports the bandwidth h used for estimation. *, **, and *** respectively denote significance at the 10%, 5%, and 1% levels.

Table 4: RD Estimates for Log Backlog: E-procurement and Paper-Based Auctions in Indonesia

procurement auctions. Even if E-procurement reduces corruption, the effects on auction outcomes will likely be modest if bidders are colluding. While it is unclear whether or not E-procurement facilitates collusion, our results suggest that collusion did not cease to exist under E-procurement.[18] Regardless of the type of auction, colluding bidders are likely to submit bids that are close to the reserve price.

Placebo Test If a cartel uses a bid rotation scheme to allocate projects, the auction winner is necessarily going to have lower backlog than the losers. However, unlike for the winner, there is no compelling reason for the cartel to have specific rules for who bids what

[18] While it is hard to cleanly identify the causal effect of introducing E-procurement auctions on collusion, we document evidence that collusion became more pervasive in later periods of our sample in Online Appendix OC. In Online Appendix OC, we partition the sample in half, before Feb 21, 2007 and after that date and redo the analysis on each subsample. We find that the RD estimates are not statistically significant for the first half for the sample, but they are statistically significant for the second half. These results suggest that the form of collusion that we detect in the paper became more pervasive over time. Because all provinces are relatively well represented in all years, these results are unlikely to be explained by compositional effects.



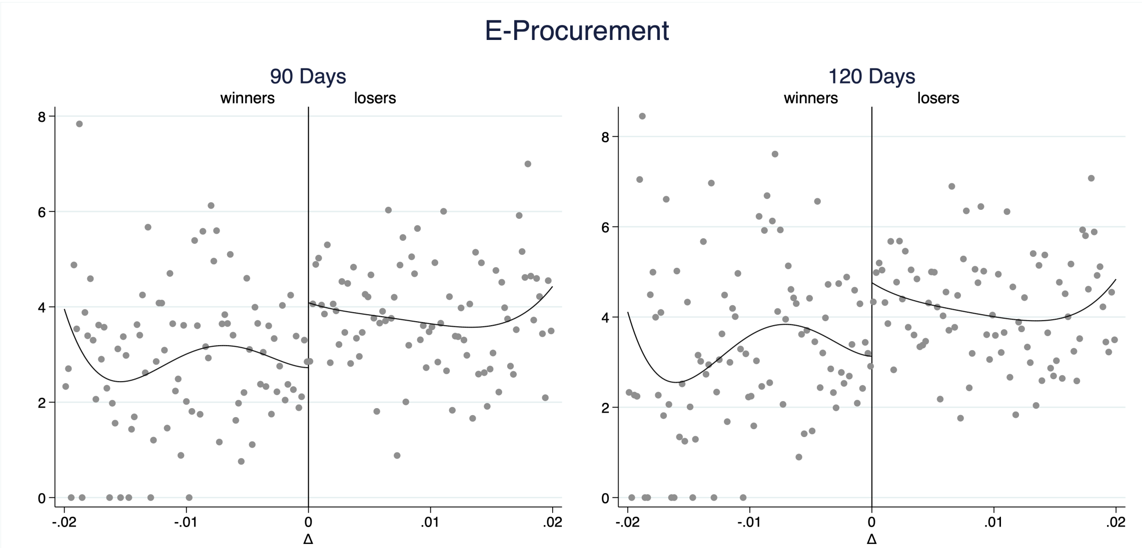
Note: Left panel corresponds to the first column of the top panel of Table 4. Right panel corresponds to the second column. The curves correspond to 4th order (global) polynomial approximations of the conditional means.

Figure 3: Binned Scatter Plot for 30-Day and 60-Day Log Backlog: E-Procurement Auctions from Indonesia.

among the designated losers. The primary role that designated losers play in the auction is to create the appearance of competition by bidding above the designated winner.

This suggests a placebo test that compares the backlog of marginal second and marginal third place bidders. To be more precise, define $\Delta^2_{i,t} \equiv \frac{b_{i,t} - \min\{b_{j,t} \text{ s.t. } i \neq j \text{ and } j \text{ loses}\}}{r_t}$ for bidders other than the lowest bidder. Bid difference $\Delta^2_{i,t}$ is negative for the second place bidder and positive for bidders who bid above the second place bidder. We do not compute $\Delta^2_{i,t}$ for the lowest bidder. Even under collusion, we do not expect significant differences in the backlog between marginal second place and marginal third place bidders. If this is indeed the case, this finding provides additional support to the interpretation that the RD estimates in Tables 3 and 4 reflect patterns of collusive bid rotation.

The top panel of Table 5 reports the RD estimates with $\Delta^2_{i,t}$ as the running variable for the full sample. We find that the RD estimates are small and statistically insignificant. The middle and bottom panels of Table 5 report the results for E-procurement and paper-based auctions. We find that none of the estimates are statistically significant. Taken together,



Note: Left panel corresponds to the third column of the top panel of Table 4. Right panel corresponds to the fourth column. The curves correspond to 4th order (global) polynomial approximations of the conditional means.

Figure 4: Binned Scatter Plot for 90-Day and 120-Day Log Backlog: E-Procurement Auctions from Indonesia.

the results reported in Tables 3 through 5 imply a conspicuous discontinuity in firm backlog between the marginal winner and the marginal loser, but not between second and third place bidders. These results are unlikely to be rationalized by competitive bidding. On the other hand, these results are consistent with a bid rotation scheme in which bidders take turns winning the auction and designated losers submit uncompetitive bids.

How Wide-Spread is Bid-rigging? The foregoing analysis suggests that collusion occurs in Indonesia to such an extent that collusive bid rotation patterns can be discerned in the full sample of public works data from the MPW. In order to obtain a better sense of the extent of collusion, we now consider a slight modification of the RD regression by changing the outcome variable. Specifically, let $Y_{i,t}$ be equal to $Y_{i,t} = \sin(k \log(1 + B^T_{i,t}))$ where k is a constant chosen such that we have $Y_{i,t} = 1$ for the largest backlog in the sample, i.e., $k = \pi/(2 \max_{i,t} \log(1 + B^T_{i,t}))$. Note that $Y_{i,t}$ is bounded below by 0 and above by 1 for all of

	All			
	30 Days	60 Days	90 Days	120 Days
$\hat{\beta}$	0.145	0.026	0.332	0.271
	(0.270)	(0.256)	(0.314)	(0.312)
p-value	[0.591]	[0.918]	[0.290]	[0.384]
h	0.016	0.023	0.014	0.016
Obs.	48,246	48,246	48,246	48,246
	E-Procurement			
	30 Days	60 Days	90 Days	120 Days
$\hat{\beta}$	-0.010	0.031	0.562	0.315
	(0.369)	(0.385)	(0.480)	(0.470)
p-value	[0.978]	[0.935]	[0.241]	[0.503]
h	0.023	0.026	0.017	0.020
Obs.	27,052	27,052	27,052	27,052
	Paper Based			
	30 Days	60 Days	90 Days	120 Days
$\hat{\beta}$	-0.028	0.034	0.129	0.209
	(0.324)	(0.344)	(0.384)	(0.414)
p-value	[0.930]	[0.922]	[0.738]	[0.614]
h	0.022	0.021	0.017	0.014
Obs.	21,305	21,305	21,305	21,305

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

Table 5: RD Estimates of Log Backlog for Marginal 2nd and 3rd Place Bidders: Indonesia

our sample. Now, consider the regression discontinuity estimate for $Y_{i,t}$:

$$\beta = \lim_{\Delta_{i,t} \searrow 0^+} \mathbf{E}[Y_{i,t}|\Delta_{i,t}] - \lim_{\Delta_{i,t} \nearrow 0^-} \mathbf{E}[Y_{i,t}|\Delta_{i,t}].$$

If we let A_{comp} and A_{uncomp} denote the set of competitive auctions and the set of uncompetitive auctions, we have

$$\mathbf{E}[Y_{i,t}|\Delta_{i,t}] = \Pr(A_{\mathsf{comp}}|\Delta_{i,t})\mathbf{E}[Y_{i,t}|\Delta_{i,t}, A_{\mathsf{comp}}] + \Pr(A_{\mathsf{uncomp}}|\Delta_{i,t})\mathbf{E}[Y_{i,t}|\Delta_{i,t}, A_{\mathsf{uncomp}}]$$

for each $\Delta_{i,t}$. Because the regression discontinuity is zero for the set of competitive auctions,

$$\begin{aligned}\beta &= \Pr(A_{\mathsf{uncomp}}|\Delta_{i,t}=0)\left(\lim_{\Delta_{i,t}\searrow 0^+}\mathbf{E}[Y_{i,t}|\Delta_{i,t},A_{\mathsf{uncomp}}]-\lim_{\Delta_{i,t}\nearrow 0^-}\mathbf{E}[Y_{i,t}|\Delta_{i,t},A_{\mathsf{uncomp}}]\right)\\ &\leq \Pr(A_{\mathsf{uncomp}}|\Delta_{i,t}=0), \qquad (2)\end{aligned}$$

where we have used the fact that $Y_{i,t}$ is bounded between 0 and 1 to obtain the last inequality. By modifying the outcome variable so that it is bounded (in the case of $Y_{i,t}=\sin(k\log(1+B^T_{i,t}))$, it is bounded by 0 and 1), we can derive a relationship between the RD coefficient, β, and the fraction of uncompetitive auctions, $\Pr(A_{\mathsf{uncomp}}|\Delta_{i,t}=0)$. We now use this inequality to obtain a lower bound on the fraction of uncompetitive auctions, $\Pr(A_{\mathsf{uncomp}}|\Delta_{i,t}=0)$.

Table 6 reports the RD estimates for $Y_{i,t}$ for the set of all auctions (top panel) and for the set of E-procurement auctions (bottom panel). We find that the RD estimates is as high as 0.030 in the top panel and as high as 0.051 in the bottom panel. These results suggest that the proportion of noncompetitive auctions is at least about 3.0 percent for all auctions and about 5.1 percent for E-procurement auctions (among auctions that are close). Note however, that these estimates are lower bound estimates and that the true extent of collusion is likely to be higher. This is because inequality (2) is very conservative, obtained under the assumption that the RD coefficient is 1 under collusion.[19] Moreover, our test has power only against cartels that allocate auctions using rotation.

3.2 Georgia, Mongolia, Malta, and California

In this section, we discuss the institutional details, data, and the results for Georgia, Mongolia, Malta and California.

[19]The RD coefficient is likely to be substantially less than 1 even under collusion.

	All			
	30 Days	60 Days	90 Days	120 Days
$\hat{\beta}$	0.023**	0.030***	0.027**	0.029**
	(0.010)	(0.012)	(0.012)	(0.013)
p-value	[0.025]	[0.010]	[0.026]	[0.020]
h	0.024	0.022	0.022	0.022
Obs.	55,506	55,506	55,506	55,506
	E-Procurement			
	30 Days	60 Days	90 Days	120 Days
$\hat{\beta}$	0.042***	0.051***	0.048***	0.049***
	(0.015)	(0.015)	(0.016)	(0.017)
p-value	[0.004]	[0.001]	[0.003]	[0.005]
h	0.030	0.038	0.038	0.039
Obs.	30,719	30,719	30,719	30,719

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

Table 6: Lower Bound on the Proportion of Uncompetitive Auctions, Indonesia

3.2.1 Institutional Background

Georgia We collected bidding data on procurement auctions from the website of the Georgian electronic Government Procurement (Ge-GP) system.[20] The data include procurement contracts from years between 2016 through 2019 for construction work, services, and goods. The auction format is first-price sealed bid with a public reserve price.

Mongolia We scraped bidding data on public procurement auctions covering construction work, goods, and services from the public procurement system of Mongolia (PPSM) from April 2018 to April 2022.[21] The PPSM began recording bidding data from April 2011. The auction format is first-price sealed bid.[22] There is no reserve price for the procurement

[20] Ge-GP website: https://tenders.procurement.gov.ge/login.php

[21] PPSM website: https://www.tender.gov.mn/en/index/

[22] Bidders must submit documents to prove that they satisfy the criteria for financial capacity, technical capacity, and experience. The evaluation committee reviews bidders and awards the contract to the lowest bidder meeting these criteria.

auctions.

Malta We scraped the website of the electronic public procurement system (ePPS) to obtain bidding data for public procurement contracts in Malta.[23] The ePPS website began listing bidding data from 2011, and since 2016, public entities are required to post procurement projects exceeding 5,000 euros on the ePPS website. The awarded contracts include public works contracts as well as purchases of goods and services.

The auction format depends on the type of project and the contracting authority. Some use reverse English auctions and others use a first-price sealed bid format.[24] There is no reserve price for the auctions. We use all procurement auctions regardless of auction format for the construction of backlog measures, but we use only first-price sealed bid auctions for the RD analysis.[25] The sample includes auctions let between 2011 to 2020.

California We obtained bidding data on construction contracts let by the California Department of Transportation (Caltrans) between 2014 and 2020 from its website.[26] The auction format is first-price sealed bid.[27] Caltrans publishes the engineer's estimate of the costs of the project, but the auctions do not have a public reserve price. Because the website does not have information on the awarded contractor for auctions before July 2016, we treat the lowest bidder as the winner for that period.

Table 7: Summary Statistics for Georgia, Mongolia, Malta and California

	Georgia		Mongolia		Malta		California	
	Mean	Obs.	Mean	Obs.	Mean	Obs.	Mean	Obs.
Low bid	158.44 (1,176.82)	39,434	1.98 (379.91)	59,832	44.32 (391.15)	20,089	5.29 (14.11)	3,081
# Bids	2.16 (1.72)	39,434	2.17 (1.94)	59,832	3.55 (2.93)	20,089	5.23 (2.41)	3,081
Reserve	178.10 (1,280.79)	39,434	- (-)	-	- (-)	-	- (-)	-
Engineer's Estimate	- (-)	-	- (-)	-	- (-)	-	5.44 (14.33)	3,081
				By Bidders				
# Participation	34.81 (97.90)	9,138	6.39 (14.13)	2,215	26.33 (199.11)	2,705	13.44 (33.85)	10,840
# Winning	3.87 (8.79)	9,138	0.67 (2.00)	2,215	3.23 (23.60)	2,705	3.90 (10.96)	10,840
30-Day Backlog	26.39 (216.21)	9,138	259.11 (1,974.26)	2,215	2.60 (17.74)	2,705	31.11 (273.37)	10,840
60-Day Backlog	41.97 (304.39)	9,138	435.65 (2,517.78)	2,215	6.94 (70.20)	2,705	52.39 (427.12)	10,840
90-Day Backlog	54.20 (364.00)	9,138	574.04 (2,983.67)	2,215	9.45 (77.42)	2,705	68.25 (554.19)	10,840
120-Day Backlog	69.81 (600.60)	9,138	703.12 (3,466.73)	2,215	13.12 (102.21)	2,705	86.60 (893.87)	10,840

Note: Low Bid, Reserve, Engineer's Estimates, and Raw Backlog are reported in thousand Laris for Georgia, million Dollars for California, thousand Euros for Malta, and billion Tugrik for Mongolia. Auctions for Malta and Mongolia do not have reserve prices.

3.2.2 Summary Statistics

Table 7 reports the summary statistics of the four datasets. The top panel of the table reports the summary statistics by auction and the bottom panel reports the summary statistics by

[23] ePPS website: https://www.etenders.gov.mt/epps/home.do

[24] In Malta, a firm is allowed to submit multiple bids. We use the lowest bid submitted by the contract winner to construct the winning bid.

[25] Even for sealed bid auctions, the bidders are reviewed by the evaluation committee for eligibility and technical compliance. Award of the contract is subject to approval by the evaluation committee.

[26] Caltrans website: http://ppmoe.dot.ca.gov/des/oe/planholders/bidsum.php

[27] More precisely, bidders submit unit prices on each line item. The total bid is the dot product of the vector of unit prices and estimated quantities. The bidder who submits the lowest total bid wins the auction.

	30 Days	60 Days	90 Days	120 Days	30 Days	60 Days	90 Days	120 Days
	Georgia				Caltrans			
$\hat{\beta}$	0.176	0.311	0.209	0.176	0.403	-0.045	-0.251	-0.405
	(0.162)	(0.206)	(0.206)	(0.201)	(0.474)	(0.539)	(0.561)	(0.573)
p-value	[0.277]	[0.131]	[0.310]	[0.382]	[0.395]	[0.934]	[0.655]	[0.480]
h	0.075	0.047	0.048	0.051	0.072	0.074	0.074	0.073
Obs.	57,502	57,502	57,502	57,502	12,695	12,695	12,695	12,695
	Malta				Mongolia			
$\hat{\beta}$	-0.229	-0.146	-0.015	-0.138	0.125	0.128	0.052	0.004
	(0.159)	(0.174)	(0.178)	(0.170)	(0.210)	(0.222)	(0.211)	(0.212)
p-value	[0.149]	[0.402]	[0.935]	[0.417]	[0.551]	[0.562]	[0.806]	[0.987]
h	0.334	0.315	0.307	0.351	0.052	0.053	0.061	0.059
Obs.	59,109	59,109	59,109	59,109	88,434	88,434	88,434	88,434

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

Table 8: RD Estimates of Log Backlog for Four Countries: Georgia, Mongolia, Malta and California

bidder. The mean low bid in Georgia is about 158 thousand Laris or about 53.7 thousand US dollars. The mean reserve price is about 178 thousand Laris. The auction averages about 2.16 bidders and the average bidder in the Georgian dataset participates in about 34.81 auctions and wins about 3.87 auctions.

For Mongolia, the mean low bid is about 1.98 billion Tugrik, or about 630,000 US dollars. The mean number of bidders is about 2.17. For Malta, the mean low bid is about 44,300 Euros and the mean number of bidders is about 3.55. Finally, the average low bid for Caltrans data is about 5.29 million dollars and the average number of bidders is about 5.23.

3.2.3 Results

Table 8 reports the RD estimates with log backlog, $\log(1 + B^T_{i,t})$, as the outcome variable for each of the four countries. For Georgia, the running variable is the margin by which bidder i

won or lost as a percentage of the reserve price, as we defined in expression (1). Because there is no reserve price for Caltrans auctions, we normalize the bids by the engineer's estimate. For Malta and Mongolia, we normalize the bids by the lowest bid of each auction.[28]

We find that, for all of the four countries and for all four measures of backlog, the estimated coefficients are statistically indistinguishable from zero. These results imply that our tests cannot reject the null of competition for these countries. Our findings do not preclude, however, the possibility that there exist forms of collusion other than bid rotation or that there exist cartels that use bid rotation among subsets of the data that our test has too little power to detect.

4 Conclusion

This paper tests for collusion using bidding data on public procurement contracts from five countries, Indonesia, Georgia, Malta, Mongolia, and the U.S. (California). While we do not find evidence of bid rotation in Georgia, Mongolia, Malta and the U.S., we find evidence of collusion occurring in Indonesia to such an extent as to be discernible in the dataset that aggregates public works contracts let by the Ministry of Public Works. Our findings from Indonesia highlight the importance of reducing collusion in order to increase the efficiency of public procurement.

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[28]To be more precise, for Malta and Mongolia, we define the running variable as follows:

$$\Delta_{i,t} = \frac{b_{i,t} - \min_{j \neq i} b_{j,t}}{\min_j b_{j,t}}.$$

The bid differences are normalized in terms of percentages of the lowest bid.

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Online Appendix: A Study of Bid-rigging in Procurement Auctions: Evidence from Indonesia, Georgia, Mongolia, Malta, and State of California

Kei Kawai, Jun Nakabayashi, and Daichi Shimamoto

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Abstract

This Online Appendix to "A Study of Bid-rigging in Procurement Auctions: Evidence from Indonesia, Georgia, Mongolia, Malta, and State of California" provides additional results omitted from the main text.

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†U.C. Berkeley, kei@berkeley.edu
‡Kyoto University, nakabayashi.jun.8x@kyoto-u.ac.jp
§Kindai University, d.shimamoto@eco.kindai.ac.jp

OA Histogram of the Running Variable

Figure OA.1 plots the histogram of $\Delta_{i,t}$ for the Indonesian auctions. The top panel of Figure OA.1 corresponds to the histogram for the sample of all Indonesian auctions. The middele and bottom panels correspond to the subset of paper-based and E-procurement auctions, respectively.

OB Binned Scatter Plots for Paper-Based Auctions

Figure OB.1 corresponds to the binned scatter plots for paper-based auctions. As we report in Table 4 of the main text, we do not find statistically significant differences in the log backlog between marginal losers and winners. Accordingly, the discontinuity at zero is not easily visible.

OC Binned Scatter Plots for the Placebo Test

In Section 3.1 of the main text, we conduct a placebo test in which we take the running variable to be $\Delta^2_{i,t}$, comparing marginal second place bidders and marginal third place bidders (Table 5). Figure OC.1 corresponds to the binned scatter plots for the the full sample that includes both paper-based and E-procurement auctions. Figure OC.2 corresponds to the binned scatter plots for paper-based auctions. Figure OC.3 corresponds to the binned scatter plots for E-procurement auctions.

OD Further Analysis of E-Procurement and Paper-Based Auctions

In the main text, we find statistically significant estimates for E-procurement auctions but not for paper-based auctions in Indonesia. Because different provinces introduced E-procurement at different points in time, our results may simply reflect compositional effects

	First Half			
	30 Days	60 Days	90 Days	120 Days
$\hat{\beta}$	0.355	0.334	0.323	0.558
	(0.295)	(0.315)	(0.331)	(0.348)
p-value	[0.230]	[0.288]	[0.330]	[0.109]
h	0.023	0.023	0.022	0.019
Obs.	27,274	27,274	27,274	27,274
	Second Half			
	30 Days	60 Days	90 Days	120 Days
$\hat{\beta}$	0.998**	1.382***	1.364***	1.423***
	(0.388)	(0.448)	(0.460)	(0.461)
p-value	[0.010]	[0.002]	[0.003]	[0.002]
h	0.027	0.025	0.027	0.030
Obs.	28,242	28,242	28,242	28,242

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

Table OD.1: RD Estimates for Log Backlog: First Half and Second Half, Indonesia

or an actual change in the extent to which bidders collude. While it is difficult to identify the causal effect of introducing E-procurement auctions on collusion, we find evidence suggesting that there is more collusion in later periods of our sample than in earlier periods that cannot be rationalized by simple compositional effects. We discuss this finding in this section.

For our analysis, we partition our sample in half, those let between the beginning of the sample to Feb 21, 2007 and those let after that date. The first half consists mostly of paper-based auctions, accounting for 75.89 percent, or 3,038 auctions. E-procurement auctions account for 24.13 percent, or 966 auctions. Because E-procurement auctions were introduced in the middle of the sample, that second half consists mostly of E-procurement auctions, accounting for 76.31 percent, or 3,051 auctions. Paper-based auctions account for 23.69 percent, or 947 paper-based auctions. There are a total of 4,004 auctions in the first half and 3,998 auctions in the second half.

Table OD.1 reports the RD results with $\log(1+B_{i,t}^T)$ as the outcome variable with T equal to 30, 60, 90, and 120 days. The top panel corresponds to the first half of the sample and the bottom panel corresponds to the second half. We find that none of the RD estimates are statistically significant in the first panel while the estimates in the bottom panel are statistically significant at the 5% level (30 days) or at the 1% level (60, 90, and 120 days). These results suggest that there is much more collusion in the second half of the sample.

Because all regions are relatively well represented in both samples, the differences between the top and bottom panels of table OD.1 cannot be driven simply by compositional effects. These results imply that collusion is more prevalent in later years than in earlier years, although it is difficult to identify whether this is because of introduction of E-procurement auctions or because of other factors.

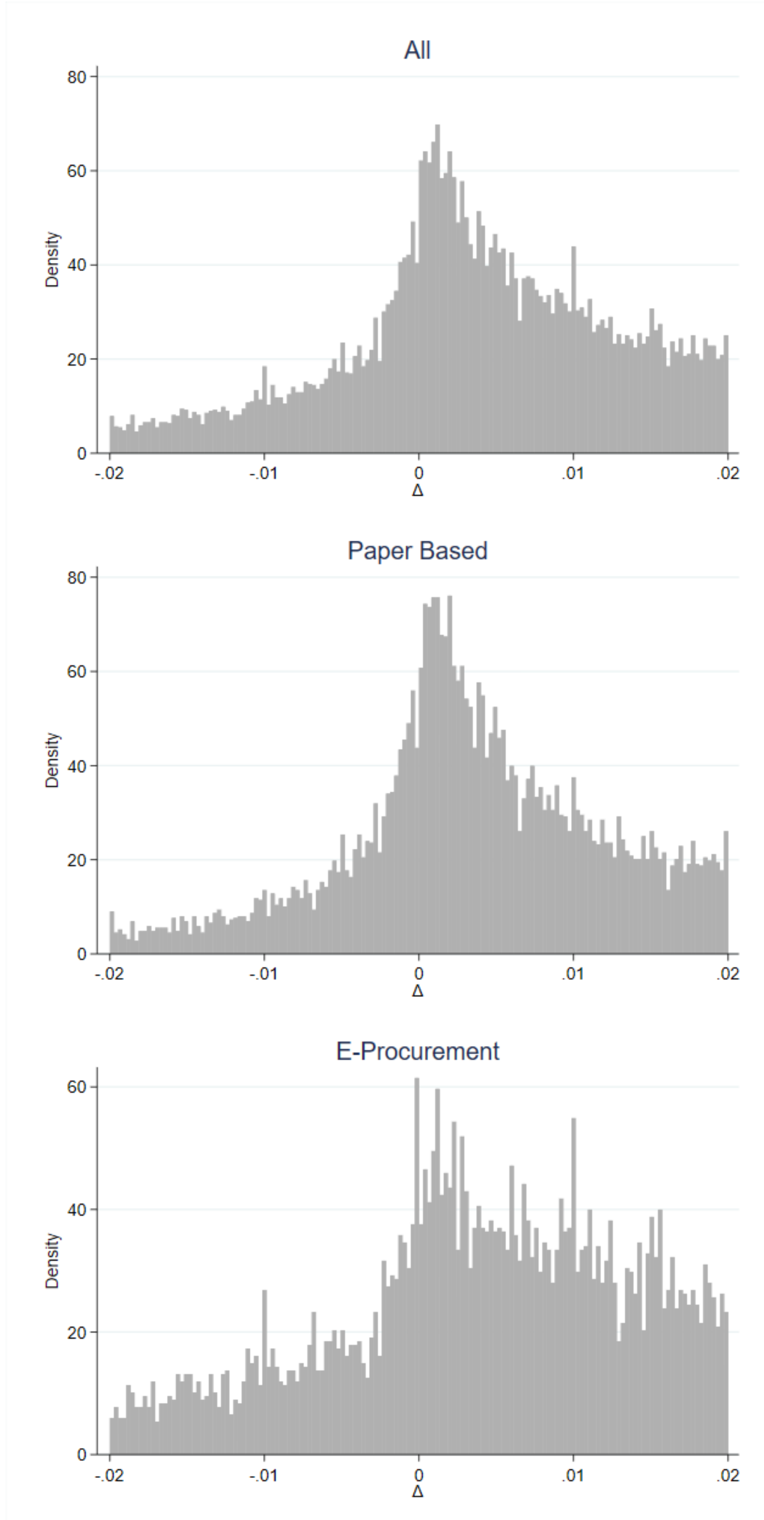
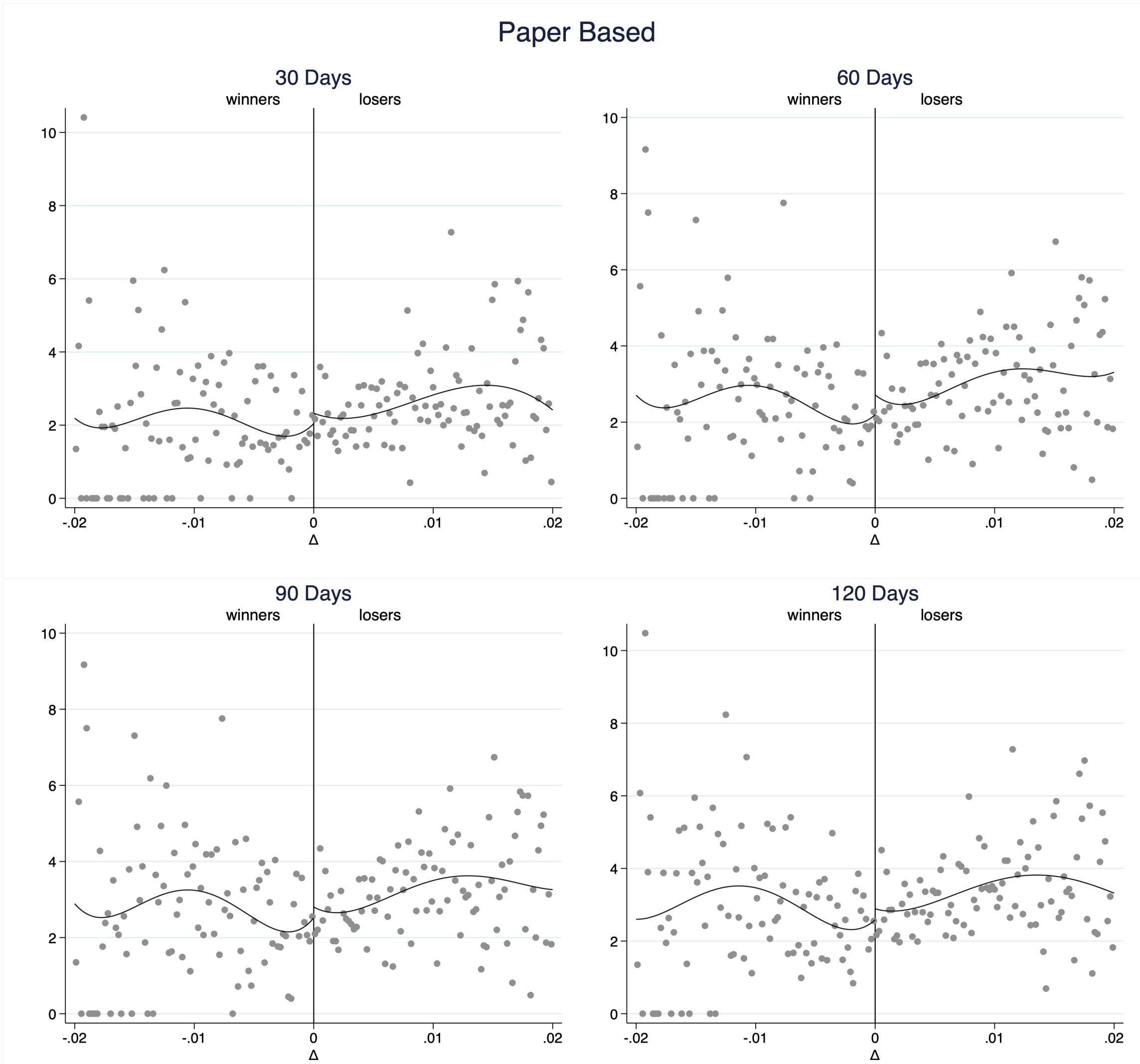
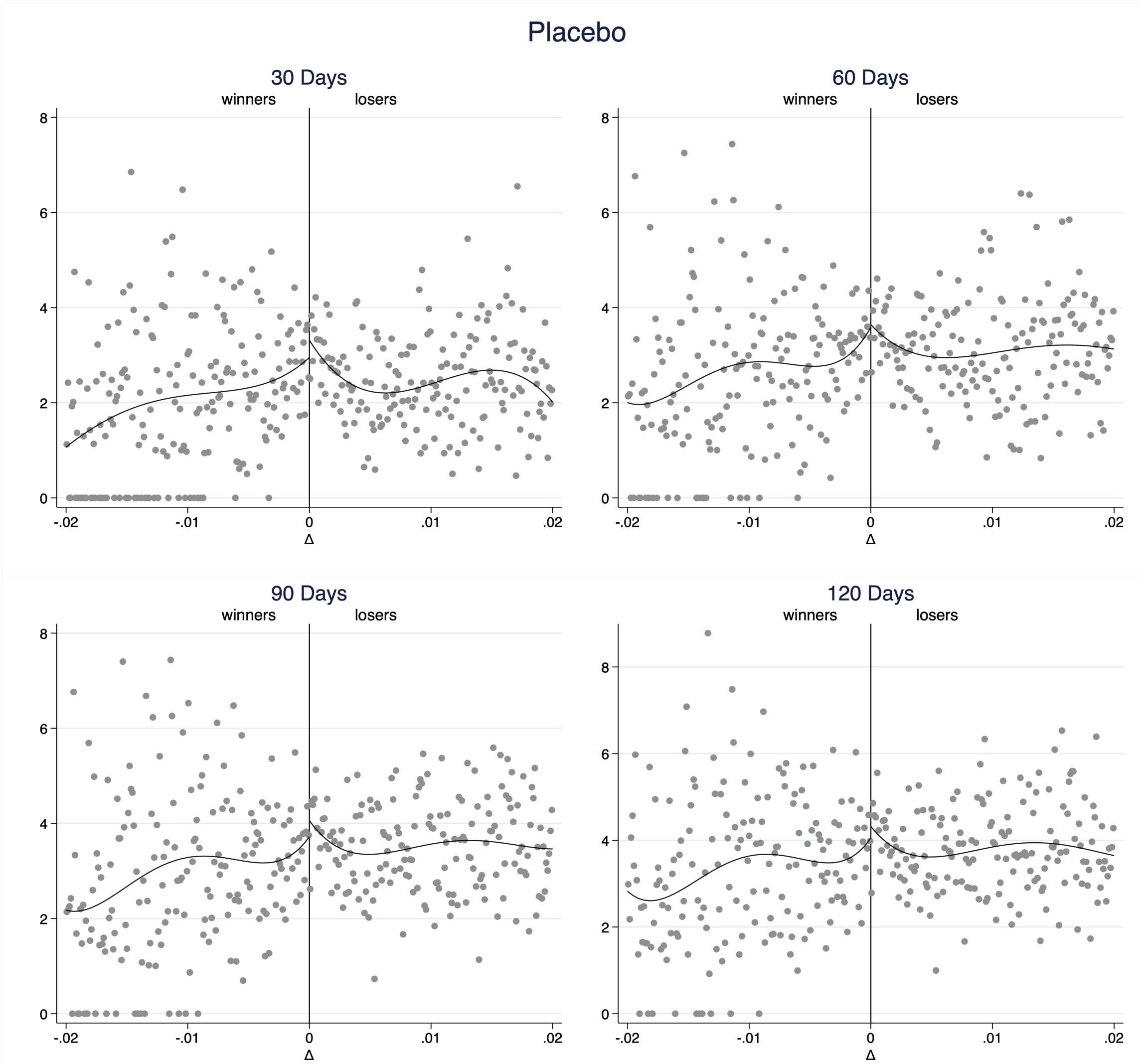


Figure OA.1: Indonesia, Running Variables



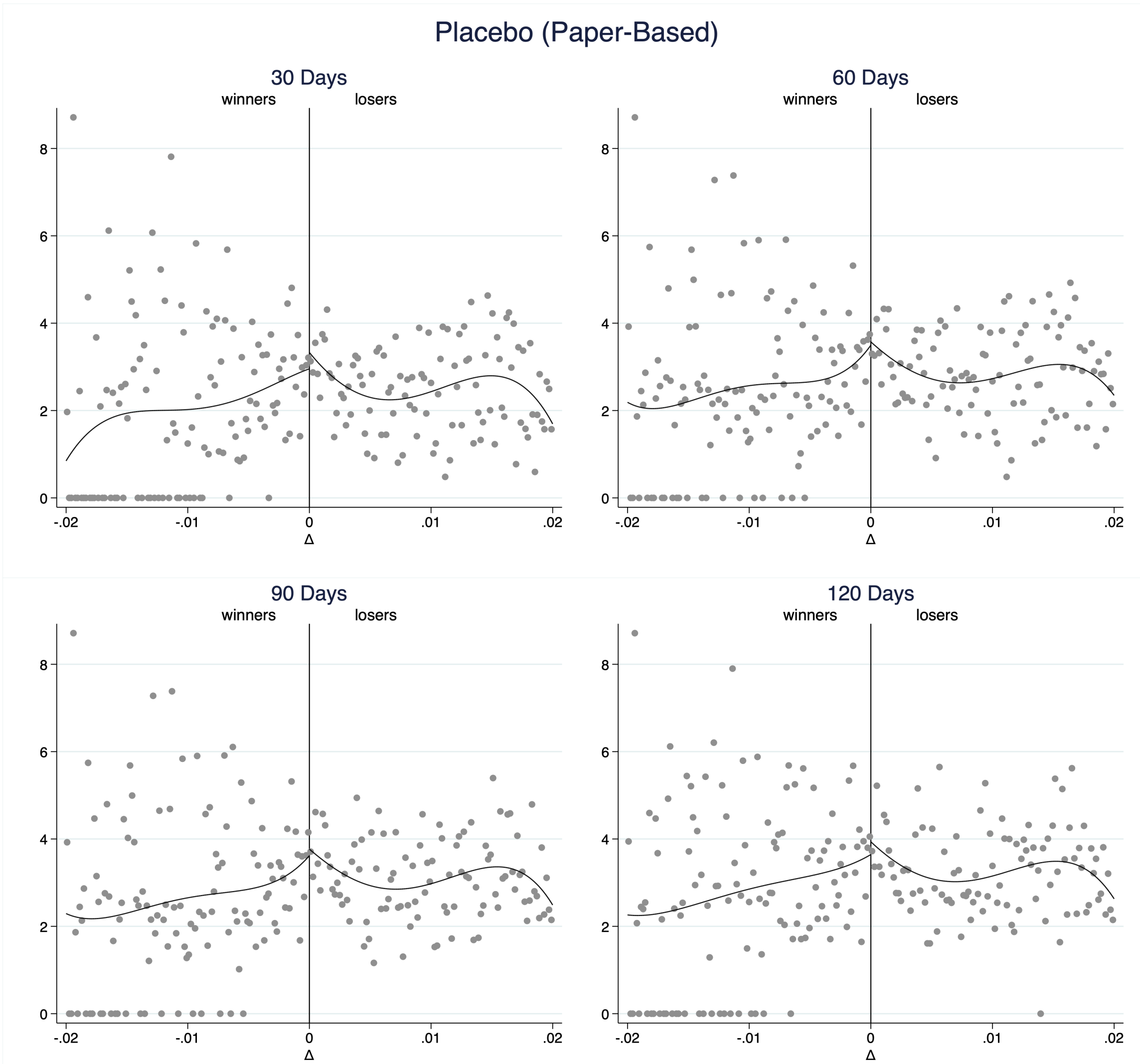
Note: The top left panel corresponds to the first column of the bottom panel of Table 5. The top right panel corresponds to the second column of the bottom panel of the table. The bottom left and the bottom right panels correspond to the third and fourth columns of the bottom panel, respectively. The curves correspond to 4th order (global) polynomial approximations of the conditional means.

Figure OB.1: Binned Scatter Plot for Log Backlog: Paper based Auctions from Indonesia



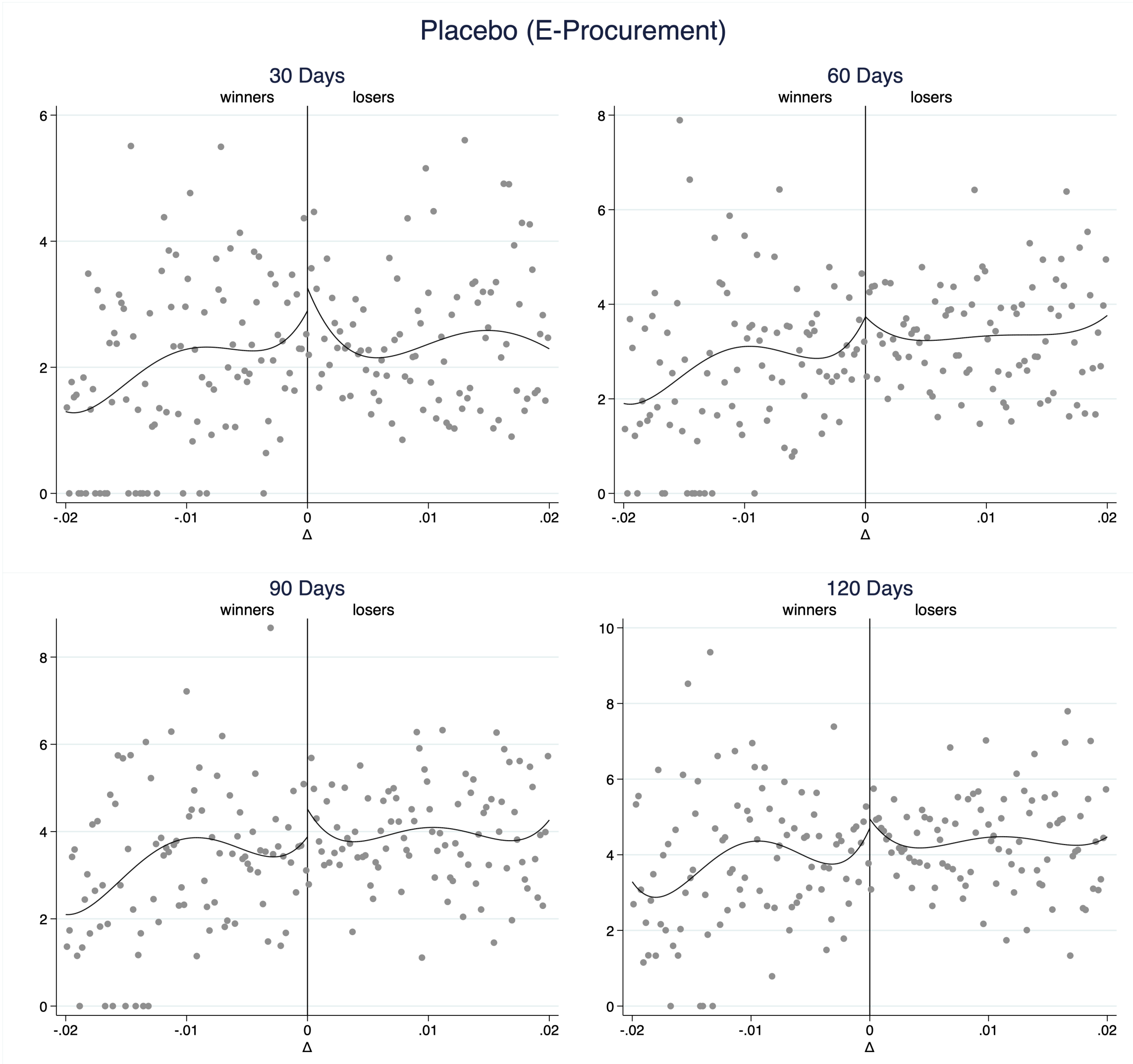
Note: The top left and right panels correspond to the first and second columns of the top panel of Table 5. The bottom left and right panels correspond to the third and fourth columns of the top panel of Table 5. The curves correspond to 4th order (global) polynomial approximations of the conditional means.

Figure OC.1: Binned Scatter Plot for Log Backlog for Marginal 2nd and 3rd Place Bidders: Indonesia



Note: The top left and right panels correspond to the first and second columns of the bottom panel of Table 5. The bottom left and right panels correspond to the third and fourth columns of the bottom panel of Table 5. The curves correspond to 4th order (global) polynomial approximations of the conditional means.

Figure OC.2: Binned Scatter Plot for Log Backlog for Marginal 2nd and 3rd Place Bidders: Paper-based Auctions from Indonesia



Note: The top left and right panels corresponds to the first and second columns of the middle panel of Table 5. The bottom left and right panels correspond to the third and fourth columns of the middle panel of Table 5. The curves correspond to 4th order (global) polynomial approximations of the conditional means.

Figure OC.3: Binned Scatter Plot for Log Backlog for Marginal 2nd and 3rd Place Bidders: E-procurement Auctions from Indonesia