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APPLICATION PERIOD IN REVERSE AUCTIONS

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Application Period in Reverse Auctions*

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Abstract

The duration to apply for participation in auctions affects entry costs and eventually the allocation and prices of contracts. The role of the application period is studied using Russian public procurement data on gasoline in 2011-2013. By relying on formal rules on the determination of the application period, I find that longer periods enhance competition and lead to price reductions. Moreover, I show that public buyers avoid long application periods. They shorten the period if they need gasoline immediately but I further argue that it facilitates favoritism. Finally, evidence is provided of collusion sustaining favoritism.

Keywords: public procurement, auction design, corruption, regulation

JEL classification: H57, K42

1 Introduction

Do rules with the objective to increase competition in reverse auctions[1] and consequently the efficient allocation of contracts serve their purpose? In this article, I evaluate the implications of the duration to apply for participation

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[1] In reverse auctions, the buyer demands a good and suppliers compete to supply the good while in ordinary auctions the supplier offers a good and buyers compete to buy the good.

on auction outcomes – in particular entry and prices – and subsequently check whether the duration is manipulated by corrupt buyers to facilitate favoritism. Data on Russian procurement of gasoline in 2011-2013 is employed. In Russia, the length of the application period depends on the reserve price.[2] Auctions with a reserve price exceeding the predefined thresholds are obliged to have a longer application period than those below the thresholds. In other words, larger purchases have to be announced well in advance. Additionally, application periods have to be extended if there is only one entrant.

Given the procurement rule defining a cutoff point, a regression discontinuity design is adopted to assess the effect of the application period on the number of applying suppliers, the number of bidding suppliers and contract prices. As public buyers manipulate reserve prices to avoid long application periods by setting the prices just below or equal to the thresholds, the analysis is repeated in the framework of the donut regression discontinuity which basically implies that observations at the thresholds or where manipulation occurs are dropped (Barreca et al., 2016). The analysis is conducted separately for sealed bid and electronic open bid auctions (e-auctions). The results show that auctions above the thresholds attract more entrants but only in sealed bid auctions. I further find significantly more bidders and eventually lower contract prices. Multiple checks demonstrate the robustness of the findings. Furthermore, I clarify buyers' preference for short application periods. First, a measure for urgency is generated to distinguish between urgent and less urgent procurement. Manipulation of reserve prices is found in both subsamples, suggesting that urgency only explains partially why buyers opt for short application periods. By estimating the number of extended application periods for different intervals of the reserve price, I find that buyers who manipulate prices also avoid extensions. They prevent extensions by ensuring exactly two applicants in auctions who are likely to be colluding, pointing towards collusion sustaining corruption.

The study contributes to the literature on entry costs in auctions, including

[2]The reserve price is the maximum price the buyer is willing to pay for the procurement. In Russia, it is mandatory to set the price and make it public. The reserve price is binding as bids above the reserve price are automatically rejected.

theoretical models with endogenous entry (Samuelson, 1985; Levin and Smith, 1994) and empirical work. For example, Bajari and Hortacsu (2003) point out that entry is determined by the level of the reserve price. Others showed that the auction procedure matters for suppliers' participation decision (Cai et al., 2013; Knack et al., 2017; Palguta and Pertold, 2017).[3] Selection into auctions – especially by SMEs – can further be influenced by the level of bureaucracy (OECD, 2016). This study is closely linked to the work done by Coviello and Mariniello (2014) which points out that the media used for the announcement of auctions has a significant impact on selection into auctions. To the best of my knowledge, this is the first study linking entry to the duration to apply for participation or the application period. Another strand of literature this study contributes to is the manipulation of the auction design. Corruption in auctions takes many forms such as bid readjustments (Compte et al., 2005; Menezes and Monteiro, 2006; Koc and Neilson, 2008; Lengwiler and Wolfstetter, 2010), manipulation of the evaluation criteria (Vagstad, 1995; Celentani and Ganuza, 2002; Burguet and Che, 2004), inflated reserve prices (Atmaca et al., 2019) and the implementation of auction procedures that come along with discretion or low transparency (Auriol, 2006; Cai et al., 2013; Knack et al., 2017; Palguta and Pertold, 2017).[4] I find evidence of public buyers shortening the application period to limit competition to facilitate favoritism. Buyers abuse regulation by manipulating reserve prices. In addition, indications of collusion sustaining corruption is provided.[5]

The remainder of the paper is structured as follows. Section 2 contains the mechanisms and predictions. Section 3 describes the data and the variables. The methodology is explained in section 4 and empirical evidence on the causal relation between the application period and auction outcomes is given in section 5. Section 5 further discusses the determination of the duration to apply

[3] Coviello et al. (2017), though, do not obtain any effects in Italian procurement.

[4] An overview of corruption in the various stages is outlined by Boehm and Olaya (2006).

[5] Corruption facilitating collusion is documented theoretically by Compte et al. (2005). Collusion in auctions is mainly detected by studying deviations from competitive bidding (Porter and Zona, 1993, 1999; Bajari and Summers, 2002; Aryal and Gabrielli, 2013).

for participation. Sensitivity analysis is performed in section 6 and section 7 concludes.

2 Theoretical predictions

The application period influences the extent suppliers are informed about planned auctions. Once suppliers know about auctions they further need time to decide whether they will apply for participation depending on the contract specifications and odds of winning. For instance, suppliers can refrain from participating if the size of the contract is beyond their capacity or if they already have to deliver for other procurement contracts. Other conditions such as the delivery or payment method can affect their ability or willingness to participate. In addition, buyers can put supplier-specific requirements. The location of the supplier, for example, can be stipulated. Given that there are competitors and costs associated with taking part in auctions, suppliers also have to evaluate their probability of winning in the application period. Furthermore, sufficient time is needed to prepare the documents and accomplish the application. Potential entrants have to decide whether they will incur these costs to enter a bid (Samuelson, 1985; Levin and Smith, 1994). Finally, if there are various planned auctions they will be weighed against each other. For each auction, suppliers have to go through this costly process. Yet, the variable costs associated with entry may decrease for homogeneous goods and recurrent procurement. Furthermore, suppliers could incur fixed costs of entry. The electronic platforms where e-auctions take place can charge a fee while entry in sealed bid auctions happens through post or e-mail. In the end, the length of the application period could influence both the number and pool of entrants.

After receiving the applications, buyers evaluate suppliers' eligibility. As suppliers in sealed bid auctions submit their bid along with the application for participation, buyers' evaluation will also determine which bids are considered in the determination of the winner of the auction. Thus, the number of bidders in sealed bid auctions can deviate from the number of applicants if buyers disapprove applications. In e-auctions, 1) suppliers apply for participation, 2) buyers approve them to bid and 3) authorized suppliers decide whether to place a bid. Contrary to sealed bid auctions, the number of bidding suppliers does not necessarily match the number of authorized suppliers. Bids are submitted sequentially on an online platform and are visible to the competitors. Thus, the length of the application period can affect the number of bidders in both procedures through the number of applicants but the effect may diminish or stay off as the number of bidders is further a result of buyers' evaluation of applications and the subsequent decision to bid in e-auctions.[6]

The application period can affect the contract price that equals the lowest bid through its impact on the (expected) number of applicants, especially in sealed bid auctions because suppliers bid simultaneously and bids are submitted along with the applications. Suppliers in e-auctions will estimate their bid given the expected number of applicants to see whether it is worthwhile to apply for participation. The actual bid, however, is set afterward and further shaped by the bids which are observable as suppliers bid sequentially. In sum, the application period can affect contract prices through the number of applicants in both auction procedures but the effect may be weak or nonexistent in e-auctions. In theory, the relationship between competition and prices depends on the assumptions of the underlying model and is not necessarily monotonic.[7] There is a distinction between models with exogenous and endogenous entry.

Exogenous entry In private and common value models,[8] increasing the number of potential bidders reduces procurement costs through the competition effect (Krishna, 2009). The competition effect entails that bidders bid more aggressively as they expect more actual bidders, leading to lower prices in reverse auctions. Yet, prices may increase due to the affiliation and winner's curse

[6] The exact procedure is dependent upon the context.

[7] Although I refrain from explicitly classifying the procurement of gasoline into a particular auction type as arguments can be put forward for each classification, I will provide an overview of the effects of the number of applicants on prices from which we can conclude that the relation is not necessarily monotonic irrespective of the auction type.

[8] In private value models, bidders know their cost of supplying the good but not their opponents' costs. In common value models, the cost is identical for the bidders but they receive different signals about it.

effect in respectively affiliated private value and common value models. In case of the affiliation effect, competition can turn out lower than anticipated by the winner of the auction (Pinkse and Tan, 2005). The winning bidder takes this into account by entering a higher bid. The higher the number of bidders, the higher the probability that this is the case and the higher the winning bid. Procurement costs could also rise because of the winner's curse effect which only occurs in common value auctions (Bulow and Klemperer, 2002; Hong and Shum, 2002). Conditional on winning, there is a higher probability that the bid is lower than the actual cost of supplying the good and therefore a higher probability of a negative payoff. In equilibrium, rational bidders bid more conservatively given the winner's curse effect. If the number of potential bidders increases the winner's curse effect will be more likely.

Endogenous entry Also in independent private value models, a higher number of potential bidders does not necessarily reduce procurement costs (Li and Zheng, 2009). A positive association between the number of potential bidders and procurement costs occurs if the entry effect dominates the competition effect. According to the entry effect an increase in the number of potential bidders decreases the probability of entry, leading to less actual bidders and less aggressive bidding.[9]

Buyers who need the good quickly are likely to opt for short application periods. They will keep the whole procurement process relatively short including the application period. Besides urgency, favoritism can explain the length of the application period. Corrupt buyers can exploit the negative relation between the application period and competition in auctions to facilitate favoritism. They can more easily allocate the contract to favored suppliers by reducing competition through short application periods. If the negative effect of competition on prices dominates they can even conclude contracts at more favorable terms.

[9] The entry effect is also confirmed empirically by Li and Zheng (2009).

3 Data and descriptive statistics

3.1 Data

Russian public procurement data is employed to analyze the importance of the duration to apply for participation in reverse auctions. The procurement system in Russia was unified by the Federal Law No.94 of 21/7/2005. Public contracts offered by federal, regional and municipal authorities are subject to law. The data used in this study comes from the official website containing information on Russian public procurement.[10] The focus is the procurement of gasoline. There are different types of gasoline dependent upon the octane rating and contracts can contain multiple types. Nevertheless, gasoline is a homogeneous good. This feature restrains suppliers from influencing product quality, rendering corrupt opportunities in the allocation and prices of contracts. As gasoline is a standardized good it is more difficult for buyers to hinder applications through product-specific requirements. The data is limited to gasoline supplied through gas stations to reduce variation in delivery costs. These stations supply gasoline to both the government and consumers, meaning that they cannot supply gasoline of inferior quality to the government without providing the same gasoline to consumers and risking to lose them. Furthermore, the regional market price of gasoline which is a proper benchmark for prices is available on a frequent basis. For the analyses, I use the monthly regional market price per liter of the different types of gasoline provided by the Federal State Statistics Service (Rosstat).

The good can be purchased through sealed bid auctions, e-auctions or single-source contracting.[11] The sample is restricted to sealed bid and e-auctions.

[10]The website is http://www.zakupki.gov.ru. I would like to thank the Center for Institutional Studies for the provision of data from which I depart and extend in the paper.

[11]In sealed bid auctions, suppliers submit their bid simultaneously. In e-auctions, suppliers bid sequentially and observe competitors' bids but they cannot change their own bid. E-auctions are mandatory for contract value above 500,000 RUB and if the total value of the procurement of similar goods per quarter and procurer exceeds 500,000 RUB. In contrast to sealed bid and e-auctions, single-source contracting is non-competitive and contract prices ought to be below 100,000 RUB. It can be implemented by natural monopolies, for the procurement of military or cultural goods, works or services and in case of emergency (Article 55 Federal Law No.94). Yet, the identification strategy renders the latter procedure irrelevant.

Contracts allocated through these auction procedures are awarded to suppliers with the lowest bid. The dataset comprises the period 2011-2013 as e-auctions were introduced in 2011 and the Federal Law No.94 was replaced by the Federal Law No.44 of 5/4/2013 effective as of 1/1/2014. The initial data consists of 171,984 auctions for 83 Russian regions but most of the analyses are based on a sample of sealed bid auctions with a reserve price between 200,000 and 300,000 RUB and e-auctions with a reserve price between 2.4 and 3.6 million RUB. The motivation for the sample is related to the identification strategy which is outlined in section 4.

3.2 *De jure* and *de facto* application period

The variable of interest is the application period which is defined as the number of days between the auction announcement and the deadline to apply for participation.[12] Sealed bid auctions also require suppliers to submit their bid by this deadline. E-auctions consist of two stages and bidding happens in the second stage. In the first stage, suppliers apply for participation. The applications are then evaluated by the buyer to decide which suppliers can bid in the second stage of the auction. Conceptually, suppliers face an application deadline in both auction procedures. According to Article 45.1, application periods of sealed bid auctions with contract value exceeding 250,000 RUB have to be at least 7 working days while contracts with a value below or equal to 250,000 RUB have to be published at least 4 working days before the deadline (table 1). Thus, larger purchases by the government have to be published well in advance. In case of failed competition – auctions with only 1 applicant – buyers are required to extend the application period by 4 working days and announce the extension within 1 working day after the application deadline (Article 46.6). A similar procurement rule applies to e-auctions but with the difference that the threshold is 3 million RUB (Article 41.5). Application periods below this threshold have to be at least 7 days and 20 days otherwise. There is no rule on

[12] The application period after possible extensions is considered.

the extension of the application period for e-auctions in contrast to sealed bid auctions.

Table 1: *De jure* application period

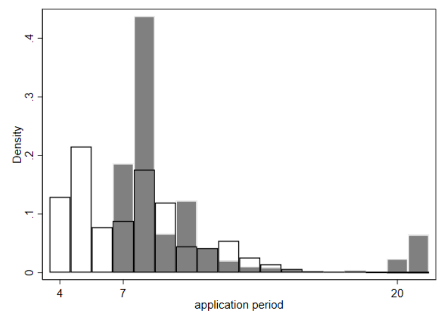
	Reserve price	Application period
Sealed bid auction	$\leq$ 250,000 RUB	$\geq$ 4 working days
	$>$ 250,000 RUB	$\geq$ 7 working days
E-auction	$\leq$ 3,000,000 RUB	$\geq$ 7 days
	$>$ 3,000,000 RUB	$\geq$ 20 days

The procurement rules are reflected in the actual application periods. Figure 1 shows the histogram of the time suppliers get to apply for participation by auction procedure. The application period in e-auctions is the number of days between auction announcement and the application deadline. In accordance with the regulation for sealed bid auctions, it is calculated in number of workings days.[13] The white histogram shows the bimodal distribution of the application period in sealed bid auctions. Most of the sealed bid auctions have an application period close to either 4 or 7 working days. The mass of observations in e-auctions is also near the minimum legal application periods, namely 7 and 20 days. The average duration over the centered reserve price by auction procedure is depicted in figure 2. The reserve price in sealed bid and e-auctions is centered around respectively 250,000 and 3 million RUB, meaning that the thresholds are represented by zero. The sample is restricted to sealed bid auctions with reserve prices $\in$]200,000;300,000[RUB and e-auctions $\in$]2,400,000;3,600,000[RUB, corresponding to a bandwidth of 20% of the thresholds on either side. I further created bins of 2% of the thresholds for both procedures, resulting in 10 bins on either side. From the figure we can immediately observe the discontinuity at the threshold in both auction procedures. The duration to apply for participation is much longer above the thresholds than below. 42.2% (91.2%) of the sealed bid auctions (e-auctions) below the threshold have a duration below 7 (20) days. The average duration for sealed bid auctions below the threshold is 5 days and above the threshold 9 days. In sealed bid auctions, application periods are

[13] In the remainder of the paper, I will speak in terms of days while I mean working days for sealed bid auctions.

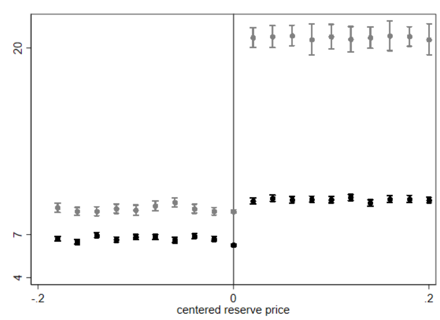
especially low just below the threshold.[14] In e-auctions, suppliers get on average 9 days to apply for participation if the contract value is smaller or equal to 3 million and 21 otherwise.

Figure 1: Histogram of the application period



Notes: Distribution of the application period in sealed bid (white histogram) and e-auctions (gray histogram). The sample is restricted to application periods up to 23 days and sealed bid auctions (e-auctions) with a reserve price ∈]200,000;300,000[(]2,400,000;3,600,000[) RUB and without missing contract prices.

Figure 2: Application period over the centered reserve price



Notes: Average application period and 95% confidence interval over the centered reserve price in sealed bid auctions (in black) and e-auctions (in gray). The horizontal axis is the relative distance to the threshold value of 250,000 (3 million) RUB in sealed bid auctions (e-auctions) and grouped in 20 bins of equal size. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price ∈]200,000;300,000[(]2,400,000;3,600,000[) RUB and without missing contract prices.

[14]This pattern is discussed in depth in section 4.

3.3 Auction outcomes

The first part of the study is on the association between the duration to apply for participation and auction outcomes. First, I examine the number of applicants *n*.[15] Competition is rather low in the procurement of gasoline, particularly in e-auctions. The average number of applicants in sealed bid and e-auctions is respectively 1.9 and 1.6 (table 2). Second, I estimate the effect on the number of bidders *nbid*. The buyer can restrain applicants from taking part in the auction if they do not fulfill the requirements to participate. The number of bidders is thus smaller or equal to the number of applicants. The average is 1.7 and not very different from the average number of applicants. The third outcome variable is the ratio between the contract price per liter of gasoline and the monthly regional market price of gasoline *p*, corrected for outliers. As contracts can contain multiple types of gasoline I calculate the weighted average market price using the volumes of the distinct types of gasoline as weights. The contract price equals the lowest bid because gasoline is procured through first-price auctions with the lowest bid as award criterion.[16] The contract price is on average slightly higher than the market price and in two thirds of the sample above the market price.

3.4 Other variables

Gasoline is mainly procured through sealed bid auctions. 84.8% of the auctions are sealed bid and 15.2% e-auctions (table 2). The dummy variable *e-auction* equals 1 for e-auctions and 0 for sealed bid actions. The variable *extension* indicates whether the application was extended. Extensions can only occur in sealed bid auctions. In about a third of the sealed bid auctions, the application period was extended. Next, the reserve price per liter of gasoline *r* is calculated. The variable corrected for outliers ranges between 23.2 and 36.5 RUB, corresponding

[15] The final number of applicants or the number of applicants after potential extensions of the application period is considered.

[16] There is an exemption on the rule. In e-auctions with only one bidder, the contract price is set at the reserve price instead of the lowest bid.

to 0.6 and 0.9 EUR.[17] On average, the reserve price per liter is 29.1 (30) RUB in sealed bid auctions (e-auctions). Finally, *outsourcing* is an indicator variable for outsourced procurement. 25.5% of the sealed bid and 37.6% of the e-auctions in the sample were conducted by another buyer.

Table 2: Descriptive statistics

	N	mean	sd	min	max
Sealed bid auction					
n	16,174	1.9	0.7	1	16
nbid	16,174	1.8	0.7	1	7
p	16,174	1	0.1	0.6	1.5
1(reserve price-c>0)	16,174	0.3	0.5	0	1
D	15,337	0.6	0.5	0	1
Extension	16,174	0.3	0.5	0	1
r	16,002	29.1	2.7	23.2	36.5
Outsourcing	16,174	0.3	0.4	0	1
E-auction					
n	2,900	1.6	1	1	12
nbid	2,900	1.3	0.6	1	5
p	2,900	1	0.1	0.8	1.4
1(reserve price-c>0)	2,900	0.1	0.3	0	1
D	2,525	0.1	0.3	0	1
r	2,857	30	2.7	23.4	36.5
Outsourcing	2,900	0.4	0.5	0	1

Notes: n is the number of applicants, *nbid* is the number of bidders, p is the contract price per liter divided by the regional market price per liter, D equals 1 if the application period is at least 7 (20) days in sealed bid auctions (e-auctions), *extension* indicates whether the application period was extended, r is the reserve price per liter and *outsourcing* is an indicator variable for outsourced procurement. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price $\in$]200,000;300,000[(]2,400,000;3,600,000[) RUB and without missing contract prices.

4 Methodology

The section begins with the identification strategy for the effects of the application period and continues with the determinants of the period. I will be able to analyze both the implications and determinants by considering different samples of the data. The time of the mandatory announcement on the centralized

[17]Calculated at the average exchange rate in the sample period, 1 RUB = 0.0244 EUR.

platform is considered but buyers can inform suppliers about planned purchases beforehand. I do not have information on informal notices, implying that the formal application period will be a lower bound in case buyers inform suppliers earlier. On the other hand, the formal notice is more informative as it stipulates the concrete contractual terms. The analysis is performed separately for sealed bid and e-auctions.

4.1 Effects of the application period

The dependent variables are the number of applying suppliers n, the number of bidding suppliers $nbid$ and the contract price p. The following models are estimated to assess the effects of the duration to apply for participation:

$$\mathrm{y_{ijt}} = \alpha_0 + \alpha_1 \, 1(\mathrm{reserve\ price_{ijt}} - \mathrm{c} > 0) + \alpha_2 \, (\mathrm{reserve\ price_{ijt}} - \mathrm{c}) + \mu_{\mathrm{ijt}} \tag{1}$$

$$= \beta_0 + \beta_1 \, \mathrm{D_{ijt}} + \beta_2 \, (\mathrm{reserve\ price_{ijt}} - \mathrm{c}) + \epsilon_{\mathrm{ijt}} \tag{2}$$

with buyer i, supplier j and time t. The reserve price is centered around the threshold value c: 250,000 and 3 million RUB in respectively sealed bid and e-auctions. To identify a causal relation, I rely on the rules stating that the minimum application period has to be at least 7 days if the reserve price of sealed bid auctions is higher than 250,000 RUB and at least 4 days otherwise. The threshold in e-auctions is 3 million RUB. Below the threshold auctions have to be announced at least 7 days before the deadline to apply for participation and above the threshold at least 20 days. Regression discontinuity design is adopted to evaluate the implications of the application period (Lee and Lemieux, 2010). The dependent variables are first regressed via ordinary least squares (OLS) on a dummy variable which equals 1 if the reserve price in sealed bid auctions (e-auctions) exceeds 250,000 (3 million) RUB and 0 otherwise, resulting in the intention-to-treatment effect (ITT). Second, long application periods are differentiated from short ones through a dummy variable D_{ijt} which takes the value 1 if the application period is at least 7 (20) days in sealed bid auctions (e-auctions). Since auctions below the thresholds can also have a long application period the former dummy variable *1(reserve price*$_{ijt}$*-c¿0)* is used as excluded instrument for D_{ijt} in the two stage least squares (IV) estimation which returns the local average treatment effect (LATE). In both models the centered reserve price is part of the right-hand side. The sample is restricted to sealed bid auctions around 250,000 RUB and e-auctions around 3 million RUB to control for (un)observed characteristics. Specifically, auctions with a reserve price deviating at most 20% from the threshold values or sealed bid auctions with a reserve price $\in$]200,000;300,000[RUB and e-auctions $\in$]2,400,000;3,600,000[RUB are kept. Finally, auctions with missing price and extended application periods are dropped because of reverse causality. Application periods in sealed bid auctions have to be extended if there is only one applying supplier.

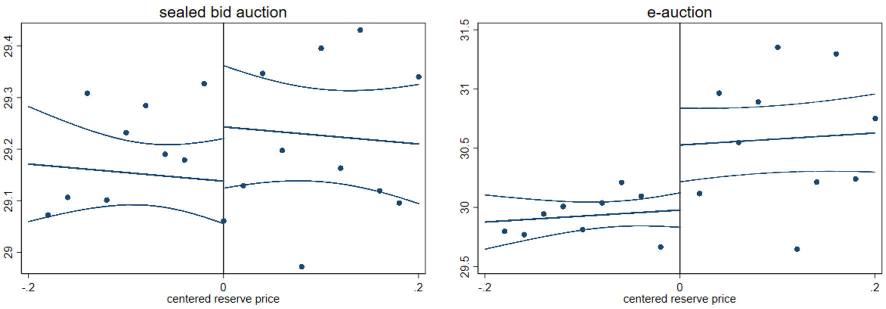
The sensitivity of the results is tested in section 6 by using different bandwidths around the thresholds including the bandwidth selected using the procedure by Calonico et al. (2014), estimating the effect of the application period non-parametrically, fully interacting the model with *e-auction*, altering the order of the polynomial of the running variable, adding additional control variables including an interaction between the running variable and the main independent variable, clustering the standard errors and accounting for year-end spending. In addition, the analysis is repeated using placebo thresholds to demonstrate that the effects are only present at the actual thresholds.

4.1.1 Validity of RD

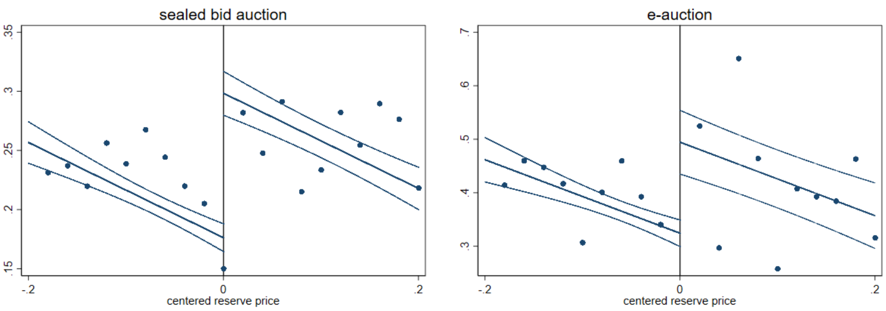
To ensure that the identification strategy returns unbiased estimates, two explanatory variables are checked for discontinuity at the threshold values. Figure 3 shows the number of outsourced auctions and the reserve price per liter around the thresholds. The reserve price per liter is statistically higher above the threshold but only in e-auctions. The graphical analysis further reveals the discontinuity in outsourcing in both auction procedures. Hence, the analysis will be extended by dropping outsourced auctions from the sample.

Figure 3: Discontinuity in control variables

Reserve price per liter



Outsourcing



Notes: The reserve price per liter (upper figures) and outsourced procurement (lower figures) over the centered reserve price in sealed bid auctions (right figures) and e-auctions (left figures). The horizontal axis is the relative distance to the threshold value of 250,000 (3 million) RUB in sealed bid auctions (e-auctions) and grouped in 20 bins of equal size for the scatter plot which shows the average reserve price per liter and outsourced procurement per bin. The lines depict the fitted value and the 95% confidence interval from a linear regression. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price $\in$]200,000;300,000[(]2,400,000;3,600,000[) RUB and without missing contract prices. Extended application periods are dropped.

Furthermore, I test for manipulation of the running variable which is the centered reserve price. The white (gray) histogram in figure 4 shows the distribution of the centered reserve price around the threshold in sealed bid auctions (e-auctions). The null hypothesis of no discontinuity at the threshold is rejected in both procedures (McCrary, 2008). Buyers set reserve prices just below or equal to the thresholds to avoid long application periods, providing evidence of the relevance of this element in auction design. On the one hand, reserve prices of contracts that would otherwise exceed the thresholds can be manipulated downward. This would lead to a shift of observations from above the thresholds to below. On the other hand, the reserve price of contracts well below the thresholds can be inflated to conclude the contract at the highest possible price given a short application period. Barreca et al. (2016) demonstrate that manipulation leads to composition changes which renders the observations on both sides of the thresholds incomparable. The local randomization will be invalidated if, for example, corruption determines the reserve price and the outcome variables at the same time. Corrupt agents would sort at the threshold to avoid long application periods to decrease competition, which may affect the estimated treatment effect. The composition bias is dealt with by dropping the observations at the thresholds.[18] By restricting the sample to the observations which are not manipulated, the RD assumptions are not violated and unbiased estimates are obtained.[19] The cost of this approach is the decline in observations and nothing can be said about the treatment effect in this area. A donut of 0.8% of the thresholds or 0.4% on either side of the thresholds is used, implying that sealed bid and e-auctions with a reserve price $\in$ [249,000;251,000] RUB and [2,988,000;3,012,000] RUB respectively are left out to account for the shift of observations from above and below the thresholds.[20] In addition to the donut approach, contracts with inflated reserve prices (Atmaca et al., 2019) are excluded from the regression (see section 6).

4.2 Determinants of the application period

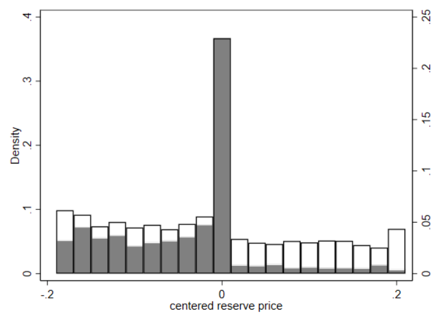
The data reveals that public buyers circumvent long application periods in sealed bid auctions and e-auctions by setting reserve prices just below or equal to the thresholds of 250,000 and 3 million RUB. The preference for short periods can be explained by the urgent need for gasoline. If gasoline is needed immediately, buyers will shorten the whole procurement process including the application

[18] Barreca et al. (2011) used this approach to estimate the effect of very low birth weight classification on infant mortality.

[19] The assumption here is that the approach can effectively remove the manipulated reserve prices.

[20] Section 6 tests robustness to the size of the donut.

Figure 4: Sorting



Notes: Distribution of the reserve price in sealed bid (white histogram) and e-auctions (gray histogram). The horizontal axis is the relative distance to the threshold value of 250,000 (3 million) RUB in sealed bid auctions (e-auctions). The sample is restricted to sealed bid auctions (e-auctions) with a reserve price ∈]200,000;300,000[(]2,400,000;3,600,000[) RUB and without missing contract prices. Extended application periods are dropped.

period. Alternatively, corrupt buyers can opt for short application periods to limit competition to increase the probability that favored suppliers win auctions.

4.2.1 Urgency

Both motives, urgency and favoritism, can be separated by plotting the distribution of the centered reserve price of urgent and less urgent purchases. In case urgency is the sole explanation for short application periods, we should observe sorting at the thresholds only for urgent purchases. However, if there is an alternative explanation for the manipulation of reserve prices then we also expect sorting for less urgent purchases. I differentiate between urgent and less urgent purchases by checking whether there was time left before the first day of delivery of gasoline that could have been used to extent the application period. More specifically, I calculate the time between the application deadline and day of delivery and deduct the legally required time to conclude contracts. I then construct two indicators for urgency. First, I generate a dummy variable which is equal to 1 if there was time left that could have been used to extend the period by at least 1 day. The second dummy variable indicates whether there was sufficient time left that could have been used to conduct an auction with a long application period instead of a short one. Long is defined as a minimum duration of 7 and 20 days in respectively sealed bid and e-auctions. For example, if the application period is 5 days in sealed bid auctions at least 2 additional days are needed to have at least 7 days which is the minimum for contracts with a reserve price above the threshold. Similarly, an e-auction with 15 days has to be extended by 5 days to reach the legal minimum of 20 days. By applying text analysis on the delivery period, I was able to retrieve the delivery date and define urgency for 11,589 out of 19,074 auctions.[21]

4.2.2 Favoritism

To facilitate the allocation of public contracts to favored suppliers, buyers can limit competition through short application periods. In sealed bid auctions, the law provides that the application period has to be extended if only one applicant shows up in the auction. Corrupt agents can only keep the application period short and prevent this legal extension if there are at least two applicants. Therefore corrupt contracting parties will be inclined to opt for auctions with exactly two applicants in sealed bid auctions. As the rule on the extension of application periods is absent for e-auctions, however, buyers do not have such an incentive to have exactly two applicants in e-auctions. To verify whether buyers who chose short application periods are also more likely to conduct auctions with precisely two applicants, I will estimate the probability of two applicants for both auction procedures with e-auctions as the control group. The auction procedure in this model is exogenous as the reserve prices of the auction procedures are from a different order – around 250,000 RUB in sealed bid auctions and 3 million RUB in e-auctions – and e-auctions are mandatory above 500,000 RUB.[22] The area around the thresholds is split into bins that are then interacted with the procedure variable. Three bins are generated for the centered reserve price

[21]The descriptive statistics of the reduced sample are comparable to the statistics of the initial sample (table A4.1 in the appendix).

[22] Buyers could split procurement with value above 500,000 RUB and procure multiple times to circumvent e-auctions and conduct sealed bid auction instead. However, it is unlikely that a procurement with value around 3 million RUB is split and brought back to a value around 250,000 RUB.

which are defined as the percentage deviation from the thresholds:]-20,-0.4],]-0.4,0],]0,20[respectively below, at and above the sorting area.[23] The latter bin will be the reference group in the empirical model as short application periods are absent above the thresholds. Favoritism is expected to occur more at the sorting area because 1) buyers can reduce the cost of favoritism by shortening the application period and 2) the contract can be concluded at the highest possible price given a short application period. The probability of two applicants is estimated through a logistic regression using the sample including extended application periods.

$$
\begin{aligned}
2\text{ applicants} = \gamma_0 &+ \gamma_1\,\text{sorting}_{\text{ijt}} + \gamma_2\,\text{below sorting}_{\text{ijt}} + \gamma_3\,\text{e auction}_{\text{ijt}} \\
&+ \gamma_4\,\text{sorting}_{\text{ijt}} * \text{e auction}_{\text{ijt}} \\
&+ \gamma_5\,\text{below sorting}_{\text{ijt}} * \text{e auction}_{\text{ijt}} + \nu_{\text{ijt}} \qquad (3)
\end{aligned}
$$

The second applicant who is likely to lose the auction in the presence of favoritism could be a real competitor or colluder. A colluder takes part in the auction to fake competition to prevent the extension of the application period. Eventually, the minimum number of applicants will be reached and the extension of the application period will be prevented. To study whether collusion sustains corruption, I will create a proxy for collusion.[24] First, I calculate the fraction of auctions the second applicant lost. Since it is costly to take part in auctions, suppliers will be reluctant to keep on losing auctions unless they fake competition. Then, I calculate the relative number of auctions in which the winning and losing applicant both took part. The number of common auctions is divided by the number of auctions the second applicant participated in to say something about how often these two act together and its importance for the second supplier. Colluding suppliers are expected to participate together more

[23] The sorting area refers to the area just below and at the thresholds where buyers who manipulate reserve prices to avoid long application periods locate.

[24] The type of collusion I look at is complementary bidding. There are also other types such as bid rotation but these are less straightforward to proxy empirically.

often. Finally, I look into the relative difference between the reserve and contract price.[25] The relative difference at a given interval of the centered reserve price should be on average smaller if there is collusion. Given that the award criterion is the lowest bid, a small difference would enable the favored supplier to conclude the contract at a high price. The three proxies in themselves might be unrelated to collusion. Therefore I combine them into a single collusion measure through a principal component analysis. Equation 3 is estimated replacing the dependent variable by the collusion measure and restricting the sample to auctions with only two applicants.

5 Results

I depart from the sample consisting of auctions with a reserve price deviating at most 20% from the threshold values and without extended application period (model 1). Gradually, I account for the tests of validity of the research design. Outsourced auctions are first dropped because of the discontinuity at the thresholds (model 2).[26] Subsequently, auctions at the thresholds are left out because of manipulation of the running variable (model 3) and finally both outsourced auctions and auctions at the thresholds are excluded (model 4).

5.1 Graphical analysis

The implications of the application period are depicted in figure 5.[27] A positive and significant relation between the application period and the number of applicants in auctions is expected. The earlier buyers announce auctions, the lower entry costs and the higher the probability of participation. The figure

[25] In table A4.2, I replaced the variable by the relative difference in the first and second bid because of potential endogeneity bias. Corrupt buyers could manipulate the reserve price as shown by Atmaca et al. (2019) and at the same time the application period. Collusion should further lead to a small difference in bids to ensure that the favored supplier wins the auction at the highest possible price.

[26] The findings for outsourced auctions are reported in the annex because the number of observations is relatively low. The effects obtained in table A4.3 are line with the baseline estimates.

[27] The graphical analyses based on the altered samples are part of the appendix (figures A4.1, A4.2 and A4.3).

reveals that this is the case for sealed bid auctions. The relation in e-auctions is also positive but not as significant. Similarly, the number of bidders in sealed bid auctions is statistically higher above the threshold and the relative contract price is statistically lower which is most likely the result of the increased competition. The effects are mainly found in sealed bid auctions.

5.2 Falsification test

In figure 6, the effects at placebo thresholds besides the actual ones are plotted.[28] The placebo tests do not deliver any significant estimates, supporting our initial findings.[29]

5.3 Model specification

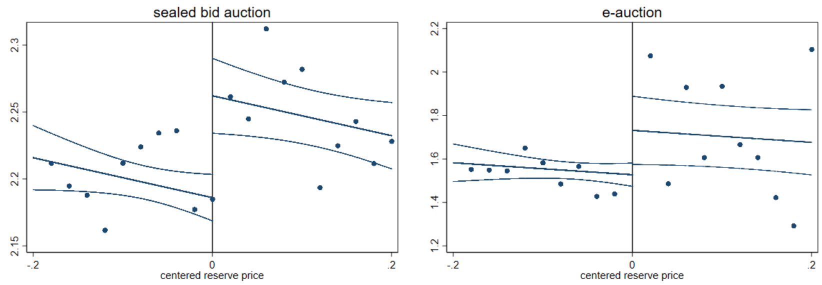
Table 3 contains the ITT and LATE for the different model specifications. The impact of the length of the application period in sealed bid auctions (e-auctions) is given in columns 1-3 (4-6). Both the ITT and LATE on the number of applicants in columns 1 and 4 are positive. The effects are always statistically significant in sealed bid auctions whereas the significance in e-auctions depends on the model. Nevertheless, the impact on the number of applicants in e-auctions is always positive. The ITT in sealed bid auctions ranges between 0.0579 and 0.087 and are as expected smaller in magnitude than the LATE. The effects are rather small but we have to take into account that there are on average about two applying suppliers. Moreover, buyers care about the length of the period as they circumvent long application periods by setting reserve prices below the thresholds. The results confirm that decreased entry costs lead ceteris paribus to more competition. Next, the effect of application periods on

[28] Extended application periods – occurring when there is only one applicant – are dropped from the baseline regressions because of reverse causality. As I only have data on the application periods of auctions around the actual thresholds and not around the placebo thresholds I cannot perform the exact same regression. For this reason, I will drop auctions with one applicant from the placebo tests to be as close as possible to the baseline specification and include in figure 6 the estimates at the actual thresholds given the sample restriction used for the placebo.

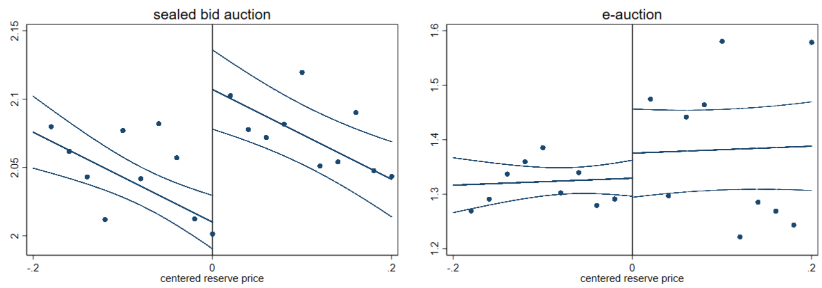
[29] Robustness of the falsification test is presented in tables A4.10, A4.11 and A4.12 in appendix.

Figure 5: Discontinuity in outcome variables

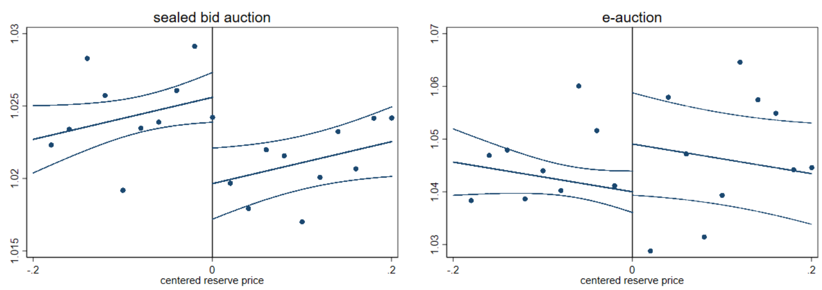
Number of applying suppliers



Number of bidding suppliers



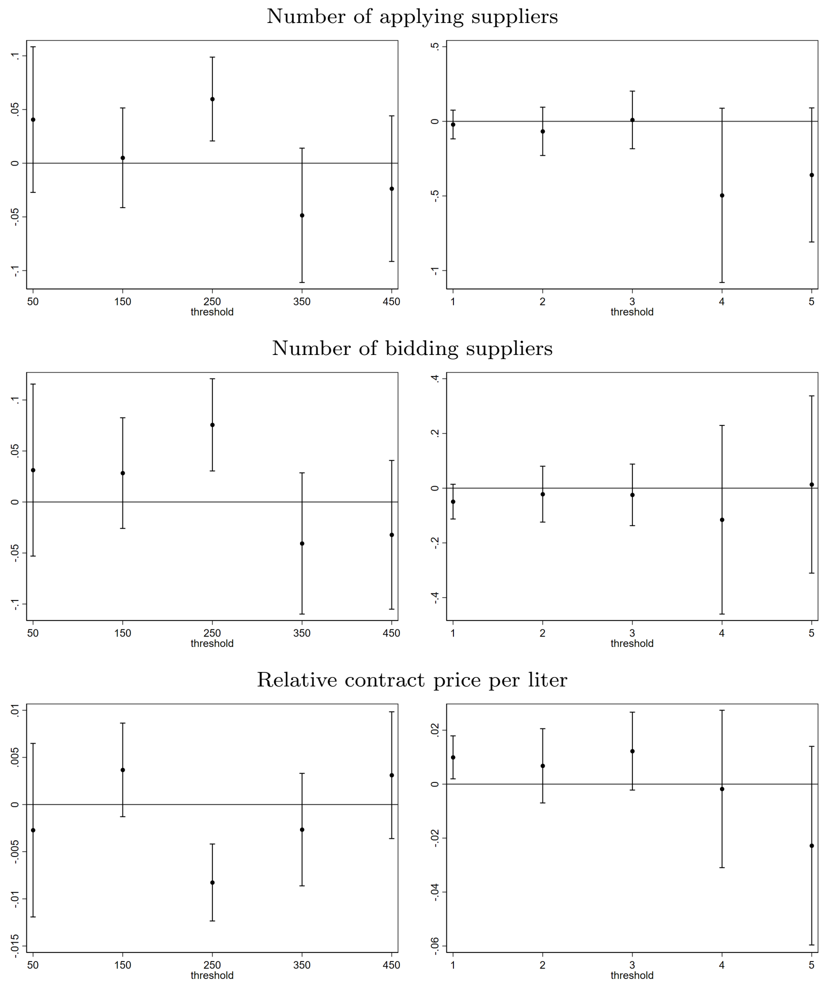
Relative contract price per liter



Notes: The dependent variables from top to bottom are the number of applying suppliers, the number of bidding suppliers and the contract price per liter divided by the market price in sealed bid auctions (left figures) and e-auctions (right figures). The horizontal axis is the relative distance to the threshold value of 250,000 (3 million) RUB in sealed bid auctions (e-auctions) and grouped in 20 bins of equal size for the scatter plot which shows the averages per bin. The lines depict the fitted value and the 95% confidence interval from a linear regression. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price ∈]200,000;300,000[(]2,400,000;3,600,000[) RUB and without missing contract prices. Extended application periods are dropped.

the number of bidders is presented in columns 2 and 5 of table 3. The bidders are the applicants whose bids are considered in the determination of the winner

Figure 6: Placebo



Notes: The dependent variables from top to bottom are the number of applying suppliers, the number of bidding suppliers and the contract price per liter divided by the market price in sealed bid auctions (left figures) and e-auctions (right figures). The horizontal axis shows the actual and placebo threshold values expressed in thousands (millions) for sealed bid auctions (e-auctions). The graphs show the estimated coefficient and 95% confidence interval. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price ∈]200,000;300,000[(]2,400,000;3,600,000[) RUB and without missing contract prices. Auctions with at least two applicants are kept.

of the auction. The coefficient is only significant in sealed bid auctions and positive. The longer the application period, the higher the number of bidders. The size of the significant coefficients does not differ much from the effect on the number of applicants. Finally, the impact of the time to apply for participation on contract prices is estimated. The regression results of table 3 show that longer application periods decrease the ratio between the contract per liter and the regional market price per liter, which can be attributed to the positive effect of longer application periods on competition. The finding is in place for sealed bid auctions. Hence, public buyers can obtain higher price reductions in sealed bid auctions if they increase the time to apply for participation. The sign of the coefficient in e-auctions is ambiguous. The ITT of the second model and the LATE of the first two models are significant and positive but not stable across the various specifications.

Dropping outsourced auctions from the sample leads in general to smaller effects of the application period on the outcome variables. The donut RD yields estimates that are qualitatively similar to the standard RD. The effect on the number of applicants estimated by means of the donut RD are also quantitatively in line with the standard RD. The coefficients differ 2 to 10%, suggesting that the standard identification strategy is valid. Yet, the donut RD alters the effects on the number of bidders and prices considerably, pointing towards the composition bias. The donut RD estimates in columns 2 and 3 decrease in comparison with the standard RD. In other words, dropping the observations at the threshold reduces the effect of the application period on the number of bidders while the effect on prices increases in absolute terms. If corruption underlies the sorting behavior, this is what we expect to find in terms of competition. Corrupt agents who manipulate reserve price are inclined to limit competition much more to enable favoritism. Hence, dropping the observation at the threshold will reduce the effects on competition. However, prices do not rise as a result. This can be related to auctions that jump from above the threshold to below by lowering the reserve price which is the maximum price at which the contract can be concluded. By lowering the cap the contract price may decline as well. As such, the sample without price manipulation could produce a larger price difference between short and long application periods.

Table 3: Effect of the application period

	Sealed bid auction			E-auction		
	(1)	(2)	(3)	(4)	(5)	(6)
	n	nbid	p	n	nbid	p
ITT	0.0761***	0.0970***	-0.00596***	0.204**	0.0460	0.00906
	(0.0200)	(0.0213)	(0.00183)	(0.0920)	(0.0489)	(0.00588)
Observations	11,553	11,553	11,553	2,900	2,900	2,900
LATE	0.0870***	0.119***	-0.00624***	0.141	-0.0207	0.0195***
	(0.0230)	(0.0242)	(0.00210)	(0.102)	(0.0528)	(0.00671)
Observations	10,912	10,912	10,912	2,525	2,525	2,525
ITT, no outsourcing	0.0579***	0.0735***	-0.00812***	0.00955	-0.0245	0.0122*
	(0.0210)	(0.0236)	(0.00208)	(0.0985)	(0.0574)	(0.00737)
Observations	8,982	8,982	8,982	1,810	1,810	1,810
LATE, no outsourcing	0.0666***	0.0887***	-0.00762***	0.0565	-0.0207	0.0173**
	(0.0240)	(0.0269)	(0.00241)	(0.119)	(0.0664)	(0.00847)
Observations	8,454	8,454	8,454	1,613	1,613	1,613
ITT, donut	0.0691***	0.0683***	-0.00777***	0.221*	0.0305	-0.000533
	(0.0249)	(0.0260)	(0.00227)	(0.116)	(0.0621)	(0.00727)
Observations	9,720	9,720	9,720	2,109	2,109	2,109
LATE, donut	0.0848***	0.0910***	-0.00920***	0.142	-0.0359	0.00886
	(0.0294)	(0.0306)	(0.00271)	(0.126)	(0.0658)	(0.00798)
Observations	9,173	9,173	9,173	1,747	1,747	1,747
ITT, no outsourcing & donut	0.0588**	0.0487*	-0.0104***	0.0714	-0.00142	-8.14e-05
	(0.0258)	(0.0290)	(0.00261)	(0.128)	(0.0738)	(0.00887)
Observations	7,411	7,411	7,411	1,265	1,265	1,265
LATE, no outsourcing & donut	0.0735**	0.0637*	-0.0112***	0.139	0.00509	0.00357
	(0.0305)	(0.0342)	(0.00317)	(0.152)	(0.0842)	(0.00984)
Observations	6,969	6,969	6,969	1,071	1,071	1,071

Notes: The dependent variable n is the number of applying suppliers, $nbid$ the number of bidding suppliers and p the contract price per liter divided by the market price. ITT returns the intention-to-treatment effect and $LATE$ the local average treatment effect of the application period for sealed bid auctions in columns 1-3 and e-auctions in columns 4-6. The centered reserve price which is the running variable is controlled for. The sample is restricted to sealed bid and e-auctions with a reserve price deviating at most 20 percent from respectively 250,000 and 3 million RUB threshold values and without missing contract prices. Extended application periods are dropped. Outsourced procurement is dropped in the second specification. The third model excludes auctions with reserve price deviating at most .04 percent from the thresholds. The final panel is estimated using the intersection of both subsamples. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

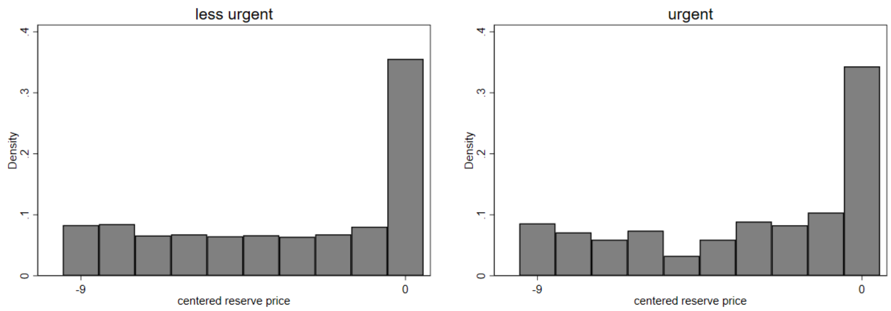
5.4 Urgency and favoritism

The theoretical prediction that longer application periods attract more entrants and eventually enhance competition is verified. Moreover, we have seen that public buyers abuse regulation on application periods by making sure that reserve prices do not exceed the threshold values to limit the time suppliers get to apply for participation. This behavior can be explained by urgency and favoritism. Buyers who need gasoline in the short run will shorten the whole procurement process including the application period. Alternatively, buyers can reduce competition through short application periods to facilitate favoritism. The variables for urgency show that in 93.8% of the auctions the buyer could have extended the application period by at least 1 day and in 75% there was room for conducting auctions with a long application period instead of a short one. The histograms for urgent and less urgent purchases are plotted in figure 7. From the figures on the right we can conclude that buyers avoid long application period because of urgency as sorting at the thresholds is present. Also, in the subsample of less urgent purchases we observe that buyers sort to circumvent long application periods. Hence, it can be confirmed empirically that the preference for short application periods cannot solely be attributed to the urgent need for gasoline but also to alternative explanations such as the unfair creation of entry barriers to favor suppliers.

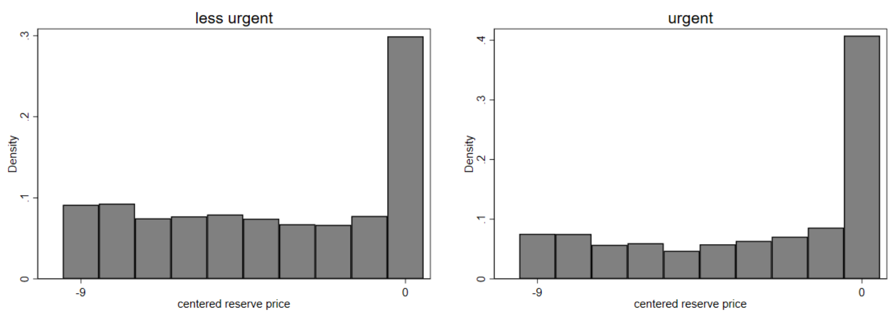
We can observe in figure 8 where buyers avoid long application periods a significant reduction in extensions. Not only do buyers opt for short application periods they also aim at keeping it short by avoiding extensions. Application periods are not extended if at least two suppliers apply for participation. The auctions in the sorting area or auctions with reserve prices which are presumably manipulated to prevent long application periods are statistically more likely to have two applicants than the auctions above the threshold (column 1 of table 4). This result holds for sealed bid auctions because the rule on extensions only exists for this auction procedure. The coefficient for below the sorting area is also positive and significant but much smaller in magnitude. The second applicant could be a real competitor or a colluder. It follows that the second applicant in sealed bid auctions has a lower fraction of wins at the sorting area in comparison with above the threshold (column 2 of table 4). Second, the number of auctions in which the winning and losing applicant took part in together constitutes a larger share of the total applications of the latter. Third, the winning rebate or the relative difference between the reserve and contract price is smallest in this area. Finally, the estimation using the first principal component based on

Figure 7: Sorting by urgency

Application period could have been extended by 1 day



Application period could have been at least 7
(20) days in sealed bid auctions (e-auctions)

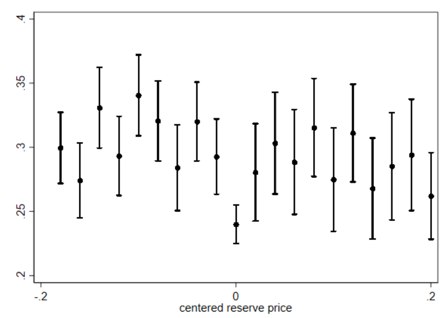


Notes: Distribution of the reserve price for less urgent (on the left) and urgent purchases (on the right) in sealed bid and e-auctions using two measures for urgency. Procurement is less urgent if there was time left that could have been used to extend the period by at least 1 day (upper figures) or the application period could have been at least 7 days in sealed bid auctions and at least 20 days in e-auctions (lower figures). The horizontal axis is the relative distance to the threshold value of 250,000 (3 million) RUB in sealed bid auctions (e-auctions) and grouped in 10 bins of equal size. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price $\in$]200,000;300,000[(]2,400,000;3,600,000[) RUB and without missing contract prices.

all three the proxies indicates that the second applicant is more likely to be a possible colluder in case of manipulated reserve prices.[30] These findings only appear in sealed bid auction since the interaction between *sorting* and *e-auction* is never significant. Hence, favoritism sustained by collusion could further explain why buyers avoid long application periods and sort at the threshold.

[30]The number of observations in columns 5 and 6 is lower because the sample is restricted to at least two bidders instead of two applicants as is the case in columns 2 to 4. Not every applicant is bidding. There are no sample restrictions regarding the number of applicants or bidders in the first column.

Figure 8: Extensions



Notes: Average number of extended application periods and 95% confidence over the reserve price. The horizontal axis is the relative distance to the threshold value of 250,000 (3 million) RUB in sealed bid auctions (e-auctions) and grouped in 20 bins of equal size. The sample is restricted to sealed bid auctions with a reserve price $\in$]200,000;300,000[RUB and without missing contract prices.

6 Robustness

In this section, sensitivity analysis is performed for each of the four models. The corresponding figures and tables are part of the appendix.

6.1 Bandwidth and donut

First, the robustness of the results is assessed to the window around the thresholds. In the baseline specification, the bandwidth on either side of the thresholds is 20% of the threshold values. In figures A4.4, A4.5, A4.6 and A4.7 sensitivity is tested using different bandwidths including the bandwidth selected using the procedure by Calonico et al. (2014) which varies with the regression. Overall, the results are invariant to altering the bandwidth. The only systemic change we observe is the effect on contract prices in sealed bid auctions which is no longer significant at 5% when using the bandwidth selector by Calonico et al. (2014) across the models. In figures A4.8 and A4.9, the donut is redefined on either side of the threshold in both auction procedures to 0.6, 0.8 and 1%. In the benchmark, the observations with a reserve price around the thresholds were left out of the regressions because of price manipulation. A donut of 0.4% was

Table 4: Collusion

	(1) 2 applicants	(2) Rel_win	(3) Rel_overlap	(4) Rebate	(5) Collusion
Sorting	0.347***	-0.0204*	0.0269**	-0.359***	0.108**
	(0.0520)	(0.0113)	(0.0136)	(0.126)	(0.0521)
Below sorting	0.0797**	-0.0199**	0.0123	0.129	0.0450
	(0.0355)	(0.00804)	(0.00964)	(0.101)	(0.0371)
E-auction	-1.604***	0.311***	-0.360***	2.061***	-1.500***
	(0.142)	(0.0259)	(0.0191)	(0.620)	(0.0926)
Sorting*E-auction	-0.197	-0.00741	-0.0149	0.659	-0.0908
	(0.171)	(0.0321)	(0.0248)	(0.772)	(0.123)
Below sorting*E-auction	0.109	-0.000546	0.00526	0.821	-0.0793
	(0.154)	(0.0284)	(0.0216)	(0.713)	(0.107)
Constant	0.237***	0.342***	0.452***	2.626***	0.188***
	(0.0282)	(0.00647)	(0.00773)	(0.0762)	(0.0298)
Observations	19,074	8,464	8,459	9,098	7,616

Notes: The first dependent variable equals 1 if the number of applicants is two and 0 otherwise. *Rel_win* is the number of wins divided by the number of participations of the second applicant, *rel_overlap* is the number of auctions in which the first and second applicant both take part in divided by the total number of participations of the latter and *rebate* is the relative difference between the reserve and contract price. The dependent variable in the last column is the first component of the principal component analysis using the previous three variables. *Sorting* equals 1 if the reserve price $\in$ [249,000;250,000] ([2,988,000;3,000,000]) RUB in sealed bid auctions (e-auctions) and *below sorting* if less than 249,000 (2,988,000) RUB. *E-auction* is 1 if gasoline is procured via e-auctions and 0 if sealed bid auctions. The sample is restricted to sealed bid and e-auctions with a reserve price deviating at most 20 percent from respectively 250,000 and 3 million RUB threshold values and without missing contract prices. The sample in columns 2-5 is restricted to auctions with two applicants. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

taken at either side of the thresholds which is also depicted in the figures. The estimations with larger donuts are qualitatively and quantitatively similar to the baseline.

6.2 Nonparametric estimation

Besides the parametric approach, the impact of the application period is estimated through a local linear regression. The results are given in tables A4.4, A4.5, A4.6 and A4.7. I repeat the baseline model and gradually introduce the bandwidth selected using the procedure by Calonico et al. (2014) and second order polynomial. Most of the results are in line with the baseline estimates. Significance is sometimes lost using the bandwidth selector by Calonico et al.

(2014) in the estimation of the number of applicants and bidders in sealed bid auctions, which could be due to the drop in the number of observations.

6.3 Fully interacted model

The regressions so far were performed separately for sealed bid and e-auctions. To investigate whether and to what extent the effects differ in both auction procedures, a fully interacted model is estimated. The independent variables are interacted with the auction procedure (tables A4.8, A4.9, A4.10 and A4.11 in appendix). The effects in sealed bid auctions are similar to the baseline results. The interaction terms are in most of the specifications insignificant, meaning that the effects in e-auctions do not differ from the effects in sealed bid auctions. In model 1 and 3, however, the interaction term in the estimation of the number of bidders becomes negative and significant. The finding implies that e-auctions with long application periods are characterized by a lower number of bidders in comparison with sealed bid auctions, leading to significant price increases. In general, the effects in e-auctions are rather ambiguous.

6.4 Other checks

Tables A4.12, A4.13, A4.14 and A4.15 include higher order polynomial terms of the reserve price and allow the effect to differ on either side of the thresholds. The findings for both auction procedures are invariant. In the first model, however, the effect on the number of bidding suppliers in e-auctions becomes significant at the 10% significance level. Robustness checks are also performed and presented in tables A4.16, A4.17, A4.18 and A4.19. Additional control variables are introduced to increase the efficiency of the estimators: the reserve price per liter, year, month and region fixed effects. In models 1-4, significance is lost in the estimation of the price in sealed bid auctions. I also test for robustness using standard errors clustered at regional level. Furthermore, Atmaca et al. (2019) provided evidence of inflated reserve prices by corrupt buyer-supplier pairs. In combination with sorting at the threshold, it implies that overpriced auctions occur on average less above the thresholds than below. This is to some degree dealt with as observations just above and below the thresholds are dropped in the donut regression discontinuity framework. I further resolve this by dropping the buyer-supplier pairs that are found to be inflating reserve prices according to Atmaca et al. (2019).[31] The drop in observations results in a loss in significance, yet the sign of the coefficients are in line with the baseline results. In addition, Liebman and Mahoney (2017) found higher procurement spending along with lower quality at the end of the year. To account for year-end budget effects, December is dropped from our sample and the models are re-estimated. Year-end spending is also addressed by including month fixed effects. Overall, the results for sealed bid auctions are robust while the effect on the number of applicants in e-auctions is no longer significant and the effect on the number of bidders and prices remains ambiguous.

7 Conclusion

The impact of the period to apply for application on competition and prices in reverse auctions is studied. I found that longer application periods lead to more competition because of decreased entry costs. Consequently, auctions are on average concluded at lower contract prices. Public buyers can obtain higher price reductions if they increase the time suppliers get to apply for participation. Their preference for short periods is partly explained by the urgent need for goods. Buyers who need goods in the short run will limit the whole procurement process including the application period. The alternative explanation is favoritism. Corrupt buyers can increase suppliers' probability of winning auctions by shortening application periods. If suppliers are less exposed to information on planned procurement and have less time to prepare their application, they will be less likely to participate in auctions. The decreased competition enables buyers to allocate contracts to favored suppliers. I further added that

[31] Corrupt buyer-supplier pairs are dropped and the pairs that are not found to overprice contracts and those for which the authors could not empirically verify overpricing are kept.

collusion between two suppliers can sustain this form of corruption.

The focus of the study is the formal application period. In reality, it is likely that the buyer informs suppliers about planned auctions before the formal announcement of auctions. The effect of the application period would then increase as suppliers have more time to prepare their application. On the other hand, the formal announcement contains the concrete contractual terms which will further shape suppliers' decision to participate. Furthermore, I had to drop observations in the discontinuity analysis because of manipulation of the running variable. In addition, the effects of the application period is evaluated using gasoline data. The effects could be larger for other types of goods, services and works. The application period is expected to be especially of importance for the latter as these are less standard to deliver and unique in nature compared to the procurement of gasoline. I also focused on one type of collusion. Future research is needed to get a better understanding of the relevant types and the magnitude of collusion to circumvent extensions of the application period.

The findings suggest that explicit rules on application periods are effective in enhancing competition in auctions and saving public money. However, regulation can create undesired incentives as it is the case in Russia. Public buyers abuse regulation, which complicates the achievement of policy objectives.

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Table A4.1: Descriptive statistics

	Sample			Reduced sample		
	N	mean	sd	N	mean	sd
Sealed bid auction						
n	16,174	1.9	0.7	10,085	1.9	0.7
nbid	16,174	1.8	0.7	10,085	1.8	0.7
p	16,174	1	0.1	10,085	1	0.1
1(reserve price-c>0)	16,174	0.3	0.5	10,085	0.3	0.5
D	15,337	0.6	0.5	10,085	0.6	0.5
Extension	16,174	0.3	0.5	10,085	0.3	0.5
r	16,002	29.1	2.7	9,974	29.1	2.7
Outsourcing	16,174	0.3	0.4	10,085	0.3	0.4
E-auction						
n	2,900	1.6	1	1,504	1.6	1
nbid	2,900	1.3	0.6	1,504	1.3	0.6
p	2,900	1	0.1	1,504	1	0.1
1(reserve price-c>0)	2,900	0.1	0.3	1,504	0.1	0.3
D	2,525	0.1	0.3	1,504	0.1	0.3
r	2,857	30	2.7	1,482	29.6	2.7
Outsourcing	2,900	0.4	0.5	1,504	0.4	0.5

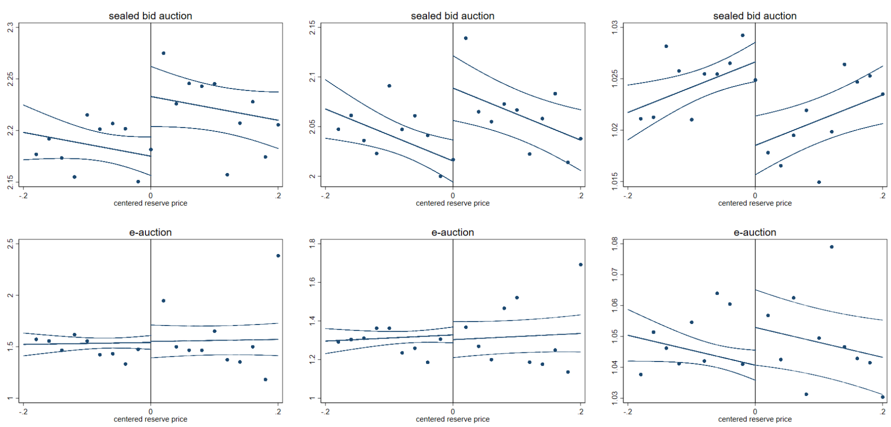
Notes: n is the number of applicants, *nbid* is the number of bidders, p is the contract price per liter divided by the regional market price per liter, D equals 1 if the application period is at least 7 (20) days in sealed bid auctions (e-auctions), *extension* indicates whether the application period was extended, r is the reserve price per liter and *outsourcing* is an indicator variable for outsourced procurement. The sample is restricted to sealed bid auctions (e-auctions) with reserve price $\in$]200,000;300,000[(]2,400,000;3,600,000[) RUB and without missing contract prices. The reduced sample is further without missing values for the variables measuring urgency.

Table A4.2: Collusion

	(1) 2 applicants	(2) Rel_win	(3) Rel_overlap	(4) Rel_bid	(5) Collusion
Sorting	0.347***	-0.0204*	0.0269**	-0.00194***	0.114**
	(0.0520)	(0.0113)	(0.0136)	(0.000609)	(0.0503)
Below sorting	0.0797**	-0.0199**	0.0123	-0.00109**	0.0810**
	(0.0355)	(0.00804)	(0.00964)	(0.000452)	(0.0358)
E-auction	-1.604***	0.311***	-0.360***	-0.00512***	-1.270***
	(0.142)	(0.0259)	(0.0191)	(0.000691)	(0.0818)
Sorting*E-auction	-0.197	-0.00741	-0.0149	0.00182*	-0.0276
	(0.171)	(0.0321)	(0.0248)	(0.00103)	(0.106)
Below sorting*E-auction	0.109	-0.000546	0.00526	0.00182**	-0.00643
	(0.154)	(0.0284)	(0.0216)	(0.000892)	(0.0914)
Constant	0.237***	0.342***	0.452***	0.0117***	0.131***
	(0.0282)	(0.00647)	(0.00773)	(0.000371)	(0.0288)
Observations	19,074	8,464	8,459	8,417	8,331

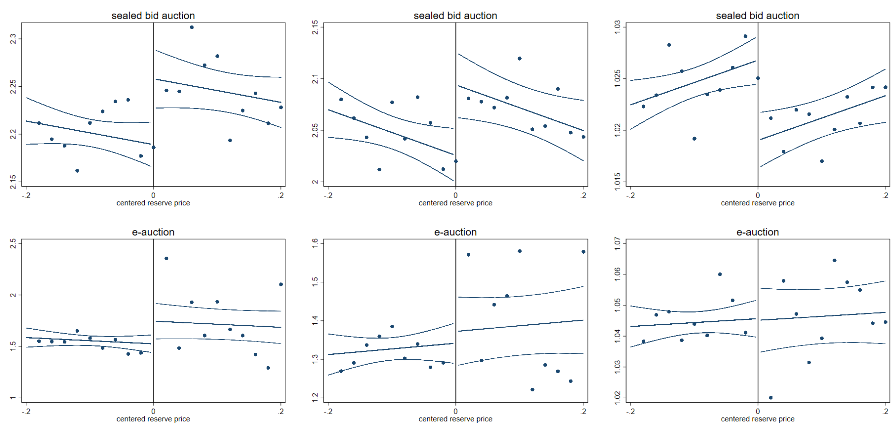
Notes: The first dependent variable equals 1 if the number of applicants is two and 0 otherwise. *Rel_win* is the number of wins divided by the number of participations of the second applicant, *rel_overlap* is the number of auctions in which the first and second applicant both take part in divided by the total number of participations of the latter and *rel_bid* is the relative difference between their bids. The dependent variable in the last column is the first component of the principal component analysis using the previous three variables. *Sorting* equals 1 if the reserve price $\in$ [249,000;250,000] ([2,988,000;3,000,000]) RUB in sealed bid auctions (e-auctions) and *below sorting* if less than 249,000 (2,988,000) RUB. *E-auction* is 1 if gasoline is procured via e-auctions and 0 if sealed bid auctions. The sample is restricted to sealed bid and e-auctions with reserve price deviating at most 20 percent from respectively 250,000 and 3 million RUB threshold values and without missing contract prices. The sample in columns 2-5 is restricted to auctions with two applicants. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Figure A4.1: Discontinuity in outcome variables, model 2



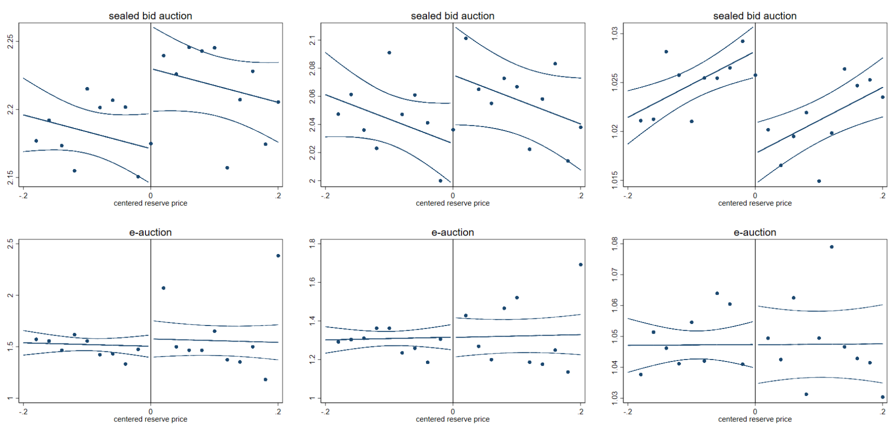
Notes: From left to right, the number of applying suppliers, the number of bidding suppliers and the contract price per liter divided by the market price in sealed bid auctions (upper figures) and e-auctions (lower figures). The horizontal axis is the relative distance to the threshold value of 250,000 (3 million) RUB in sealed bid auctions (e-auctions) and grouped in 20 bins of equal size for the scatter plot which shows the averages per bin. The lines depict the fitted value and the 95% confidence interval from a linear regression. The control variable is the centered reserve price which is the running variable. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price $\in$]200,000;300,000[(]2,400,000;3,600,000[) RUB and without missing contract prices. Extended application periods and outsourced auctions are dropped.

Figure A4.2: Discontinuity in outcome variables, model 3



Notes: From left to right, the number of applying suppliers, the number of bidding suppliers and the contract price per liter divided by the market price in sealed bid auctions (upper figures) and e-auctions (lower figures). The horizontal axis is the relative distance to the threshold value of 250,000 (3 million) RUB in sealed bid auctions (e-auctions) and grouped in 20 bins of equal size for the scatter plot which shows the averages per bin. The lines depict the fitted value and the 95% confidence interval from a linear regression. The control variable is the centered reserve price which is the running variable. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price ∈]200,000;249,000[or]251,000;300,000[(]2,400,000;2,988,000[or]3,012,000;3,600,000[) RUB and without missing contract prices. Extended application periods are dropped.

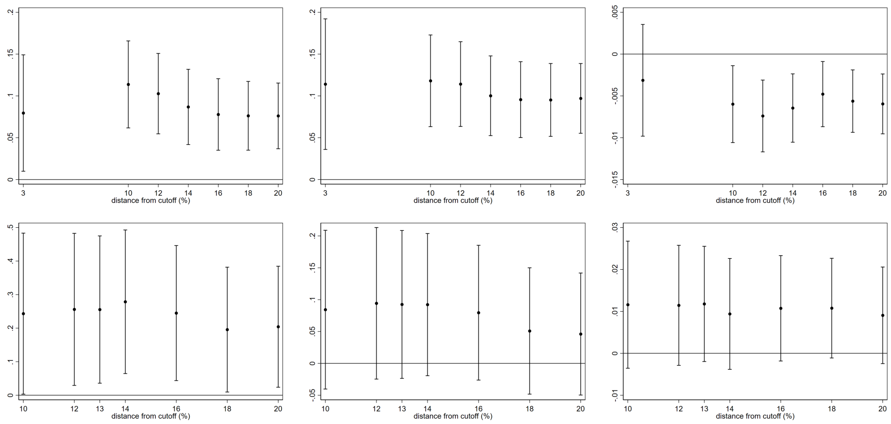
Figure A4.3: Discontinuity in outcome variables, model 4



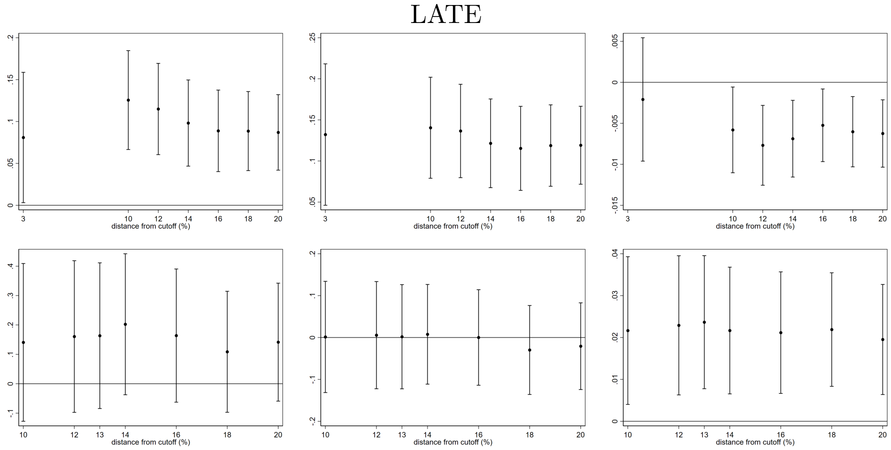
Notes: From left to right, the number of applying suppliers, the number of bidding suppliers and the contract price per liter divided by the market price in sealed bid auctions (upper figures) and e-auctions (lower figures). The horizontal axis is the relative distance to the threshold value of 250,000 (3 million) RUB in sealed bid auctions (e-auctions) and grouped in 20 bins of equal size for the scatter plot which shows the averages per bin. The lines depict the fitted value and the 95% confidence interval from a linear regression. The control variable is the centered reserve price which is the running variable. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price ∈]200,000;249,000[or]251,000;300,000[(]2,400,000;2,988,000[or]3,012,000;3,600,000[) RUB and without missing contract prices. Extended application periods and outsourced auctions are dropped.

Figure A4.4: Bandwidth sensitivity, model 1

ITT

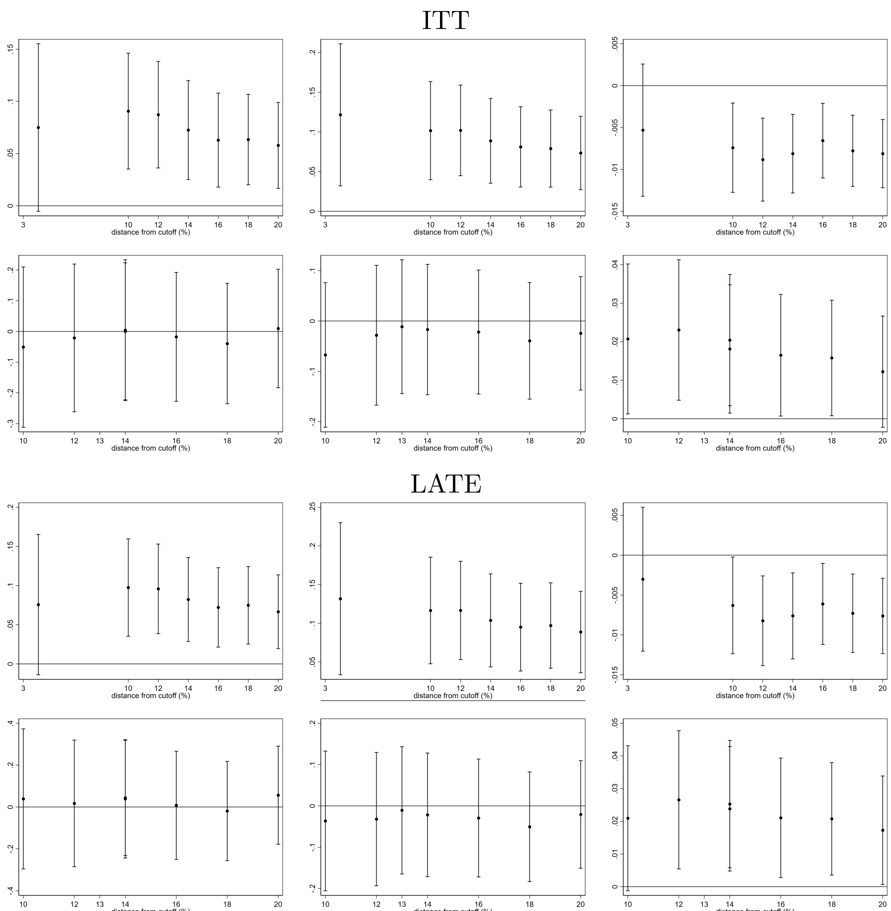


LATE



Notes: From left to right, the number of applying suppliers, the number of bidding suppliers and the contract price per liter divided by the market price in sealed bid auctions (upper figures) and e-auctions (lower figures). The graphs show the estimated coefficient and 95% confidence interval of the OLS (upper panel) and IV (lower panel) regression for varying bandwidth depicted by the horizontal axis. The control variable is the centered reserve price which is the running variable. Auctions without contract prices and extended application periods are dropped.

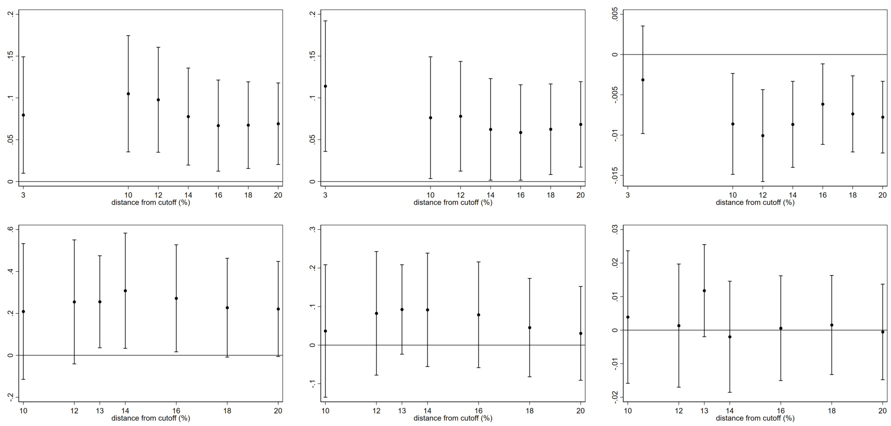
Figure A4.5: Bandwidth sensitivity, model 2



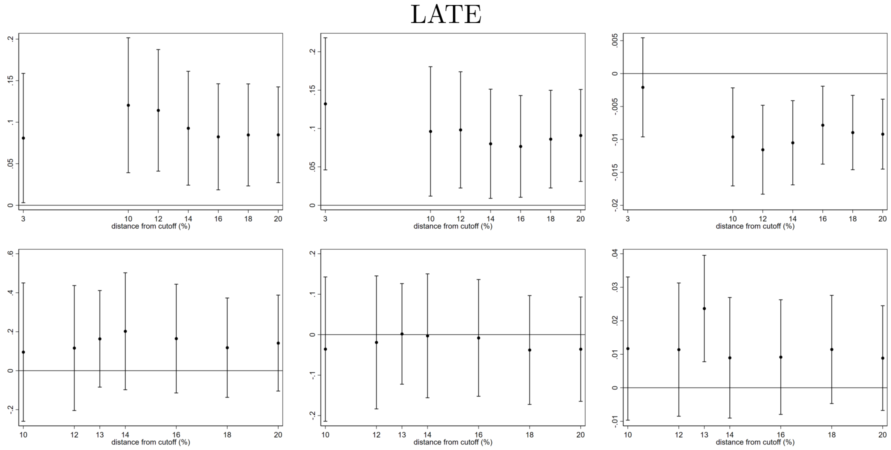
Notes: From left to right, the number of applying suppliers, the number of bidding suppliers and the contract price per liter divided by the market price in sealed bid auctions (upper figures) and e-auctions (lower figures). The graphs show the estimated coefficient and 95% confidence interval of the OLS (upper panel) and IV (lower panel) regression for varying bandwidth depicted by the horizontal axis. The control variable is the centered reserve price which is the running variable. Auctions without contract prices and extended application periods are dropped. The sample is restricted to auctions which are not outsourced.

Figure A4.6: Bandwidth sensitivity, model 3

ITT

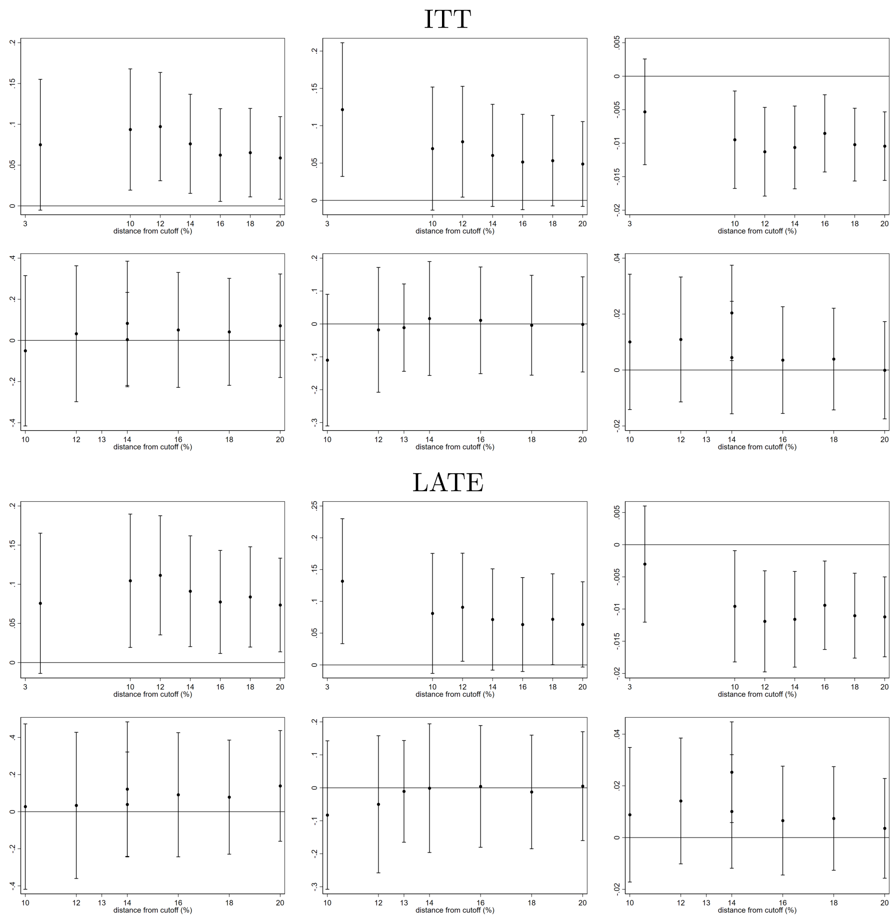


LATE



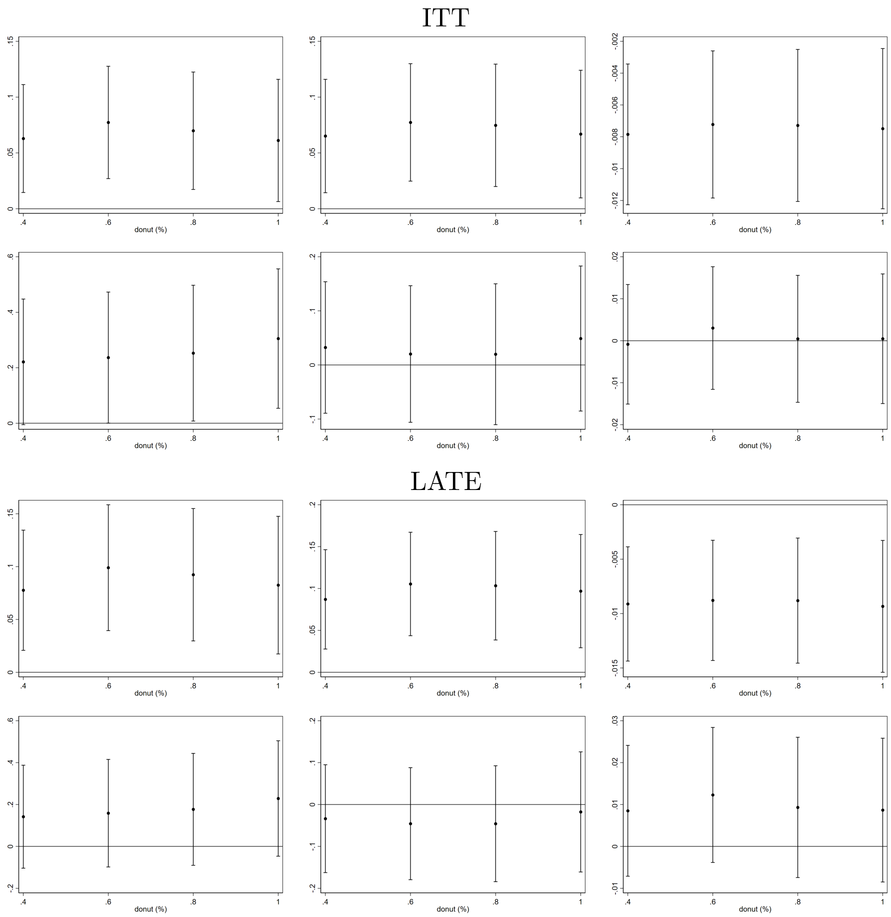
Notes: From left to right, the number of applying suppliers, the number of bidding suppliers and the contract price per liter divided by the market price in sealed bid auctions (upper figures) and e-auctions (lower figures). The graphs show the estimated coefficient and 95% confidence interval of the OLS (upper panel) and IV (lower panel) regression for varying bandwidth depicted by the horizontal axis. The control variable is the centered reserve price which is the running variable. Auctions without contract prices and extended application periods are dropped. Auctions with a reserve price deviating at most .4 percent from the thresholds are excluded.

Figure A4.7: Bandwidth sensitivity, model 4



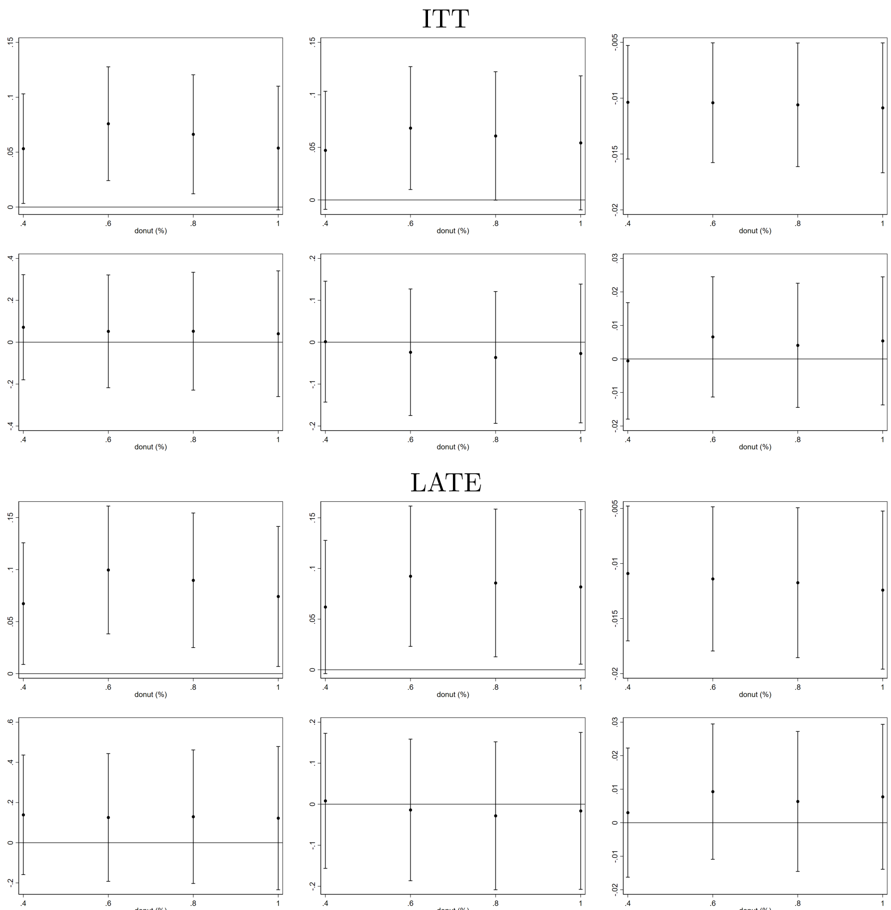
Notes: From left to right, the number of applying suppliers, the number of bidding suppliers and the contract price per liter divided by the market price in sealed bid auctions (upper figures) and e-auctions (lower figures). The graphs show the estimated coefficient and 95% confidence interval of the OLS (upper panel) and IV (lower panel) regression for varying bandwidth depicted by the horizontal axis. The control variable is the centered reserve price which is the running variable. Auctions without contract prices and extended application periods are dropped. The sample is restricted to auctions which are not outsourced and auctions with a reserve price deviating at most .4 percent from the thresholds are excluded.

Figure A4.8: Donut sensitivity, model 3



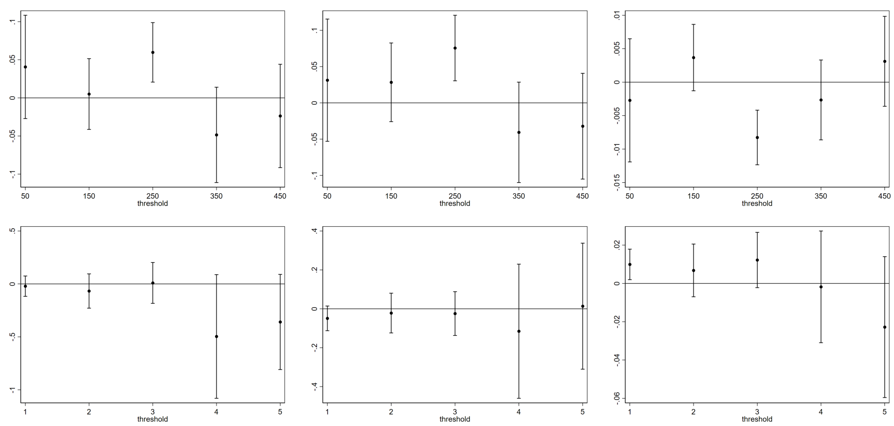
Notes: From left to right, the number of applying suppliers, the number of bidding suppliers and the contract price per liter divided by the market price in sealed bid auctions (upper figures) and e-auctions (lower figures). The graphs show the estimated coefficient and 95% confidence interval of the OLS (upper panel) and IV (lower panel) regression for varying donut depicted by the horizontal axis. The control variable is the centered reserve price which is the running variable. The sample is further restricted to auctions with a reserve price deviating at most 20 percent from the thresholds.

Figure A4.9: Donut sensitivity, model 4



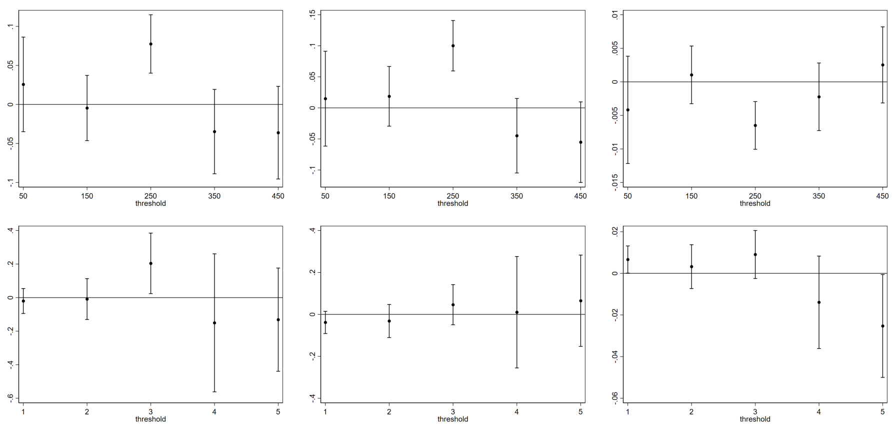
Notes: From left to right, the number of applying suppliers, the number of bidding suppliers and the contract price per liter divided by the market price in sealed bid auctions (upper figures) and e-auctions (lower figures). The graphs show the estimated coefficient and 95% confidence interval of the OLS (upper panel) and IV (lower panel) regression for varying donut depicted by the horizontal axis. The control variable is the centered reserve price which is the running variable. The sample is further restricted to auctions with a reserve price deviating at most 20 percent from the thresholds which are not outsourced.

Figure A4.10: Falsification test, model 2



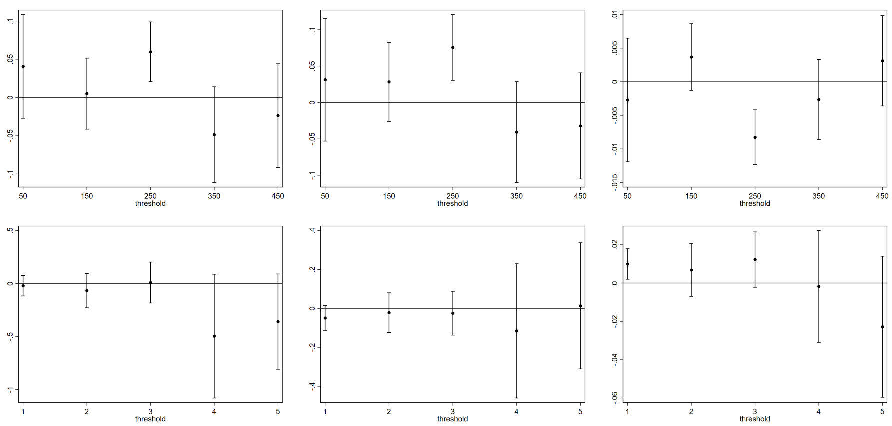
Notes: From left to right, the intention-to-treatment effect on the number of applying suppliers, the number of bidding suppliers and the contract price per liter divided by the market price and 95% confidence interval in sealed bid auctions (upper figures) and e-auctions (lower figures). The horizontal axis shows the actual and placebo threshold values expressed in thousands (millions) for sealed bid auctions (e-auctions). The control variable is the centered reserve price which is the running variable. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price ∈]200,000;300,000[(]2,400,000;3,600,000[) RUB which are not outsourced and sealed bid auctions with at least two applicants.

Figure A4.11: Falsification test, model 3



Notes: From left to right, the intention-to-treatment effect on the number of applying suppliers, the number of bidding suppliers and the contract price per liter divided by the market price and 95% confidence interval in sealed bid auctions (upper figures) and e-auctions (lower figures). The horizontal axis shows the actual and placebo threshold values expressed in thousands (millions) for sealed bid auctions (e-auctions). The control variable is the centered reserve price which is the running variable. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price $\in$]200,000;249,000[or]251,000;300,000[(]2,400,000;2,988,000[or]3,012,000;3,600,000[) RUB and sealed bid auctions with at least two applicants.

Figure A4.12: Falsification test, model 4



Notes: From left to right, the intention-to-treatment effect on the number of applying suppliers, the number of bidding suppliers and the contract price per liter divided by the market price and 95% confidence interval in sealed bid auctions (upper figures) and e-auctions (lower figures). The horizontal axis shows the actual and placebo threshold values expressed in thousands (millions) for sealed bid auctions (e-auctions). The control variable is the centered reserve price which is the running variable. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price ∈]200,000;249,000[or]251,000;300,000[(]2,400,000;2,988,000[or]3,012,000;3,600,000[) RUB which are not outsourced and sealed bid auctions with at least two applicants.

Table A4.3: Outsourcing

	Sealed bid auction			E-auction		
	(1)	(2)	(3)	(4)	(5)	(6)
	n	nbid	p	n	nbid	p
ITT	0.0981*	0.177***	0.00295	0.461***	0.132	0.00612
	(0.0521)	(0.0495)	(0.00387)	(0.167)	(0.0838)	(0.00961)
Observations	2,571	2,571	2,571	1,090	1,090	1,090
LATE	0.113*	0.218***	2.87e-05	0.273	-0.0212	0.0243**
	(0.0591)	(0.0556)	(0.00429)	(0.183)	(0.0866)	(0.0110)
Observations	2,458	2,458	2,458	912	912	912
ITT, donut	0.0699	0.123**	0.00170	0.392*	0.0525	0.000466
	(0.0636)	(0.0585)	(0.00458)	(0.206)	(0.106)	(0.0123)
Observations	2,309	2,309	2,309	844	844	844
LATE, donut	0.0842	0.163**	-0.00186	0.122	-0.106	0.0184
	(0.0737)	(0.0667)	(0.00515)	(0.214)	(0.105)	(0.0134)
Observations	2,204	2,204	2,204	676	676	676

Notes: The dependent variable n is the number of applying suppliers, $nbid$ the number of bidding suppliers and p the contract price per liter divided by the market price. ITT returns the intention-to-treatment effect and $LATE$ the local average treatment effect of the application period for sealed bid auctions in columns 1-3 and e-auctions in columns 4-6. The centered reserve price which is the running variable is controlled for. The sample is restricted to outsourced sealed bid and e-auctions with reserve price deviating at most 20 percent from respectively 250,000 and 3 million RUB threshold values and without missing contract prices. Extended application periods are dropped. The second model excludes auctions with reserve price deviating at most .04 percent from the thresholds. Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table A4.4: Local linear regression, model 1

	Sealed bid auctions			E-auctions		
	(1)	(2)	(3)	(4)	(5)	(6)
	n	nbid	p	n	nbid	p
ITT	0.0346*	0.0363*	-0.00699***	0.271***	0.0956	-0.000589
	(0.0207)	(0.0218)	(0.00186)	(0.102)	(0.0593)	(0.00682)
Observations	11,553	11,553	11,553	2,911	2,911	2,911
ITT, h*	-0.0315	-0.0201	-0.00632**	0.180**	0.0556	0.00298
	(0.0282)	(0.0311)	(0.00255)	(0.0879)	(0.0512)	(0.00554)
Observations	3,800	4,376	4,901	4,980	4,748	5,211
ITT, p=2	0.0346*	0.0363*	-0.00699***	0.271***	0.0956	-0.000589
	(0.0207)	(0.0218)	(0.00186)	(0.102)	(0.0593)	(0.00682)
Observations	11,553	11,553	11,553	2,911	2,911	2,911
LATE	0.0548*	0.0675**	-0.0108***	0.439*	0.0986	0.00555
	(0.0324)	(0.0339)	(0.00293)	(0.231)	(0.135)	(0.0163)
Observations	10,912	10,912	10,912	2,525	2,525	2,525
LATE, h*	-0.116	-0.0631	-0.0149*	0.628*	0.113	0.00315
	(0.0831)	(0.0946)	(0.00814)	(0.381)	(0.229)	(0.0274)
Observations	3,549	3,544	3,585	1,729	1,729	1,729
LATE, p=2	0.0548*	0.0675**	-0.0108***	0.439*	0.0986	0.00555
	(0.0324)	(0.0339)	(0.00293)	(0.231)	(0.135)	(0.0163)
Observations	10,912	10,912	10,912	2,525	2,525	2,525

Notes: The dependent variable n is the number of applying suppliers, $nbid$ the number of bidding suppliers and p the contract price per liter divided by the marketprice. ITT returns the intention-to-treatment effect and $LATE$ the local average treatment effect of the application period for sealed bid auctions in columns 1-3 and e-auctions in columns 4-6. The centered reserve price which is the running variable is controlled for. The effect of the application period is estimated using a local linear regression. The optimal bandwidth is used in the second specification. The order of the polynomial in the third model is two. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price $\in$]200,000;300,000[(]2,400,000;3,600,000[) RUB. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A4.5: Local linear regression, model 2

	Sealed bid auctions			E-auctions		
	(1)	(2)	(3)	(4)	(5)	(6)
	n	nbid	p	n	nbid	p
ITT	0.0225	0.0149	-0.00910***	0.168	0.0845	0.00261
	(0.0212)	(0.0239)	(0.00212)	(0.128)	(0.0757)	(0.00940)
Observations	8,982	8,982	8,982	1,818	1,818	1,818
ITT, h*	-0.0111	-0.0358	-0.00784***	0.0844	0.0320	0.00222
	(0.0287)	(0.0337)	(0.00277)	(0.0982)	(0.0667)	(0.00712)
Observations	3,945	3,552	4,269	3,618	2,715	3,952
ITT, p=2	0.0225	0.0149	-0.00910***	0.168	0.0845	0.00261
	(0.0212)	(0.0239)	(0.00212)	(0.128)	(0.0757)	(0.00940)
Observations	8,982	8,982	8,982	1,818	1,818	1,818
LATE	0.0369	0.0299	-0.0137***	0.586	0.247	-0.00181
	(0.0354)	(0.0397)	(0.00359)	(0.369)	(0.215)	(0.0256)
Observations	8,454	8,454	8,454	1,613	1,613	1,613
LATE, h*	-0.121	-0.150	-0.0168*	1.069	0.305	-0.00100
	(0.102)	(0.113)	(0.0101)	(0.749)	(0.441)	(0.0522)
Observations	2,942	2,963	2,941	1,061	1,066	1,066
LATE, p=2	0.0369	0.0299	-0.0137***	0.586	0.247	-0.00181
	(0.0354)	(0.0397)	(0.00359)	(0.369)	(0.215)	(0.0256)
Observations	8,454	8,454	8,454	1,613	1,613	1,613

Notes: The dependent variable n is the number of applying suppliers, $nbid$ the number of bidding suppliers and p the contract price per liter divided by the market price. ITT returns the intention-to-treatment effect and $LATE$ the local average treatment effect of the application period for sealed bid auctions in columns 1-3 and e-auctions in columns 4-6. The centered reserve price which is the running variable is controlled for. The effect of the application period is estimated using a local linear regression. The optimal bandwidth used in the second specification. The order of the polynomial in the third model is two. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price $\in$]200,000;300,000[(]2,400,000;3,600,000[) RUB. which are not outsourced. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A4.6: Local linear regression, model 3

	Sealed bid auctions			E-auctions		
	(1)	(2)	(3)	(4)	(5)	(6)
	n	nbid	p	n	nbid	p
ITT	0.0798***	0.0674**	-0.00803***	0.386**	0.110	-0.00449
	(0.0271)	(0.0277)	(0.00238)	(0.152)	(0.0787)	(0.00920)
Observations	9,720	9,720	9,720	2,120	2,120	2,120
ITT, h*	0.0565	0.0509	-0.00511	0.423***	0.0777	-0.00105
	(0.0605)	(0.0577)	(0.00509)	(0.152)	(0.0704)	(0.00792)
Observations	2,100	2,884	2,713	2,045	2,675	2,873
ITT, p=2	0.0798***	0.0674**	-0.00803***	0.386**	0.110	-0.00449
	(0.0271)	(0.0277)	(0.00238)	(0.152)	(0.0787)	(0.00920)
Observations	9,720	9,720	9,720	2,120	2,120	2,120
LATE	0.100***	0.0931***	-0.00985***	0.251	0.0109	0.00516
	(0.0323)	(0.0329)	(0.00286)	(0.165)	(0.0800)	(0.0108)
Observations	9,173	9,173	9,173	1,747	1,747	1,747
LATE, h*	0.0586	0.0406	-0.00559	0.455	0.155	-0.00269
	(0.0713)	(0.0665)	(0.00604)	(0.387)	(0.243)	(0.0223)
Observations	1,932	2,663	2,505	507	415	682
LATE, p=2	0.100***	0.0931***	-0.00985***	0.251	0.0109	0.00516
	(0.0323)	(0.0329)	(0.00286)	(0.165)	(0.0800)	(0.0108)
Observations	9,173	9,173	9,173	1,747	1,747	1,747

Notes: The dependent variable n is the number of applying suppliers, $nbid$ the number of bidding suppliers and p the contract price per liter divided by the market price. ITT returns the intention-to-treatment effect and $LATE$ the local average treatment effect of the application period for sealed bid auctions in columns 1-3 and e-auctions in columns 4-6. The centered reserve price which is the running variable is controlled for. The effect of the application period is estimated using a local linear regression. The optimal bandwidth used in the second specification. The order of the polynomial in the third model is two. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price $\in$]200,000;249,000[or]251,000;300,000[(]2,400,000;2,988,000[or]3,012,000;3,600,000[) RUB. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A4.7: Local linear regression, model 4

	Sealed bid auctions			E-auctions		
	(1)	(2)	(3)	(4)	(5)	(6)
	n	nbid	p	n	nbid	p
ITT	0.0683**	0.0530*	-0.0110***	0.0755	0.0111	0.00464
	(0.0273)	(0.0309)	(0.00281)	(0.178)	(0.0873)	(0.0122)
Observations	7,411	7,411	7,411	1,273	1,273	1,273
ITT, h*	0.0752	0.0758	-0.0114**	0.0311	-0.0251	0.00775
	(0.0552)	(0.0589)	(0.00550)	(0.159)	(0.0888)	(0.0100)
Observations	2,305	2,495	2,604	1,502	1,311	1,878
ITT, p=2	0.0683**	0.0530*	-0.0110***	0.0755	0.0111	0.00464
	(0.0273)	(0.0309)	(0.00281)	(0.178)	(0.0873)	(0.0122)
Observations	7,411	7,411	7,411	1,273	1,273	1,273
LATE	0.0873***	0.0705*	-0.0121***	0.207	0.0276	0.00313
	(0.0326)	(0.0368)	(0.00344)	(0.246)	(0.107)	(0.0144)
Observations	6,969	6,969	6,969	1,071	1,071	1,071
LATE, h*	0.0831	0.0695	-0.0113*	0.416	0.0100	0.0250
	(0.0619)	(0.0665)	(0.00651)	(0.603)	(0.493)	(0.0355)
Observations	2,169	2,341	2,448	366	254	392
LATE, p=2	0.0873***	0.0705*	-0.0121***	0.207	0.0276	0.00313
	(0.0326)	(0.0368)	(0.00344)	(0.246)	(0.107)	(0.0144)
Observations	6,969	6,969	6,969	1,071	1,071	1,071

Notes: The dependent variable n is the number of applying suppliers, $nbid$ the number of bidding suppliers and p the contract price per liter divided by the market price. ITT returns the intention-to-treatment effect and $LATE$ the local average treatment effect of the application period for sealed bid auctions in columns 1-3 and e-auctions in columns 4-6. The centered reserve price which is the running variable is controlled for. The effect of the application period is estimated using a local linear regression. The optimal bandwidth used in the second specification. The order of the polynomial in the third model is two. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price $\in$]200,000;249,000[or]251,000;300,000[(]2,400,000;2,988,000[or]3,012,000;3,600,000[) RUB which are not outsourced. Standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table A4.8: Fully interacted, model 1

	(1) n	(2) nbid	(3) p
ITT	0.0761***	0.0970***	-0.00596***
	(0.0200)	(0.0213)	(0.00183)
ITT*e-auction	0.128	-0.0510	0.0150**
	(0.0942)	(0.0533)	(0.00615)
Observations	14,453	14,453	14,453
LATE	0.0870***	0.119***	-0.00624***
	(0.0230)	(0.0242)	(0.00210)
LATE*e-auction	0.0545	-0.140**	0.0258***
	(0.105)	(0.0581)	(0.00703)
Observations	13,437	13,437	13,437

Notes: The dependent variable n is the number of applying suppliers, $nbid$ the number of bidding suppliers and p the contract price per liter divided by the market price. ITT returns the intention-to-treatment effect and $LATE$ the local average treatment effect of the application period by auction procedure. The control variables include the centered reserve price which is the running variable, the auction procedure and the interaction of both variables. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price $\in$]200,000;300,000[(]2,400,000;3,600,000[) RUB. Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table A4.9: Fully interacted, model 2

	(1) n	(2) nbid	(3) p
ITT	0.0579***	0.0735***	-0.00812***
	(0.0210)	(0.0236)	(0.00208)
ITT*e-auction	-0.0483	-0.0979	0.0203***
	(0.101)	(0.0620)	(0.00765)
Observations	10,792	10,792	10,792
LATE	0.0666***	0.0887***	-0.00762***
	(0.0240)	(0.0269)	(0.00241)
LATE*e-auction	-0.0101	-0.109	0.0249***
	(0.122)	(0.0717)	(0.00880)
Observations	10,067	10,067	10,067

Notes: The dependent variable n is the number of applying suppliers, $nbid$ the number of bidding suppliers and p the contract price per liter divided by the market price. ITT returns the intention-to-treatment effect and $LATE$ the local average treatment effect of the application period by auction procedure. The control variables include the centered reserve price which is the running variable, the auction procedure and the interaction of both variables. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price $\in$]200,000;300,000[(]2,400,000;3,600,000[) RUB which are not outsourced. Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table A4.10: Fully interacted, model 3

	(1)	(2)	(3)
	n	nbid	p
ITT	0.0691***	0.0683***	-0.00777***
	(0.0249)	(0.0260)	(0.00227)
ITT*e-auction	0.152	-0.0379	0.00724
	(0.118)	(0.0673)	(0.00761)
Observations	11,829	11,829	11,829
LATE	0.0848***	0.0910***	-0.00920***
	(0.0294)	(0.0306)	(0.00271)
LATE*e-auction	0.0568	-0.127*	0.0181**
	(0.129)	(0.0726)	(0.00842)
Observations	10,920	10,920	10,920

Notes: The dependent variable n is the number of applying suppliers, $nbid$ the number of bidding suppliers and p the contract price per liter divided by the market price. ITT returns the intention-to-treatment effect and $LATE$ the local average treatment effect of the application period by auction procedure. The control variables include the centered reserve price which is the running variable, the auction procedure and the interaction of both variables. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price $\in$]200,000;249,000[or]251,000;300,000[(]2,400,000;2,988,000[or]3,012,000;3,600,000[) RUB. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A4.11: Fully interacted, model 4

	(1)	(2)	(3)
	n	nbid	p
ITT	0.0588**	0.0487*	-0.0104***
	(0.0258)	(0.0290)	(0.00261)
ITT*e-auction	0.0126	-0.0501	0.0104
	(0.131)	(0.0792)	(0.00924)
Observations	8,676	8,676	8,676
LATE	0.0735**	0.0637*	-0.0112***
	(0.0305)	(0.0342)	(0.00317)
LATE*auction	0.0654	-0.0586	0.0148
	(0.155)	(0.0909)	(0.0103)
Observations	8,040	8,040	8,040

Notes: The dependent variable n is the number of applying suppliers, $nbid$ the number of bidding suppliers and p the contract price per liter divided by the market price. ITT returns the intention-to-treatment effect and $LATE$ the local average treatment effect of the application period by auction procedure. The control variables include the centered reserve price which is the running variable, the auction procedure and the interaction of both variables. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price $\in$]200,000;249,000[or]251,000;300,000[(]2,400,000;2,988,000[or]3,012,000;3,600,000[) RUB which are not outsourced. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A4.12: Specification, model 1

	Sealed bid auctions			E-auctions		
	(1)	(2)	(3)	(4)	(5)	(6)
	n	nbid	p	n	nbid	p
ITT, p=2	0.0894***	0.0963***	-0.00676***	0.293**	0.103	0.00894
	(0.0230)	(0.0237)	(0.00200)	(0.130)	(0.0659)	(0.00796)
ITT, spline	0.0909***	0.0920***	-0.00707***	0.334**	0.104	0.00161
	(0.0246)	(0.0251)	(0.00211)	(0.147)	(0.0724)	(0.00896)
Observations	11,553	11,553	11,553	2,900	2,900	2,900
LATE, p=2	0.106***	0.123***	-0.00755***	0.172	0.00296	0.0224**
	(0.0267)	(0.0272)	(0.00232)	(0.149)	(0.0705)	(0.00940)
LATE, spline	0.107***	0.0915***	-0.00755***	0.217	0.0166	0.0101
	(0.0284)	(0.0283)	(0.00239)	(0.172)	(0.0764)	(0.0107)
Observations	10,912	10,912	10,912	2,525	2,525	2,525

Notes: The dependent variable n is the number of applying suppliers, $nbid$ the number of bidding suppliers and p the contract price per liter divided by the market price. ITT returns the intention-to-treatment effect and $LATE$ the local average treatment effect of the application period for sealed bid auctions in columns 1-3 and e-auctions in columns 4-6. The centered reserve price which is the running variable is controlled for. The order of polynomial in the first model is two and the second model includes the interaction with the running variable. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price $\in$]200,000;300,000[(]2,400,000;3,600,000[) RUB. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A4.13: Specification, model 2

	Sealed bid auctions			E-auctions		
	(1)	(2)	(3)	(4)	(5)	(6)
	n	nbid	p	n	nbid	p
ITT, p=2	0.0739***	0.0814***	-0.00921***	-0.0473	-0.0426	0.0217**
	(0.0237)	(0.0266)	(0.00233)	(0.142)	(0.0757)	(0.0103)
ITT, spline	0.0790***	0.0818***	-0.0100***	0.0352	-0.0134	0.0138
	(0.0255)	(0.0286)	(0.00249)	(0.166)	(0.0825)	(0.0120)
Observations	8,982	8,982	8,982	1,810	1,810	1,810
LATE, p=2	0.0886***	0.101***	-0.00910***	-0.00113	-0.0505	0.0254**
	(0.0274)	(0.0306)	(0.00274)	(0.186)	(0.0900)	(0.0121)
LATE, spline	0.0977***	0.0875***	-0.00930***	0.154	0.0101	0.0104
	(0.0293)	(0.0326)	(0.00293)	(0.221)	(0.0971)	(0.0143)
Observations	8,454	8,454	8,454	1,613	1,613	1,613

Notes: The dependent variable n is the number of applying suppliers, $nbid$ the number of bidding suppliers and p the contract price per liter divided by the market price. ITT returns the intention-to-treatment effect and $LATE$ the local average treatment effect of the application period for sealed bid auctions in columns 1-3 and e-auctions in columns 4-6. The centered reserve price which is the running variable is controlled for. The order of polynomial in the first model is two and the second model includes the interaction with the running variable. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price $\in$]200,000;300,000[(]2,400,000;3,600,000[) RUB which are not outsourced. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A4.14: Specification, model 3

	Sealed bid auctions			E-auctions		
	(1)	(2)	(3)	(4)	(5)	(6)
	n	nbid	p	n	nbid	p
ITT, p=2	0.0791***	0.0688**	-0.00812***	0.338**	0.101	-0.00129
	(0.0265)	(0.0273)	(0.00234)	(0.160)	(0.0808)	(0.00930)
ITT, spline	0.0798***	0.0674**	-0.00803***	0.386**	0.111	-0.00510
	(0.0271)	(0.0278)	(0.00237)	(0.169)	(0.0830)	(0.00976)
Observations	9,720	9,720	9,720	2,109	2,109	2,109
LATE, p=2	0.0993***	0.0944***	-0.00992***	0.186	-0.00386	0.0101
	(0.0315)	(0.0322)	(0.00280)	(0.181)	(0.0859)	(0.0105)
LATE, spline	0.101***	0.0681**	-0.00784***	0.251	0.0424	0.00479
	(0.0297)	(0.0297)	(0.00250)	(0.192)	(0.0841)	(0.0107)
Observations	9,173	9,173	9,173	1,747	1,747	1,747

Notes: The dependent variable n is the number of applying suppliers, $nbid$ the number of bidding suppliers and p the contract price per liter divided by the market price. ITT returns the intention-to-treatment effect and $LATE$ the local average treatment effect of the application period for sealed bid auctions in columns 1-3 and e-auctions in columns 4-6. The centered reserve price which is the running variable is controlled for. The order of polynomial in the first model is two and the second model includes the interaction with the running variable. The sample is restricted to sealed bid auctions (e-auctions) with reserve price a $\in$]200,000;249,000[or]251,000;300,000[(]2,400,000;2,988,000[or]3,012,000;3,600,000[) RUB. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A4.15: Specification, model 4

	Sealed bid auctions			E-auctions		
	(1)	(2)	(3)	(4)	(5)	(6)
	n	nbid	p	n	nbid	p
ITT, p=2	0.0678**	0.0533*	-0.0109***	0.00863	-0.0159	0.00839
	(0.0270)	(0.0306)	(0.00273)	(0.175)	(0.0925)	(0.0112)
ITT, spline	0.0683**	0.0530*	-0.0110***	0.0715	0.0103	0.00392
	(0.0275)	(0.0312)	(0.00278)	(0.188)	(0.0933)	(0.0118)
Observations	7,411	7,411	7,411	1,265	1,265	1,265
LATE, p=2	0.0868***	0.0710**	-0.0119***	0.0815	-0.0197	0.00936
	(0.0321)	(0.0362)	(0.00332)	(0.233)	(0.112)	(0.0128)
LATE, spline	0.0852***	0.0563*	-0.00927***	0.188	0.0430	0.00160
	(0.0297)	(0.0338)	(0.00305)	(0.255)	(0.109)	(0.0131)
Observations	6,969	6,969	6,969	1,071	1,071	1,071

Notes: The dependent variable n is the number of applying suppliers, $nbid$ the number of bidding suppliers and p the contract price per liter divided by the market price. ITT returns the intention-to-treatment effect and $LATE$ the local average treatment effect of the application period for sealed bid auctions in columns 1-3 and e-auctions in columns 4-6. The centered reserve price which is the running variable is controlled for. The order of polynomial in the first model is two and the second model includes the interaction with the running variable. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price $\in$]200,000;249,000[or]251,000;300,000[(]2,400,000;2,988,000[or]3,012,000;3,600,000[) RUB which are not outsourced. Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table A4.16: Other robustness checks, model 1

	Sealed bid auctions			E-auctions		
	(1)	(2)	(3)	(4)	(5)	(6)
	n	nbid	p	n	nbid	p
ITT, controls	0.0551***	0.0650***	-0.00102	0.160*	0.00594	0.00186
	(0.0194)	(0.0206)	(0.00131)	(0.0863)	(0.0467)	(0.00482)
Observations	11,428	11,428	11,428	2,857	2,857	2,857
ITT, se region	0.0761***	0.0970***	-0.00596**	0.204	0.0460	0.00906
	(0.0202)	(0.0221)	(0.00235)	(0.245)	(0.0818)	(0.00670)
Observations	11,553	11,553	11,553	2,900	2,900	2,900
ITT, overpricing	0.0837***	0.101***	-0.00690**	-0.0180	0.0190	0.0132
	(0.0292)	(0.0336)	(0.00275)	(0.128)	(0.0850)	(0.00867)
Observations	4,483	4,483	4,483	913	913	913
ITT, December	0.101***	0.118***	-0.00699***	0.138	-0.00405	0.0176***
	(0.0225)	(0.0237)	(0.00199)	(0.107)	(0.0565)	(0.00671)
Observations	9,602	9,602	9,602	2,234	2,234	2,234
LATE, controls	0.0627***	0.0814***	-0.000962	0.122	-0.0324	0.00600
	(0.0223)	(0.0235)	(0.00151)	(0.0948)	(0.0495)	(0.00494)
Observations	10,795	10,795	10,795	2,495	2,495	2,495
LATE, se region	0.0870***	0.119***	-0.00624**	0.141	-0.0207	0.0195**
	(0.0237)	(0.0249)	(0.00261)	(0.205)	(0.0709)	(0.00773)
Observations	10,912	10,912	10,912	2,525	2,525	2,525
LATE, overpricing	0.0904***	0.122***	-0.00555*	0.0385	0.0504	0.0143
	(0.0329)	(0.0378)	(0.00320)	(0.151)	(0.0995)	(0.00950)
Observations	4,236	4,236	4,236	817	817	817
LATE, December	0.115***	0.146***	-0.00775***	0.120	-0.0323	0.0214***
	(0.0260)	(0.0271)	(0.00230)	(0.119)	(0.0605)	(0.00751)
Observations	9,070	9,070	9,070	2,059	2,059	2,059

Notes: The dependent variable n is the number of applying suppliers, $nbid$ the number of bidding suppliers and p the contract price per liter divided by the market price. ITT returns the intention-to-treatment effect and $LATE$ the local average treatment effect of the application period for sealed bid auctions in columns 1-3 and e-auctions in columns 4-6. The centered reserve price which is the running variable is controlled for. The reserve price per liter, region, year and month fixed effects are included in the first model. The standard errors are clustered at region level in the second specification. Third, inflated reserve prices are dropped and fourth December is left out. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price $\in$]200,000;300,000[(]2,400,000;3,600,000[) RUB. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A4.17: Other robustness checks, model 2

	Sealed bid auctions			E-auctions		
	(1)	(2)	(3)	(4)	(5)	(6)
	n	nbid	p	n	nbid	p
ITT, controls	0.0477**	0.0497**	-0.00284*	0.0232	-0.0495	0.00544
	(0.0202)	(0.0228)	(0.00149)	(0.101)	(0.0561)	(0.00567)
Observations	8,876	8,876	8,876	1,786	1,786	1,786
ITT, se region	0.0579***	0.0735***	-0.00812***	0.00955	-0.0245	0.0122
	(0.0212)	(0.0234)	(0.00295)	(0.173)	(0.0786)	(0.00788)
Observations	8,982	8,982	8,982	1,810	1,810	1,810
ITT, overpricing	0.0837***	0.101***	-0.00690**	-0.0180	0.0190	0.0132
	(0.0292)	(0.0336)	(0.00275)	(0.128)	(0.0850)	(0.00867)
Observations	4,483	4,483	4,483	913	913	913
ITT, December	0.0811***	0.0948***	-0.00885***	-0.0745	-0.0940	0.0251***
	(0.0234)	(0.0262)	(0.00225)	(0.122)	(0.0675)	(0.00869)
Observations	7,505	7,505	7,505	1,379	1,379	1,379
LATE, controls	0.0551**	0.0616**	-0.00241	0.0889	-0.0367	0.00349
	(0.0232)	(0.0260)	(0.00171)	(0.118)	(0.0613)	(0.00615)
Observations	8,355	8,355	8,355	1,596	1,596	1,596
LATE, se region	0.0666***	0.0887***	-0.00762**	0.0565	-0.0207	0.0173*
	(0.0240)	(0.0252)	(0.00339)	(0.198)	(0.0939)	(0.00892)
Observations	8,454	8,454	8,454	1,613	1,613	1,613
LATE, overpricing	0.0904***	0.122***	-0.00555*	0.0385	0.0504	0.0143
	(0.0329)	(0.0378)	(0.00320)	(0.151)	(0.0995)	(0.00950)
Observations	4,236	4,236	4,236	817	817	817
LATE, December	0.0913***	0.115***	-0.00886***	-0.0377	-0.0703	0.0260***
	(0.0269)	(0.0299)	(0.00263)	(0.140)	(0.0763)	(0.00960)
Observations	7,071	7,071	7,071	1,291	1,291	1,291

Notes: The dependent variable n is the number of applying suppliers, $nbid$ the number of bidding suppliers and p the contract price per liter divided by the market price. ITT returns the intention-to-treatment effect and $LATE$ the local average treatment effect of the application period for sealed bid auctions in columns 1-3 and e-auctions in columns 4-6. The centered reserve price which is the running variable is controlled for. The reserve price per liter, region, year and month fixed effects are included in the first model. The standard errors are clustered at region level in the second specification. Third, inflated reserve prices are dropped and fourth December is left out. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price $\in]200,000;300,000[$ ($]2,400,000;3,600,000[$) RUB which are not outsourced. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A4.18: Other robustness checks, model 3

	Sealed bid auctions			E-auctions		
	(1)	(2)	(3)	(4)	(5)	(6)
	n	nbid	p	n	nbid	p
ITT, controls	0.0619***	0.0563**	-0.00194	0.172	-0.00737	-0.00106
	(0.0240)	(0.0251)	(0.00162)	(0.105)	(0.0586)	(0.00585)
Observations	9,606	9,606	9,606	2,078	2,078	2,078
ITT, se region	0.0691***	0.0683**	-0.00777***	0.221	0.0305	-0.000533
	(0.0241)	(0.0259)	(0.00268)	(0.271)	(0.0945)	(0.00691)
Observations	9,720	9,720	9,720	2,109	2,109	2,109
ITT, overpricing	0.0589	0.0572	-0.00702**	-0.00972	-0.0304	0.000781
	(0.0363)	(0.0418)	(0.00342)	(0.159)	(0.111)	(0.0110)
Observations	3,704	3,704	3,704	638	638	638
ITT, December	0.0884***	0.0843***	-0.00810***	0.199	0.0190	0.00555
	(0.0282)	(0.0293)	(0.00250)	(0.135)	(0.0720)	(0.00828)
Observations	8,087	8,087	8,087	1,626	1,626	1,626
LATE, controls	0.0750***	0.0738**	-0.00196	0.111	-0.0464	0.00273
	(0.0285)	(0.0295)	(0.00194)	(0.114)	(0.0617)	(0.00587)
Observations	9,065	9,065	9,065	1,728	1,728	1,728
LATE, se region	0.0848***	0.0910***	-0.00920***	0.142	-0.0359	0.00886
	(0.0308)	(0.0312)	(0.00309)	(0.218)	(0.0788)	(0.00812)
Observations	9,173	9,173	9,173	1,747	1,747	1,747
LATE, overpricing	0.0728*	0.0815*	-0.00677	0.0565	0.00975	0.00166
	(0.0421)	(0.0486)	(0.00415)	(0.186)	(0.127)	(0.0119)
Observations	3,503	3,503	3,503	542	542	542
LATE, December	0.105***	0.112***	-0.00995***	0.174	-0.00956	0.00850
	(0.0338)	(0.0348)	(0.00301)	(0.146)	(0.0750)	(0.00892)
Observations	7,632	7,632	7,632	1,460	1,460	1,460

Notes: The dependent variable n is the number of applying suppliers, $nbid$ the number of bidding suppliers and p the contract price per liter divided by the market price. ITT returns the intention-to-treatment effect and $LATE$ the local average treatment effect of the application period for sealed bid auctions in columns 1-3 and e-auctions in columns 4-6. The centered reserve price which is the running variable is controlled for. The reserve price per liter, region, year and month fixed effects are included in the first model. The standard errors are clustered at region level in the second specification. Third, inflated reserve prices are dropped and fourth December is left out. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price ∈]200,000;249,000[or]251,000;300,000[(]2,400,000;2,988,000[or]3,012,000;3,600,000[) RUB. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A4.19: Other robustness checks, model 4

	Sealed bid auctions			E-auctions		
	(1)	(2)	(3)	(4)	(5)	(6)
	n	nbid	p	n	nbid	p
ITT, controls	0.0598**	0.0454	-0.00400**	0.0654	-0.0310	-0.00172
	(0.0247)	(0.0279)	(0.00185)	(0.127)	(0.0717)	(0.00670)
Observations	7,314	7,314	7,314	1,248	1,248	1,248
ITT, se region	0.0588**	0.0487	-0.0104***	0.0714	-0.00142	-8.14e-05
	(0.0247)	(0.0311)	(0.00289)	(0.196)	(0.0943)	(0.00870)
Observations	7,411	7,411	7,411	1,265	1,265	1,265
ITT, overpricing	0.0589	0.0572	-0.00702**	-0.00972	-0.0304	0.000781
	(0.0363)	(0.0418)	(0.00342)	(0.159)	(0.111)	(0.0110)
Observations	3,704	3,704	3,704	638	638	638
ITT, December	0.0740**	0.0632*	-0.0101***	0.0270	-0.0340	0.0103
	(0.0290)	(0.0325)	(0.00286)	(0.160)	(0.0877)	(0.0104)
Observations	6,195	6,195	6,195	976	976	976
LATE, controls	0.0733**	0.0580*	-0.00357	0.145	-0.0112	-0.00572
	(0.0294)	(0.0331)	(0.00223)	(0.144)	(0.0771)	(0.00704)
Observations	6,877	6,877	6,877	1,061	1,061	1,061
LATE, se region	0.0735**	0.0637*	-0.0112***	0.139	0.00509	0.00357
	(0.0300)	(0.0364)	(0.00337)	(0.214)	(0.105)	(0.00908)
Observations	6,969	6,969	6,969	1,071	1,071	1,071
LATE, overpricing	0.0728*	0.0815*	-0.00677	0.0565	0.00975	0.00166
	(0.0421)	(0.0486)	(0.00415)	(0.186)	(0.127)	(0.0119)
Observations	3,503	3,503	3,503	542	542	542
LATE, December	0.0854**	0.0792**	-0.0112***	0.0969	-0.00289	0.00956
	(0.0347)	(0.0387)	(0.00350)	(0.180)	(0.0974)	(0.0112)
Observations	5,831	5,831	5,831	889	889	889

Notes: The dependent variable n is the number of applying suppliers, $nbid$ the number of bidding suppliers and p the contract price per liter divided by the market price. ITT returns the intention-to-treatment effect and $LATE$ the local average treatment effect of the application period for sealed bid auctions in columns 1-3 and e-auctions in columns 4-6. The centered reserve price which is the running variable is controlled for. The reserve price per liter, region, year and month fixed effects are included in the first model. The standard errors are clustered at region level in the second specification. Third, inflated reserve prices are dropped and fourth December is left out. The sample is restricted to sealed bid auctions (e-auctions) with a reserve price $\in$]200,000;249,000[or]251,000;300,000[(]2,400,000;2,988,000[or]3,012,000;3,600,000[) RUB which are not outsourced. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1