

Data transparency, public oversight and collusion in e-procurement *

Bruno Baránek[†]

Leon Musolff[‡]

Vítězslav Titl[§]

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Abstract

In this paper, we study an e-procurement market in Ukraine. We develop a novel structural test to detect collusive behavior, document that the bidding patterns in the data are incompatible with a competitive equilibrium, and identify pairs of colluding firms. We validate the soundness of our collusion detection algorithm on a large sample of prosecuted companies. In Ukraine, a broad policy reform created an unprecedented scale of data transparency and an online monitoring system. Numerous NGOs and educated volunteers started to monitor the market for public procurement. We document that this new system of supervision effectively reduces collusion and prices on the market; in particular, prices decrease by 20.6%. Finally, we estimate the deadweight loss and find a possible sizeable overall welfare gain from the additional oversight due to e-procurement of between 2.68% and 3.11% of the total procurement spending.

Keywords: Public procurement, Collusion, Oversight, Online markets

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[†]Electronic address: bbaranek@princeton.edu; Department of Economics, Princeton University

[‡]Electronic address: lmusolff@princeton.edu; Department of Economics, Princeton University

[§]Electronic address: titl.vitezslav@gmail.com; Utrecht University School of Economics, Utrecht University

1 Introduction

The World Bank considers the adoption of e-procurement an essential step towards lowering corruption, collusion, and costs in public procurement systems in developing countries (World Bank, 2017). But why would the mere digitization of the procurement process yield such benefits? While previous research such as Coviello and Mariniello (2014) considers the benefits of wider publication of tenders, digitization may also boost citizens' efforts in monitoring and oversight. Exploiting a rich dataset from Ukraine, we show that creating opportunities for public oversight is indeed a critical channel through which e-procurement lowers costs. We present evidence that NGOs' oversight constitutes a cheap and effective way to reduce prices and collusion in public procurement.

In 2015, a group of Ukrainian volunteers spearheaded by Transparency International concluded that the only antidote to low levels of trust in government was transparency and public oversight. Inspired by the successful first wave of adoptions of e-procurement across the globe, they set out to build a system designed from the ground up with one goal in mind: to be as transparent as possible. They dubbed their e-tendering platform 'ProZorro.' The project was initially run entirely independent from the government. Due to its success, they later became the official system for Ukrainian public procurement.

The ProZorro system received several prizes, such as the annual prize of the Open Government Awards 2016. The system is unique in its openness. Data about all public procurement with all possible details are accessible online in a user-friendly environment. Nevertheless, ProZorro could not entirely stop corruption and collusion in the market. Since 2016, more than 1000 firms were successfully prosecuted for collusion. The data from ProZorro became vital during a large number of these lawsuits. The anti-monopoly agencies used IP addresses of bidders to prove collusion and heavily relied on the public's help for collecting evidence. Shortly after the founding of the tendering platform ProZorro, the society and NGOs set up the monitoring platform DoZorro, designed from the ground up for the sole task of helping procurers, tenderers, and third parties monitor the procurement market. 30 NGOs and many highly-educated volunteers have offered their help to fight corruption and collusion in Ukraine. There are about 150,000 reviews submitted by 20,000 users in the Dozorro

database as of March 2020.

Volunteers and NGOs conduct the majority of monitoring on Dozorro. Thus, their expertise essentially constitutes a monitoring tool that helps discipline outcomes – and, most importantly, is entirely free from the government’s perspective! Our research highlights a formerly understudied channel through which data transparency increases the efficiency of procurement markets: allowing highly skilled individuals to help the government detect collusion. By providing a one-stop place that aggregates reviews, complaints, and worries of citizens and NGOs alike, the monitoring platform harnesses motivated volunteers’ free labor. Crucially, this harnessing mechanism is not dependent on the exact auction procedure, making our findings relevant in other countries – especially those with weaker institutions and educated labor force (such as many post-soviet countries).

We introduce the unique multi-round auction mechanism used on ProZorro. The mechanism proceeds by initially letting interested bidders submit bids simultaneously. Subsequently, all bidders can access an online-auction where they compete for the contract. The online auction allows the bidders to lower their bids in three consecutive rounds sequentially. The bidding order is determined by the order of bids in the previous round, and the bidder with the highest initial bid starts bidding in the online auction. This setup can be understood as a mechanism where bidders initially bid for the order in which they will submit a final bid. Naturally, there is an advantage for the last bidder as nobody is given the chance to react to her bid.

In the first part of the paper, we solve this mechanism’s equilibrium and show that initial bids in this setup are entirely analogous to bids in first-price procurement auctions. Furthermore, bidders should almost always update their initial bids by undercutting each other by a small ϵ^1 . Contrary to this theoretical prediction, we see low activity during the online auctions in the data. Most initial bids are never updated. The lack of undercutting is consistent with a cartel set up where members initially agree on allocating projects and thus lack incentives to underbid each other. We show that low frequency of bid updating would cause a significant drop in profits of competitive firms.

Based on the theoretical discussion, we construct a novel approach to measure collusion and

¹This is caused due to an introduction of a low probability of not being able to respond to any submitted bid. Our data suggest that such friction is appropriate

identify bidding cartels in public procurement: the pairwise fixed-effect procedure for identifying cartels. We analyze the probability that a given firm underbids a particular competitor. The theoretical model allows us to compute the predicted probabilities of undercutting a competitor. Comparing observed behavior and model predictions, we find a significant mass of firm-pairs which are very unlikely to compete against each other. We argue that such firms with low pairwise fixed-effect values are likely members of a cartel and successfully verify this proposition on a sample of prosecuted firms. The identification of cartels via the pairwise fixed-effect procedure constitutes the first significant contribution of this paper.

In the second part of the study, we argue that data transparency and a robust online public monitoring system can facilitate the procurement market's cheap and efficient supervision. In the past years, it became more common for governments worldwide to publish data about public procurement. This increase in data transparency led to the construction of new online platforms focused on supervising and assessing the work of procurement authorities. For example, *contratobook.org* in Mexico uses machine learning to detect potentially corrupt contracts, *zindex.cz* monitors and grades every single procurement authority in the Czech Republic, and *sinarproject.org* focuses on identifying corrupt individuals delivering procurement contracts in Malaysia.

These examples indicate a current trend: increasingly, NGOs use publicly available data and data science to construct platforms that hold both procurers and tenderers accountable. Although these platforms have received plenty of attention among international organizations, policymakers, and private donors, academic literature has not so far studied their potential as cost-effective monitoring devices.

We use the entry of specialized NGOs to study the impact of public oversight on collusion. Using a difference-in-differences methodology, we identify the effect of an NGO focusing on the supervision of the medical tools market entering the Dozorro platform. We show that – in the areas where such NGOs entered – prices decline while the level of competition remains unchanged or slightly lower. This two-fold effect can be explained once we employ our previously developed measure of collusion. We find that the entry of the NGO leads to a decline in the participation of

collusive firms.

Furthermore, all of these effects are only present in above-the-threshold contracts with higher incentives for collusion. These contracts get canceled if only one bid is submitted, which increases the incentives for at least two cartel members to participate. For below-threshold contracts where a cartel can ex-ante agree on how to split the market, we do not observe the decline in colluding firms' participation.

Finally, we present estimates of welfare gain due to monitoring by NGOs. Prices drop, and the governments subsequently purchase more goods leading to a welfare gain equal to 0.48% of GDP in the short run and up to 0.56% in the long run. Our study presents the first welfare evaluation of open data access in public procurement.

2 Literature survey

Our paper contributes to several previously disjoint research areas. Firstly, we contribute to the literature studying collusion in auctions. We built on the literature pioneered in Porter and Zona (1993) and Porter and Zona (1999) that identify collusive behavior by showing that the behavior in data is inconsistent with a competitive equilibrium. Such an approach was further developed and modified in Bajari and Ye (2003), Conley and Decarolis (2016) and Chassang and Ortner (2019). Our structural model and the resulting pairwise fixed effect approach allow us to identify pairs of collusive bidders (i.e., not single firms likely in a cartel). To the best of our knowledge, this is the first attempt in the literature to identify directly collusive pairs of firms. Like Asker (2010), Kawai and Nakabayashi (2014), and more recently De Leverano (2019) and Clarka et al. (2020), we also provide an explanation of how current cartels operate based on prosecution data. In a closely related study, Kawai and Nakabayashi (2014) present a data anomaly suggesting the presence of collusion and then verify their empirical approach on a set of prosecuted colluders. Our paper extends the literature as we can solve for the competitive equilibrium and show that the lack of underbidding violates it. Furthermore, we can find whether each pair of bidders is collusive or not, thus allowing

for a firm to be collusive in some settings but not in others.

Secondly, we relate to studies examining the effect of oversight on public procurement market outcomes. So far, the literature mostly focused on the oversight of the actual implementation of the contracts (Calvo et al., 2019; Giuffrida and Rovigatti, 2019), in which they find the oversight leads to excessive red tape and lowers the efficiency of the market. Our study differs because oversight is focused on the allocation of the contract. There is a vast literature showing that contracts' allocation is often associated with corruption and inefficiencies more generally (Baranek and Titl, 2020; Schoenherr, 2019). Thus, oversight during this stage might have the largest potential for improving outcomes (Coviello and Mariniello, 2014). We extend the literature by showing that open data facilitates oversight by NGOs. As these organizations are mostly independent of the government and thus are not paid from public resources, this highlights how opening procurement data can lead to a new system of oversight in public procurement. Closely related, Werker and Ahmed (2008) theoretically discuss that NGOs can be used as a cheap platform outsourcing initially governmental tasks. We confirm this statement empirically.

Thirdly, our paper also broadly contributes to the relatively scarce literature studying procurement markets in developing countries. Lewis-Faupel et al. (2016) show that in Indonesia and India moving to an online procurement system lead to higher qualities of the project but find no effect on price. Bandiera et al. (2020) and Lehne et al. (2018) study the effects of bureaucratic competency and corruption respectively. E-procurement is a possible way how to mitigate both of the problems.

3 Description of the market

3.1 Rise of E-procurement in Ukraine

Ukraine is one of the very few countries in Europe that could be classified as 'developing'; it has the second lowest GDP per capita in the region². In recent history, it has battled enormous problems with corruption. According to the Corruption Perception Index by Transparency International, it

²After Moldova, see International Monetary Fund (2018).

is the most corrupt country in Europe³. The combination of a high share of public procurement (18% of GDP) and high levels of corruption makes for high total costs of corruption. It should be noted that while such high corruption and share of public procurement are uncommon among other European countries, they are representative of other developing countries in Africa, Asia, and South America.

To tackle this corruption issue, a group of volunteers started the ProZorro platform in February 2015. ProZorro was successful and later became compulsory for all public entities. At its core, ProZorro is (i) a unified central database of all public procurement projects conducted in Ukraine and (ii) an API for interacting with this database. Appropriate legislation ensures that procurers post all public tenders to this database, and read-only access (e.g., for monitoring or research) is always free.⁴

The whole system around ProZorro is often referred to as ‘eBay for public procurement’ in the media. Such simplification, however, falsely suggests that the main innovation of the system is the easy access to new tenderers through the use of information technology. While this plays a part in the success of ProZorro, the platform’s primary purpose is better described by its name: ‘transparency.’ By design, all the information that exists about a tender is readily available publicly. All interested parties can, therefore, easily monitor procurement contracts.

3.2 Monitoring of public procurement

This level of data access facilitated several monitoring projects by the non-profit sector. Most importantly, TI Ukraine launched the website ‘DoZorro’ in November 2016. Here, anyone can review tenders with the design of the feedback process consisting of both ‘qualitative’ (i.e., textual) and ‘quantitative’ (i.e., star rating) components, similar to sites such as Amazon or eBay. The website also automatically computes risk indicators for tenders and aggregates scores for both procuring

³If Russia is considered part of Europe, then Ukraine ranks 2nd

⁴Procuring entities and tenderers interact with the database via one of several profit-oriented marketplaces that each allow posting of and participation in tenders via their unique interfaces. However, the ‘auctions’ themselves are run by the central database so that marketplaces cannot unduly influence their result.

entities and tenderers. Finally, and perhaps most interestingly, the website provides an interface for NGOs and private citizens to exercise their right to report potential violations of laws and any suspicious activity to the Anti-Monopoly Committee of Ukraine (AMCU).⁵

The data confirm that the Ukrainian public indeed use these options for monitoring (Partnership, 2020): by July 2017, a total of fifty independent organizations was supervising the public procurement market, reporting an average of 408.7 tenders to the AMCU (an increase of 427% when compared with the February 2015 baseline). The increase in reports has led to increased activity of the AMCU, which now cancels 43.8 tenders per month on average.

The joint introduction of ProZorro and DoZorro has been widely lauded as an extremely positive step for public procurement in Ukraine. Indeed, ProZorro has received several awards (such as being rated #1 by the World Procurement awards 2016 in the Public Sector nomination), and the World Bank in 2020 assigned the Ukraine letter-grades of A in nearly all scored dimensions of public procurement (Bank, 2020).

3.3 Friction in the market

While the formal institutions in Ukraine have greatly improved, a closer examination of the market shows that corruption and collusion are still present. Indeed, only 13.3% of respondents in a 2017 survey agreed that ‘the system helps increase competition and achieves value for money’ (Partnership, 2020). When asked a similar question in 2019, this number improved, and 46.3% of respondents said that the level of corruption in public procurement had slightly or significantly decreased after the launch of ProZorro (Transparency International Ukraine, 2019). However, 24.2% still stated that they had personally encountered situations in which they were ‘forced’ to pay a bribe or resort to nepotism after ProZorro was launched, and 34.2% say that corruption is the most severe problem facing the platform. Our analysis will support public perceptions of widespread corruption and collusion. However, we will also show that the monitoring system does indeed work, and NGO

⁵Indeed, NGOs compete for badges such as ‘The Best Informant’ or ‘DoZorro Hero,’ which are awarded based on, e.g., the highest number of reported cases of collusion (as confirmed by the AMCU).

oversight leads to collusive firms' exit.

3.4 Exact Tender Procedure

Small purchases⁶ can be conducted without an online auction.⁷ Larger purchases generally have to be conducted as open tenders with a slightly different rule set applying depending on whether or not the anticipated purchase amount is large enough to fall under EU regulations.

Our analysis will focus on competitive tenders both below- and above-threshold, i.e., we will focus on whether an auction was run, not whether it was compulsory. There is a critical difference between below- and above-threshold contracts that will be relevant to our analysis. Below-threshold agreements did not require an auction in the first place; they can be awarded to the sole bidder should only one bidder participate in the sale. By contrast, above-threshold auctions must be repeated or canceled altogether if there is only one auction participant.

We now discuss the details of the open tendering procedure for the above-threshold contracts. The tender begins with the procuring entity uploading documentation for the tender to ProZorro, at which point the period of proposal submission begins and lasts for at least 15 calendar days. Once the end of the proposal submission period is reached, the tender is automatically canceled if only one proposal has been submitted. This part does not apply to below threshold auctions. If there are multiple proposals, the system automatically schedules and runs an online auction, which we discuss below. While the auction is run, the bidders do not yet have access to each others' documents. They are made aware of the number of opposing bidders the moment the online auction starts. Still, they remain unaware of their identity or specific proposals until the sale ends.

⁶A purchase is small if it is (i) a good/service bought by an ordinary contracting authority worth less than 0.2M UAH, (ii) a works purchase purchased by a standard contracting authority worth less than 1.5M UAH, (iii) a good/service bought by a 'special' contracting authority worth less than 1M UAH or (iv) a works purchase by a 'special' CA worth less than 5M UAH (Supreme Council of Ukraine, 2015).

⁷Though the data has to enter ProZorro as a 'report on concluded agreement.'

3.5 The ProZorro Auction

The tendering process's critical element is the online auction, during which bidders compete for the right to complete the contract for the government. First, initial bids are submitted together with technical proposals. Initial bids can thus be understood to be submitted 'simultaneously' because bidders are not aware of each others' bids at this stage. Secondly, bidders enter the online auction. Now they are given a chance to update their bids three times in a unique mechanism, unlike anything most economists (or at least the authors) have encountered before⁸:

1. Bidders are ordered in descending order according to their initial bids, and the first updating round begins:
 - (a) The bidder with the highest initial bid goes first, observes all initial bids and has the possibility to update her bid. However, she can only lower her bid.
 - (b) After the first bidder moves, the bidder with the second highest bid observes all bids, i.e. initial bids and the update by the originally highest bidder. This (second highest) bidder then again is given a chance to lower her original bid.
 - (c) All the bidders move sequentially in this fashion until the lowest has chosen whether to update her bid.
2. Bidders are ordered based on the size of their updated bids and again sequentially move.
3. Finally, there is a 3rd round of bidding in which bidders are ordered based on their bids from (2). The bidder with the lowest bid then wins and becomes the vendor of this project.

This mechanism essentially emulates a sequential Bertrand-game. As the last-mover in a sequential Bertrand game is advantaged, bidders are incentivized to submit low initial bids. However, as bids can only be lowered in the updating rounds, there is no incentive to submit arbitrarily low bids in,

⁸While the mechanism does feel unique, note that Georgia uses the same mechanism. Furthermore, Moldova now uses the same mechanism after adapting open-source ProZorro to create their e-procurement platform, and indications are that other countries will follow.

e.g., the initial round. We will analyze this auction below and find that it is surprisingly similar to a mix between a first- and second-price auction, the latter having no impact in equilibrium.

The reader should note that while the initial bid submission period is typically lengthy (at least 15 days, as we discuss above), the online auction proceeds in about 15 minutes (the exact length depends on the number of participants).

4 Model and equilibrium

We now discuss the intuition behind the equilibrium of the ProZorro Auction, with details and a proof relegated to the appendix. To this purpose, consider a simplified version of the auction in which there are only two players and just one updating round. The timing is as follows:

1. Bidders submit their initial bids simultaneously.
2. The initial ‘loser’ (the agent that submitted the higher bid) is given a chance to update his bid.
3. The initial ‘winner’ is given a chance to update her bid.

We note that bidders can only update their bids downwards, i.e. initial bids are not just cheap talk. As the timing makes clear, equilibrium will hinge on the amount of information revealed in the initial stage of the auction. Hence, we require

Assumption 1 (Fully Revealing Strategies) *There exists a function $b : \mathbb{R}^+ \rightarrow \mathbb{R}^+$ such that $b_i^1 = b(c_i)$ for all players i .*

This assumption ensures that, in equilibrium, agents are fully informed about each other’s cost types after the initial stage. This, in turn, generates a potential multiplicity issue: the initial loser may realise that he will lose the overall auction no matter what he bids. To resolve this multiplicity, we introduce a small probability of any given bid update to not be successfully submitted. This probability captures the natural fact that if you know you will lose if your rival reacts, you may as well bid in such a way as to maximize your surplus if for some reason your rival fails to react.

Taken together, our assumptions imply that when submitting the last bid in the auction, the initial winner will simply beat the current standing bid by the minimum amount necessary, if doing so is feasible. Just before this, the initial loser will predict what sort of bids the initial winner can beat: if there are bids that she cannot beat and that give the initial loser positive surplus, he will make the largest bid satisfying these criteria. If there are none, he will simply update his bid to the current winning bid (hoping for the small chance that his rival fails to update). More rigorously, the payoff to type c_1 from pretending to be type \tilde{c} in the initial bidding round is given by

$$\begin{aligned}
V(\tilde{c}) = & \mathbb{P}\left(b(\tilde{c}) < b(c_2) \cap c_1 < c_2\right) \left(b(\tilde{c}) - c_1\right) + \\
& \mathbb{P}\left(b(\tilde{c}) < b(c_2) \cap c_1 > c_2\right) \left(b(\tilde{c}) - c_1\right) + \\
& \mathbb{P}\left(b(\tilde{c}) > b(c_2) \cap c_1 < c_2\right) \mathbb{E}[\min\{c_2, b(\tilde{c})\} - c_1 | c_1 < c_2, b(\tilde{c}) > b(c_2)] + \\
& \mathbb{P}\left(b(\tilde{c}) > b(c_2) \cap c_1 > c_2\right) \times 0
\end{aligned}$$

The four lines of this expression correspond to the four cases that could transpire: the agent could pretend to be strong and actually be strong (first line), he could pretend to be strong and actually be weak (second line), he could pretend to be weak and actually be strong (third line) or he could pretend to be weak and actually be weak (fourth line). The astute reader will no doubt have noticed that (i) the first two lines combine to the payoffs from a first-price auction in which each bidder bids according to $b(\cdot)$ and (ii) the last two lines can be related to the expected payoff from a second price auction so that we can write the overall payoff as

$$V(\tilde{c}) = V^{FP}(\tilde{c}) + \mathbb{P}(b(\tilde{c}) > b(c_2)) \mathbb{E}[V^{SP} | \underline{c}_{-1} < \tilde{c}]$$

where we use $\underline{c}_{-1} := \min_{j \neq 1} c_j$ as more general notation to emphasize that this way of expressing the payoffs does not depend on the fact that there are exactly two players playing the game; indeed we have the following result:

Proposition 1 *The expected payoff from pretending to be type \tilde{c} is given by $V(\tilde{c})$ no matter the*

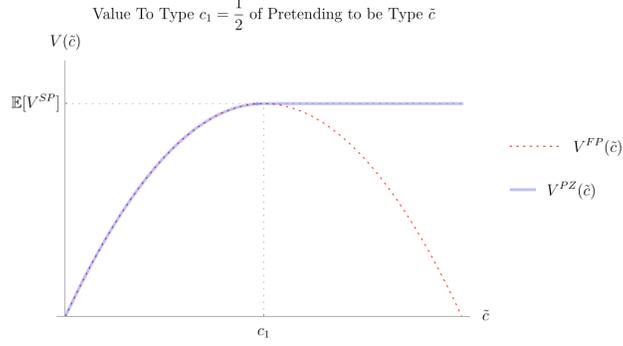


Figure 1: The Equilibrium of the PZA Auction

Notes: The expected utility to an agent of a given type from participating in the ProZorro auction reaches its peak at the same time as that of participating in a FP auction, but the second-price component ensures it never drops from this level.

number of updating rounds or number of players.

We illustrate this function in Figure 13 for the case of $c_i \sim U[0, 1]$. Naturally, if $\tilde{c} < c_1$, then the expected value from a second price auction conditional on $c_2 < \tilde{c} < c_1$ is going to be zero, and hence $V^{PZA}(\tilde{c}) = V^{FP}(\tilde{c})$ to the left of $\tilde{c} = c_1$. Furthermore, $V^{FP}(1) = 0$. Thus, $V^{PZA}(1) = \mathbb{E}[V^{SP}]$. But we know that the expected rent that bidders earn in a second-price auction is exactly equal to the expected rent they earn in a first-price auction when pretending to be their true type. Thus, $V^{PZA}(1) = V^{PZA}(c_1)$. It turns out that the effects of decreasing rent from the first-price component of the auction and increasing rent from the second-price component of the auction exactly cancel and hence $V^{PZA}(\cdot)$ is flat to the right of \tilde{c} . A more formal version of this heuristic argument in the appendix allows us to conclude:

Proposition 2 *Assuming fully-revealing strategies, the updating strategies of Proposition 7 together with initial bids given by*

$$b(c) = \frac{1}{[1 - F(c)]^{n-1}} \int_c^{c_{max}} s(n-1)f(s)[1 - F(s)]^{n-2} ds$$

form the unique PBE of the PZA with $k \geq 1$ updating rounds and $n \geq 1$ players.

Thus, we conclude that the initial bids in the ProZorro auction must come from exactly the same bidding function that they would come from in a first-price auction.

5 Data and summary statistics

We use data from three data sources. Firstly, we use publicly available procurement data from ProZorro. This data contains detailed information about the final price, industry code, delivering firm, procuring authority, or reserve price for each contract procuring by any public entity in Ukraine. Secondly, we scrape the auction platform employed by ProZorro to complement this data with detailed bidding data (including bids linked to bidder identities at all stages of the online auction). Thirdly, courtesy of Transparency International, we obtained the database underlying the monitoring platform DoZorro with information about reviews and complaints lodged by procurers, NGOs, and third parties. We isolate all auctions where our model is likely to apply. In particular, we drop auctions with suspiciously low bids that are unlikely to deliver the demanded product. We describe this phenomenon and how we adjust the data in the Appendix.

5.1 Key features of auction data

There is low competition in the market

Even though there is a minimum number of participants for all the above-threshold contracts, the average number of participants is 2.54 bidders, with the median number of participants of only 2 bidders. This low number of participants cannot be explained by small contracts being published as compared to most countries that only publish data about reasonably big contracts. Actually, the competition is comparable for big contracts above 25,000,000 UAH (about 1,000,000 USD) with an average of 2.59 bidder and a median of 2.

Not updating leaves money on the table

51% of all submitted initial bids are never updated, leading to no competition during the online auction for 45% of all sales. For big contracts, the number of auctions without competition during the online phase is even 55%. This finding contrasts with our reasoning about the optimal behavior of participants. To further argue that such bidding behavior likely leads to money left on the table

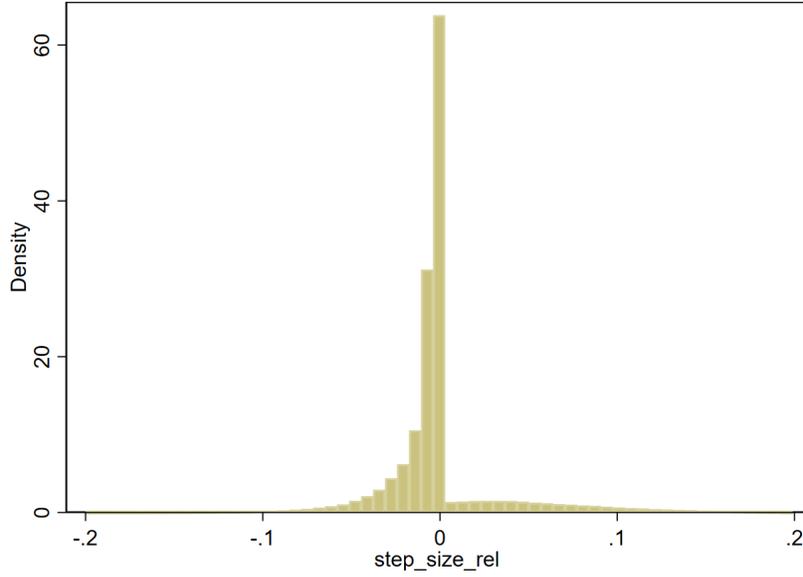


Figure 2: The Distribution of Relative Step Size of Undercutting Steps

Notes: This figure shows the step sizes, i.e. the relative decrease an updated bid represents over the current winning bid. Note that positive fractions indicate that not all bids are actually updated in a way that the bidder can win the auction.

by losing bidders, we compute the probability of winning conditional on not being the initial winner and undercutting the initial winner at least once. This probability is 18.8%, which shows significant incentives for undercutting the initial winner.

Realized updates are small

Our equilibrium discussion predicts most updates being very small and equal to the minimum bid decrement. We restrict attention to updates (i.e., situations in which a bidder lowered their bid when compared to their bid in the previous round) and define the relative step size as $\frac{bid_{l,s+1} - bid_{winner}}{bid_{l,s}}$ where $bid_{l,s}$ is the bid of a firm currently losing an auction in stage s and bid_{winner} is the bid of the current winner. Note that a ‘positive update’ means a bidder lowered their bid, but not by enough to beat the current standing winner; such ‘ineffective’ updates make up 17% of all updates. In Figure 2, we exhibit the histogram of step sizes: we can see that the mass of bid updates is very close to zero, with a median update of -0.1% (the median ‘effective’ update is -0.4%).

Table 1: Summary of procurement data

Variable	Mean	Median	Std. Dev.
<i>Panel A: All contracts</i>			
Price	2,068,509	114,999	25,026,318
Relative p	.89	.91	.09
N bidders	2.54	2.00	1.04
Is updated	.55	1.00	.49
Update size	.00	-0.001	
Colluder participates	0.07	0.00	.30
<i>N</i>		354,642	
<i>Panel B: Big contracts</i>			
Price	101,800,000	49,283,750	204,000,000
Relative price	.95	.98	.05
N bidders	2.59	2.00	4.15
Is updated	.45	.00	0.49
Update size	.003	.00	.03
Colluder participates	0.11	0.00	.30
<i>N</i>		4,151	

Notes: Relative prices are final prices divided by the reserve price.

Prosecuted collusion is a widespread phenomenon

Among vendors of public procurement, the Ukrainian Anti-monopoly Agency banned 863 firms for collusion since 2015. The majority received the universal penalty for collusion, a three-year ban from participating in procurement tenders. These companies participated in roughly 23, 515 tenders accounting for 7% of all procurement contracts but 9.4% of the total value. Prosecuted colluders also generally update their bids less, 58.4% of their bids never updates. Contracts delivered by a prosecuted colluder are on average⁹ more expensive: the median contract provided by a colluding firm costs 90.9% of the estimate, whereas contracts delivered by companies not prosecuted cost 89.6%.

⁹Note that this is a simple average, i.e., we are not controlling for anything here.

Table 2: Summary statistics contract-level

Variable	Mean	Median	Std. Dev.
Price	448,115	46,185	3,904,957
Relative p	.60	.62	.27
N bidders	3.13	3	1.64
Colluder participates	.28	0	.45
<i>N</i>	9,612		

Notes: Summary statistics on the sub-sample of the market for medical devices. Relative prices are final prices divided by the reserve price.

5.2 Market with NGO supervision: medical devices

In the last part of this paper, we will investigate the effects of online public oversight on the medical devices' market. We choose to focus on this market due to the feasibility of studying the impact of oversight there. It is one of the most important procurement markets, and we observe NGOs entering this market differentially across regions. Differential entry allows us to identify the effects of NGO oversight. Other markets are supervised as well, but there is less variation that could be used for identification.

We report summary statistics about procurement contracts on this sub-market in Table 2. The average final and relative prices are smaller than for the rest of the procurement contracts. About 34% of these procurement contracts exceed the Ukrainian thresholds. And the average number of bidders (3.1) is comparable to the average in the complete sample.

In total, there were 30 NGOs active in Dozorro as of March 2020. Across sectors, 150,000 reviews, abuse reports, and similar were submitted by the NGOs and 20,000 other users (private citizens). Regarding the medical services market, we provide an overview of NGOs active in this sector in Table 9 in the Appendix. Five such NGOs have submitted about 4,200 violations reports as of May 2020 with 69% success rater (meaning that a violation was proven) of the finished violation detection procedures. The Ukrainian authorities found almost two-thirds of these reports justified and imposed fines on the involved firms and procurers.

6 Empirical Model

6.1 Reduced form evidence

In this section, we present evidence that collusion is widespread throughout the market for public procurement. First, we show suggestive evidence based on patterns in the bidding data that are hard to explain in competitive equilibrium. In the next section, we present a formal test that will isolate colluding pairs of firms.

Based on our discussion of the equilibrium, initial bids are strictly increasing in the underlying costs. So we can infer that if two bidders submit sufficiently close initial bids, their costs should also be close. A natural prediction in such an environment is that we should see more competition and undercutting in auctions where the initial bids are near. We test this prediction in Figure 12, where we plot the fraction of auctions in which the initial loser updates their bid against the difference of initial bids. A competitive model would predict a declining function. This prediction partially holds on the left panel of Figure 12, where we analyze below-threshold auctions.

On the right panel, we observe the opposite: close initial bids are associated with decreased competition as measured by the likelihood of bid updating. Recall that there are increased incentives for collusion above the threshold due to single bidding contracts' canceling.

To further demonstrate this pattern, we plot¹⁰ the probability of winning against the initial difference of bids in Figure 4. There is an apparent discontinuity that is explained by the second-mover advantage of the initial winner. We document that submitting a bid just slightly above the opponent leads to a lower realized probability of winning than submitting a bid much above the opponent.

Such patterns are not consistent with a competitive equilibrium where close cost draws imply increased competition. However, bidding patterns are consistent with a cartel where bidders agree on who will be the winner ex-ante. Members submit bids close to each other and do not compete in the online auction. In the Appendix, we show that a simple collusion model can reproduce such

¹⁰For simplicity, we restrict the sample of auctions for this figure to those with precisely two bidders.

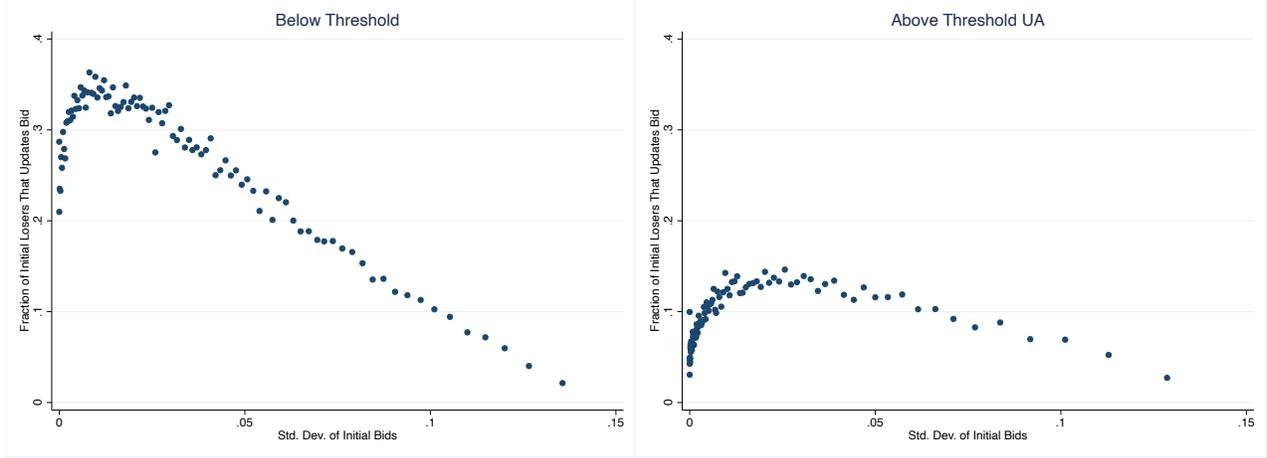


Figure 3: Fraction of Initial Losers That Updates Bid (Binscatter)

Notes: This figure is a binscatter of the fraction of initial losers that updates their bid against the standard deviation of initial bids.

patterns in the data.

6.2 Pairwise fixed-effect approach

Based on our discussion in the previous sections, we now construct a market-wide test for collusion and develop a methodology that estimates the likelihood of collusion by employing fixed effects regressions.

To begin with, define a function g in the following way: $g(i, l, w) = 1$ if bidder l updates his bid against current lowest bidder w in auction i and $g(i, l, w) = 0$ otherwise. From the discussion of the equilibrium, we know that bidders should update as long as the standing lowest bid is above their costs¹¹. However, as we argue in the equilibrium section, under Assumption 4, there is a unique and strictly increasing function $b(\cdot)$ that maps costs to initial bids. Thus, we can use the initial bids to control for costs of all players and write:

$$\begin{aligned}
 g(i, l, w) &= 1\{b^{-1}(b_l) < b_w\} \\
 &= \phi(b_l, b_w).
 \end{aligned}$$

¹¹As in the discussion of the equilibrium, we will assume an arbitrarily small minimum bid decrement.

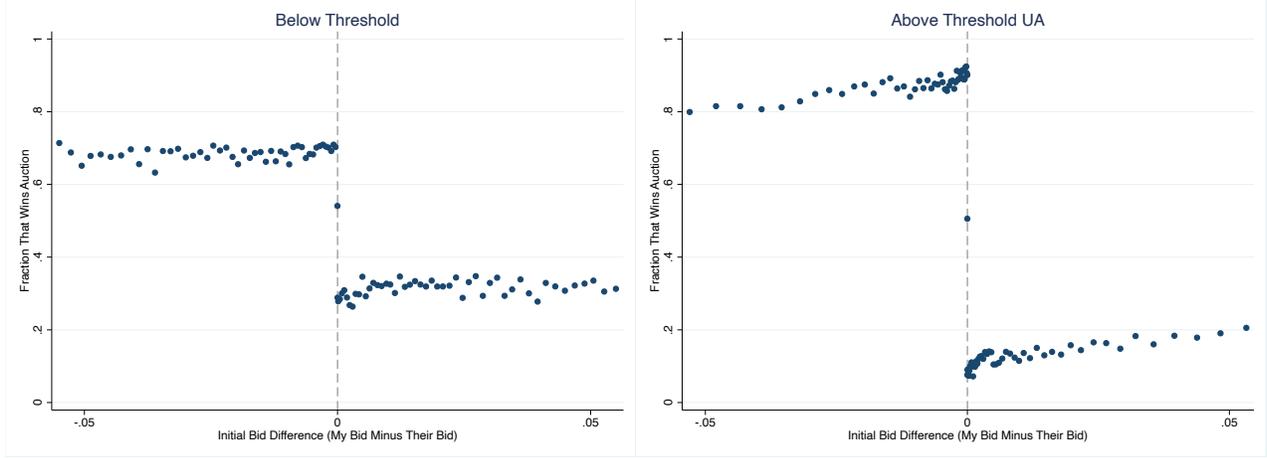


Figure 4: Probability of Winning Given Initial Bid Difference (Binscatter)

Notes: This figure is a binscatter of the probability of winning against the initial bid difference. For easier visibility, we have restricted the sample to an absolute initial bid difference below the 75th percentile.

Here, ϕ is a non-parametric function. As argued before, we allow for an idiosyncratic chance of bid submission failure. We also extend the model by allowing a bidder to erroneously undercut if they should not do so. We formalize this by introducing an idiosyncratic shock to undercutting ϵ_u where $\mathbb{E}[\epsilon | \phi(b_l, b_w)] = \alpha$. The bidder then undercuts as long as

$$\alpha + \phi(b_l, b_w) + \epsilon_{u,i}^d \geq 0 \quad (1)$$

with $\epsilon_{u,i}^d$ being the demeaned shock. We supplement the model with the pairwise fixed effect $\delta_{\ell(i), w(i)}$, which reflects tendency of the current loser $\ell(i)$ to undercut against the current winner $w(i)$. Due to the nature of the data we both observe the bidders in numerous auctions and we can track their true identity. The panel nature of our data allows us to estimate these fixed effects.

In a competitive model, these fixed effects are irrelevant as only the costs of bidders matter for their undercutting behavior, and we can control for them¹². However, this might not be the case in a collusive model: e.g., we argued above that prosecuted cartels are much less likely to undercut each others' bids in the online auction. In the competitive model, the true value of any pairwise FE is

¹²Also, it is worth stressing the bidders do not know the identities of other participants as they only observe generic names of participants such as *Bidder 1*.

thus $\delta = 0$. The bidder updates if

$$\alpha + \phi(b_{\ell(i)}^1, b_{w(i)}^1) + \delta_{\ell(i),w(i)} + \epsilon_{u,i}^d \geq 0. \quad (2)$$

This equation will be the baseline of our estimation routine. We estimate a linear approximation of Equation 2 via OLS. We linearize the model due to the infeasibility of estimating a nonlinear model with a very high number of fixed effects. The following Proposition summarizes the asymptotic properties of the OLS estimator under the assumption of competitive bidding.

Proposition 3 *In data generated by a competitive equilibrium, $\widehat{\delta_{\ell(i),w(i)}^{OLS}} \sim N(0, \sigma^2)$ for some σ^2 while imposing the constraint $\sum_{l,w} \widehat{\delta_{\ell(i),w(i)}^{OLS}} = 0$.*

We provide proof of the proposition in the appendix. The intuition is that OLS estimates of $\delta_{\ell(i),w(i)}$ are noisily estimated zero coefficients under the competitive assumption. Linearization of the model doesn't affect the consistency of the estimation because the true value of the fixed effects δ is zero. As the fixed effects are not separately identified from the intercept, we normalize their mean to zero.

We estimate the model in (1) and plot the empirical distribution of the fixed effects in Figure 5. When compared to a Normal distribution, the plotted data has an excess mass below the mean. Using the Kolmogorov-Smirnov test, we reject the hypothesis that the distribution is normal. We estimate fixed-effects only for pairs that we repeatedly observe in the data. As the sample size might still be limited for some pairs, we apply Empirical Bayes shrinkage to the fixed effects (Chandra et al., 2016). The additional mass on the left side of the distribution shows a significant number of pairs that are less likely to undercut each other's bid compared to the competitive baseline – an observation that would be expected on the market with lots of collusive firms.

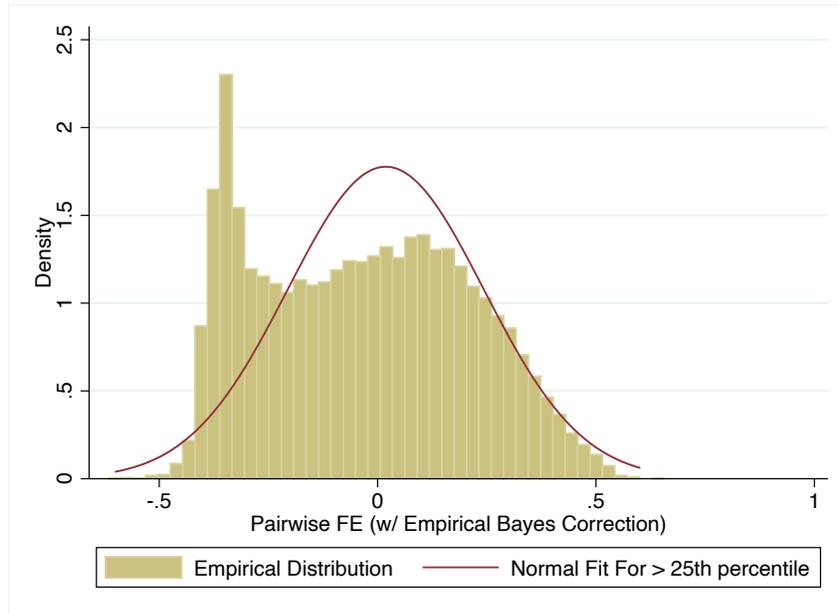


Figure 5: Distribution of Pairwise Fixed Effects

Notes: We show the distribution of the pairwise fixed-effects of equation (1). There is excess mass on low fixed-effects, indicating that certain bidder pairs never undercut each other.

Interpretation of the fixed effects

We based our previous discussions only on the concept of a competitive equilibrium. We now add some simple assumptions on a cartel’s behavior that will help us explain the anomalies in data and translate the fixed-effects into probabilities of being in a cartel. We will consider two additional assumptions.

Assumption 2 *Cartels collude by not undercutting each other with some probability p .*

This assumption formalizes our previous discussion. We assume one of the features of a cartel is that the colluding firms do not undercut each other with some probability. This assumption is relatively general as it allows for different cartel strengths, with $p = 1$ being a perfect cartel and $p = 0$ approaching the competitive case. However, it excludes sophisticated behavior on the side of the cartel where cartels imitate a competitive equilibrium. In this sense, we only identify a subset of all possible cartels, which is in line with classic results suggesting that we can never rule out anti-competitive behavior as sufficiently sophisticated firms could always emulate equilibrium play

(Bajari and Ye, 2003).

Assumption 3 *The probability of being in a cartel is independent from optimal competitive behavior.*

This assumption will allow us to derive a simple formula for the probability of a pair being in a cartel. In particular, we assume that the auction characteristics do not influence the likelihood of cooperating. We can then write the probability of updating as:

$$\begin{aligned} P(k \text{ updates against } l) &= P(k \text{ updates against } l \text{ under competition} \cap k, l \text{ are not a cartel}) \\ &= g(i, b_k, b_l, r) \times P(k, l \text{ not in a cartel}) \end{aligned}$$

Proposition 4 *Under Assumptions 1-3 we can rewrite the probability of being in a cartel as*

$$P(k, l \text{ in a cartel for project } i) = 1 - \frac{g(i, b_k, b_l, r)}{g(i, b_k, b_l, r) + \delta_{k,l}}.$$

In this case, there is a unique mapping from the fixed effect value to the probability of being a cartel: lower value of δ suggests a higher likelihood of being in a cartel. This equation holds for each project i . We could estimate the average probability of two bidders being in a cartel by averaging over all observations i on the right-hand side. In Appendix A, we conduct simulations to show how adding only these few simple assumptions on the cartel's behavior helps explain most of the anomalies we observe in the data.

Verification of the Pairwise Fixed Effect Algorithm

In Figure 6, we compare the estimated pairwise fixed effect for firm pairs that the courts identify as colluders. We observe that the identified colluding pairs are concentrated in the left part of the distribution with the suspicious additional mass. However, even among firms that were not prosecuted, there is still excess mass on the left, suggesting that the courts did not identify all colluding firms. The figure shows that our algorithm works very well¹³ for the subset of identified

¹³The relevant t-statistic from the regression of the dummy of being a collusive pair on the size of the pairwise FE is -17.06 .

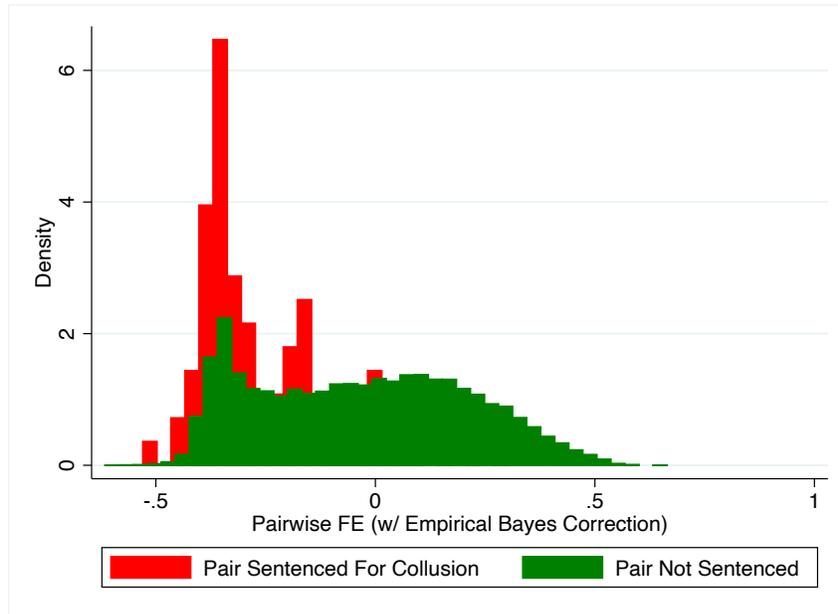


Figure 6: Pairwise FE: Sentenced Colluders vs Non-Sentenced

Notes: We break up the distribution of pairwise fixed-effects by whether a pair was mentioned in a successfully prosecuted collusion case or not. Clearly, sentenced colluding pairs are more likely to have lower fixed-effects (the t-stat from a binary linear probability model is 17.06).

colluders and could be used for further identification of other suspicious firms.

7 NGO Oversight

A vital aspect potentially influencing the Ukrainian procurement market is the online monitoring system ‘DoZorro.’ This platform congregates non-governmental organizations (NGOs) and volunteers that subsequently inspect the procurement contracts. We employ difference-in-differences as the primary empirical strategy to study the effects of the oversight system on procurement outcomes and colluding firms’ participation.

The Ukrainian system is amenable to the difference-in-differences analysis. Some NGOs focus on particular regions and particular sectors of the economy, which creates the necessary variation to define treated and control groups. For any given geographical area, we can find neighboring regions that can act as a control group. The timing of when treatment in a given region starts is observable from our data, as we know when NGOs submitted the first abuse reports in the region. We can

identify the effect of NGO oversight on market outcomes by comparing the market’s evolution in the treated contracts (i.e., those for which the NGO conducts monitoring) to the control contracts (in neighboring regions without NGO oversight) in the same sector.

An inspection of abuse reports suggests focusing on medical devices is convenient as NGOs are specializing in this sector, and the existence of such NGOs varies by region. The choice where to operate and which sectors to oversee is often dependent on available staff. Moreover, these devices have similar prices worldwide, so after controlling for specific contract type fixed effects, we can remove potential bias from unobservables (unlike, e.g., in the less normed IT sector). We then employ the following empirical specification:

$$outcome_i = \alpha + \beta_1 post_{t(i)} + \beta_2 oversight_{r(i)} + \beta_3 post_{t(i)} * oversight_{r(i)} + \delta_{c(i),m(i)} + \varepsilon_i \quad (3)$$

where i stands for contract, r for region, t for time, c for type of contract, m for calendar months, δ_{cm} for the contract type-month fixed effects. The dummy variable $oversight_r$ is equal to 1 for procurement contracts procured by procuring authorities based in the regions where an overseeing NGO became active in the studied period and 0 otherwise. The variable $post_t$ is equal to 1 when the treatment starts and afterwards and 0 otherwise. The basic outcome measures are the relative price (the final price divided by the estimated cost), the number of bidders, and the share of colluding bidders.

To analyze comparable periods before and after the oversight started, we choose to limit the sample to procurement contracts awarded in the period from April 2016 to April 2017 (the dummy variable $post_t$ is 0 in this period) and in the period from July 2017 to July 2018 ($post_t$ is 1). We exclude the period from April 1st 2016 to June 30th to mitigate the possible effects of this “transitional period”. The results do not substantially change when we include the “transitional period” or extend the sample until March 2020.¹⁴

The activity of NGOs differs geographically across 24 regions (“Oblast” in Ukrainian). In 7 regions, there are NGOs active in the procurement market of medical devices. In the rest of them,

¹⁴Extending the sample makes our results statistically stronger.

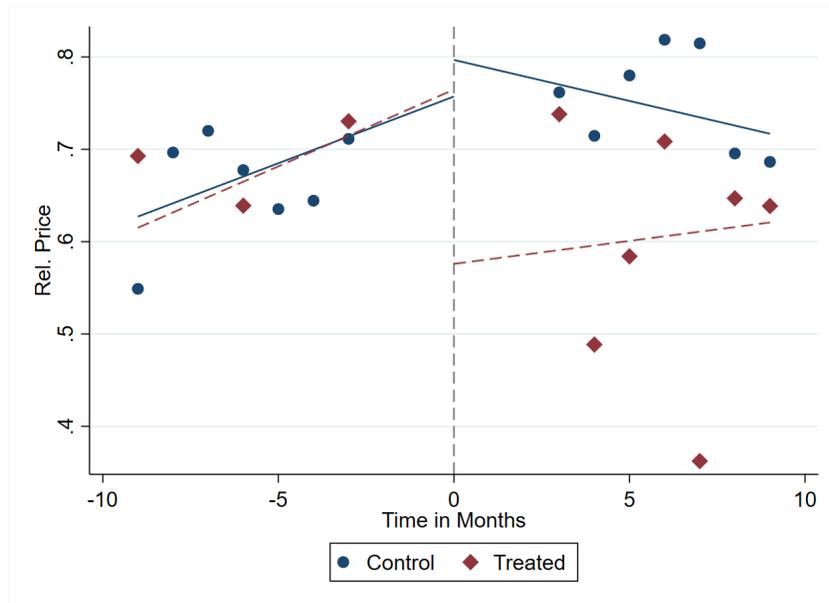


Figure 7: Parallel Trends

Notes: The figure depicts monthly averages of relative prices for procurement contracts in treated (diamonds) and control (circles) groups.

there are no NGOs with this specialization. The contracts procured in the regions with the NGOs actively overseeing medical devices are considered treated. In Appendix, we provide a detailed overview of treated and control regions (Table 7), information about the timing of the first reports submitted in each area (Table 8), and an overview of NGOs active in the medical sector in the treated regions (Table 9). The first reports in each treated region were submitted at a similar point time, thus, the treatment starts at the same time for all treated regions.

An essential assumption behind the difference-in-differences estimation is the assumption of parallel trends. In Figure 7, we visually inspect whether this assumption is satisfied and plot relative prices over time for the groups of treated and control procurement contracts. Despite relatively high noise in the relative costs, the assumption of trends before parallel before the treatment appears to be satisfied.

Given the different incentives in below- and above-the-threshold procurement contracts, we present the results for below-threshold contracts in Table 3 and above-threshold contracts in Table 4. Among the below-threshold contracts, we find that online oversight causes a decline in the number

of bidders and also an increase in the number of updates per bidders. The decrease in the number of bidders is economically significant since the average number of bidders was 2.36 among contracts in the studied regions. We do not find any significant effect on the relative price among these contracts.

Table 3: Difference-in-differences – below-threshold procurement contracts

	(1)	(2)	(3)
	Rel. Price	Bidders	Updates
Post	0.110***	-0.425***	-0.522***
	(0.0131)	(0.0619)	(0.0556)
Oversight	-0.0482	0.270	-0.0678
	(0.0707)	(0.2430)	(0.1826)
Post × Oversight	0.0134	-0.482*	0.598**
	(0.0722)	(0.2682)	(0.2838)
Sector-month FE	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
N	3622	8370	4112

Notes: Standard errors clustered at procurer level in parentheses. Other controls include evaluation criteria, status (not in (3)), number of lots, number of items and the type of procuring entity. *Relative prices* are final prices divided by the reserve price. *Bidders* is the number of bidders participating in the auction. *Updates* is the total number of updates per bidder. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For the above-the-threshold contracts, we also find the effect of online oversight on the number of updates per bidder is positive and significant. We do find evidence for a decline in the number of bidders. However, we observe a substantial decrease in prices. This could suggest that collusive bidders were pushed out of the market, which enables a real competition.

Table 4: Difference-in-differences – above-the-threshold procurement contracts

	(1)	(2)	(3)
	Rel. Price	Bidders	Updates
Post	0.0677***	-0.0619	-0.227**
	(0.0250)	(0.1510)	(0.0999)
Oversight	0.129**	0.496	-0.361
	(0.0609)	(0.6338)	(0.3136)
Post × Oversight	-0.206***	-0.400	0.670**
	(0.0655)	(0.6220)	(0.3383)
Sector-month FE	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
N	1453	2150	1990

Notes: Standard errors clustered at procurer level in parentheses. Other controls include evaluation criteria, status (not in (3)), number of lots, number of items and the type of procuring entity. *Relative prices* are final prices divided by the reserve price. *Bidders* is the number of bidders participating in the auction. *Updates* is the total number of updates per bidder.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Table 5, we examine whether online oversight affects the participation of firms that we found to be colluding in the previous section. While we do not see any significant effect among below-threshold contracts, we find that oversight leads to a decrease in the participation of colluding firms for all above-the-threshold contracts. Such a finding is not surprising given that the motivation to collude is much lower among below-threshold contracts as there is no requirement of a minimum of 2 bidders.

Table 5: Difference-in-differences – procurement contracts

	All Contracts	Below	Above
	(1)	(2)	(3)
Colluding Pair among Bidders			
Post	0.0216 (0.0184)	0.00919 (0.0181)	0.0404 (0.0393)
Oversight	-0.00797 (0.0438)	-0.0643** (0.0312)	0.0817 (0.0983)
Post × Oversight	-0.0379 (0.0502)	0.0429 (0.0384)	-0.265** (0.1108)
Sector-month FE	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
N	17222	13187	3921

Notes: Standard errors clustered at procurer level in parentheses. Other controls include evaluation criteria, status (not in (3)), number of lots, number of items and the type of procuring entity. The dependent variable is a dummy variable equal to 1 if the contract was delivered by a firm detected as a colluding firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We are aware that the treatment assignment may be non-random, for instance, when NGOs may first appear in regions with the largest share of colluding firms. If other essential assumptions, such as the parallel trends assumption and the composition of treated and control groups, are satisfied, our results are internally valid and informative about the effects of interest. We are particularly interested in the local effect of online public monitoring in the markets that suffer from imperfection rather than in perfectly competitive markets.

Zooming in on an example

We showed the aggregate effects of NGO supervision. These NGOs can enforce proper conduct by writing abuse reports in Dozorro. Hence, to add credibility to our analysis, we empirically

describe an example of how the oversight and enforcement work. Abuse reports submitted by NGOs are tracked in the Dozorro database until a conclusion for the report is reached. We thus observe what type of report was submitted and whether the report was found justified – i.e., leading to, for example, cancellation of a contract or an initiation of criminal proceedings. This section shows that the market responds to reports by NGOs. In particular, we focus on reports about firms unjustifiably winning contracts. After such reports are officially presented, we observe that procuring agencies stop abusing their discretion to exclude bidders from the tender. There is a higher chance that the lowest bidder wins.

We study the changes in procurement outcomes after the first successful report about the unjustified contract award. Dummy variable *After first report* equals to 1 if the contract was awarded after the first successful abuse report “unwarranted choice of the winner” was submitted in Dozorro about a procurement contract in the same sector¹⁵ and procured by the same procuring authority, otherwise equal to 0. In Table 6, we report results from regressing the probability that the lowest bid wins (Column (1)), the number of bidders (Column (2)), and the relative price (Column (3)) on the dummy variable for the first report (*After first report*). The coefficient on the dummy variable then measures the difference in the three procurement outcomes for contracts of similar goods or services (as defined by CPV) procured by the same entity before and after the first successful abuse report was submitted by any NGO.

We find that that probability that the lowest bid wins increases and that the number of bidders declines. The decrease in the number of bidders is consistent with the previous finding that colluding firms leave the market in regions after NGOs’ entrance, which induces a higher threat of an inspection by NGO. The increase in the ex-post probability of the lowest bid winning again suggests that Ngo’s presence and activity enforce the proper conduct of procuring authorities.

¹⁵Defined as 4 digits CPV

Table 6: First abuse report

	(1)	(2)	(3)
	Lowest bid wins	Bidders	Rel. Price
After first report	0.200***	-0.547**	0.00377
	(0.0637)	(0.2449)	(0.0072)
Year FE	Yes	Yes	Yes
Sector-procuring entity FE	Yes	Yes	Yes
N	168201	168201	168201

Standard errors in parentheses

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

Notes: Standard errors clustered at procurer level in parentheses. The independent variable *After first report* is a dummy variable equal to 1 if the contract was awarded after the first successful abuse report “unwarranted choice of the winner” was submitted in Dozorro about a procurement contract in the same sector (defined as 4 digits CPV) procured by the same procuring authority, otherwise equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Welfare impact of oversight

In the previous section, we establish that oversight leads to a drop in procurement prices. Now we quantify what the potential welfare gains due to this price decrease are. In particular, the change in prices does not only redistribute rents from producers to the government (which in itself may be desirable). As demand for public procurement is not infinitely inelastic, there is the potential for a deadweight loss to society. To estimate the deadweight loss, we assume that government demand for public procurement takes a constant-elasticity form and calculate the relevant integral (see Appendix I).

The key challenge is thus computing the elasticity of demand. Gibson (1980) computes a long-run demand elasticity using survey demand and estimates an elasticity of -1.08 ¹⁶.

¹⁶There are multiple specifications, and the results depend on exact products. We use the result from highways and constructions that are closest to the basket of procurement in Ukraine. Other elasticity’s of commonly procured goods are also around -1

We complement this back-of-the-envelope calculation with our estimates using annual data from Ukraine. We want to compute the response of the volume of procurement demand to the change in market prices. Market prices might be endogenous as the procurers might influence the prices paid for their projects. We propose to instrument for own procurement prices by a price index that is a function of prices paid by other procurement agencies in the same sector and region. We then compute the index as an average of other procurement agencies' relative prices in the same area and industry. Prices paid by other procurers should be exogenous from a procurement agency's perspective but correlated as they capture the same supply shocks. Such supply shocks can then identify demand. Then we project :

$$\log(\text{procurement}_{p,i,y}) = \alpha + \beta \cdot \log(\text{price}_{p,i,y}) + \delta_{p,i} + \delta_{i,y} + \delta_{y,p} + \epsilon_{p,i,y} \quad (4)$$

where p denotes the procurer, i the industry, and y the year, and we instrument the own price with the price index. We also control for a rich set of fixed effects to isolate a procurer/industry specific heterogeneity, time trends, et cetera. The resulting estimate is $\beta = -.238$ and hence the estimated elasticity of quantity (as opposed to spending) with respect to price is¹⁷ -1.23 . These results are of the same order of magnitude as other estimates in the literature.

Using the elasticity from the literature and elasticity estimated in our data, we get bounds on the total welfare effects. These amount to between 2.68% (Gibson's elasticity) and 3.11% (our elasticity) of procurement spending. This translates to 0.48% to 0.56% of Ukrainian GDP, showing a possible sizeable welfare gain from the additional oversight due to e-procurement.

8 Conclusion

This paper exploits a unique setting in Ukraine to show that online public monitoring of procurement markets eliminates collusion and improves market outcomes. The reform from 2016, which made all

¹⁷Note that $\frac{\partial \log pq}{\partial \log p} = \frac{\partial \log q}{\partial \log p} + 1$.

public procurement in Ukraine electronic and transparent. This paper uses this unique setting to study the effects of an online monitoring system introduced after the 2016 reform of public procurement on collusion and other outcomes. This online monitoring system allows citizens to observe complete information about procurement contracts and comment, review, monitor, and submit abuse reports. About 30 NGOs and highly-educated volunteers have sent nearly 150,000 reviews and abuse reports as of March 2020. This is especially interesting and important in developing countries with low government capacity and highly educated citizens. Such a monitoring system allows the government to harness this potentially important source of oversight for free.

In the first part of this paper, we develop a new technical tool to detect collusion and show that collusion is widespread in the Ukrainian public procurement market. In this algorithm, we exploit the multi-stage nature of the Ukrainian auction mechanism and detect pairs of firms that repeatedly do not behave competitively against each other in procurement auctions. In our setting, this means that they do not update their bids against each other and only wait till the auction ends. We verify our detection algorithm's reliability on a dataset of 863 successfully prosecuted firms by the Ukrainian Anti-monopoly Agency.

In the second part, we analyze the effects of the public online monitoring system on collusion and other procurement outcomes. Using the different entry of monitoring NGOs and the differential extent of monitoring for identification, we find a sizeable reduction in prices and collusion after introducing the monitoring by citizens. The findings suggest that collusive bidders were pushed out of the market, which enabled a real competition.

Our results are relevant outside the Ukrainian context. Countries such as Moldova and Georgia have already implemented identical e-procurement systems, ensuring that our results are immediately applicable. Furthermore, high levels of corruption and collusion and government's low efficiency are typical for other developing countries. In such countries, public monitoring and data transparency might increase procurement markets' efficiency.

References

- Asker, J. (2010). A study of the internal organization of a bidding cartel. *American Economic Review*, 100(3):724–62.
- Bajari, P. and Ye, L. (2003). Deciding between competition and collusion. *Review of Economics and Statistics*, 85(4):971–989.
- Bandiera, O., Best, M. C., Khan, A. Q., and Prat, A. (2020). The allocation of authority in organizations: A field experiment with bureaucrats. Technical report, National Bureau of Economic Research.
- Bank, W. (2020). 2019 Public Expenditure and Financial Accountability (PEFA) Performance Assessment Report.
- Baranek, B. and Titl, V. (2020). The cost of favoritism in public procurement. *FEB Research Report Department of Economics*.
- Calvo, E., Cui, R., and Serpa, J. C. (2019). Oversight and efficiency in public projects: A regression discontinuity analysis. *Management Science*, 65(12):5651–5675.
- Chandra, A., Finkelstein, A., Sacarny, A., and Syverson, C. (2016). Health care exceptionalism? performance and allocation in the us health care sector. *American Economic Review*, 106(8):2110–44.
- Chassang, S. and Ortner, J. (2019). Collusion in auctions with constrained bids: Theory and evidence from public procurement. *Journal of Political Economy*, 127(5):2269–2300.
- Clarka, R., Coviello, D., and De Levanoc, A. (2020). Complementary bidding and the collusive arrangement: Evidence from an antitrust investigation.
- Conley, T. G. and Decarolis, F. (2016). Detecting bidders groups in collusive auctions. *American Economic Journal: Microeconomics*, 8(2):1–38.

- Coviello, D. and Mariniello, M. (2014). Publicity requirements in public procurement: Evidence from a regression discontinuity design. *Journal of Public Economics*, 109:76–100.
- De Leverano, A. (2019). Collusion through market sharing agreements: Evidence from quebec's road paving market. *ZEW-Centre for European Economic Research Discussion Paper*, (19-053).
- Demokratizatsiya, S. S. (2017). Public procurement reform in Ukraine: the implications of neopatrimonialism for external actors. *demokratizatsiya.pub*.
- Gibson, B. B. (1980). Estimating demand elasticities for public goods from survey data. *The American Economic Review*, 70(5):1069–1076.
- Giuffrida, L. M. and Rovigatti, G. (2019). Supplier selection and contract enforcement: Evidence on performance bonding.
- Greene, W. (2003). Econometrics. *Various Editions*.
- Greene, W. H. (1983). Estimation of limited dependent variable models by ordinary least squares and the method of moments. *Journal of Econometrics*, 21(2):195 – 212.
- International Monetary Fund (2018). World economic outlook database. data retrieved from <https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD>.
- Kawai, K. and Nakabayashi, J. (2014). Detecting large-scale collusion in procurement auctions. *Available at SSRN 2467175*.
- Lehne, J., Shapiro, J. N., and Eynde, O. V. (2018). Building connections: Political corruption and road construction in india. *Journal of Development Economics*, 131:62–78.
- Lewis-Faupel, S., Neggers, Y., Olken, B. A., and Pande, R. (2016). Can electronic procurement improve infrastructure provision? evidence from public works in india and indonesia. *American Economic Journal: Economic Policy*, 8(3):258–83.
- Partnership, O. C. (2020). Ukraine S&L: MEL Framework. pages 1–20.

- Porter, R. H. and Zona, J. D. (1993). Detection of bid rigging in procurement auctions. *Journal of political economy*, 101(3):518–538.
- Porter, R. H. and Zona, J. D. (1999). Ohio school milk markets: An analysis of bidding. *RAND Journal of Economics*, 30(2):263–288.
- Schoenherr, D. (2019). Political connections and allocative distortions. *The Journal of Finance*, 74(2):543–586.
- Supreme Council of Ukraine (2015). Ukrainian Public Procurement Law. pages 1–41.
- Transparency International Ukraine (2017). Co-Creation of ProZorro: An Account of the Process And Actors. Technical report.
- Transparency International Ukraine (2019). Behind the Scenes of ProZorro. Does Ukrainian business trust public procurement? Technical report.
- Werker, E. and Ahmed, F. Z. (2008). What do nongovernmental organizations do? *Journal of Economic Perspectives*, 22(2):73–92.
- World Bank (2017). Benchmarking Public Procurement 2017: Assessing Public Procurement Regulatory Systems in 180 Economies. Technical report.

A Institutional background

The story of public procurement in Ukraine is long and complicated (for a summary see Transparency International Ukraine, 2017). While a first real effort to develop procurement legislation in 1997 was motivated by the need to harmonize regulations with WTO standards, the resulting law (in 2000) was lacking in detail and clarity (Transparency International Ukraine, 2017). The situation deteriorated substantially when the newly established ‘Tender Chamber of Ukraine’ was put in charge of all public procurement in 2005 and promptly began exercising its power to unduly influence

bidder selection (Demokratizatsiya, 2017). An interim period followed in which there were several unsuccessful attempts to fix the system.

In 2013, the suspension of negotiations with the European Union by Ukrainian president Viktor Yanukovich sparked demonstrations and marked the beginning of a period of political turmoil, the 'Euromaidan'. As protests spread, Yanukovich fled the country and parliament relieved him of his duty. While an interim government led the country, the head of the Ministry of Economic Development and Trade (MoE) asked for volunteers to organize themselves and research possibilities for reforming various governmental institutions, public procurement being one of them. After meetings with Georgian and EU procurement experts, the volunteers agreed to model their system on the Georgian example.

However, two issues remained. There was a worry that a centrally administrated system would not provide sufficient incentives for ease-of-use. Furthermore, there was currently no apparent source of funding for the project: perhaps surprisingly, the official procurement department did not yet support the reform. Ukraine adopted a 'hybrid' system in which access to a central database of procurement contracts is mediated by various marketplaces that are allowed to charge a fee for this access but, in turn, provided initial funding for the development of the system. Transparency International Ukraine agreed to manage the budget during the pilot phase of the project, collected the contributions from the marketplaces, and selected a company for the necessary software development.

With initial funding secured, a pilot of what would eventually become the ProZorro e-procurement system was live in February 2015. However, at this stage, the project was still entirely a volunteer-led reform initiative: things only changed when a volunteer representative became the head of the Department of Public Procurement Regulation in March 2015. The status of the project thus having been elevated, parliament passed new legislation in November 2015, and new funding from multiple international organizations allowed various refinements of the pilot necessary for full deployment. Finally, in April (August) 2016, the use of ProZorro became compulsory for many (all) public entities.

At its core, ProZorro is (i) a unified central database of all public procurement projects conducted

in Ukraine and (ii) an API for interacting with this database. Appropriate legislation ensures that procurers post all public tenders to this database, and (crucially!) read-only access (e.g., for monitoring or research) is always free. Procuring entities and tenderers interact with the database via one of several profit-oriented marketplaces that each allow the (free) posting of and (fee-incurring) participation in tenders via their unique interfaces. The ‘auctions’ themselves, however, are run by the central database so that marketplaces cannot unduly influence their result.

The marketplaces (or the whole system) are often referred to as ‘eBay for public procurement’ in the media. Such simplification, however, falsely suggests that the main innovation of the system is the easy access to new tenderers through the use of information technology. While this plays a part in the success of ProZorro, the platform’s primary purpose is better described by its name: ‘transparency’. By design, all the information that exists about a tender is readily available publicly. All interested parties can, therefore, easily monitor procurement contracts.

The fact that transparency was the primary purpose of the development of ProZorro becomes even more salient when we examine several initiatives built to complement and support the platform. Firstly, there is the ‘analytics module’, which allows quick access to summary statistics; the module is sufficiently interactive to allow for productive exploration of the data at a journalistic level. Furthermore, the MoE and ProZorro have introduced several procurement qualifications. While the university courses mostly aim at teaching potential future civil servants how to *run* successful tenders, there are also online courses with a more explicit focus on monitoring, e.g., the aptly named ‘Monitoring of Public Procurement; Or: How To Look for Betrayal’.

First and foremost, however, there is the establishment of the monitoring portal DoZorro by TI Ukraine in November 2016. Here, tenders can be reviewed by anyone, with the design of the feedback process consisting of both ‘qualitative’ (i.e., textual) and ‘quantitative’ (i.e., star rating) components, similar to sites such as Amazon or eBay. The website also automatically computes risk indicators for tenders (e.g., ‘winner disqualified’) and aggregates scores for both procuring entities and tenderers. Finally, and perhaps most interestingly, the website provides an interface for NGOs (and private citizens) to exercise their right to report potential violations of laws and any

suspicious activity to the Anti-Monopoly Committee of Ukraine (AMCU). Indeed, NGOs compete for badges such as ‘The Best Informant’ or ‘DoZorro Hero’, which are awarded based on e.g., the highest number of reported cases of collusion (as confirmed by the AMCU).

The data confirm that the Ukrainian public indeed use these options for monitoring (Partnership, 2020): by July 2017, a total of fifty independent organizations was supervising the public procurement market, reporting an average of 408.7 tenders to the AMCU (an increase of 427% when compared with the February 2015 baseline). The increase in reports has led to increased activity of the AMCU, which now cancels 43.8 tenders per month on average (as opposed to 11.4 in the baseline). The number of complaints that end in civil or criminal punishment has also increased from 35 to 56.

The joint introduction of ProZorro and DoZorro has been widely lauded as an extremely positive step for public procurement in Ukraine. Indeed, ProZorro has received several awards (such as being rated #1 by the World Procurement awards 2016 in the Public Sector nomination) and the World Bank in 2020 assigned the Ukraine letter-grades of A in nearly all scored dimensions of public procurement. The sole exception was the ‘procurement methods’ score since only 78.1% of the total cost of all public procurement covered by the relevant law in 2018 was tendered in competitive procedures (Bank, 2020).

We will argue that while the formal institutions in Ukraine have indeed greatly improved, a closer examination of the bidding suggests that collusion and shill-bidding have become costly problems. Indeed, only 13.3% of respondents in a 2017 survey agreed that ‘the system helps increase competition and achieves value for money’ (Partnership, 2020). When asked a similar question in 2019, this number improved, and 46.3% of respondents said that the level of corruption in public procurement had slightly or significantly decreased after the launch of ProZorro (though 12.2% said it had increased) (Transparency International Ukraine, 2019). However, 24.2% still stated that they had personally encountered situations in which they were ‘forced’ to pay a bribe or resort to nepotism after ProZorro was launched, and 34.2% say that corruption is the most severe problem facing the platform. Our analysis will support public perceptions of widespread corruption and collusion. However, we will also show that the monitoring system does indeed work, and NGO

oversight leads to the exit of, particularly, collusive firms.

B Model of collusion

Here we present a model of collusion that likely reflects the behavior of actual cartels in our data. We will conduct simulations for auctions with exactly two players. There are two possibilities: either the auction is competitive, or there is a collusive pair participating.

In the competitive situation, the bidders act in line with their equilibrium strategies. Collusive pairs, on the other hand, are modelled in the following way. The pair designates a winner ex-ante; the designated loser just exists to submit a phantom bid thereby causing the auction to go ahead (and perhaps ensuring regulators do not investigate the relevant market). Thus, the designated loser simply submits a bid $(1 + a)b_{c,w}$, where a is a small constant and $b_{c,w}$ is the bid of the designated winner. The designated winner submits a bid above the equilibrium competitive bid. Collusive bidders do not undercut each other as they have no incentive to do so.

We present results of a simulation where bidders have uniform costs, i.e. $c_i \sim U[0, 1]$. We furthermore parametrize the model for our simulation. We simulate 400 bidders, each of which interacts with all other bidders in exactly 2 auctions. Of all bidding pairs, 3% are in a cartel.

Using data from this model we reproduce Figures 4 and 12. We see that patterns in these figures can be explained with this simple model of collusion. The above-threshold auctions have a higher incentive for collusion and are comparable to the simulation of collusive behavior. By contrast, below-threshold auctions are comparable to the competitive ones.

It is hard to argue that this model of collusion is the unique model as collusive agreements can have many different forms. However, it is striking that we can explain all anomalies in our data with such a simple model.

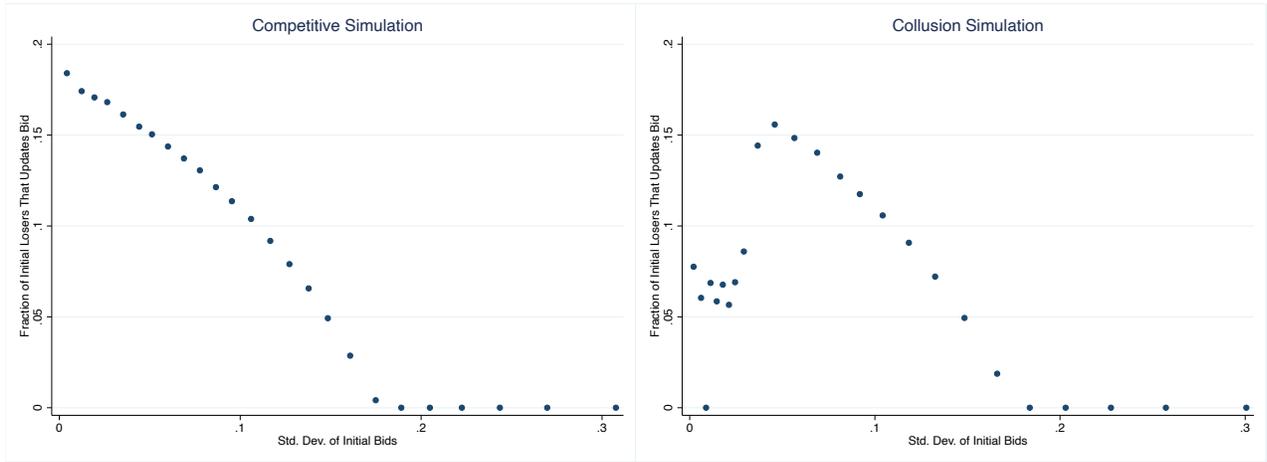


Figure 8: Simulation: Fraction of Initial Losers That Updates Bid (Binscatter)

Notes: This figure is a binscatter of the fraction of initial losers that updates their bid against the standard deviation of initial bids.

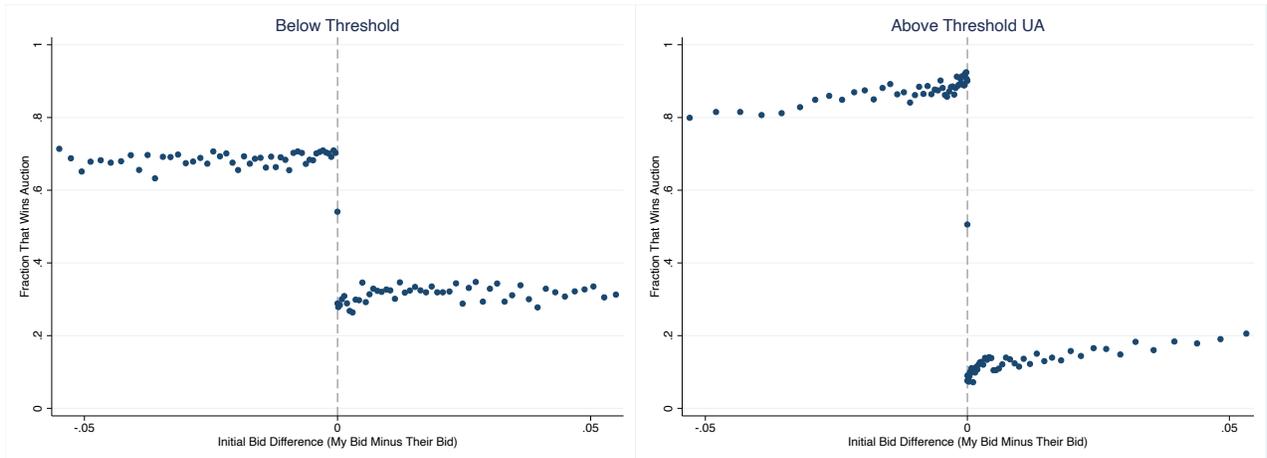


Figure 9: Simulation: Probability of Winning Given Initial Bid Difference (Binscatter)

Notes: This figure is a binscatter of the probability of winning against the initial bid difference. For easier visibility, we have restricted the sample to an absolute initial bid difference below the 75th percentile.

C Simulations

Here we include simulations of the model with two additional assumptions and show that it emulates data well.

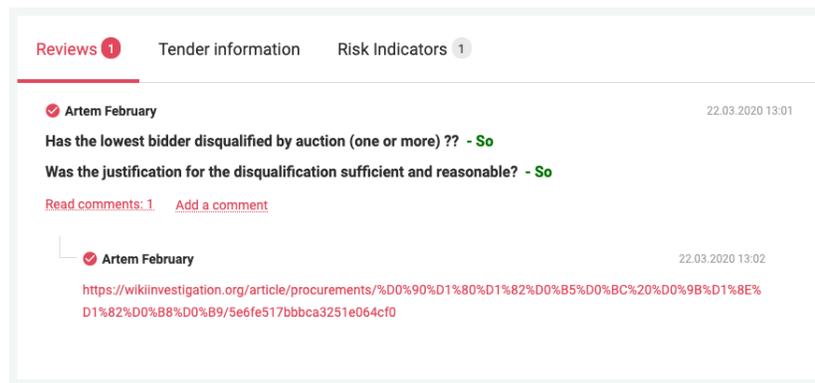
Figure 10: suspiciously close bids and no undercutting

Initial bids	
 ТДВ Облдоррембуд	31 864 899,19 UAH / 1,00 <small>minimum</small>
 ТОВ "СЛАВДОРСТРОЙ"	31 864 900,00 UAH / 1,00

Notes: These are two initial bids in an auction where no subsequent bids happened.

D Motivating examples and evidence

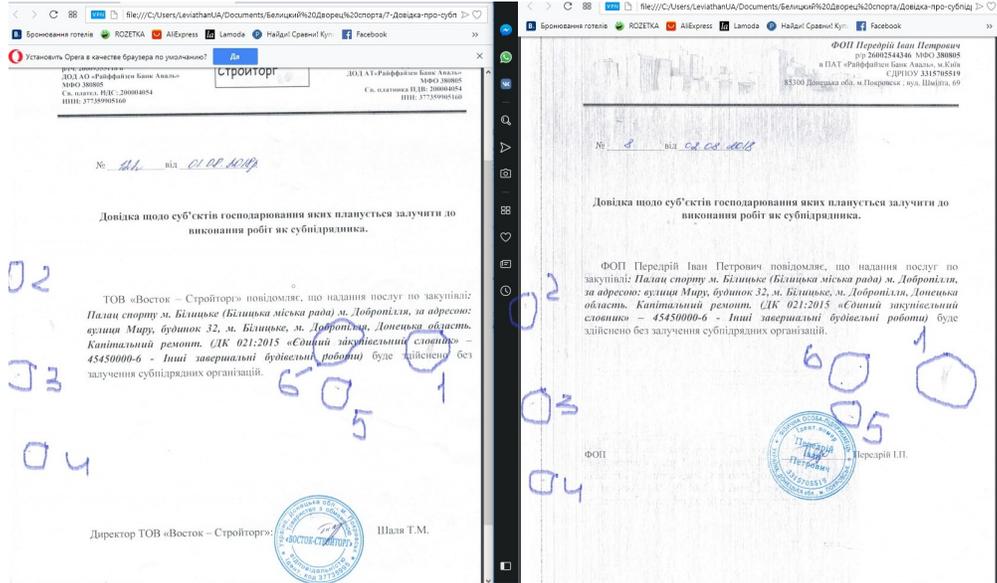
Figure 11: Example of a review



The screenshot shows a review interface with three tabs: "Reviews" (1), "Tender information", and "Risk Indicators" (1). The "Reviews" tab is active. A review by "Artem February" is displayed, dated "22.03.2020 13:01". The review text asks: "Has the lowest bidder disqualified by auction (one or more) ?? - So" and "Was the justification for the disqualification sufficient and reasonable? - So". Below the review, there are links for "Read comments: 1" and "Add a comment". A second review by "Artem February" is partially visible, dated "22.03.2020 13:02", with a URL: "https://wikiinvestigation.org/article/procurements/%D0%90%D1%80%D1%82%D0%B5%D0%BC%20%D0%9B%D1%8E%D1%82%D0%B8%D0%B9/5e6fe517bbca3251e064cf0".

Notes: This is a translated screenshot of a review that we describe in the introduction.

Figure 12: Evidence of collusion



Notes: This is a document added to a review where the author compares the technical documentation of two separate bidders. He shows that the documents show the same scanner imperfection.

E Equilibrium of ProZorro Auction

We now solve the equilibrium of the ProZorro Auction (PZA). To avoid open set problems, we will assume that bidders have to update their bids by a minimum bid decrement Δ if they choose to update their bids¹⁸, but we will let $\Delta \rightarrow 0$ in our main analysis. We will furthermore assume that there is a positive but small chance p that an attempted update to a bid is not submitted at the updating stage; we discuss where this assumption matters below but also let $p \rightarrow 0$. Thus, the assumption acts exclusively as equilibrium selection tool akin to a trembling hand equilibrium.

Consider a simplified version of the PZA in which there are two players and just one updating round. The timing of the game is as follows:

1. At $t = 1$, both players submit initial bids (b_1^1, b_2^1) .

¹⁸This assumption is close to but not exactly what happens on ProZorro in reality: the real rule states that if you update, your bid must decrease by the minimum bid decrement when compared to your *own* last bid. However, this change merely complicates the analysis as it requires the introduction of another minimum bid decrement (between your own bid and the current winning bid) to deal with open set problems.

2. At $t = 2.1$, with probability $1 - p$, the initial loser ℓ submits her updated bid $b_\ell^2 \in \{b_\ell^1\} \cup [0, b_w^1 - \Delta]$; with probability p , $b_\ell^2 = b_\ell^1$.
3. At $t = 2.2$, with probability $1 - p$, the initial winner w submits her updated bid $b_w^2 \in \{b_w^1\} \cup [0, \min\{b_w^1, b_\ell^2\} - \Delta]$; with probability p , $b_w^2 = b_w^1$.

To solve the auction, we need to assume that behavior in the initial bidding round is fully revealing of the cost-types.

Assumption 4 (Fully Revealing Strategies) *There exists a function $b : \mathbb{R}^+ \rightarrow \mathbb{R}^+$ such that $b_i^1 = b(c_i)$ for all players i .*

Given this assumption, agents will immediately infer everyone's costs from their initial bids. Note, however, that they need not necessarily infer the correct costs under deviations: e.g. if a player considers a deviation in which he pretends to be type $\tilde{c} \neq c_1$ by bidding $b(\tilde{c})$ in the initial round, his opponent will (incorrectly) infer that he is actually type \tilde{c} and hence base his behaviour on this assumption. Furthermore, as initial bids are *fully* revealing, agents do not update their beliefs based on any behaviour that takes place outside the initial bids.

We now proceed to solving the bidding game by backwards induction. The payoff to the initial winner from her final move at $t = 2.2$ is

$$\pi_w^2 = \begin{cases} (1-p)(b_w^2 - c_w) & \text{if } b_w^2 \leq b_\ell^2 - \Delta \text{ or } b_w^2 = b_w^1 \leq b_\ell^2 \\ 0 & \text{o/w.} \end{cases}$$

She will solve $\max_{b_w^2 \in \{b_w^1\} \cup [0, \min\{b_w^1, b_\ell^2\} - \Delta]} \pi_w^2$ and thus, independently of the values of p and Δ she will choose the largest bid that still ensures victory as long as victory is possible, i.e.

$$b_w^2 = \begin{cases} b_\ell^2 - \Delta & \text{if } c_w < b_\ell^2 - \Delta < b_\ell^2 < b_w^1 \\ b_w^1 & \text{o/w.} \end{cases}$$

Anticipating this and letting $\hat{c}_w = b^{-1}(b_w^1)$ be the type the initial loser infers the initial winner to

have, the initial loser will choose

$$b_\ell^2 = \begin{cases} \hat{c}_w + \Delta & \text{if } c_\ell < \hat{c}_w + \Delta, \\ b_w^1 - \Delta & \text{if } b_1^w - \Delta > c_\ell > \hat{c}_w, \\ b_\ell^1 & \text{o/w.} \end{cases}$$

There are several things going on here. Firstly, note that (perhaps obviously) b_ℓ^2 does not depend on c_w but only on \hat{c}_w : if an agent deviates from the equilibrium strategy, she can deceive her opponent. On path, however, $\hat{c}_w = c_w$. Secondly, note that the initial loser will ‘scoop’ his opponent if this is possible, i.e. he will bid his opponent valuation plus bid decrement: this is the largest bid he can make that ensures that his opponent cannot reply. Finally, what happens if scooping is not profitable? If there was no chance of bid submission failure (i.e. if $p = 0$), then the initial loser would infer that no matter what he bid, his opponent would just undercut him. Thus, he would be indifferent between many strategies. However, this indifference is at odds with the data, where we find that it is in fact quite likely that his opponent will ‘forget’ to update her bid. We will model this by assuming that there is a chance of $p > 0$ (but small) that his opponent does not get the chance to submit her update. Thus, the initial loser can still win with probability $p > 0$ as long as he beats the current standing bid of the initial winner. If he cannot even do this profitably, he will not update his bid. We can understand the assumption that $p > 0$ but p arbitrarily close to zero as a trembling hand perfection requirement that we impose on equilibrium.

Given the best responses worked out above, as $\Delta \rightarrow 0$ and $p \rightarrow 0$, the initial winner anticipates winning at the initial bid. More rigorously, the payoff to type c_1 from pretending to be type \tilde{c} is given

by

$$\begin{aligned}
V(\tilde{c}) &= \mathbb{P}\left(b(\tilde{c}) < b(c_2) \cap c_1 < c_2\right) \left(b(\tilde{c}) - c_1\right) + \\
&\quad \mathbb{P}\left(b(\tilde{c}) < b(c_2) \cap c_1 > c_2\right) \left(b(\tilde{c}) - c_1\right) + \\
&\quad \mathbb{P}\left(b(\tilde{c}) > b(c_2) \cap c_1 < c_2\right) \mathbb{E}[\min\{c_2, b(\tilde{c})\} - c_1 | c_1 < c_2, b(\tilde{c}) > b(c_2)] + \\
&\quad \mathbb{P}\left(b(\tilde{c}) > b(c_2) \cap c_1 > c_2\right) \times 0
\end{aligned}$$

The four lines of this expression correspond to the four cases that could transpire: the agent could pretend to be strong and actually be strong (first line), he could pretend to be strong and actually be weak (second line), he could pretend to be weak and actually be strong (third line) or he could pretend to be weak and actually be weak (fourth line). The first two lines combine to the payoff from a first-price auction in which each bidder bids according to $b(\cdot)$. The last two lines can be related to the expected payoff from a second-price auction. Thus, we can write the overall payoff as

$$V(\tilde{c}) = V^{FP}(\tilde{c}) + \mathbb{P}(b(\tilde{c}) > b(c_2)) \mathbb{E}[V^{SP} | \underline{c}_{-1} < \tilde{c}]$$

where we use $\underline{c}_{-1} := \min_{j \neq 1} c_j$ as more general notation to emphasize that this way of expressing the payoffs does not depend on the fact that there are exactly two players playing the game; indeed we have the following result:

Proposition 5 *The expected payoff from pretending to be type \tilde{c} is given by $V(\tilde{c})$ no matter the number of updating rounds or number of players.*

We illustrate this function in Figure 13 for the case of $c_i \sim U[0, 1]$. Naturally, if $\tilde{c} < c_1$, then the expected value from a second price auction conditional on $c_2 < \tilde{c} < c_1$ is going to be zero, and hence $V^{PZA}(\tilde{c}) = V^{FP}(\tilde{c})$ to the left of $\tilde{c} = c_1$. Furthermore, $V^{FP}(1) = 0$. Thus, $V^{PZA}(1) = \mathbb{E}[V^{SP}]$. But we know that the expected rent that bidders earn in a second-price auction is exactly equal to the expected rent they earn in a first-price auction when pretending to be their true type. Thus, $V^{PZA}(1) = V^{PZA}(c_1)$. It turns out that the effects of decreasing rent from the first-price component

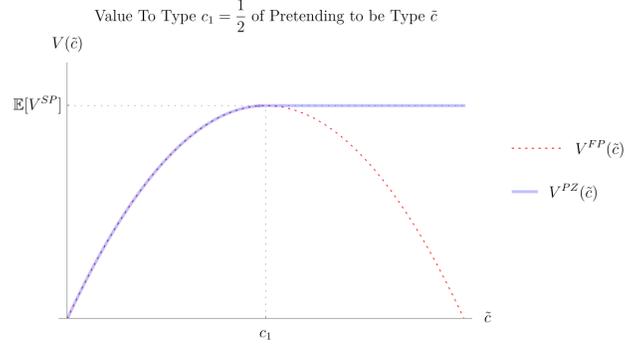


Figure 13: The Equilibrium of the PZA Auction

Notes: The expected utility to an agent of a given type from participating in the ProZorro auction reaches its peak at the same time as that of participating in a FP auction, but the second-price component ensures it never drops from this level.

of the auction and increasing rent from the second-price component of the auction exactly cancel and hence $V^{PZA}(\cdot)$ is flat to the right of \tilde{c} . A more formal version of this heuristic argument in the appendix allows us to conclude:

Proposition 6 *Assuming fully-revealing strategies, the updating strategies of Proposition 7 together with initial bids given by*

$$b(c) = \frac{1}{[1 - F(c)]^{n-1}} \int_c^{c_{max}} s(n-1)f(s)[1 - F(s)]^{n-2} ds$$

form the unique PBE of the PZA with $k \geq 1$ updating rounds and $n \geq 1$ players.

Thus, we conclude that the initial bids in the PZA auction must come from exactly the same bidding function that they would come from in a first-price auction.

Proposition 7 *The expected payoff from pretending to be type \tilde{c} is given by $V(\tilde{c})$ no matter the number of updating rounds or number of players.*

Proof. We consider the PZA auction with $k + 1$ rounds (i.e. k updating rounds) and n players; we will index rounds by r and players by i . We will refer to the bid by player i in round r as b_i^r and use \underline{b}_i^r to notate the standing lowest bid *before* i moves in round r . Note that bidding in updating rounds is not (necessarily) in order of player indices as updating priority is based on the ranking of the bids

from the previous round; hence, we also introduce $\sigma(r, t)$ as notation for the index of the player that moves in position $t = 1, \dots, n$ in round r . Thus, e.g. $b_{\sigma(2,3)}^1$ refers to the first round bid by the player who moves third in the second round.

We assume that initial bids are fully revealing, and hence can let $\hat{c}_i := b^{-1}(b_i^1)$ be the shared (point-)belief of $j \neq i$ about the cost type of player i . As we are considering only deviations by P1 (wlog), we have $\hat{c}_i = c_i$ for all $i \neq 1$. This also implies that all bidders but P1 move in order of their costs in the first updating round; the position of P1 is determined by the cost-type he chooses to imitate.

We will regularly need to refer to the optimal bid of a player i who anticipates that no firm moving after her is capable of beating a standing bid of x but at least one is capable of beating all higher bids. Such a player would like to bid x , but may be constrained by her own cost. If x is below her cost, the player – anticipating that she will be beaten – would be indifferent between all other bids were it not for the possibility of bid submission failure. As it is, however, there is a small but positive probability $p > 0$ that any given subsequent bid submission attempt will fail. This gives her a chance to nevertheless win the auction: e.g. if there is just one player to move after her that could beat $y > c_i$, she could submit y and hope that this player will fail to submit his bid. Even if she believes that all players to move after her can beat her own cost c_i (as all players believe in equilibrium), there is still a chance that they all fail (repeatedly) at submitting their bids, in which case she can win by undercutting the standing winning bid by Δ . More generally, we will refer to the optimal undercut as $\Delta^*(i, r)$ without characterizing it further and introduce the following notation for the optimal bid of a player i in round r who anticipates that he would not be beaten if she bid x :

$$g_i^r(x) = \begin{cases} \max\{b : b \leq x, b \leq \underline{b}_i^r - \Delta, b \geq c_i\} & \text{if this set is nonempty,} \\ \underline{b}_i^r - \Delta^*(i, r) & \text{o/w and if } \underline{b}_i^r - \Delta^*(i, r) \geq c_i \\ \underline{b}_i^{r-1} & \text{o/w.} \end{cases}$$

It of course remains to characterize the value of x after each history, which we will now do by

proceeding with a backwards induction. Firstly, noting that $\sigma(k + 1, n)$ is the last player to move in the last round, we claim that in any SPE,

$$b_{\sigma(k+1,n)}^{k+1} = \begin{cases} b_{\sigma(k+1,n)}^k & \text{if } b_{\sigma(k+1,n)}^k = \underline{b}_{\sigma(k+1,n)}^{k+1} \\ g_{\sigma(k+1,n)}^{k+1}(\underline{b}_{\sigma(k+1,n)}^{k+1}) & \text{o/w} \end{cases}$$

Thus, the last agent to move will simply undercut by as much as necessary in order to win the contract (assuming this yields positive profit). Anticipating this, all other agents in the last round would like to scoop, i.e. ensure that their bid cannot be undercut by anyone moving after them. Hence, they will anticipate that they can win if and only if they bid no more than the bid decrement Δ above the cost of whoever they believe to be the lowest cost agent moving after them. They thus bid

$$\forall t < n : b_{\sigma(k+1,t)}^{k+1} = g_{\sigma(k+1,t)}^{k+1} \left(\min\{\hat{c}_{\sigma(k+1,s)} \mid s > t\} + \Delta \right).$$

It should be noted that if $k = 1$, this implies that all players but P1 and $\sigma(k + 1, n)$ will simply undercut the current standing bid by Δ (if possible without going under their cost). This is because the order in which players are moving is exactly the order of player strength given their beliefs: hence they anticipate never being able to win the auction if no bid submission failure occurs. The same is true for P1 as long as he is pretending to be either a stronger type than he actually is or his true type. If he is pretending to be a weaker type, then and only then can he successfully ‘scoop’.

If $k > 1$, the argument in the preceding paragraph still applies as long as the order of players hasn’t changed between updating rounds. However, it may change due to the behaviour of P1. Nevertheless, the strategies stated above are still optimal.

Moving backwards, given the situation in the last updating round, all agents anticipate that the agent with the lowest cost will win. Thus, all agents (including P1) are in the same situation in round k as in $k + 1$, and hence they will play essentially the same strategies: all players but P1 undercut in the hope of a bid submission failure, and P1 scoops if he is actually the lowest type but was initially pretending not to be. Why does P1 scoop ‘early’ rather than ‘late’? By scooping early,

he guards against the fact that his own late scooping bid may not go through. Thus, strategies in earlier updating rounds are mostly unchanged from later updating rounds:

$$\forall 1 < r < k + 1 : \forall t : b_{\sigma(r,t)}^r = g_{\sigma(r,t)}^r \left(\min\{\hat{c}_{\sigma(r,s)} | s = 1, \dots, n\} + \Delta \right).$$

Finally, note that if $\tilde{c} \leq c_1$, then $\Delta^*(i, r) \equiv \Delta$ as all agents (including P1) anticipate that all agents moving after them can beat their own costs. If $\tilde{c} > c_1$, this is not true anymore: in particular, P1 may anticipate that some firms that will get to update their bid after him cannot beat his costs. However, either c_1 is the lowest cost draw or not. If it is, then P1 will never be forced to contemplate the case in which he relies on bid submission failure to win, and as $p \rightarrow 0$, his payoff from pretending to be \tilde{c} will converge towards that he would get if there was no bid submission failure chance. If it is not the lowest cost, then with probability approaching one, P1 will not win the auction. Hence, his payoff will be zero, no matter what complicated undercutting strategies Δ^* he employs in the meantime.

Thus, as we take the limits $p \rightarrow 0$, $\Delta \rightarrow 0$, the strategies derived in this proof imply the following payoff from pretending to be type \tilde{c} in the initial round (when your true type is c_1):

$$\begin{aligned} V(\tilde{c}) &= \mathbb{P}\left(b(\tilde{c}) < \min_{j \neq 1} b(c_j)\right) \left(b(\tilde{c}) - c_1\right) + \\ &\quad \mathbb{P}\left(b(\tilde{c}) > \min_{j \neq 1} b(c_j) \cap c_1 < \min_{j \neq 1} c_j\right) \times \\ &\quad \mathbb{E}[\min\{c_j : c_j < \tilde{c}\} - c_1 | c_1 < \min_{j \neq 1} c_j, b(\tilde{c}) > \min_{j \neq 1} b(c_j)] \end{aligned}$$

■

Proposition 6 *Assuming fully-revealing strategies, the updating strategies of Proposition 7 together with initial bids given by*

$$b(c) = \frac{1}{[1 - F(c)]^{n-1}} \int_c^{c_{max}} s(n-1)f(s)[1 - F(s)]^{n-2} ds$$

form the unique PBE of the PZA with $k \geq 1$ updating rounds and $n \geq 1$ players.

Proof. We have

$$V(\tilde{c}) = \mathbb{P}\left(b(\tilde{c}) < \min_{j \neq 1} b(c_j)\right) \left(b(\tilde{c}) - c_1\right) + \\ \mathbb{P}\left(b(\tilde{c}) > \min_{j \neq 1} b(c_j) \cap c_1 < \min_{j \neq 1} c_j\right) \mathbb{E}[\min\{c_j : c_j < \tilde{c}\} - c_1 | c_1 < \min_{j \neq 1} c_j, b(\tilde{c}) > \min_{j \neq 1} b(c_j)]$$

Say $c_i \sim F(\cdot)$ with $\max \text{supp } c_i = c_{max}$. We will use

$$G(\tilde{c}) = 1 - [1 - F(\tilde{c})]^{n-1}$$

as a short-hand to refer to the distribution of the minimum of the $n - 1$ other costs. Then

$$V(\tilde{c}) = [1 - G(\tilde{c})](b(\tilde{c}) - c_1) + [1 - G(c_1)] \times \\ \max\left\{\frac{G(\tilde{c}) - G(c_1)}{1 - G(c_1)}, 0\right\} \left(\frac{1}{G(\tilde{c}) - G(c_1)} \int_{c_1}^{\tilde{c}} cdG(c) - c_1\right),$$

where we used the fact that $\min\{c_j : c_j < \tilde{c}\} = \min_{j \neq 1} c_j$ given that $\tilde{c} > \min_{j \neq 1} c_j$.

Although on first glance it may seem¹⁹ like $V(\tilde{c})$ is not differentiable at $\tilde{c} = c_1$, this is in fact wrong because the potentially non-differentiable part of $V(\tilde{v})$ is multiplied by the expected rent from a second price auction conditional on your strongest opponent having a cost draw below \tilde{c} , which tends to zero as $\tilde{c} \rightarrow c_1$. After recognizing this, it is easy to see that

$$V'(c_1) = (1 - G(c_1))b'(c_1) - (b(c) - c)g(c),$$

where $g(c) = G'(c)$. Together with the boundary condition $b(c_{max}) = 0$, this differential equation is uniquely solved by

$$b(c) = \frac{1}{1 - G(c)} \int_c^{c_{max}} sdG(s),$$

which is just the classic first-price auction equilibrium bidding strategy. ■

¹⁹As $\max\left\{\frac{G(\tilde{c}) - G(c_1)}{1 - G(c_1)}, 0\right\}$ is not differentiable at this point.

F Data manipulation

Some bids are implausibly low

We note that a large share of bids are ‘too good to be true’. Such bids are likely to be provided without showing that the company is reliably able to deliver the demanded project which leads to the subsequent disqualification of the bids. As other firms can see such low bids at the start of the auction and anticipate that the suspiciously low bidder will be disqualified. In such cases the optimal behavior would change and the bidders would only compete against other bidders and not the low bidder. To alleviate this problem we conduct our analysis only on the sample without very low bids, which we define as any auction where the lowest bid is below a conservative threshold of 80% of the highest bid of other participants. This leads to omitting around 35% of all auctions. Our results are robust to both using the specified sub-sample or the whole sample of all auctions. There are also other reasons why a firm might get disqualified but as these are not easily predicted both from the data available to companies before the auction starts and also from the ex post data available to researchers we choose to not explicitly model them.

G Estimation

Proposition 3 *In data generated by a competitive equilibrium, $\widehat{\delta_{\ell(i),w(i)}^{OLS}} \sim N(0, \sigma^2)$ for some σ^2 while imposing the constraint $\sum_{\ell,w} \widehat{\delta_{\ell(i),w(i)}^{OLS}} = 0$.*

Proof. $\widehat{\delta_{\ell(i),w(i)}}$ is the OLS estimate of $\delta_{\ell(i),w(i)}$. Recall that the bidder undercuts if and only if

$$\alpha + \phi(b_{\ell(i)}^1, b_{w(i)}^1) + \delta_{\ell(i),w(i)} + \epsilon_i^d \geq 0, \quad (5)$$

where the true value of the $\delta_{\ell(i),w(i)} = 0$ in a competitive model and ϵ^d is a random shock with $\mathbb{E}(\epsilon|X, \delta) = 0$. We estimate a linear analog of this equation:

$$\alpha^{OLS} + \phi(b_{\ell(i)}^1, b_{w(i)}^1) + \delta_{\ell(i),w(i)}^{OLS} + \epsilon_i^{OLS} \quad (6)$$

The parameters δ^{OLS} and α^{OLS} are not identified as the fixed effects cannot be identified separately from α^{OLS} by the standard argument. For the estimation we impose the additional constraint that $\sum_{\ell(i),w(i)} \widehat{\delta_{\ell(i),w(i)}^{OLS}} = 0$. Now, it follows directly by Greene (1983) that the OLS estimator of a coefficient from a probit model will converge in probability to the true value multiplied by a scalar a . So $\widehat{\delta_{\ell(i),w(i)}^{OLS}} \rightarrow a \cdot (\delta_{\ell(i),w(i)} - \overline{\delta_{\ell(i),w(i)}})$. But recall that the true values $\delta_{\ell(i),w(i)} = 0$ and $\overline{\delta_{\ell(i),w(i)}} = 0$ implying that $\widehat{\delta_{\ell(i),w(i)}^{OLS}} \rightarrow 0$ proving the consistency of this estimator. Normality then follows by the central limit theorem (Greene, 2003). ■

H Online monitoring

Table 7: Treated and control regions

	Region	NUTS 2 Codes
Treated	Odesa Oblast, Kherson Oblast, Mykolaiv Oblast	65-68, 73-75, 54-57
	Lviv Oblast, Chernivtsi Oblast, Luhansk Oblast	79-82, 58-60, 91-94
	Kharkiv Oblast	61-64
Control	Dnipropetrovsk Oblast, Donetsk Oblast, Ivano-Frankivsk Oblast	49-53, 83-87, 76-78
	Khmelnyskyi Oblast, Kiev, Kiev Oblast, Kirovohrad Oblast	29-32, 01-06, 07-09, 25-28
	Rivne Oblast, Sevastopol, Sumy Oblast	33-35, 99, 40-42
	Ternopil Oblast, Vinnytsia Oblast, Volyn Oblast	46-49, 69-72, 10-13
	Zakarpattia Oblast, Zaporizhzhia Oblast, Zhytomyr Oblast	21-24, 43-45, 88-90
Excluded	Poltava Oblast	36-39

Notes: This table shows which regions had an active NGO monitoring medical devices.

Table 8: First abuse reports in the treated regions

Region	First abuse report	NGO
Odesa Oblast	2017-05-29	Криворізький Центр Розслідувань
Kherson Oblast	2017-06-17	Криворізький Центр Розслідувань
Mykolaiv Oblast	2017-05-14	Криворізький Центр Розслідувань
Lviv Oblast	2017-06-27	БО "БТ "Мережа"м. Львів
Chernivtsi Oblast	2017-06-27	ОРПП Кельзен
Luhansk Oblast	2017-06-21	Харківський антикорупційний центр
Kharkiv Oblast	2017-04-20	Криворізький Центр Розслідувань

Notes: This table summarizes which NGOs were active in the monitoring of the medical devices. We denote the NGO active in a region after the first complaint in the particular area.

Table 9: NGOs active on medical device markets

NGO	Name in English	Region/s
Криворізький Центр Розслідувань	Kryvyi Rih Investigation Center	65-68,73-75,54-57
БО "БТ "Мережа"м. Львів	BO "BT" Network "Lviv	79-82
ОРПП Кельзен	ORPP Kelzen	58-60
Харківський антикорупційний центр	Kharkiv Anti-Corruption Center	91-94,61-64
ГО "Офіс регіонального розвитку"	NGO "Regional Development Office"	65-68

I Welfare Calculations

Assume demand for public procurement takes the form $D(p) = Ap^{-\epsilon}$, where ϵ is the price elasticity of demand. The percentage welfare loss from a price $p_2 > p_1$ (assuming both p_2 and p_1 exceed

marginal costs) is given by

$$L = \frac{1}{p_2 D(p_2)} \int_{p_1}^{p_2} D(p) - D(p_2) dp.$$

Evaluating the integral, setting $p_1 = r \times p_2$ and simplifying yields

$$L = \frac{r^{-\epsilon}(r + (\epsilon(r - 1) - r)r^\epsilon)}{\epsilon - 1}.$$