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Collusion in Public Procurement Auctions: Evidence from Russia

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Abstract

This paper documents collusion between firms using micro-level data on 4.4 million first-price sealed-bid procurement auctions conducted in Russia in $2011-2017$. The data contains unique information on the timestamps of all bids and the bidding data itself. This study is one of the first to use bid timing to design a method for detecting collusion between firms based on a simultaneous bidding pattern: bidders place bids simultaneously or within a small time interval. The method performs well and identifies at least $7-25\%$ of winner — runner-up bid pairs as collusive in validation subsamples: the pharmaceutical industry, known for its propensity to collusion in Russia, and three cartels formed by pharmaceutical firms. In the main data, the share of collusive winner — runner-up bid pairs varies between 8% and 23%. For a more general case that considers the pairs of each bidder with four other auction participants closest in the rank price, the share of collusive bid pairs is around 13%. In both cases, the share of collusive bid pairs is the highest in two-bidder auctions and gradually declines as the number of bidders increases. Collusive firms tend to place bids simultaneously more frequently when a few bidders participate in auctions, because of higher chances of manipulating auction outcomes. I also document that higher contract prices and smaller differences between winner and runner-up bids characterize bid pairs submitted simultaneously. Controlling for industry, public body, and region fixed effects, collusion increases final contract prices by 10.9% on average and makes simultaneous bids up to 50% closer to each other. Collusion affected contract prices totaling 1.49 billion U.S. dollars over 6.5 years. If I interpret these estimates as causal, eliminating collusion would have saved around 162 million U.S. dollars.

Key words: Collusion, Simultaneous Bidding, Procurement Auctions, Russia

Abstrakt

Tato práce se zabývá analýzou koluzí mezi společnostmi na základě údajů o 4,4 milionu tajných dražeb s první cenou v sektoru veřejných zakázek v Rusku v letech 2011-2017. V datech jsou kromě informací o samotných aukcích obsaženy unikátní údaje o času podání jednotlivých nabídek účastníků. Tato studie je jednou z prvních, která využívá data o času podání nabídek k vývoji metody identifikace koluzí mezi firmami na základě souběžného podání žádostí: účastníci podávají žádosti současně nebo v krátkém časovém intervalu. Metoda je testována na ověřovacích vzorcích, kterými jsou farmaceutický průmysl, známý svým sklonem ke koluzím v Rusku, a tři kartely tvořené farmaceutickými společnostmi. Metoda se osvědčuje a odhaluje tajné dohody mezi vítězem a uchazečem s nejnižší další nabídkou nejméně v $7-25\%$ takových dvojic. V datech se všemi aukcemi se podíl párů, mezi jejichž účastníky existuje koluze, pohybuje mezi 8 a 23%. V obecnějším případě, pokud analyzujeme páry každého uchazeče s dalšími čtyřmi uchazeči, kteří jsou si cenově nejblíže, činí podíl dvojic v tajné dohodě přibližně 13%. V obou případech je podíl párů s koluzí nejvyšší v aukcích se dvěma účastníky a postupně klesá s rostoucím počtem účastníků. Když je počet účastníků aukce malý, společnosti, mezi nimiž existují nekalé praktiky, častěji podávají nabídky současně, protože mají větší šanci manipulovat s výsledky aukce. V rámci této práce se také pozorujeme vyšší ceny zakázek a menší rozdíl mezi nabídkami vítěze a účastníka s nejnižší další sázkou v těch párech žádosti, které jsou podány současně. Vzhledem k heterogenitě aukcí napříč odvětvími, regiony a státními orgány, který aukci pořádají, koluze zvyšuje konečnou cenu zakázky v průměru o $10,9\%$ a sbližuje souběžné nabídky až o 50%. Koluze ovlivnila ceny zakázek v celkové výši 1,49 miliardy amerických dolarů za 6,5 roku. Pokud tyto odhady interpretuji jako kauzální, odstranění koluze by ušetřilo přibližně 162 milionů amerických dolarů.

Klíčová slova: Koluze, Souběžné Podávání Nabídek, Aukce Veřejných Zakázek, Ruská federace

Declaration of Authorship

I hereby proclaim that I wrote my master thesis on my own under the leadership of my supervisor and that the references include all resources and literature I have used.

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Prague, Czech Republic

Signature

August 31, 2023

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Master's Thesis Proposal

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Research question and motivation
Governments worldwide devote considerable resources to different areas, including auctions, in order to detect any behavior limiting competition. Depending on the type of auction and the probability of being revealed, bidders can coordinate and make different coalitions to win a contract at a higher price. Therefore, multiple collusion detection methods should be applied to an auction to detect such behavior and prevent it later. The aim of my thesis is to analyze a data set on Russian procurement auctions and detect collusion in first-price sealed-bid public procurement auctions based on simultaneous bids, i.e., bids sealed next to each other within approximately 30-minutes intervals. The existing literature on collusion detection in auctions has not employed the timing of bids as an indicator of collusion between firms because of the lack of suitable micro-level data.

Contribution
This study aims to contribute to the literature on detecting the strategic behavior of bidders based on the timing of bids. Previous empirical papers (Bajari and Hortaçsu, 2003; Saeedi and Hopenhayn, 2015) employ timing to detect colluding behavior in online second-price open-bid auctions — eBay and Amazon auctions. In contrast, my study will analyze micro-level data on first-price sealed-bid public procurement auctions in a less developed country. Novel data on 4.4 million procurement auctions in Russia collected from the Russian government procurement server contains unique information on the timestamps of all bids, which allows the development of a new method of collusion detection based on simultaneous bids. Furthermore, this method would expose colluding firms and estimate the damage they have caused.

Methodology
In this study, I will assume that the joint distribution of hours and minutes of bidding should be the same on different days, and will test for the equality of the distributions of hours for the pair of bids sealed on different days to detect collusion. Furthermore, I will

estimate the share of auctions affected by collusion in simultaneous bids by running a linear regression of the difference in the time of placing bids within a 30-minute interval on the placement of bids in one day. In addition, I will use a linear regression model with an outcome of an auction as a left-side variable, and the placement of bids in one day, the placement of bids within 30 minutes, and their cross-product as right-side variables to estimate the increase in prices due to simultaneous bidding.

Outline

1. Introduction
2. Literature review
3. Data description
4. Methods for collusion detection
5. Regression analysis
6. Discussion
7. Conclusion

List of academic literature:

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Introduction

Competition is highly encouraged in all areas of economic activities because it leads to the efficient allocation of resources, continuous improvement of goods and services quality, and maintaining fair prices. However, some firms still attempt to restrict competition in various ways to gain advantages over their competitors. Governments worldwide dedicate substantial resources to detecting collusive behavior and developing regulations to prevent it. For instance, in the European Union, one of the main anti-monopoly laws is the Treaty on the Functioning of the European Union — Article 101 (2008), while in the U.S., it is the United States Congress Sherman Anti-Trust Act (1890). In the Russian context, the primary law protecting competition is Federal Law of Russia 135-FZ (2006). These laws prohibit coordinated actions between parties that restrict competition and strengthening of dominant market positions to prevent inefficient allocation of goods and services.

Auctions are one of the areas where collusive behavior is frequently detected by Anti-Monopoly Services in different countries. Many forms of collusive behavior were investigated by the literature, including bidding rings (Whinston et al., 2008; Marshall and Marx, 2014), price fixing (Block et al., 1981; Connor, 2001), bid-rigging (Porter and Zona, 1993; Kawai et al., 2023) and other more specific forms. The literature suggests various methods for detecting collusion in auctions adapted to auction formats and available prior information.

In the absence of bid timing data, the literature detects colluding firms or collusive auctions by testing the consistency of firms behavior with the competitive model assumptions (Bajari and Ye, 2003; Chassang et al., 2019), identifying structural breaks in the behavior of firms (Abrantes-Metz et al., 2006), testing differences in the behavior of suspected colluding firms and competitive benchmarks (Porter and Zona, 1993, 1997; Ishii, 2009; Asker, 2010; Conley and Decarolis, 2016), or estimating structural competitive and collusive models of prices or bids using cost or demand shifters and testing the data fit of models (Baldwin et al., 1997; Pesendorfer, 2000).

Traditional antitrust literature primarily analyzes developed countries (Porter, 2005), whereas this study designs a new method for detecting collusion in first-price sealed-bid auctions using an extended micro-level data set from Andreyanov et al. (2017) on Russian procurement auctions held in $2011-2017$. The data contain unique information on the timing of bids that allows documenting that many bids were submitted simultaneously or within a small time interval. I call this pattern *simultaneous bidding* and use it to detect and measure collusion.

I suppose that simultaneous bidding arises from direct monitoring of each other actions by colluding firms to ensure the implementation of the agreement. For example, two bidders can place their applications from the same email or laptop on the auction platform or submit the envelopes with their bids together. However, the time convenience during the day may also lead to simultaneous bidding. To control this issue, I normalize the probability of bidding within a small time interval on the same day and show that it is still considerably higher than the probability of bidding within a simultaneous bidding interval but on different days.

This study builds the method using assumptions on the distribution of hours for pairs of bids submitted within the same day and on different days. The method uses the difference in the probabilities of placing a pair of bids within a simultaneous bidding interval for the same and different days and shows that if the difference is zero, then the analyzed auctions are competitive. This method also produces the estimate for the share of collusive bid pairs in the data. To assess the performance of the method, I firstly apply it to four validation subsamples: the pharmaceutical industry and three cartels in it, similar to Conley and Decarolis (2016) and Kawai and Nakabayashi (2022). I form cartel subsamples from auctions in which at least two participating firms are under investigation for violations of anti-monopoly laws.

The method performs well and identifies that 7–38% of winner — runner-up pairs are collusive in three validation subsamples: the pharmaceutical industry and Cartel I and II, where the number of potential colluding firms is large. In Cartel III data, the estimates of collusion are higher — 17–53%, because the cartel contains only four relatively similar firms that mostly participate in two-bidder auctions. The estimates of the share of collusive pairs are highest in two-bidder auctions and decrease with the number of bidders.

In the main data, the method detects collusive patterns in around 28% of two-bidder auctions. The share of collusive winner — runner-up bid pairs in K-bidder auctions is lower than in two-bidder auctions — the share varies between 8% and 23%. For winner — runner-up and third-best bidder pairs, the method produces similar results: $9-26\%$ collusive pairs in K-bidder auctions. In a more general case that considers the pairs of each bidder with four other auction participants closest in the rank price, the share of collusive bid pairs submitted within a 30-minute interval is around 13%.

The relationship between the share of collusive pairs and the number of bidders in auctions is negative, which is consistent with Ivaldi et al. (2003) and Klemperer (2003). For closest-in-price-rank bid pairs in K-bidder auctions with increasing K, the downward trend is smooth until the number of bidders is too large. I assume that collusive firms tend to place bids simultaneously more frequently when a few bidders participate in auctions, because of higher chances of manipulating auction outcomes.

In the next step, this study develops a method that quantifies the impact of collusion in the form of simultaneous bidding on final contract prices, winning bids, and bid differences, the difference between runner-up and winner bids. Collusion decreases bid differences by up to 50%. The negative impact of collusion varies considerably from 14.3% to 56.3% in the largest 24 industries. The pharmaceutical industry has the highest negative effects of collusion on bid differences — 51.4%. Controlling for a public body, region, and industry fixed effects, the decline in bid differences lowers to 25.2% in all auction data.

The impact of collusion on prices is less severe than on winner —runner-up bid differences. However, collusion still increases prices by 10.1% in K-bidder auctions. When I include fixed effects, the estimate slightly increases to 10.9%. If I interpret this estimate as causal, eliminating collusive patterns in procurement auctions would have saved around 0.16 billion U.S. dollars over 6.5 years, considering that the total amount of affected contracts was 1.49 billion U.S. dollars. However, the amount that could have been saved may be lower, because of other factors affecting the auction outcomes that are out of the scope of this study.

To the best of my knowledge, this study is one of the first that uses timestamps of bids to detect collusion between firms. This paper contributes to the literature that develops methods for detecting collusion in auctions at an aggregated level without identification of colluding firms (Kawai and Nakabayashi, 2022; Conley and Decarolis, 2016; Haile et al., 2012; Ishii, 2009; Bajari and Ye, 2003; Porter and Zona, 1997). Furthermore, this study contributes to the scarce literature that analyses bidding behavior based on the time of bidding (Saeedi and Hopenhayn, 2015; Ockenfels and Roth, 2006; Bajari and Hortaçsu, 2003; Ockenfels and Roth, 2002). However, these papers only describe the patterns of strategic bidding in eBay or Amazon online auctions, such as incremental bidding and sniping, that are not directly linked to collusion between firms.

The rest of the paper is organized as follows. Section 1 introduces the theory of collusion and methods for its detection. Section 2 describes the Russian procurement market regulations and explains the simultaneous bidding pattern that I use to detect collusion. Section 3 describes the main auction data set, explains the formation of validation subsamples, and illustrates simultaneous bidding patterns in the data. Section 4 develops a method for detecting collusion, proposes an estimation approach based on OLS, and assesses the performance of the method on validation subsamples and all auction data. Section 5 quantifies the impact of collusive patterns on prices and the difference between winner and runner-up bids. Section 6 discusses the results and proposes future extensions.

1. Theory of Collusion and Methods for Detecting Collusion

1.1 Mechanisms of Collusion

A group of companies known as a cartel may agree to collude to limit market competition. If all cartel members follow an agreement, they may generate higher profits than competitive firms by overpricing their products and services. Cartels may be formed in different areas, including procurement auctions. State and Federal authorities strictly prohibit such agreements between firms to protect consumers from collusive behavior, support a competitive market environment, and prevent the socially undesirable distribution of resources.

Collusion is highly driven by reciprocity – in exchange for a favor, agent A offers a side transfer to benefit agent B. In practice, side transfer diversity may be relatively high: from money bribes to favors and friendly relationships. Tirole (1993) describes several mechanisms for enforcing such side contracts with different side transfers. Cartels are prohibited in most countries; therefore, side contract enforcement relies on non-judicial mechanisms such as revenge, "word of honor," and reputation. Following the revenge enforcement mechanism, agent A commits to the agreement to avoid agent B's revenge for a breach of the agreement. The "word of honor" mechanism presumes that a colluding agent abides by his commitment in explicit and implicit agreements. In contrast, "word of honor" and revenge mechanisms perform in a one-shot exchange of favors. The reputation mechanism operates in short- and long-term relationships. Agents use the reputation mechanism if agent A does a favor to agent B because he expects reciprocation in the future.

The two parties of an agreement evaluate the optimal size of side transfer differently. For a briber, the transfer cost is usually higher than the value of it for the recipient. Therefore, the side transfer may cause deadweight loss (Tirole, 1993). Corruption may be even more distortionary and costly than taxation due to the imperative of bribes secrecy in some less developed countries (Shleifer and Vishny, 1993). Gould and Amaro-Reyes (1983), Klitgaard (1991), and Harrington (2005) also underline the effect of collusion on the stability of market shares and prices and the relationships between a firm's prices and the movements of demand, among other factors that may lead to a detrimental impact of corruption on an economy.

A crucial determinant of corruption in government-related areas, including procurement auctions, is the structure of government institutions and political processes (Shleifer and Vishny, 1993). Weak governments that poorly control their agencies may experience high corruption because such an environment reduces the probability of detecting collusion. The problem of weak governments is mostly relevant to developing countries. For instance, corruption is persuasive in post-Communist Russia and North Korea today, where paying a bribe assures a person or a company that they may obtain a desired government good. However, in these countries, bribing does not guarantee a requested government permit due to the multi-level bureaucratic system.

Overall, collusion in all areas, collusion causes an inefficient allocation of goods and contracts. That is why detecting collusion and monitoring areas prone to forming cartels are essential to maintaining a competitive environment for all market agents. In the following sections, I discuss various approaches to detecting collusion in different settings under data availability, prior information on collusion, and other factors.

1.2 Collusion Types: Explicit and Tacit

Collusion may be of two types — explicit and tacit. Explicit collusion involves secret coordinated agreements between firms and sharing private information to avoid price wars. In contrast, tacit or implicit collusion implies no direct communication between firms and forming agreements between firms. Tacit collusion may also involve price wars on the equilibrium path (Garrod and Olczak, 2018). In tacit collusion, firms may coordinate by responding to the behavior of each other in a market, considering that firms have a shared understanding of their actions and the outcome of the market.

Explicit collusion is illegal and implies the risk of different sanctions. Tacit collusion, as opposed to an explicit one, is not explicitly prohibited by competition laws because there is no direct evidence of communication and coordination between firms. Andres et al. (2023) demonstrates that firms are more likely to collude implicitly using indirect messages in the presence of sanctioning institutions. The authors also show that indirect communication may be misleading and affect prices negatively. Andres et al. (2023)'s results contradict the findings of Fonseca and Normann (2012) who show that explicit communication positively affects profits for Bertrand oligopolies. However, the benefit of communicating is not monotonic in the number of firms.

Garrod and Olczak (2018) also demonstrates that the probability of forming an explicit agreement is lower in markets with a few symmetric firms because tacit collusion is relatively more attractive. Moreover, tacit collusion is relatively successful after disabling explicit communication, especially for medium-sized markets (Fonseca and Normann, 2012). Ivaldi et al. (2003) suggest that explicit agreements between many competitors may be harder to maintain. When such agreements imply sharing the collusive profit, each firm obtains a smaller share of the profit, and the share declines with the increase in the number of firms. Therefore, explicit collusion is less likely to arise in markets with many firms. Posner (1970), on the contrary, claims that larger cartels are more likely to survive longer than cartels with fewer members.

1.3 Approaches to Detecting Collusion Without Knowledge of the Timing of Bids

This section discusses possible methods for detecting collusion, depending on the availability of information on firms suspected of colluding, and models applied to auctions based on data with and without time stamps on bids. The section is organized as follows. I first define possible groupings of methods for detecting collusion. Then I introduce four approaches to detecting collusion: testing the consistency of the behavior of firms with the competition, identifying structural breaks in the behavior of firms, testing differences in the behavior of firms suspected of colluding and some competitive benchmarks, and testing data fit of structural competitive and collusive models of prices or bids using cost or demand shifters. Furthermore, I discuss possible drawbacks of these approaches and implementation strategies, relying on the literature.

1.3.1 Groupings of Methods Without Knowledge of the Timing of Bids

The methods for detecting colluding firms may be partitioned into structural and behavioral. The structural approach aims to identify industries that may provide a conducive environment for collusion. The probability of cartel formation is higher in industries with a small number of firms, a high degree of product homogeneity, and stable demand (Motta 2004; Grout and Sonderegger 2005). Furthermore, low-advertising and low-R&D industries are more conducive to forming cartels, because the probability of being detected is lower (Symeonidis, 2003). In contrast, the behavioral approach includes methods for detecting channels and inspecting the final results of firms coordination (Harrington, 2005). In auctions, the collusive and competitive behavior of firms may depend on the cost structure of the firms (Bajari and Summers, 2002), the particular rules of an auction, and the nature of an object auctioned off (Hendricks and Porter 1989; Bajari and Summers 2002). These characteristics of firms and auctions tend to be considered in detecting collusion by the structural and behavioral approaches.

Empirical behavioral methods for detecting collusion are more specific to an industry and an auction structure than structural ones. Porter (2005) proposes several indicators for detecting collusion considering problems that colluding firms face. Firstly, colluding firms may be detected by antitrust authorities or the victims of such behavior. Secondly, new firm entry into the industry may expose non-inclusive cartels because new entrants serve as a benchmark for comparison with other firms suspected of colluding. Addressing this problem, Porter and Zona (1993) distinguished bids placed by competitive firms and non-winning cartel members in a first-price sealed-bid procurement auction conducted for highway construction contracts in the United States. Porter and Zona (1997) applied a similar strategy to detecting cartels in school milk auctions in the 1980s in the United States. The authors showed that the behavior of some Ohio dairies was inconsistent with competitive bidding behavior in auctions. The bids of three Cincinnati dairies follow a decreasing function of the distance between a school district and the nearest plant of these dairies. In contrast, the bidding function of other dairies assumed to be competitive demonstrates the opposite dependence. Porter and Zona (1997) designed a model based on this empirical evidence.

Thirdly, colluding firms may have to reconcile an agreement if their interests differ. Otherwise, a cartel may risk being detected or exposed by its members. The reasons that may lead to disparate interests may be diverse — disagreement with the historical division of vintages and different costs, pricing, and inter-temporal discount rates (Porter, 2005). Moreover, the payouts of colluding firms may be exposed to imperfectly correlated shocks. Cartel members may solve problems caused by disparate interests by side payments and non-overlapping assignment of market territories to members with guaranteed wide latitude within boundaries. The significant drawback of side payments is that they are illegal and unenforceable. In addition, making side payments under weak conspiracy may be nearly impossible. Pesendorfer (2000) showed that cartel members might successfully maintain relatively constant market shares under such conditions.

Finally, colluding firms need to respond to new circumstances, such as changes in costs and market demand, to maintain their agreement and avoid exposure. If firms can communicate, they can reach new agreements in response to market changes to continue price manipulations. The Sugar Institute in the United States, operating in the 1920s-1930s, is an example of the adjustment of cartel members' behavior due to market changes. The sugar-refining cartel holds weekly meetings to coordinate joint actions and ensure that the actions of cartel members are not interpreted as cheating by Anti-Monopoly Services (Genesove and Mullin, 2001).

The problems of cartels that Porter (2005) suggests addressing to detect collusion are mainly related to differences in the behavior of competitive firms and firms suspected of colluding. However, there are other methods for detecting cartels in auctions. I rely on the aggregated groups of detecting collusion methods suggested by Harrington (2005) and develop this classification for broader literature on auctions. I divide the literature into the following groups:

1. testing the consistency of the behavior of firms with the competition;
2. identifying structural breaks in the behavior of firms;
3. testing differences in the behavior of firms suspected of colluding and some competitive benchmarks;
4. estimating structural competitive and collusive models of prices or bids using cost

or demand shifters and testing the data fit of models.

Methods from the first and second groups are used predominantly as screening tools and demonstrate the inconsistency in the behavior of firms with competition. However, these methods do not provide evidence of collusion in auctions. In contrast, the methods of the third and fourth groups serve verification purposes. The major difference between the last two groups is the data used to create the competitive benchmark: data from firms suspected of colluding or competitive firms.

These methods may be applied to auctions that disclose information on participants and those that do not. I contribute to the literature that focus on detecting collusion in different types of auctions, in which colluding firms are not observed directly (Kawai and Nakabayashi, 2022; Conley and Decarolis, 2016; Athey et al., 2011; Ishii, 2009; Bajari and Ye, 2003; Porter and Zona, 1997). In the following sections, I review these four approaches to detecting collusion in auctions in more detail.

1.3.2 Consistency of the Behavior of Firms with Competitive Behavior Properties

The behavior of firms under competition should always satisfy some relevant properties for least a broad class of competitive models. This group of methods focuses on the consistency of the behavior of firms with competitive one. These methods identify the properties of competitive behavior and test their presence in an industry, market, or auction. This approach mainly involves testing the null hypothesis that an industry is competitive. However, rejecting this hypothesis may not imply the presence of colluding agents. Such a result only shows that agents behavior in an observed industry is inconsistent with the behavioral properties of firms specified in a class of competitive models. As a result, methods testing the consistency of firms behavior with competitive one should be used primarily as a preliminary diagnostic tool.

A falsely rejected null hypothesis might occur if the competitive model is misspecified due to omitted variables. Addressing this issue, Bajari and Ye (2003) considers that publicly observed independent variables may correlate between firms. This assumption requires all relevant variables that may cause correlation in the costs of firms to be included in the model. For instance, the costs of firms may be correlated if firms work with the same subcontractor. In this case, the bids of these firms would also be correlated. Thus, the assumption of the independence of the bids of firms is violated even though firms do not collude.

Misspecification of the model may also be a result of wrong assumptions (Harrington, 2005). For instance, Schurter (2017) proposes a strategy to identify colluding firms in first-price auctions based on the assumption that private valuations of bidders are independently distributed. Considering that failure of this assumption may lead to the misspecification of the model, the author applies a one-sided version of the Kolmogorov-Smirnov type statistic or Kendall's τ statistic (when the variation in competition is not binary) as a test of the valuations of bidders being independent of the competition to simulated auction data. These tests then control the probability of type I errors even when the preferences of bidders are misspecified.

Another assumption that some papers make is a symmetry assumption (Pesendorfer, 2000; Bajari and Ye, 2003; Kawai and Nakabayashi, 2022), which is relatively strong. Symmetry assumptions may be violated depending on the settings and auction types, Pesendorfer (2000) and Bajari and Ye (2003) developed tests aimed at detecting collusion in first-price auctions based on the costs of bidders that are asymmetric. The papers tested their approach on the data on school milk contracts and a first-price sealed bid procurement auction for contracts on pavement seal coating in the U.S., respectively. Schurter (2017) also makes an asymmetry assumption for bidders' valuation of contracts to detect collusion in first-price timber auctions in British Columbia.

Finally, methods that test the consistency of firms' behavior with a range of properties of competitive models. However, when firms obtain knowledge of detecting and monitoring methods used by authorities, they may adapt their behavior. Chassang et al. (2019, 2022) claims that even if it is the case, using tests is still beneficial because it may constrain the set of bids that firms can use to support collusion. The author also suggests that colluding firms may fail some tests even when firms know the tests anti-monopoly authorities use. Chassang et al. (2019) proposes a robust data-driven method based on tests that competitive bidders pass with probability one, while firms suspected of colluding tend to fail them. The method was developed and tested on data on national-level procurement auctions in Japan between 2001 and 2006.

1.3.3 Structural Breaks in Firms Behavior

Searching for a structural break in the behavior of firms is a second approach to detecting collusion. A break may indicate the creation of a cartel. However, it may also be a signal of the demise of a cartel. The ambiguity of the cause of a structural break suggests that this approach should be mainly applied as a screening tool, similar to testing the consistency of the behavior of firms with competition, followed by other verification methods. Another possible drawback that may hinder the implementation of these methods is that the approach requires long panel data on periods before and after a suspected structural break.

Harrington (2005) proposes several types of factors that lead to cartel formation and, hence, serve as potential breaking points in the data. Some factors are irrelevant for auctions, including the exit and entry of firms, due to specific characteristics. Other factors may serve as indicators of structural breaks in the behavior of firms participating in different types of auctions.

Firstly, breaks may occur when firms obtain information about government investigations or private court cases. Cartel members may adjust their behavior towards more competitive strategies to decrease the probability of detection by Antitrust Authorities. Abrantes-Metz et al. (2006) also suggest that government investigation may even lead to the collapse of a cartel. Moreover, cartel members in relative markets may pause or cancel an agreement, because they may consider government investigation as a signal of possible inspection of their collusive activity. The authors show that a drop in price variation may track structural breaks in the behavior of firms. The price itself may not be informative for detecting collusion because the price proposed by colluding firms may differ from the price under the absence of antitrust enforcement and the competitive price (Block et al., 1981).

Secondly, the merger of firms or the creation of an association may serve as breakpoints in bidding behavior in auctions. For instance, creating a trade association may signal collusion in the industry because firms tend to create associations to cover cartel meetings. The world lysine association, which operated between 1992 and 1995, is an example of a trade association created for such purposes (Connor, 2001). Although a trade association is frequently used as cover for a cartel, there might be a structural break in prices if non-colluding firms formed a cartel. Harrington (2005) explains it by exchanging information between association members that causes the homogenization of the beliefs of firms.

Finally, the methods of exploring structural breaks in the behavior of firms may detect collusion in auctions. However, these methods have several drawbacks. The events that serve as breakpoints are limited in auctions compared to other industries of the activities of firms. Moreover, these methods require a long panel that may be unavailable. Finally, the results may be misleading because the methods may detect collusion in competitive auctions.

1.3.4 Difference in Behavior of Competitive Firms and Firms Suspected of Colluding

Methods that test the difference in the behavior of suspected colluding and competitive firms work as verification tools. This approach proposes several alternatives of a competitive benchmark — a comparable market in which firms are not suspected of collusion (Porter and Zona, 1993; Porter and Zona, 1997; Pesendorfer, 2000; Ishii, 2009; Asker, 2010; Conley and Decarolis, 2016), or a period during which suspected firms were not colluding (Harrington, 2005). In auction settings, auctions conducted in different regions or for relatively similar contracts serve as a competitive benchmark. We may also use auctions held before firms started colluding, where these firms participated. However, splitting the timeline into periods before, during, and after firms agreed may be challenging.

This approach utilizes the behavior of non-colluding firms as a competitive benchmark in auctions in which the cartel is not all-inclusive and colluding firms are identified using prior information. For example, Pesendorfer (2000) and Porter and Zona (1993, 1997) formed groups of competitive and colluding firms using previous convictions for the rigging bids of one or several cartel members in procurement auctions. Porter and Zona (1993, 1997) estimated a log-linear bidding rule for the two groups. The authors tested the difference in the estimates to detect behavior consistent with collusion in auctions for highway construction contracts in New York State from 1979 to 1985 and school milk auctions in Ohio in the 1980s. Pesendorfer (2000) also proposed a theoretical model of cartel behavior that compares colluding behavior with a competitive benchmark in a first price procurement auction and tested it on the data set of school milk cartels in Florida and Texas from 1980 to 1991.

Conley and Decarolis (2016) made a further step. The authors formed a validation sample of colluding and competitive firms under investigation and checked the performance of two tests of coordination of firms (for entry and bidding). The entry test evaluated the difference in the frequency of joint entry for a group of firms suspected of collusion and a group of competitive bidders, based on different entry–related factors. The bid test assessed the degree to which a particular group's bids shifts the winning threshold relevant to average bid auctions. The authors then applied these tests to a dataset of around 800 average bid auctions conducted in the North of Italy from 2005 to 2010, in which there was no prior knowledge of collusion. The tests detected behavior consistent with collusion in 21 percent of auctions in the data.

Testing the discrepancy in the behavior of suspected colluding with the competitive benchmark is also relevant for auctions without prior information on collusion. Ishii (2009) suggests classifying winning bids into two groups based on the win-reserve ratio and a bid variance. However, this method may not be applicable to auctions except for repeated procurement auctions specific to Japan from 1947 to 2000, where firms determined the winner in pre-auction meetings. The test identifying collusion between bidders is based on the exchange of favors between cartel members and is also specific to an auction type and country.

Taking the behavior of firms that are not cartel members as a competitive benchmark may lead to endogeneity problems. Harrington (2005) determines two directions in which endogeneity may arise in a competitive benchmark. Firstly, cartel members may differ in some way from firms that are not in a cartel. The model should control for those factors that may cause differences if the data allows that. Secondly, a competitive benchmark comes with an assumption that competitive firms would behave similarly in auctions with and without a cartel. However, this assumption may not hold, depending on the behavioral properties of non-colluding firms.

Furthermore, when no prior information exists, auctions with similar goods or services in different geographic areas may be a comparable competitive benchmark. Then the primary concern is that collusion between firms may be more effective than competition in a particular market. For instance, Pesendorfer (2000) designed a theoretical model of cartel behavior showing that school milk cartels in Florida and Texas in the 1980s were nearly efficient due to a sufficiently large number of auctioned contracts. Efficient allocation of contracts is achieved in a market divided among cartel members or a market with side payments to compensate members for not placing a bid.

Another concern is that differences in the behavior of competitive firms and firms suspected of colluding may arise from omitted variables in the model instead of market conduct (Harrington, 2005). Therefore, one should not only show that the behavior of suspected firms is inconsistent with competition, but rather design a model that would describe collusion in a market. For example, Porter and Zona (1997) empirically showed that the bidding behavior of some dairy plants is consistent with collusion. The bids of these plants are declining in the distance between a plant and a school where the dairy is transported. However, the cost functions of these firms are increasing. The authors designed a model that formalized a collusive equilibrium relying on empirical evidence.

1.3.5 Data Fit of Collusive and Competitive Models

The approach, which tests the data fit of collusive and competitive models, generally implies several components: designing competitive and collusive structural models of prices and bids, estimating these models using cost or demand shifters, and assessing the data fit of both models. This approach is flexible in the criteria for comparing the performance of the models, because there are no universal standards. In general, if the collusive model fits the data better under the chosen criteria, it is evidence of collusion.

Harrington (2005) underlines the broad applicability of this approach, because it does not require data outside of the cartel period or prior information about colluding firms. Furthermore, testing the data fit of collusive and competitive models is possible, when all firms in a market constitute a cartel. However, this approach has a significant drawback that may influence the results of estimation — misspecification of the models, which is of great concern because the results of misspecified models are usually biased and unreliable.

Baldwin et al. (1997), for instance, assume firm symmetry in the setting of Forest Service timber sales in the Pacific Northwest in the 1970s. The authors show that the collusive model outperforms the non-cooperative behavior model. However, it may be the case that the competitive model outperforms the collusive one because bidders may have had a different distribution of independent private values. Therefore, cost and demand conditions might have been misspecified. The authors applied the Kolmogorov-Smirnov test to both models to ensure that the value distribution was specified correctly and did not find any evidence that the parametric misspecification caused the increase in the log-likelihood function. Therefore, the results of Baldwin et al. (1997) are probably reliable.

Misspecification is a more substantial concern for a collusive model than a competitive one. The probability of falsely rejecting a collusive model is higher because collusive equilibria are sensitive to bid rotation and market share allocation (Pesendorfer, 2000), side payments (Baldwin et al., 1997), and other factors. If the model does not consider any essential components of the framework, the solution of the collusive model may describe the auction context inaccurately. Consequently, prior information and evidence on the colluding strategies of bidders are highly valuable for designing a collusive model that produces a correct collusive equilibrium.

For example, Pesendorfer (2000) showed that collusion can be maintained through bid rotation and market share allocation. In Florida, market shares assigned to the members of a school milk cartel were unstable, and firms used side payments as compensation for a temporary share reduction. In contrast, there was no evidence of side payments, and market shares were also stable over time, which indicates the maintenance and execution of the agreement between cartel members. Therefore, a collusive model should consider the evidence of colluding bidders' actions taken to maintain a cartel in order to avoid misspecification of a collusive model.

Another concern is erroneously treating competitive firms as colluding ones and vice versa. Such inaccuracy may occur, because colluding firms hide evidence of the cartel's actions to avoid prosecution. To partly overcome this problem, Porter and Zona (1993) use past convictions to detect likely colluding firms. The authors assumed firms that were under investigation for forming a cartel once might cooperate again if it was profitable the first time. However, this method excludes firms that avoided convictions or joined the cartel to obtain higher profits. Consequently, the approach should balance the use of prior information to detect firms suspected of colluding and a possible failure in detecting new cartel members.

1.4 Detecting Strategic Bidding Behavior Using Timing of Bids

Previous sections have discussed approaches to detecting collusion that do not consider the timing of bids. In contrast, in this section, I focus on methods that employ the knowledge of the time stamps of bids in different auction types. This study develops a method for detecting collusion based on bid timing and contributes to this scarce literature that uses timestamps of bids in identifying colluding firms in auctions. Previous papers that employ the information on the time of bidding (Saeedi and Hopenhayn, 2015; Bajari and Hortaçsu, 2003; Ockenfels and Roth, 2006; Roth and Ockenfels, 2002) analyze the strategic bidding behavior in second-price auctions run by eBay and Amazon. However, only the paper by Andreyanov et al. (2017) focuses on detecting collusion using bid timestamps in first-price sealed-bid procurement auctions.

1.4.1 Patterns of Strategic Bidding: Incremental Bidding and Sniping

The literature that exploits bid timing mainly attempts to rationalize sniping behavior, which is placing a bid seconds before an auction closing, and incremental bidding, increasing the bid over time when outbid. Researchers develop models that explain these strategic bidding patterns based on second-price Internet auctions run by eBay and Amazon (e.g., Ockenfels and Roth 2002, 2006; Saeedi and Hopenhayn, 2015). These platforms implement different auction mechanisms. Internet auctions on eBay have a hard ending, meaning that bids are accepted only by the deadline, which the seller or a platform can not extend. In contrast, the auction mechanism on Amazon has a soft ending — submitting a bid within the last few minutes before the deadline extends the auction duration by ten minutes. The extension continues until no bids are placed within the last 10-minute interval.

The first paper that discussed sniping was Roth and Ockenfels (2002). The authors studied second-price online auctions run by eBay and Amazon, and compared bidders' behavior and auction mechanisms in these online platforms. Roth and Ockenfels (2002) argued that incremental bidding is more common in eBay auctions with a hard ending. Bidders tend to gradually increase their bids if other participants outbid them. Therefore, strategic bidders that face an incremental bidder place their bids as close to the deadline as possible (usually several seconds before the deadline) to avoid outbidding. This tactic does not give time to incremental bidders to react, place higher bids, and start sniping to an auction. Conversely, sniping and incremental bidding are not typical of auctions run by Amazon, because of the soft auction deadline. Ockenfels and Roth (2006) also formalize their idea in a bidding model in Internet auctions with an automatic extension rule.

Gray et al. (2007) and Ely and Hossain (2009) run two separate experiments to test the results of Ockenfels and Roth (2002, 2006) in an empirical setting. Gray et al. (2007) identified the benefit of sniping on matched pairs of bids for identical items: video games, Hot Wheels cars, and coin sets, whereas Ely and Hossain (2009) worked only with bids for newly-released DVDs on eBay, allowing for the differences between auctions. Both papers reconfirmed the prevalence of sniping in eBay auctions noted by Ockenfels and Roth (2002, 2006). However, Gray et al. (2007) showed no significant benefit of sniping, whereas the snipping benefit of around 1 U.S. dollar per auction obtained by Ely and Hossain (2009) was statistically significant.

Even though there might be a sniping benefit (Ely and Hossain, 2009), the negative effect of such a phenomenon may be considerable for buyers and the platform. Backus et al. (2015) show that incremental bidders may be less willing to participate in auctions later if they experienced sniping and were outbid at the last seconds of the auction at a price lower than their reservation value. The authors measured the effect of a negative experience on future participation using the instrumental variables approach on a selected subsample of auctions run by eBay. Backus et al. (2015) showed that sniping leads to a decrease in returning to the platform is 4–18 percent.

Similar to the study by Gray et al. (2007), Bajari and Hortaçsu (2003) analyzed bidders' behavior on the mint and proof coin sets U.S. markets on eBay. The authors designed a model of a common value auction to explain sniping behavior. The model works for two groups of bidders — informed and uninformed. Informed bidders delay bidding until a few seconds before the auction closes to avoid revealing their private information on coin sets' value to other potential bidders. Consequently, in equilibrium, all bidders submit their bids at the very last moment, meaning, they are involved in bid sniping. Bajari and Hortaçsu (2003) claim that such bidding behavior leads to a "winner's curve," i.e., the tendency for a winning bid to exceed the true market value of an item. As a result, the winning bid is much higher with bid sniping than without it.

Saeedi and Hopenhayn (2015) extend the concepts of literature and concentrate mainly on the dynamics span within an auction. The authors design a dynamic model of bidding in second-price auctions with bidding opportunities and values of buyers following a joint Markov process, partly building the model on the results of Zeithammer (2006), Said (2011), Backus and Lewis (2012), Hendricks and Sorensen (2015), and Coey et al. (2016). Saeedi and Hopenhayn (2015) suggest that the possibility of rebidding in eBay actions may lead to adverse selection against a future self, and then not exercising the future option of rebidding correlates with lower future value, which is the indicator of bid shading. The paper demonstrates that the value gap estimate between the baseline and the efficient allocations is almost twice larger than the gap in prices, confirming bid shading in eBay auctions.

Overall, the literature has found and described two specific patterns of strategic behavior — incremental bidding and sniping — in second-price Internet auctions run by eBay. These patterns are a formalization of bidders' behavior adjusted to an auction mechanism with a hard ending. Incremental bidding and sniping are not indicators of collusion, because bidders attempt to outbid other participants and win auctions without forming an agreement between each other or with a seller. However, I can still apply information on these types of strategic behavior to understanding and detecting collusion in similar auction types.

1.4.2 Detecting Corruption Using the Timing of Bids

The literature on detecting corruption, an agreement between a firm and an auctioneer, in auctions is scarce. The only study that has built a method for detecting corruption in first-price sealed-bid procurement auctions is paper by Andreyanov et al. (2017). Moreover, the paper is the first in an empirical analysis of corruption in auctions considering an earlier study of Cai et al. (2013) of urban land sales in China. I emphasize that Andreyanov et al. (2017) and Cai et al. (2013) examine *corruption*, which is defined as an agreement between an auctioneer and a preferred bidder. *Collusion*, on the contrary, is an agreement between firms that participate in auctions. I contribute to the literature by investigating collusion, not corruption, in first-price sealed-bid procurement auctions using the knowledge on the timing of bids.

Andreyanov et al. (2017) concentrate on a specific type of corruption, called bid leakage, which is the reveal of information on all other bids in an auction to a preferred bidder by an auctioneer. Under this type of agreement, a corrupt bidder prefers submitting a bid last after obtaining information on bids of other participants from an auctioneer and adjusting a bid to this information. The authors build a model that predicts how corruption affects prices directly. The paper also discusses the indirect effect occurs though the change in the behavior of competitive bidders to corrupted circumstances by bidding more aggressively. The indirect effect may affect the equilibrium by slightly lowering the average prices of procurement contracts, but the direct effect considerably outweighs the indirect one, preventing average price decline.

In a model estimation of bid functions and costs distribution, Andreyanov et al. (2017) extend the approach of Guerre et al. (2000) by incorporating bid leakage. The results show a significantly higher probability of winning for auction participants who place their bids last. The paper detects bid leakage in 10.8 percent of auctions in Russia, with an affected contract value of 1.2 billion U.S. dollars over six years. Hence, collecting the time stamps of bids should be implemented in government regulations for the auction conduction procedure.

2. The Russian Procurement Market

This section describes the institutional background and the incentives to collude in the Russian procurement market. Firstly, I provide information on the laws regulating public procurement and the procedure of first-price sealed-bid auctions in Russia. Then, I briefly describe how bidders coordinate their actions depending on the efficiency of antitrust authorities, and explain how simultaneous bidding, which is the focus of my paper, is identified in Russian procurement auctions.

2.1 Institutional Background

The Russian public procurement sector accounted for 27% of the GDP in 2020, reaching the historical maximum — 8.9 trillion rubles (≈109 million U.S. dollars) (Accounts Chamber of the Russian Federation, 2021). The suppliers for a large share of contracts for the public procurement sector are determined though auctions. In the Russian procurement context, the most common types of auctions are *open auctions*, *open tenders*, and *requests for quotations*. The auctions differ in their form of conducting: the open auction has a format of a reverse English auction, while the open tender is held via a scoring auction. I concentrate on *requests for quotations* that are conducted as first-price sealed-bid auctions (FPAs). Throughout the paper, I refer to requests for quotations as FPAs.

In 2006-2013, Federal Law of Russia 94-FZ (2005) regulated public procurement in Russia, replaced by Federal Law of Russia 44-FZ (2013) in 2013. According to the laws, FPAs are used for selecting suppliers for smaller contracts with a reserve price of 500,000 rubles (≈6 thousand U.S. dollars) and a maximum price of 3 million rubles (≈37 thousand U.S. dollars). The limit on the total price of such contracts is 100 million rubles (≈1,2 million U.S. dollars) per year. To prevent corruption, Federal Law of Russia 44-FZ (2013) introduced a mandatory public opening of envelopes and provided open access to applications of all bidders after the auction ended.

An FPA proceeds as follows: a public body announces a maximum willingness to pay — the reserve price, the details of the job to be done, and the deadline for bid submission. The announcement is posted online, and the bid submission period should be at least seven business days. During this time, any firm can submit an application that contains a price for which the firm is willing to supply goods or services and some specified documents that prove the firm eligibility. Public bodies accept applications in different ways: by email or through an official website in online auctions, or in sealed envelopes in offline auctions.

After the auction has ended, a local committee opens and evaluates the applications. The committee rejects an application if the bidder is not eligible. The leading reason why firms are ineligible for FPAs is that they are blacklisted for either failing to deliver a contract before the deadline or for breaking anti-monopoly laws. In the next stage, the lowest non-rejected bid wins the auction. If two or several bidders submit the same price, then the bidder who submitted the application first wins. If there is only one eligible bidder, the contract is signed with this bidder. After the auction ends, the auction committee releases a protocol containing information on the auction and its results, including submitted bids, their timing, application numbers, and other information. The results are also stored on the official website and are publicly available.

The typical contracts allocated through requests for quotations are the supply of books to public schools, paper or office supplies to municipalities, and medicines to public hospitals and other state institutions. FPAs may also be conducted to select suppliers for contracts for minor equipment repair and maintenance services, street cleaning services, and other minor services. This format of auctions is technically simple and requires less paperwork and time for the public body than other auction types. However, FPAs are also less transparent for the governing authorities to monitor.

2.2 Incentives to Collude

This subsection briefly describes how collusion works in Russian FPAs. FPA participants can form an explicit or tacit agreement to suppress the competition and maintain inflated prices. An explicit agreement is easier to enforce for firms with low prosecution risk. When the monitoring efficiency of the antitrust authorities increases, firms face a trade-off between explicit and tacit collusion.

When the probability of detection is relatively low, bidders can still directly monitor each other and place bids together, observing each other's actions. Colluding bidders can place their bids simultaneously or close to each other, maintaining the integrity of the cartel. I call this behavior *"simultaneous bidding"* and classify it as explicit collusion. If there is more than one eligible bidder in FPA, the contract price should decrease relative to the start price (Balsevich and Podkolzina, 2014). However, if the decrease is marginal, simultaneous bidding may indicate collusion.

In FPAs, bidders can submit their applications in sealed envelopes or electronically. In some cases, the bidders submitted the paper envelopes together, not being concerned with a prosecution. In other cases, the Russian Federal Anti-Monopoly Service exposed firms that submitted bids from the same IP address, e-mail, or phone number (Russian Federal Anti-Monopoly Service, 2017a,c,b). Russian anti-monopoly authorities investigated several collusion cases between at least four pharmaceutical companies in different auctions with contracts for the supply of medicines, medical devices, and other equipment for the needs of medical institutions in 2016-2017. These companies used the same IP for submitting their applications. The investigation results are presented in Decisions on these cases by the Russian Federal Anti-Monopoly Service (2017a,c,b).

I suggest that colluding firms may place their bids simultaneously to control the enforcement of the agreement between participants. I hypothesize that simultaneous bidding may be a monitoring device for detecting collusion. I verify the approach by assessing its performance in investigated cartel data for the pharmaceutical industry and then expand my method to all auctions in Russia.

3. Data

In this section, I describe the main data set constructed from digital archives of procurement auctions in Russia. I focus on the number of bidders, reserve price, and winning bids of these auctions. Then, I discuss the validation samples that are constructed from pharmaceutical industry auctions which contain companies that have ever been under investigation by the Russian Federal Anti-Monopoly Service. Finally, I describe collusive patterns in the data.

3.1 Main Data

I use an extended data set from Andreyanov et al. (2017) that collects digital archive of the procurement auctions from the Russian government procurement server[1]. To my knowledge, this auction data set is the largest spanning all 85 regions of Russia and the 88 two-digit goods and service classifiers. The Russian procurement server stores information on over 32 million contracts starting in 2011, allocated through auctions or direct negotiations. Raw data are placed on the server in the archives of an unstructured text format of a large number of .xml files.

The data contain contract announcements and auction protocols. A typical announcement contains a contract description, including the deadline for supplying goods or services outlined in the contract, the reserve price, which is the initial maximum price of the contract, and the auction deadlines. Protocols, which are released by the auction committees when auctions end, contain basic information on participants, their bids, timestamps of the bids, and whether the bid was rejected. Bids are mostly rejected when bidders do not provide all required eligibility proofs in their applications.

Data contains information from announcements and protocols that are matched and all other necessary information about auctions. I clean the resulting data set and drop all of the auctions with rejected bids because the results are similar if I keep them. I also drop auctions where only one bidder participated because the method for detecting collusion is based on pairs of bids and is not applicable to these auctions. As a result, I am left with data of 1,702,436 FPAs with 4,745,713 bids starting in January 2011 and ending in August 2017.

Table 3.1 presents the summary statistics[2] for the main data set. On average, around three bidders participate in an auction in the sample, but, in some cases, the number of

[1] The Russian government procurement official website is http://www.zakupki.gov.ru.

[2] The U.S. dollar to ruble exchange rate fluctuated from 30.6 rubles per U.S. dollar in January 2011, to 58.0 rubles per U.S. dollar in August 2017. For consistency, I keep summary statistics in rubles, considering that those 500 thousand rubles in U.S. dollars were 6 thousand U.S. dollars in 2011 and 8.6 thousand U.S. dollars in 2017, while the mean reserve price in U.S. dollars is either 6.4 thousand U.S. dollars or 3.4 thousand U.S. dollars.

Table 3.1: Summary Statistics for All Data

	Mean	St. Dev.	Median	Minimum	Maximum	Observations
Number of Bidders	2.8	1.3	2.0	2.00	34	1,702,436
Reserve Price, R, th. rub.	194.7	151.6	155.0	0.00	510	1,702,436
Winning Bid, $b(1)$, th. rub.	160.8	134.8	122.2	0.00	508	1,702,436
$b(1)/R$ %	81.5	17.7	85.9	0.00	100	1,702,436
$\Delta b(12)/R$ %	5.2	8.2	1.9	0.00	100	1,702,436

Notes: Statistics for the whole sample of auctions. The Number of Bidders is the number of entities that bid in auctions in a given sample. Winning Bid and Reserve Price are winning bids and reserve prices for FPAs in a given sample, reported in rubles. $b(1)/R$ % is the ratio between the winning bid and the reserve price in %, and $\Delta b(12)/R$ % is the difference in bids for the winner and runner-up normalized by the reserve price.

bidders is more than 20. Such auctions constitute less than 1% of the data. The legal maximum reserve price for FPAs is 500 thousand rubles. In the all auction data set, the mean reserve price constitutes 39% of the maximum allowed reserve price and equates to 194.7 thousand rubles. Although the auctions are used for small contracts, the total value of contracts distributed through FPAs was 280 billion rubles in 6.5[3] years between $2011-2017$ with a total discount from the reserve price of 17.2%. The latter number is similar to the 18.5% discount from the mean ratio between the winning bids and the reserve prices in all auctions — 81.5%. Overall, the discounts achieved through FPAs are not large in absolute terms.

The time to the deadline and winner — runner-up bid differences are other important variables for my analysis. The average bid submission time before the deadline for the winner is slightly more than one day, i.e., 25.8 hours. The differences in bid pairs between the winner and runner-up bids are relatively small and constitute around 5% of the reserve price.

3.2 Pharmaceutical Cartels

To validate the new method, I focus on the pharmaceutical industry that is known for its propensity for collusion in Russia (Regnum News Agency, 2019). According to estimates in Regnum News Agency (2019), 19% of total collusion cases occurred in the pharmaceutical industry, specifically in the procurement of pharmaceuticals. Violations of anti-monopoly laws were found in 82 of the 84 regions of Russia. Moreover, the pharmaceutical industry is the one for which I observe three known cartels. I rely on information from three recent cases investigated by the Russian Federal Anti-Monopoly Service (FAS) (Russian Federal Anti-Monopoly Service, 2017a,c,b).

First, I compare summary statistics for pharmaceutical FPAs, presented in Table 3.2, to the main data set. While the FPAs for pharmaceuticals are for smaller contracts with

[3] 8.4 billion U.S. dollars when taking average exchange rates for each year based on the information from the Bank of Russia (2023) or 4.8 billion U.S. dollars in 2017 exchange rate, or 9.1 billion U.S. dollars in 2011 exchange rate.

a smaller average final price — 183.6 and 151.1 thousand rubles vs. 194.7 and 160.8 in the main data — they are practically identical in the number of bidders, the average discount from the reserve price, and the differences between the bids of a winner and a runner-up. The difference between the main data and the pharmaceutical industry is essentially zero, and statistically insignificant at the 10% level. In contrast, the differences in the ratio between the winning bid and the reserve price and the difference in bids for the winner and runner-up normalized by the reserve price are significant on the 1% level (they are 0.6% and 0.06%, respectively). Consequently, the pharmaceutical industry is reasonably relevant within the procurement data set for validation purposes.

Table 3.2: Summary Statistics

	Mean	St. Dev.	Median	Minimum	Maximum	Observations
Panel A. Pharmaceuticals						
Number of Bidders	2.8	1.3	2.0	2.00	22	205,925
Reserve Price, R, th. rub.	183.6	153.5	138.6	0.07	506	205,925
Winning Bid, $b(1)$, th. rub.	151.1	136.6	106.9	0.00	500	205,925
$b(1)/R$ %	80.9	17.7	84.8	0.00	100	205,925
$\Delta b(12)/R$ %	5.3	8.3	2.0	0.00	100	205,925
Panel B. Auctions with ≥ 2 firms from Cartel I ("R-pharm")						
Number of Bidders	2.4	1.0	2.0	2.00	9	447
$b(1)/R$ %	91.4	12.3	96.9	26.23	100	447
$\Delta b(12)/R$ %	4.2	7.9	1.1	0.00	68	447
Panel C. Auctions with ≥ 2 firms from Cartel II						
Number of Bidders	2.5	0.9	2.0	2.00	10	612
$b(1)/R$ %	89.6	15.2	96.7	10.24	100	612
$\Delta b(12)/R$ %	4.1	8.0	0.9	0.00	69	612
Panel D. Auctions with ≥ 2 firms from Cartel III						
Number of Bidders	2.4	0.9	2.0	2.00	9	175
$b(1)/R$ %	89.4	14.7	95.1	16.60	100	175
$\Delta b(12)/R$ %	3.3	6.6	0.9	0.00	60	175

Notes: Statistics for the whole sample of auctions. The Number of Bidders is the number of entities that bid in auctions in a given sample. Winning Bid and Reserve Price are winning bids and reserve prices for FPAs in a given sample, reported in rubles. $b(1)/R$ % is the ratio between the winning bid and the reserve price, and $\Delta b(12)/R$ % is the difference in bids for the winner and runner-up normalized by the reserve price.

Next, I use the data from three cartels collected from the FAS website. The first one is by far the largest in the number of accomplices and the most visible in the media (Regnum News Agency, 2018; Gritsenko, 2018). The largest Russian pharmaceutical company "R-pharm" colluded with 33 other suppliers from Moscow, Irkutsk, Krasnoyarsk, and Khakasia to control the prices in all medical procurement FPAs in Khakasia and neighboring regions. Final prices in auctions in which R-pharm participated were much higher than the competitive level. The share of companies that colluded with R-pharm in the procurement of pharmaceuticals is 8.3% of the total market. The total size of contracts was more than 3 billion rubles (>45 million U.S. dollars), and the criminal investigation took six years (Russian Federal Anti-Monopoly Service, 2017c). After the investigation in Khakasia, FAS also investigated R-pharm activity in other geographical markets. I call the group of companies “R-pharm” colluded with “Cartel I”. The subsample of Cartel I includes auctions where at least two firms from 34 were bidding. Table 3.2 Panel B presents the summary statistics for auctions for Cartel I firms. These auctions have fewer bidders, smaller discounts, and smaller winner — runner-up bid differences than other auctions in pharmaceuticals. All of these differences are significant at 1% level.

The second group of colluding firms involves seven companies: “Rosmedkomplekt”, “Ethalon-Trading”, “Market-Pharm”, “PIK”, AO “Intermedservice”, “Service-Pharm”, LLC “Intermedservice Pharma”. A bidding ring was under investigation (Russian Federal Anti-Monopoly Service, 2017a) and was also visible in media (Pakhomov, 2017). According to these sources, the total amount of contracts in the case was more than 700 contracts (not only FPAs) with a total value of 1.5 billion rubles (more than 22 million U.S. dollars). The first penalty was only 17 million rubles ($\approx$ 300 thousand U.S. dollars), followed by further investigation. I call these seven firms “Cartel II” and show summary statistics in Panel C of Table 3.2. Similarly to Cartel I, there are fewer bidders on average, smaller discounts, and smaller bid margins than in the main data.

The final cartel, “Cartel III,” includes fewer accomplices: “Pharm SKD”, “Novopharm”, and two smaller partners. These companies were active in the Samara region. They had to pay more than 90 million rubles (>1.3 million U.S. dollars) in fines, and the estimated scope of affected contracts was 400 million rubles ($\approx$7 million U.S. dollars) (Russian Federal Anti-Monopoly Service, 2017b; Portnov, 2017). The summary statistics for this cartel are in Panel D of Table 3.2, and all the results are similar to other cartels.

I use these three cartels to validate the method in the data with known cartels, similar to the validation procedure performed by Kawai and Nakabayashi (2022) and Conley and Decarolis (2016).

3.3 Simultaneous Bidding Pattern in Data

I defined simultaneous bidding as placing bids simultaneously or within a short period. This pattern is widely observed in the data — there is a substantial share of bidders who tend to submit their bids with around a 30-minute difference. When firms form a bidding ring, a designated winner is interested in monitoring the actions of other bidders to prevent violations of an agreement. Simultaneous bidding is one of the most straightforward ways to control the actions of bidding ring members: colluding firms submit their bids together in envelopes or online to ensure that they do not change their applications in the submitting process. Thus, monitoring the execution of the agreement between firms produces simultaneous bidding.

I depict the simultaneous bidding pattern in the plots of the timing of bids for all deadlines and the timing of bids normalized by the deadline time (Figures 1 and 2 in Appendix, respectively). However, the scatter plots are inconclusive due to many observations. For now, I restrict the data to auctions with a Friday 9 a.m. deadline for visual clarity, because this deadline has the maximum number of auctions. The results hold for all other deadlines separately and together. For the same logic of visual clarity, I drop bids submitted before the deadline by more than one hundred hours and during the last five hours. In the following sections, I analyze the entire data set of auctions with all deadlines.

Figure 3.1 demonstrates the relationship between the bidding time of winners (bidder with the lowest bid) and runners-up (second lowest bidder) for a chosen subsample of auctions, counting from the deadline. x-axis corresponds to the bidding time of runners-up, while y-axis corresponds to the one of winners. Point $(0,0)$ corresponds to submitting the winner and runner-up bids at the auction deadline. In the scatter plot, the most noticeable pattern is an abnormal mass of auctions with simultaneous submission of bids. On the graph, such winner — runner-up pairs are placed on the diagonal $(y = x)$.

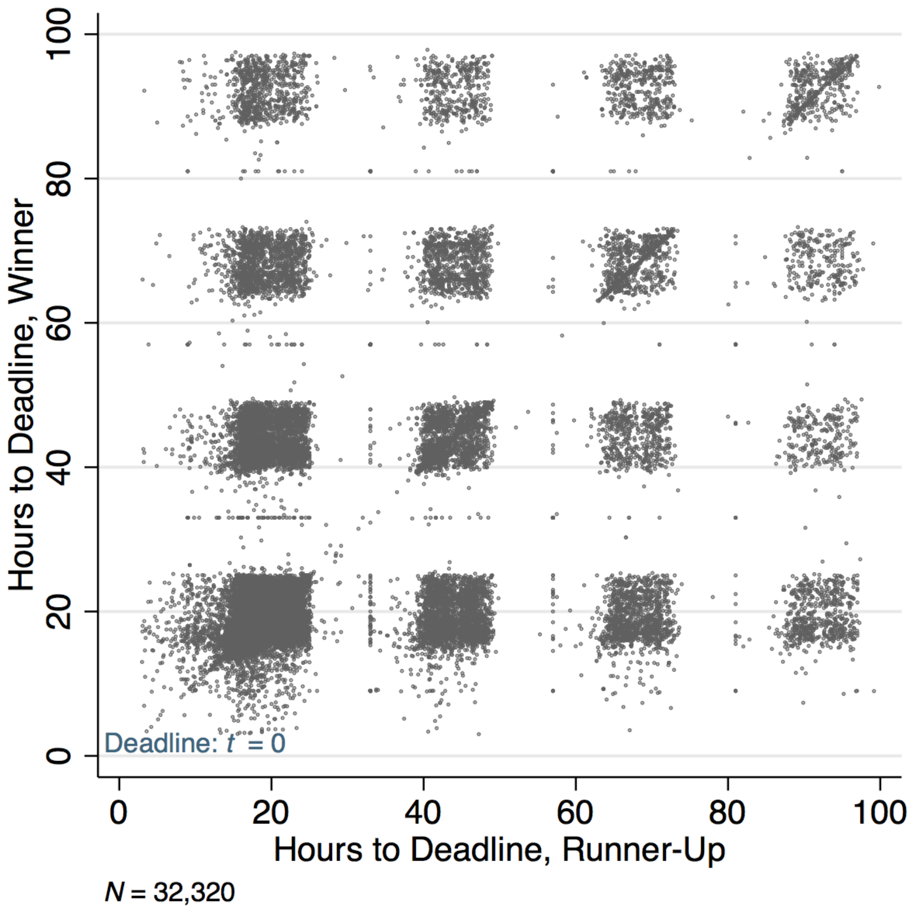
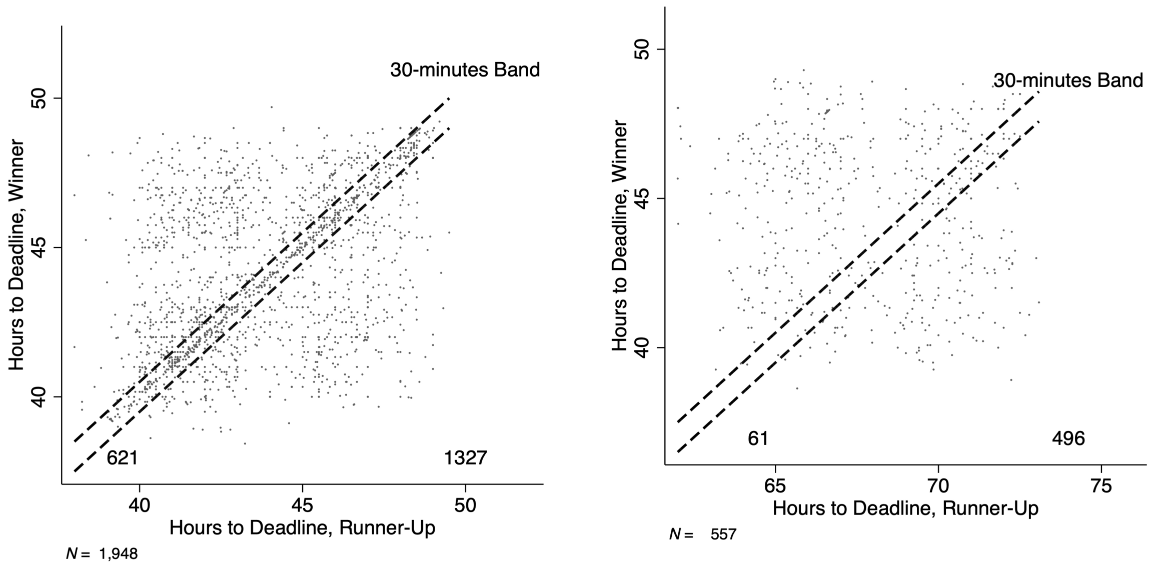


Figure 3.1: Winners and Runners-Up Bidding Time, Auctions with Deadline on Friday, 9 a.m.
Note: The figure shows the relationship between winners and runners-up bidding time in hours to the deadline.

To provide a more detailed illustration of the simultaneous bidding pattern, I zoom into Figure 3.1 and show how the relationship between winners and runners-up bidding time in hours to the deadline differs for bids submitted on the same and different days. Since Friday is the deadline, I chose Tuesday and Wednesday for the illustration and picked the following pairs of bids: both bids were placed on Wednesday, and bids are submitted on different days — Tuesday and Wednesday. Figure 3.2 shows the scatter plots for these two types of bid pairs. I choose Tuesday and Wednesday, considering the results of Andreyanov et al. (2017) that show that last-minute bidding may indicate a collusive agreement between an auctioneer and a preferred bidder in Russian procurement auctions. I intend to distinguish bid leakage and simultaneous bidding in this example.



Panel A. Both Bids are Submitted on Wednesday

Panel B. Winner Bid is Submitted on Wednesday, and Runner-up Bid on Tuesday

Figure 3.2: Bidding Time of Winners and Runners-Up in Hours: Bids Submitted on the Same and Different Days

Note: The figure shows the relationship between the bidding time of winners and runners-up for auctions with the deadline on Friday at 9 a.m. Panel A illustrates the relationship between the winner and runner-up bidding time for bids submitted on Wednesday. Panel B illustrates the relationship between the winner bidding time for bids submitted on Wednesday and the runner-up bidding time for bids submitted on Tuesday.

For Figure 3.2, I choose the band of 30 minutes to further quantify the collusion in the form of simultaneous bidding. I define a bandwidth endogenously, acknowledging that the results might be sensitive to my choice. Then I identify bid pairs that are located within a 60-minute interval within the same day as collusive. On the left graph of Figure 3.2, the share of collusive bid pairs submitted within a 60-minute interval on Wednesday is 46.8%, which is 621/1327.

However, one may argue that placing bids within a small time interval may be caused by specific characteristics of it. For instance, bidders may find it convenient to submit bids before or after lunch. To account for this issue, I suggest that the collusion measure should be a ratio between the share of bid pairs placed within the simultaneous bidding interval on the same day by the share of bid pairs submitted within the interval but on different days. This ratio corresponds to the normalization of the former parameter. On the right graph of Figure 3.2, the share of bid pairs placed within a 60-minute interval but on different days is 12.2%, which is 61/496.

Then the collusion measure is the normalized difference between the share of bids submitted within the hour interval on the same day and the share of bids submitted within an hour interval on different days. The normalization is made by the share of bids submitted on different days and not within the simultaneous bidding interval. I formalize this collusion measure as follows:

$$\hat{\nu} = \frac{\mathbb{P}\left[\text{Simult. Bidding}|\text{Same-Day Bidding}\right] - \mathbb{P}[\text{Simult. Bidding}|\text{Different-Day Bidding}]}{1 - \mathbb{P}\left[\text{Simult. Bidding}|\text{Different-Day Bidding}\right]}$$

$$= \frac{0.468 - 0.122}{1 - 0.122} = 0.394$$

The share of auctions with abnormal simultaneous bidding for the subsample under analysis is 39.4%. These auctions are subject to collusion between participants. In the next section, I formalize this intuition and show that this parameter may serve as a test for the presence of collusion and the measure of collusion.

4. Method for Detecting Collusion

This section develops an estimate for the collusive share of bid pairs based on the distribution of bid pairs submitted on the same and different days. An estimation is implemented via OLS. Then, I validate the method on the pharmaceutical industry and the cartels within the industry and show how the share of collusive pairs varies with the number of bidders in auctions. Finally, I assess how the method performs on the main data.

4.1 Collusion Measure: Share of Collusive Pairs

This section defines the framework. Assume that the data contains N_i auctions, i is an index for each auction. Auction i includes K bids, that have index k. Each bid has two characteristics: b_k^i — a price at which a firm is willing to provide the good or service and t_k^i — a time when a firm submits the bid. For now, I concentrate only on bid timing for developing the collusion measure which is the share of collusive bid pairs.

From now, I assume that bids across auctions and auctions themselves are independent and identically distributed. This assumption holds at least conditional on observable characteristics. Relying on this assumption, I remove the i subscript for every auction.

However, I emphasize that bidding time is not independent for bidders participating in the same auction. On the contrary, I suggest that the actions of some bidders are highly dependent because of simultaneous bidding.

Then, I assume that the joint distribution of hours is the same across all days of the auction for a pair of bids and define a pair of bidding times t_k and t_j in hours as

$$t_k = 24 \cdot d_k + h_k, \quad d_k = \{1, ..., 5\}, \ h_k \in [0, 24),$$

$$t_j = 24 \cdot d_j + h_j, \quad d_j = \{1, ..., 5\}, \ h_j \in [0, 24),$$

where d and h are the days and hours of bidding for bidders k and j. The variable d is discrete, while h is continuous. According to the Federal Law of Russia 44-FZ (2013) the maximum number of days the auction is open is four business days. Therefore, I define the upper boundary of five calendar days for d (four business days and two weekend days).

When t_k and t_j are selected from a joint distribution $F(t_k, t_j)$ the following holds

$$h_k \perp \ h_j | (d_k, d_j), \tag{4.1}$$

From the assumption that the joint distribution of hours is the same on all days of the auction for a pair of bids follows that the distribution of hours is the same for bids k and j submitted on different days:

$$F(h_k, h_j | d_k = d_j) = F(h_k, h_j | d_k \neq d_j), \tag{4.2}$$

Then, I formulate a test for collusion as a test for equality in 4.2 against inequality. Under no collusion, the distribution of hours on all days of an auction is the same.

I further modify the representation of the distribution of hours for a pair of bids placed on the same day. Considering that simultaneous bidding leads to a violation of bid independence within auctions, the observed joint distribution of hours within a day becomes a combination of joint distributions of hours with and without collusion. I denote the difference in hours between two randomly chosen bidders within an auction by $w = w_{kj} = h_k - h_j$ and the distribution of w with collusion by $G(w)$. I also define ν as the probability of collusion. Then the observed joint distribution of hours within a day becomes

$$F(w | d_k = d_j) = (1 - \nu) \cdot F(w | d_k \neq d_j) + \nu \cdot G(w), \tag{4.3}$$

In this setting, ν represents a test for the presence of collusion. If ν is zero, then the market is competitive. Furthermore, the estimate of ν serves as a measure of collusion in the data. In the following subsection, I suggest a functional form for $G(w)$ based on the collusive patterns in the data and design an estimation approach.

4.2 Estimation Approach

In line with the representation of the observed joint distribution of hours in equation 4.3, Figure 4.1 illustrates the kernel densities of the differences between winner and runner-up bidding time in hours for bid pairs submitted on the same day and different days. Figure 3 in Appendix repeats the exercise for the winner – runner-up and third-best bidder pairs and demonstrates a similar pattern.

Figure 4.1 shows that there is a spike in the bidding time difference, which is considerably more pronounced for bid pairs submitted on the same day. I consider that the spike is evidence of collusion in the form of simultaneous bidding. However, the distribution of the bidding time difference for bid pairs placed on different days also has a small but notable spike. Therefore, some bid pairs may be submitted simultaneously because of the time convenience during the day.

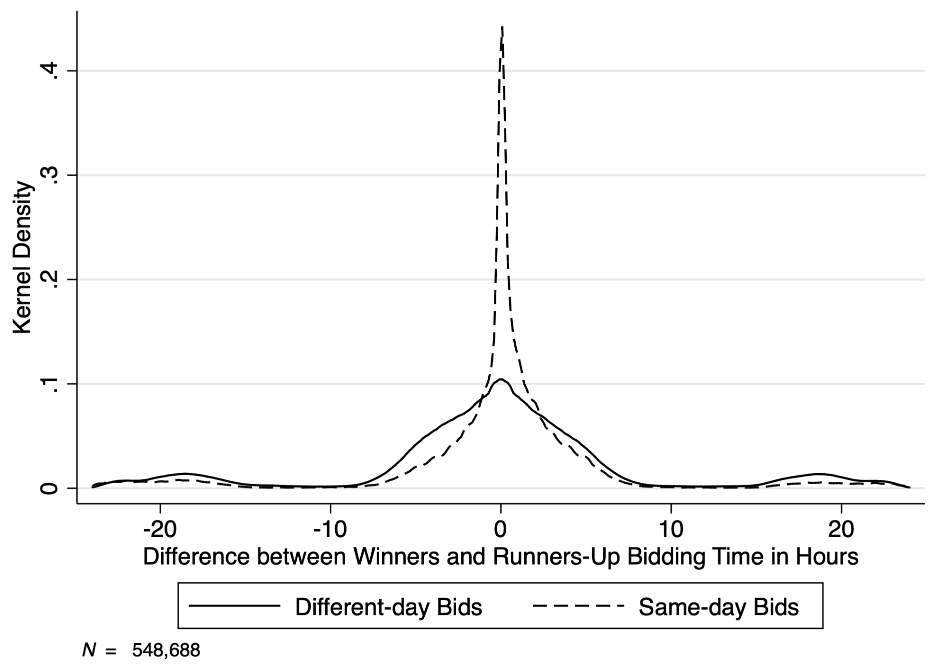


Figure 4.1: Difference between Winner and Runner-up Bidding Time in Hours
Note: The figure shows the distributions of the differences between winner and runner-up bidding time in hours for bid pairs submitted within the same day and on different days.

I choose the form of $G(w) = 1\{|w| \leq 0\}$ motivating it by Figure 4.1. $G(w)$ represents a cumulative distribution function of w, the difference in hours between winner and runner-up bids, with collusion. Then, the probability density function of w is zero at all points except where w is precisely zero, meaning that bidders place their bids at the exact same moment. At $w = 0$, the probability density function of w goes to infinity, which is close to the case that Figure 4.1 illustrates.

I derive the estimator of the scope of collusion ν based on the parametric assumption for the joint distribution of hours described by equation 4.3 and the form of distribution of w with collusion. Assuming that a bandwidth ϵ is close in magnitude to 0, I obtain the following:

$$\mathbb{P}\Big[|w| \leq \epsilon | d_k = d_j\Big] = (1-\nu) \cdot \mathbb{P}\Big[|w| \leq \epsilon | d_k \neq d_j\Big] + \nu \cdot 1(|w| \leq \epsilon), \tag{4.4}$$

by rearranging the terms, I obtain the representation of ν:

$$\nu = \frac{Pr(|w| \leq \epsilon | d_k = d_j) - Pr(|w| \leq \epsilon | d_k \neq d_j)}{1 - Pr(|w| \leq \epsilon | d_k \neq d_j)}, \tag{4.5}$$

For a fixed choice of ϵ, I can implement the scope of the collusion estimate by running the following regression:

$$1\{|w| \leq \epsilon\} = \beta_0 + \beta_1 1\{d_k = d_j\} + \epsilon_{kj}. \tag{4.6}$$

In Appendix 2, I show that equation 4.7 is a sample equivalent of 4.5, considering that the regression specification is as in 4.6.

$$\hat{\nu} = \frac{\hat{\beta}_1}{1 - \hat{\beta}_0} \tag{4.7}$$

I assess the share of collusive auctions in my data using the scope of collusion estimate. However, I first validate my scope of collusion measure on pharmaceutical industry cartels in the following subsection to assess the performance of the method.

4.3 Validation on Pharmaceutical Industry and Cartels Subsamples

Before applying the method for detecting collusion to the main data, I validate it on the subsamples earlier defined as Cartels I–III and the pharmaceutical industry. I create these subsamples based on the cases of anti-monopoly law violations in Russia. FAS produced a detailed description of the collusive actions of companies in the pharmaceutical industry, including usage of the same IP, phone, or e-mail. Therefore, I can reasonably consider that pharmaceutical companies under investigation are colluding. I then examine the performance of the method by checking how it detects the coordinated actions of these companies. Finally, I analyze how the share of collusive bid pairs varies with the number of bidders.

4.3.1 Share of Collusive Bid Pairs

In this section, I estimate OLS and compute the share of collusive bid pairs $\hat{\nu}$. For now, I focus on the winner — runner-up pair of bids and estimate the share of collusive bid pairs using the specification 4.6. I estimate the model varying cutoffs and simultaneous bidding intervals. I use two data-driven cutoffs: 5 and 12 hours to mitigate the impact of bid leakage. I observe jumps in the number of bids at 5 and 12 hours before the deadline. For a five-hour cutoff, the rise is less pronounced in the data. For simultaneous bidding intervals, I use time corridors of three different radii (5, 15, and 30 minutes) and define bid pairs with the difference in bidding time within these corridors as simultaneous bidding.

Firstly, I test the method on the pharmaceutical industry data, which insignificantly differs from the main data. Table 4.1 depicts the results. I observe that same-day bidding significantly affects simultaneous bidding: the difference in probabilities of submitting the winner — runner-up pair of bids within a simultaneous bidding interval for the same and different days significantly differs from zero.

Table 4.1: Collusion Measure: Pharmaceutical Industry

Dependent variable: Simultaneous Bidding	(1) *10-minute*	(2) *interval*	(3) *30-minute*	(4) *interval*	(5) *60-minute*	(6) *interval*
	Panel A. Two Bidders, Winner — Runner-Up Pairs					
Same-Day Bids	0.101***	0.093***	0.221***	0.202***	0.276***	0.250***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
Constant	0.049***	0.054***	0.078***	0.085***	0.122***	0.131***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Share $\hat{\nu}$	0.11	0.10	0.24	0.22	0.31	0.29
Observations	36,767	29,803	36,767	29,803	36,767	29,803
	Panel B. K Bidders, Winner — Runner-Up Pair					
Same-Day Bids	0.079***	0.071***	0.176***	0.157***	0.225***	0.197***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Constant	0.041***	0.046***	0.071***	0.079***	0.115***	0.126***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Share $\hat{\nu}$	0.08	0.07	0.19	0.17	0.25	0.23
Observations	55,484	43,791	55,484	43,791	55,484	43,791

Notes: The table shows the estimated share of collusive bid pairs. Panel A uses winner — runner-up pairs in two-bidder auctions. Panel B uses winner — runner-up pairs in K-bidder auctions, $K \geq 2$. Columns (1), (3), (5) use a 5-hour cutoff. Columns (2), (4), (6) use a 12-hour cutoff.Each observation is a pair of bids. Column (3) excludes the last auction day: $d_k, d_j > 0$. The reported values in parentheses represent robust standard errors. * p<0.1, ** p<0.05, *** p<0.01.

The method detects collusion in 7-31% auctions, depending on the cutoffs, simultaneous bidding interval, and the number of bidders. This result is consistent with the estimates in Regnum News Agency (2019). The share of collusive auctions is the largest when the simultaneous bidding interval is 60 minutes, partly because more bid pairs are placed within the interval. However, even within the 10-minute interval, the share of collusive auctions is still around 10%. I also observe a decline in the share of collusive bid pairs when I estimate the full subsample without a restriction to two-bidder auctions.

Secondly, I evaluate how the method detects the share of collusive auctions in Cartel I, which contains auctions where at least two of 34 colluding companies ("R-pharm" and the 33 other suppliers the leading company colluded with) participated. The estimation results for two-bidder and K-bidder ($K \geq 2$) auctions are presented in Table 4.2. The same-day bidding significantly affects simultaneous bidding. The share of collusive bid pairs varies between 11% and 38% of auctions in Cartel I.

Table 4.2: Collusion Measure: Cartel I

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
Simultaneous Bidding	*10-minute interval*		*30-minute interval*		*60-minute interval*	
	Panel A. Two Bidders, Winner — Runner-Up Pairs					
Same-Day Bids	0.189***	0.206***	0.272***	0.237**	0.340***	0.311***
	(0.046)	(0.050)	(0.087)	(0.092)	(0.095)	(0.101)
Constant	0.000	0.000	0.120*	0.130*	0.160**	0.174**
	(.)	(.)	(0.066)	(0.071)	(0.074)	(0.080)
Share $\hat{\nu}$	0.19	0.21	0.31	0.27	0.40	0.38
Observations	99	91	99	91	99	91
	Panel B. K Bidders, Winner — Runner-Up Pair					
Same-Day Bids	0.107**	0.116**	0.245***	0.203**	0.331***	0.285***
	(0.051)	(0.058)	(0.073)	(0.080)	(0.077)	(0.085)
Constant	0.049	0.057	0.122**	0.143**	0.146***	0.171***
	(0.034)	(0.040)	(0.051)	(0.060)	(0.056)	(0.064)
Share $\hat{\nu}$	0.11	0.12	0.28	0.24	0.39	0.34
Observations	131	116	131	116	131	116

Notes: The table shows the estimated share of collusive bid pairs. Panel A uses winner — runner-up pairs in two-bidder auctions. Panel B uses winner — runner-up pairs in K-bidder auctions, $K \geq 2$. Columns (1), (3), (5) use a 5-hour cutoff. Columns (2), (4), (6) use a 12-hour cutoff.Each observation is a pair of bids. Column (3) excludes the last auction day: $d_k, d_j > 0$. The reported values in parentheses represent robust standard errors. * p<0.1, ** p<0.05, *** p<0.01.

Thirdly, I apply the method to Cartel II, which includes auctions in which at least two of seven colluding companies participated. Table 4.3 shows estimates of the share of collusive bid pairs in two- and K-bidder auctions. In Cartel II, the share of collusive bid pairs is $8-34\%$, which is slightly lower than in Cartel I. The characteristics of firms and the agreement they have may affect the results.

Finally, I estimate the share of colluding pairs in Cartel III auctions. Table 4.4 presents the results for auctions with two and K bidders. Bidding on the same day considerably impacts simultaneous bidding for almost all cases except the regression for 10-minute intervals with the 12-hour cutoff. Even though Cartel III is similar to Cartels I and II in summary statistics, the results differ considerably. The share of collusive auctions is $17-53\%$ for two-bidder auctions and $25-50\%$ for K-bidder auctions. I suppose that the difference in the number of observations and the characteristics of collusive bidders may lead to a difference in the results.

Overall, the method performs reasonably well and detects collusion in at least $7-25\%$ of auctions, depending on the subsample, the choice of a band and a cutoff. I

Table 4.3: Collusion Measure: Cartel II

Dependent variable: Simultaneous Bidding	(1) *10-minute interval*	(2)	(3) *30-minute interval*	(4)	(5) *60-minute interval*	(6)
	Panel A. Two Bidders, Winner — Runner-Up Pairs					
Same-Day Bids	0.152***	0.099***	0.293***	0.209***	0.288***	0.195*
	(0.035)	(0.033)	(0.061)	(0.079)	(0.089)	(0.113)
Constant	0.000	0.000	0.040	0.062	0.160**	0.188*
	(.)	(.)	(0.039)	(0.061)	(0.074)	(0.099)
Share $\hat{\nu}$	0.15	0.10	0.31	0.22	0.34	0.24
Observations	130	97	130	97	130	97
	Panel B. K Bidders, Winner — Runner-Up Pair					
Same-Day Bids	0.102***	0.075***	0.242***	0.192***	0.274***	0.209**
	(0.038)	(0.026)	(0.052)	(0.060)	(0.067)	(0.085)
Constant	0.024	-0.000	0.049	0.043	0.122**	0.130*
	(0.024)	(0.000)	(0.034)	(0.043)	(0.051)	(0.071)
Share $\hat{\nu}$	0.11	0.08	0.25	0.20	0.31	0.24
Observations	175	129	175	129	175	129

Notes: The table shows the estimated share of collusive bid pairs. Panel A uses winner — runner-up pairs in two-bidder auctions. Panel B uses winner — runner-up pairs in K-bidder auctions, $K \geq 2$. Columns (1), (3), (5) use a 5-hour cutoff. Columns (2), (4), (6) use a 12-hour cutoff.Each observation is a pair of bids. Column (3) excludes the last auction day: $d_k, d_j > 0$. The reported values in parentheses represent robust standard errors. * p<0.1, ** p<0.05, *** p<0.01.

Table 4.4: Collusion Measure: Cartel III

Dependent variable: Simultaneous Bidding	(1) *10-minute interval*	(2)	(3) *30-minute interval*	(4)	(5) *60-minute interval*	(6)
	Panel A. Two Bidders, Winner — Runner-Up Pairs					
Same-Day Bids	0.266**	0.153	0.361***	0.264*	0.481***	0.403***
	(0.116)	(0.142)	(0.118)	(0.146)	(0.118)	(0.147)
Constant	0.091	0.125	0.091	0.125	0.091	0.125
	(0.088)	(0.120)	(0.088)	(0.120)	(0.088)	(0.120)
Share $\hat{\nu}$	0.29	0.17	0.40	0.30	0.53	0.46
Observations	53	44	53	44	53	44
	Panel B. K Bidders, Winner — Runner-Up Pair					
Same-Day Bids	0.294***	0.229**	0.376***	0.329***	0.478***	0.454***
	(0.086)	(0.102)	(0.089)	(0.106)	(0.089)	(0.107)
Constant	0.053	0.071	0.053	0.071	0.053	0.071
	(0.052)	(0.070)	(0.052)	(0.070)	(0.052)	(0.070)
Share $\hat{\nu}$	0.31	0.25	0.40	0.35	0.50	0.49
Observations	68	54	68	54	68	54

Notes: The table shows the estimated share of collusive bid pairs. Panel A uses winner — runner-up pairs in two-bidder auctions. Panel B uses winner — runner-up pairs in K-bidder auctions, $K \geq 2$. Columns (1), (3), (5) use a 5-hour cutoff. Columns (2), (4), (6) use a 12-hour cutoff.Each observation is a pair of bids. Column (3) excludes the last auction day: $d_k, d_j > 0$. The reported values in parentheses represent robust standard errors. * p<0.1, ** p<0.05, *** p<0.01.

observe a decline in the share of collusive bid pairs in the pharmaceutical industry and Cartels I and II data. In Cartel III data, the relationship is the opposite. The method detects collusion in up to 53% of bid pairs in Cartel III auctions when the interval is 60 minutes. I suppose that Cartels differ in the characteristics of their members that affect the use of simultaneous bidding. In Cartel III, the number of cartel members is the lowest among subsamples, and these firms participate predominantly in auctions with five or fewer bidders, meaning that colluding firms have a high chance of manipulating auction outcomes by bidding simultaneously. In contrast, Cartels I and II members participate in auctions with up to ten bidders. Moreover, the four firms that form Cartel III are relatively similar, which may be important for maintaining an agreement and colluding in the majority of auctions they participate (Tirole, 1993).

The share of 2-bidder auctions in a subsample may also affect the upper value of the share of collusive bid pairs in K-bidder auctions. In the pharmaceutical industry subsample, the share of two-bidder auctions is the lowest among validation subsamples — 56.7%. This share is even higher in Cartel subsamples — 67.4%, 65.8%, and 70.2% (in Cartels I, II, and III, respectively). In the following subsection, I discuss the relationship between the share of collusive bid pairs and the number of bidders in auctions for the pharmaceutical industry, which does not statistically differ from the main data.

4.3.2 Relationship between Share of Collusive Bid Pairs and Number of Bidders in Auctions

This section discusses the relationship between the share of collusive bid pairs and the number of bidders in pharmaceutical industry auctions. I estimate specification (4.6) using 5 and 12-hour cutoffs and 30 and 60-minute time corridors for a fixed number of bidders $K \geq 2$ in auctions. I omit the analysis of Cartels I–III, because the subsamples contain small numbers of auctions with more than four bidders that are insufficient for estimation on sub-samples with different numbers of bidders. The results for auctions with four or fewer auctions are similar to two-bidder auctions. They are insufficient for a full evaluation of the relationship between the share of collusive pairs and the number of bidders.

Tables 1 and 2 in Appendix depict the estimation results for winner — runner-up pairs using 5 and 12-hour cutoffs, respectively. I visualize the share of collusive bid pairs depending on the number of bidders in Figure 4.2 Panels A and B. The graphs show that the relationship between the share of collusive bid pairs and the number of bidders is primarily negative — the collusion measure is the highest in two-bidder auctions, and it gradually decreases with an increase in the number of participants.

The collusion measure is also generally higher when the interval is 60 minutes than when it is 30 minutes. Figure 4.2 Panel A shows that the share of collusive bid pairs within a 30-minute interval is higher for all K-bidder auctions. In Panel B, this pattern is less pronounced — for auctions with up to four bidders, the share of collusive winner — runner-up pairs decreases, followed by slight fluctuations in the collusion measure. However, the change in the share of collusive bid pairs is marginal except for auctions with a small

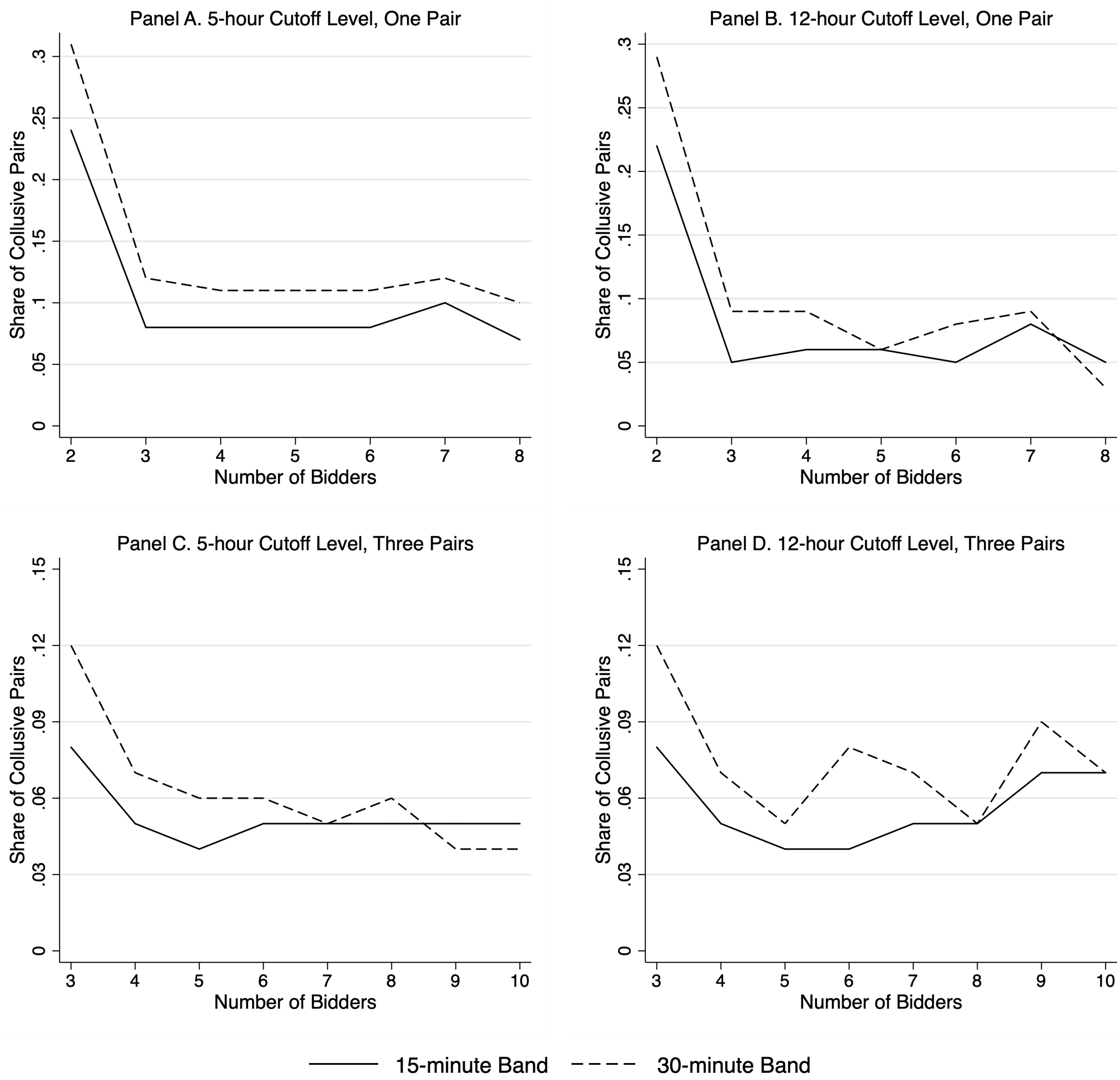


Figure 4.2: Share of Collusive Bid Pairs Depending on Number of Bidders in Pharmaceutical Industry

Note: The figure illustrates the share of collusive bid pairs depending on the number of bidders in auctions. *Panels A* and *B* shows the share of collusive winner — runner-up pairs. *Panels C* and *D* shows the share of collusive winner — runner-up and third-best bidder pairs.

number of bidders.

Furthermore, Tables 3 and 4 in Appendix depicts the results of a more general case: to winner — runner-up, and third-best bidder pairs. The share of collusive bid pairs behaves differently depending on the choice of cutoffs and band size. Figure 4.2 Panel C illustrates that the collusion measure is also generally decreasing. In contrast, in Panel D, the share of collusive pairs of winner — runner-up and third-best bids, placed within a 30-minute interval, declines in auctions with 3–6 bidders, followed by a return to almost the highest level of 7% of collusive bid pairs in auctions with ten bidders. For pairs submitted within a 60-minute interval, the collusion measure fluctuates with the number of bidders in auctions reaching the highest values in auctions with three, six, and nine bidders.

I also assess the stability of the same-day bidding estimate, which is bidding on the same day by a winner, a runner-up, or the third-best bidder. I estimate specification 4.6 adding public body fixed effects. Tables 5 and 6 in Appendix demonstrate similar results to the ones without the control variable. The estimates are notably large only for auctions with two bidders. Therefore, same-day bidding has a consistent and significant impact on simultaneous bidding, even after considering the effect of a public body.

Finally, I expand my analysis to the pairs of each bidder with four other auction participants closest in the price rank[1] for all bidders for several reasons. Firstly, all bidders may collude (not only winners, runners-up, and third-best bidders) and place bids simultaneously. Secondly, colluding bidders may submit bids simultaneously; however, their prices may not be the closest to each other in rank. Taking four closest-in-rank-price bid pairs allows me to capture more potentially colluding bidders.

I consider auctions with 15 or fewer bidders that constitute around 99.9% of all pharmaceutical industry auctions. The downward trend for the share of collusive pairs maintains for the four closest-in-rank-price bid pairs. Figure 4.3 illustrates a general decline in the share of collusive bid pairs as the number of auction participants grows. Even though the share of collusive pairs slightly fluctuates, the difference in the share between auctions with a moderate number of bidders is around 1%. The graph is based on the estimates in Table 7.

I suppose that the share of collusive bid pairs decreases with the rise in the number of auction participants, because simultaneous bidding becomes less attractive and leads to winning with a decreasing probability. In auctions with a small number of bidders, colluding firms have to take into account the applications of only a few other auction participants and have high chances to outbid them. However, as the number of bidders in auctions grows, winning becomes more complicated for colluding firms. Therefore, colluding firms submit bids simultaneously less often, and the share of collusive bid pairs falls.

In general, the relationship between the share of collusive bid pairs and the number of bidders is negative in the pharmaceutical industry. The share of collusive bid pairs gradually decreases for winner —runner-up, and third-best bidder pairs and four closest-in-price bid pairs. The average estimates of collusion are similar to the estimates in Regnum News Agency (2019). Adding public body fixed effects only marginally changes the size of the same-day bidding effect.

[1] All bidders are paired with four other participants that are closest in price rank except winners, runners-up, last, and second-last bidders. Winners are paired with runners-up and third-best bidders. Runners-up are paired with winners, third-best, and fourth-best bidders. The logic in creating pairs is the same for last and second-last bidders.

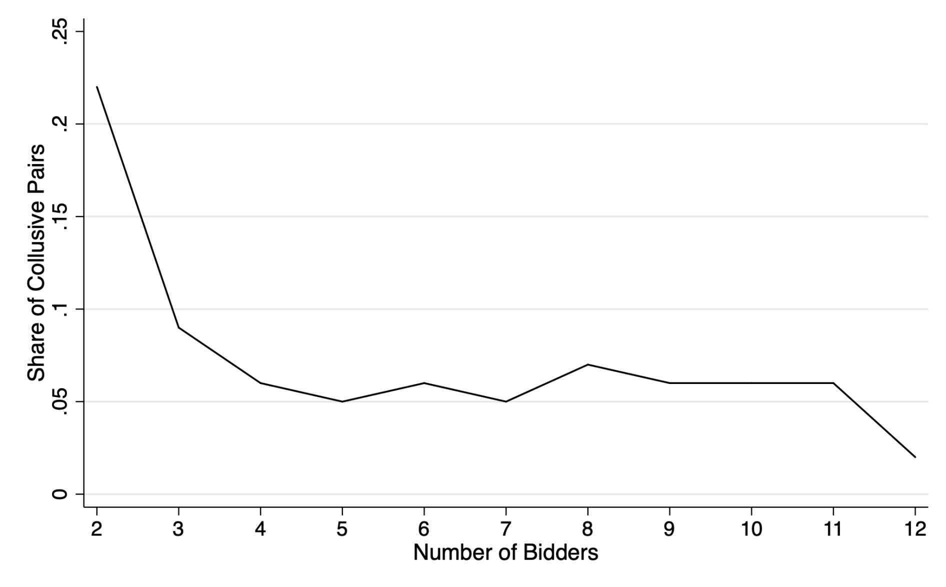


Figure 4.3: Share of Collusive Bid Pairs Depending on Number of Bidders in Main Data. Four Closest-in-Price-Rank Bid Pairs

Note: The figure illustrates the share of collusive bid pairs depending on the number of bidders in auctions. Each bidder is paired with up to four bidders closest in price rank. 15-minute band. 5-hour cutoff.

4.4 Collusion in Main Data

Now I apply the method for detecting collusive pairs of bidders to the main data for which I have no prior knowledge of colluding firms. Table 4.5 Panel A uses only two-bidder auctions, while Panel B uses all auctions with $K \geq 2$ bidders. Panel C shows a more general case: winner — runner-up, and third-best bidder pairs. Depending on the number of analyzing bid pairs and the cutoff choice, the share of collusive pairs is between 8% and 26% in K-bidder auctions. Bidding on the same day significantly predicts placing bids within a simultaneous bidding interval.

In the main data, the share of collusive bid pairs is similar to one in the pharmaceutical industry with prior knowledge of collusive firms. However, the share is smaller in K-bidder auctions. In general, the share of collusive bid pairs declines with the increase in the simultaneous bidding interval from 10 to 60 minutes: the share is more than twice higher in two-bidder auctions than in K-bidder auctions.

I suggest that in two-bidder auctions, manipulating bids may be easier and highly likely leads to winning an auction. In contrast, in K-bidder auctions, colluding firms, which submit bids simultaneously, can not fully manipulate an auction outcome, because they have to consider bids of competitive firms. Moreover, at this stage, the method detects only the share of collusive bid pairs in all winner — runner-up pairs. If collusive firms simultaneously place bids that are, at most, fourth-best, then the detecting collusion method will not consider the pairs of such bids. A similar note is relevant for winner —

Table 4.5: Collusion Measure: Main Data

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
Simultaneous Bidding	*10-minute interval*		*30-minute interval*		*60-minute interval*	
	Panel A. Two-Bidder Auctions, One Pair					
Same-Day Bids	0.204***	0.193***	0.251***	0.234***	0.271***	0.243***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Constant	0.069***	0.072***	0.117***	0.121***	0.215***	0.223***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share $\hat{\nu}$	0.22	0.21	0.28	0.27	0.35	0.31
Observations	391,441	329,968	391,441	329,968	391,441	329,968
	Panel B. K-Bidder Auctions, One Pair					
Same-Day Bids	0.076***	0.073***	0.166***	0.156***	0.206***	0.189***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.035***	0.035***	0.067***	0.069***	0.116***	0.121***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Share $\hat{\nu}$	0.08	0.08	0.18	0.17	0.23	0.22
Observations	580,618	483,425	580,618	483,425	580,618	483,425
	Panel C. K-Bidder Auctions, Three Pairs					
Same-Day Bids	0.085***	0.084***	0.183***	0.177***	0.243***	0.233***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.016***	0.016***	0.034***	0.033***	0.059***	0.059***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share $\hat{\nu}$	0.09	0.09	0.19	0.18	0.26	0.25
Observations	1180228	979,729	1180228	979,729	1180228	979,729

Notes: The table shows the estimated share of collusive bid pairs. Panel A uses winner — runner-up pairs in two-bidder auctions. Panel B uses winner — runner-up pairs in K-bidder auctions, $K \geq 2$. Panel C uses winner — runner-up and third-best bidder pairs in K-bidder auctions, $K \geq 2$. Columns (1), (3), (5) use a 5-hour cutoff. Columns (2), (4), (6) use a 12-hour cutoff. Each observation is a pair of bids. Column (3) excludes the last auction day: $d_k, d_j > 0$. The reported values in parentheses represent robust standard errors. * p<0.1, ** p<0.05, *** p<0.01.

runner-up and third-best bidder pairs in three-bidder auctions.

I also examine how the share of collusive bid pairs varies with the number of bidders in auctions. Tables 8 and 9 in Appendix depict the estimates for computing the share of collusive winner — runner-up bid pairs. Tables 10 and 11 in Appendix present the results for winner — runner-up and third-best bidder pairs in auctions with a different number of bidders. I visualize the results for 5 and 12-hour cutoffs and 15 and 30-minute bands in Figure 4.4.

The share of collusive bid pairs is the highest in two-bidder auctions and gradually declines as the number of bidders in auctions grows. The decreasing trend is smoother for winner — runner-up pairs depicted in Figure 4.4 Panels A and B than for three bidders pairs. The trend is notably more volatile for winner — runner-up and third-best bidder pairs when the number of bidders in auctions is five or larger. The decline in the share is predominantly attributable to the decrease in the same-day bidding estimate, the difference in the probabilities of placing bids within an interval on the same and different days.

For winner — runner-up and third-best bidder pairs, same-day bidding significantly

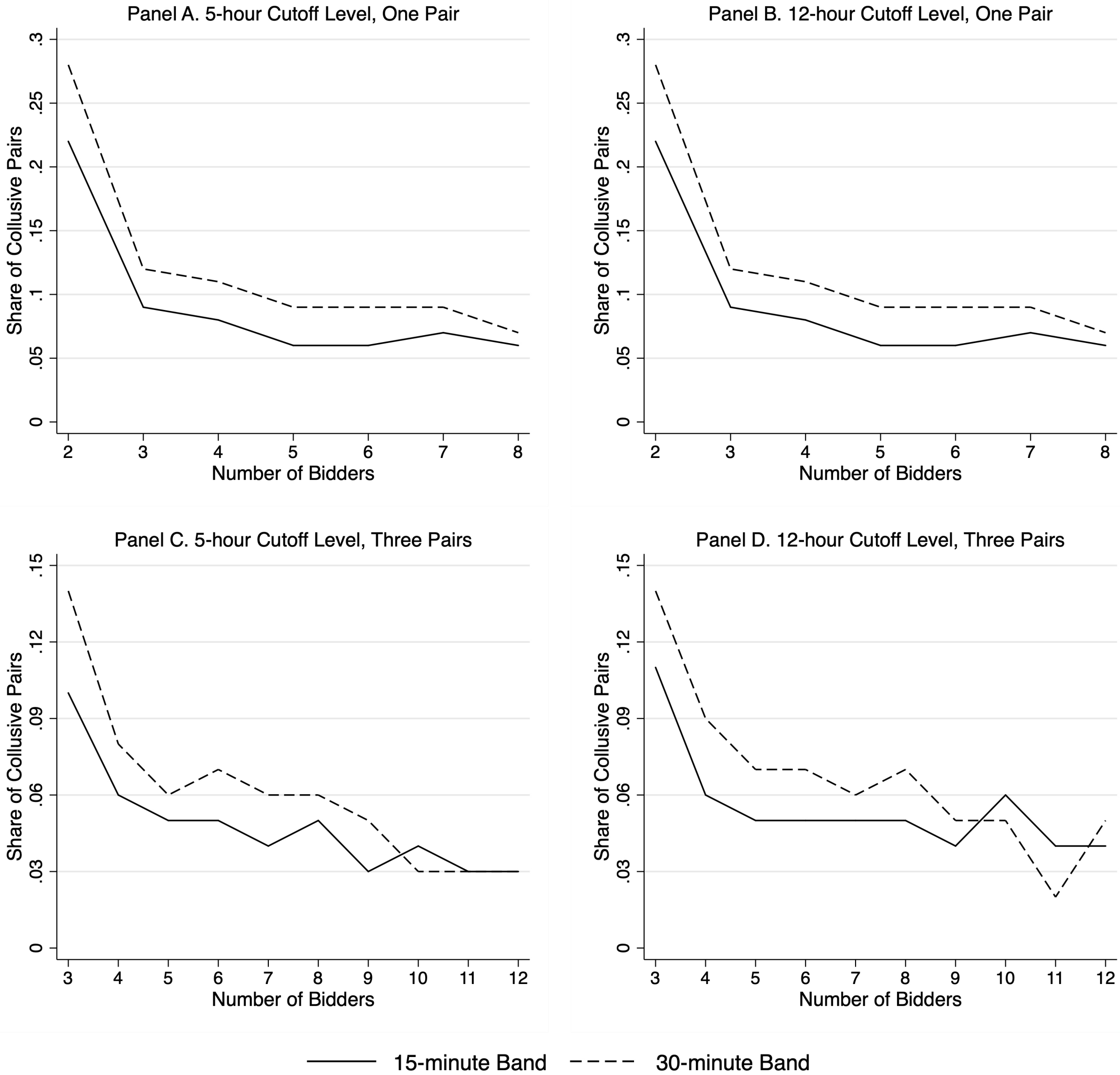


Figure 4.4: Share of Collusive Bid Pairs Depending on Number of Bidders in Main Data
Note: The figure illustrates the share of collusive bid pairs depending on the number of bidders in auctions. *Panels A* and *B* shows the share of collusive winner — runner-up pairs. *Panels C* and *D* shows the share of collusive winner — runner-up and third-best bidder pairs.

affects placing bids within a simultaneous bidding interval for auctions with ten or fewer bidders for the cases without control variables and with public body and industry fixed effects (Tables 12 and 13 in Appendix). The estimates differ minimally between these two cases. Therefore, same-day bidding has an independent of industry and public body impact on the simultaneous bidding in auctions with medium and large numbers of bidders.

Since the relationship between the share of collusive pairs and the number of bidders in auctions is not stably negative, I take a further step similar to the one in the validation section and analyze consecutive bid pairs[2] and four closest-in-price-rank bid pairs. Figure

[2]For instance, winner — runner-up pairs, runner-up — third bidder pairs, etc. In K-bidder auctions, the number of consecutive bid pairs is $K-1$.

4.5 demonstrates that the share of collusive pairs of four closest-in-price-rank bidders declines with an increase in the number of bidders until the number o bidders is too large, similar to two- and three-bidder pairs. Table 15 in Appendix shows the estimation results for every number of bidders ≤ 20.

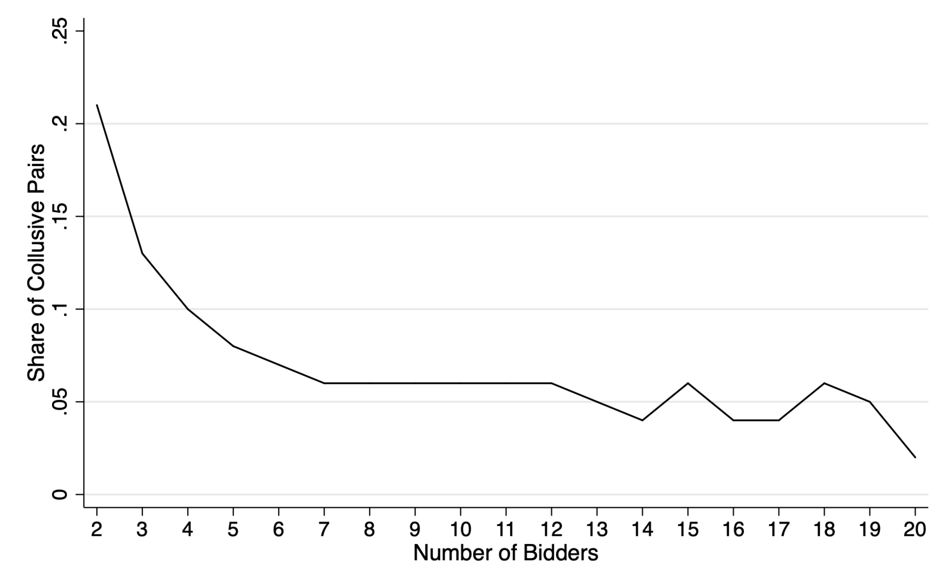


Figure 4.5: Share of Collusive Pairs of Four Closest-in-Price-Rank Bidders Depending on Number of Bidders in Main Data
Note: The figure illustrates the share of collusive bid pairs of four closest-in-price-rank bidders depending on the number of bidders in auctions. 15-minute band. 5-hour cutoff.

The downward trend is volatile when the number of bidders exceeds 14. I suspect that auctions with more than 14 bidders may differ from other auctions in individual characteristics of contracts. Moreover, the data contains a few auctions with more than 14 bidders (less than a hundred for each $K \geq 14$) that may affect the estimation results. I also measure the share of collusive pairs of four closest-in-price-rank bidders within a 30-minute interval in K-bidder auctions with $K \leq 20$, such auctions constitute 99.99% of the data set. The estimated parameter is around 13% (Table 15 in Appendix), which aligns with the estimates for winner —runner-up and third-best bidder pairs. For consecutive bid pairs, the results are similar. Figure 4 in Appendix illustrates the estimates for K-bidder auctions, $K \in [2, 20]$, presented in Table 14 in Appendix.

I suppose that firms are more likely to collude and place bids simultaneously in auctions with a few bidders, because the probability of manipulating auction outcomes is higher. When there are many bidders in auctions, collusive firms have to outbid many competitive bids, which becomes more problematic as the number of auction participants grows. Therefore, when the number of cartel members does not grow with the number of bidders, gains from simultaneous bidding decline with an increase in the number of bidders, which may explain the fall in the share of collusive pairs. Collusion may probably take other forms if it is present in auctions with a large number of bidders. However, such analysis is out of the scope of this study.

5. Implications for Prices

This section aims to understand the damages from simultaneous bidding. I visualize the potential impact of simultaneous bidding by winners and runners-up and describe the estimation that quantifies the effect of simultaneous bidding on final contract prices. Then I apply the methods to the main data and discuss the results.

5.1 Estimation Approach

In Russian first-price procurement auctions, the lowest bid wins. When a winner and a runner-up collude, they can reduce the difference between bids to manipulate an auction outcome. Then, the lowest bidder wins an auction with a higher price than in a competitive environment. The difference between winner and runner-up bids is marginal. Since I am interested in the impact of simultaneous bidding on final contract prices, which is winning bids, I focus only on winner — runner-up pairs.

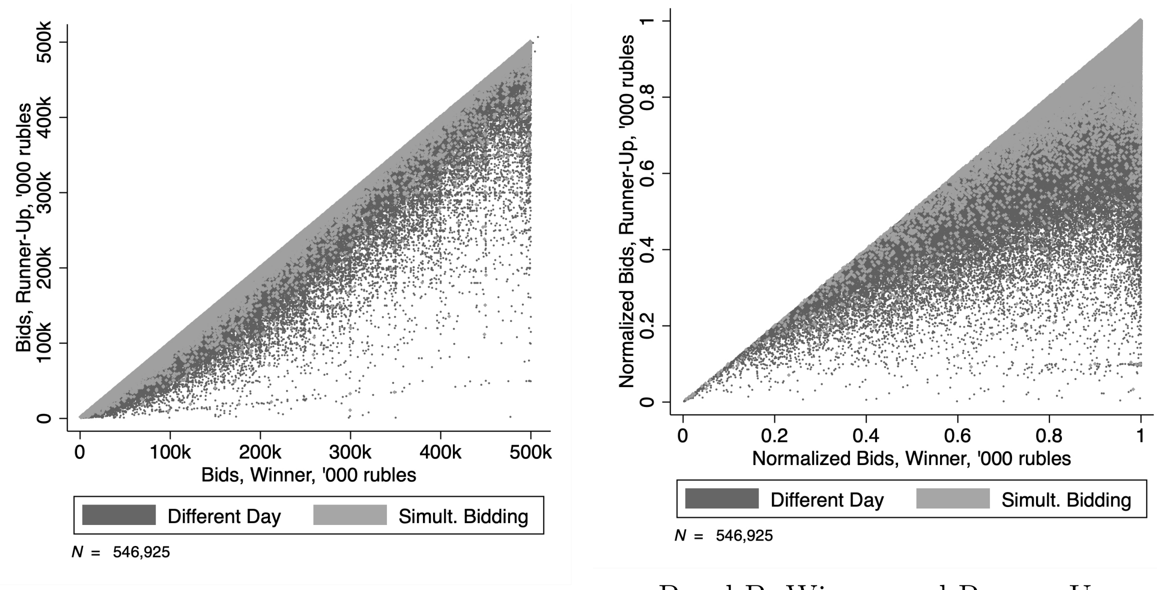
The design of an estimation approach begins with Figure 5.1 Panel A, which shows the absolute bids of winners and runners-up in all auctions in the main data. It is apparent from the scatter plot that the difference between winner and runner-up bids is higher when bids are submitted on different days. The difference between bids in a pair is notably smaller when bids are submitted simultaneously. Figure 5.1 shows a concentration of bids placed simultaneously close to the diagonal (y = x).

At the same time, the difference between bids shrinks, and final prices go up when collusion is present. I illustrate this observation by Figure 5.1 Panel A. The graph demonstrates that bid pairs submitted within a simultaneous bidding interval are closer to each other than the pairs of bids placed on different days. To show that final prices are higher under collusion, I first divide bids by the reserve price to normalize them as in Kawai and Nakabayashi (2022). Figure 5.1 Panel B demonstrates that bid pairs become close to the reserve price when submitted close to each other. Therefore, bids and final prices are higher in auctions with collusion.

To measure the impact of collusion on prices demonstrated in Figure 5.1, I run the following regressions for prices:

$$y_{kj} = \delta_0 + \delta_1 \cdot 1\{d_k = d_j\} + \delta_2 \cdot 1\{|h_k - h_j| \le \epsilon\} + \delta_3 \cdot 1\{|h_k - h_j| \le \epsilon\} \cdot 1\{d_k = d_j\} + \xi_{kj}, \quad (5.1)$$

where an outcome y_{akj} is a winning bid k in kj bid pair (k and j refer to winner and runner-up bids, respectively) and the difference between bids of winners and runners-up:



Panel A. Winner and Runner-Up Bids

Panel B. Winner and Runner-Up Normalized Bids

Figure 5.1: Prices of Winner and Runner-Up: All Deadlines

Note: The figure shows winner — runner-up bid pairs. Panel A shows the bid pairs. Panel B shows the normalized bid pairs. Auctions with all deadlines. Normalization of bids in made by dividing the bids by the reserve price for each auction.

$b^i_j - b^i_k$ for each auction i. I include bidding on the same day and within an ϵ-minute band to control for a convenient time for submitting bids during a day (for example, before or after lunch). δ_3 accounts for the impact of simultaneous bidding for bids placed on the same day and close to each other.

The estimating parameter of interest is $\delta = (\delta_1 + \delta_2 + \delta_3)/\delta_0$, corresponding to the increase in prices (decrease in runner-up and winner bid difference) with simultaneous bidding. The constant term represents an average level of an outcome y_{akj} when the right-hand side variables are zero, meaning that winner and runner-up bids are placed at different time of the day and on different days. Therefore, δ measures the deviation of an outcome from a baseline caused by simultaneous bidding and the impact of simultaneous bidding on the final price of contracts.

5.2 Impact of Collusion on Prices and Bid Differences in Main Data

I begin with applying the designed approach to two-bidder auctions that are more likely to be affected by collusion, according to the results of this study. Table 5.1 depicts the impact of simultaneous bidding within a 15-minute band on normalized prices, considering that a cutoff is five hours before the deadline. In this section, restrict the analysis to normalized bids. However, I also analyzed absolute prices and their logarithms. I present the results for these cases in Appendix: Tables 17 and 18 for two-bidder auctions and Tables 20 and 21 for K-bidder auctions.

Figure 5.1 Panel A shows that simultaneous bidding increases normalized winning bids by 6.6% in two-bidder auctions. The choice of a band changes the effect size of simultaneous bidding on prices by less than 0.6% according to Table 16 in Appendix. The estimates for K-bidder auctions in Table 5.1 Panel B are even higher — collusion increases winning bids by 10.1%. The impact of collusion on prices differs minimally with the change in band size (Table 19 in Appendix).

Table 5.1: Normalized Prices: Winner and Runner-Up Bids, Two- and K-Bidder Auctions, 30-minute Interval

Dependent variable:	(1) Winning Bid	(2) Bid Difference
	Panel A. Two-Bidder Auctions	
Same-Day Bids	0.02***	-0.01***
	(0.00)	(0.00)
30-min Interval	-0.01***	0.00**
	(0.00)	(0.00)
Same-Day Bids × 30-min Interval	0.05***	-0.02***
	(0.00)	(0.00)
Constant	0.88***	0.05***
	(0.00)	(0.00)
Price Change $\hat{\delta}$ (%)	6.55%	-39.55%
R^2	0.020	0.008
Observations	389,923	389,923
	Panel B. K-Bidder Auctions	
Same-Day Bids	0.018***	-0.005***
	(0.001)	(0.000)
30-min Interval	0.001	0.001**
	(0.001)	(0.001)
Same-Day Bids × 30-min Interval	0.064***	-0.016***
	(0.001)	(0.001)
Constant	0.821***	0.054***
	(0.000)	(0.000)
Price Change $\hat{\delta}$ (%)	10.14%	-35.67%
R^2	0.022	0.006
Observations	578,543	578,543

Notes: The table shows the estimated change in prices in % caused by collusion in two- and K-bidder auctions. Winning Bid is the bid of a winner. Bid Difference is the difference between winner and runner-up bids. The cutoff is 5 hours before the auction ends. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.
* p<0.1, ** p<0.05, *** p<0.01.

Similar regression specification also allows documenting that simultaneous bidding is associated with smaller bid differences — the difference between runner-up and winner bids. A winner aims to close the gap between their bid and the next lowest bid in auctions with collusive bidding patterns. Then the winner obtains a contract at a higher price than a competitive one. Winner — runner-up bid differences shrink by up to 42% according to Tables 16 and 19 in Appendix. The results are similar for different band choices in two and K-bidder auctions.

Since auctions are heterogeneous, I also control for industry, public body, and region in the regressions for winning bids, which are also final contract prices I am interested in, and winner — runner-up bid differences. Table 22 shows that the results do not change considerably — collusion increases prices by $9.9-11.6\%$. The effect of collusion on bid differences, on the contrary, varies notably with the inclusion of fixed effects (Table 23 in Appendix). Controlling for public body, region, and industry fixed effects reduces the bid differences from 35.7% to 25.2%.

I take a further step and analyze the impact of collusion on prices and bid differences at an industry level. I focus on the 24 largest industries where the government allocates small contracts through auctions. The difference in runner-up and winner bids in these industries varies considerably: the lowest bid differences change of -14.3% is in health services, and the highest is -56.3% in inorganic substances supply. The pharmaceutical industry is also the one with one of the largest effects of collusion on bid differences, which is -51.4%. Table 24 in Appendix depicts the results for other industries.

Overall, bid differences decrease considerably in auctions with colluding patterns, while prices increase by up to 10.9% when controlling for industry, region, and public body fixed effects. If I interpret these estimates as causal, eliminating collusion would have saved 5.4 billion rubles or 0.16 billion U.S. dollars over 6.5 years, considering that the total amount of affected contracts was 49.6 billion rubles or 1.49 billion U.S. dollars[1]. However, the amount that might have been saved, may be less due to additional factors that affect auction outcomes but are outside of this study analysis.

6. Discussion

In this section, I discuss the results of the previous sections, their place in the existing literature, and the economic intuition behind my findings. Firstly, I focus on the relationship between the share of collusive pairs and the number of bidders in auctions. Secondly, I discuss the impact of collusion on final contract prices in auctions. Finally, I discuss the limitations of the study and future extensions of the method for detecting collusion based on simultaneous bidding.

[1] I took average exchange rates for each year that I computed using the information from the Bank of Russia (2023).

6.1 Collusion and Number of Bidders

The evidence of the relationship between the collusion measure and the number of auction participants may be controversial and depend on auction design and bidder behavioral preferences (Levenstein and Suslow, 2006; Loertscher et al., 2015). This study shows a negative relationship between the share of collusive pairs and the number of bidders in Russian first-price sealed-bid procurement auctions. This result is consistent with the conventional wisdom described by Tirole (1993) that cartels are considerably more likely to arise in markets where a few firms operate, because communications, coordination of actions, reaching an agreement, and monitoring its fulfillment are easier to manage in markets with a small number of firms.

Tirole (1993) also note that firms should be relatively symmetric, and their number should be no more than three or four for more likely cartel formation. The symmetry of firms reduces the risk of gaining a considerable advantage by one or several large firms. Therefore, reaching a mutually beneficial agreement becomes easier when firms are symmetric. My findings support this idea: the share of collusive pairs is the highest (up to 50%) in Cartel III, which includes the lowest number of relatively symmetric pharmaceutical companies among validation subsamples. In contrast, the share is smaller in the pharmaceutical industry and other cartel subsamples which contain asymmetric firms. Thus, symmetric films are more likely to form cartels.

Garrod and Olczak (2018), on the contrary, claims that the probability of forming a cartel is lower in markets with a few symmetric firms than in ones with a large number of symmetric firms. The authors suggest that tacit collusion may be more appealing in such markets. My findings contradict this result showing that explicit agreements between a few competitors may be easier to maintain, similar to Ivaldi et al. (2003), because the share of collusive pairs is higher in auctions with a small number of bidders. The result holds for consecutive bid pairs and pairs of each bidder with four other participants closest in price rank.

6.2 Impact of Collusion on Prices

In this section, I compare my findings on the impact of collusion in the form of simultaneous bidding on contract prices to the results of other papers. The literature that estimates the damages of collusion (Porter and Zona, 1997; Asker, 2010; Schurter, 2017; Kawai and Nakabayashi, 2022) documents that collusive behavior increases prices in auctions. Colluding firms inflate contract prices to obtain higher profits, increasing government spending on public procurement.

This study shows that collusion leads to a 10.9% increase in winning bids that are also final contract prices. The estimated price change is slightly smaller than Kawai and

Nakabayashi (2022) obtained in first-price sealed-bid auctions with rebidding in Japan in $2003-2006$. The authors found that collusion increased the government costs on construction contracts by 8.4%. The estimated damages found by Porter and Zona (1997) are even smaller than in this study and in Kawai and Nakabayashi (2022). Porter and Zona (1997) documents that the collusive behavior of bidding ring members leads to a rise in prices by 6.5% in Ohio school milk auctions between 1980 and 1990.

The effect of collusion on prices measured in this study is considerably higher than the estimated damages of collusion in Asker (2010) and Schurter (2017). In the former paper, collusion between firms lowered the seller average revenue by 4% in the U.S. knockout auctions in the 1990s, while, in the latter paper, collusion between the two most active firms reduced expected revenue by around 1.2% in timber first-price auctions. However, the total effect of collusion on regional prices of timber was smaller.

Overall, the estimated collusion damages between firms in this study are higher than in the literature. However, the results are only relatively comparable, because the papers documented different forms of collusion in auctions of different formats.

6.3 Future Extensions and Limitations

This study develops a parametric approach to estimating the share of collusive bid pairs in auctions that requires an exogenous choice of a band and a cutoff. Even though the choice is data-driven, it may influence the estimation results. The results show that the share of collusive pairs varies with the size of the simultaneous bidding corridor, partly because the number of bid pairs submitted within the interval varies. Therefore, designing a non-parametric estimation approach that would implicitly choose a band can be one of the future extensions of this paper.

Furthermore, the analyzing data contains auctions that are heterogeneous in types of goods or services, industries, public bodies who organize actions, and probably other characteristics. I partly account for these differences by controlling for public body, region, and industry fixed effects. However, this study do not examine heterogeneity of auctions in details. Thus, further analysis of heterogeneity would be valuable for a deeper understanding of the bidding behavior of firms.

Conclusion

This study documents collusion between firms in Russian first-price sealed-bid procurement auctions using a micro-level data set collected by Andreyanov et al. (2017) from the Russian government procurement server. The data contain information on the applications of all bidders, including unique information on the timestamps of all bids. To my knowledge, this study is one of the first to use timestamps to develop a method for detecting collusion between firms that place bids simultaneously or close to each other in time.

In the data, an excessive share of bids was submitted simultaneously or within a small time interval. I call this pattern *simultaneous bidding* and use it to design a method that detects the share of collusive bid pairs in auctions. To evaluate the performance of the method, I firstly apply it to four validation subsamples: the pharmaceutical industry and three cartels formed by pharmaceutical firms, similar to Conley and Decarolis (2016). I form cartel subsamples using prior information on colluding firms based on the Decisions of the Russian Federal Anti-Monopoly Service in the pharmaceutical industry.

The method performs well and detects collusion in $7-25\%$ of winner — runner-up pairs in K-bidder auctions in the pharmaceutical industry validation subsample. In Cartels I-III data, the estimates are slightly higher because the data contain a considerably smaller number of observations and a higher share of two-bidder auctions, in which firms use simultaneous bidding the most. In the main data, the share of collusive winner — runner-up bid pairs in K-bidder auctions is similar and varies between 8% and 23%.

The share of collusive pairs is decreasing with the number of bidders in all auctions, similar to the findings of Ivaldi et al. (2003) and Klemperer (2003). This result is stable for winner — runner-up and third bidder pairs, consecutive bidder pairs, and four closest-in-price-rank bid pairs when the number of bidders is not too large. I suggest that bidders collude using simultaneous bidding more often in auctions with few participants. In these auctions, concluding firms are more likely to win, because they have to consider only a few other bids. Otherwise, simultaneous bidding leads to winning considerably less often and becomes less attractive for colluding firms.

I also measure the impact of simultaneous bidding on final contract prices (winning bids) and the difference between runner-up and winner bids — bid differences that colluding firms exploit to keep prices high. Collusion leads to a 10.9% increase in prices and makes bids closer to each other by up to 50%, when I control for heterogeneity by industry, public body, and region fixed effects. The total amount of contracts that were affected by collusion is 1.49 billion U.S. dollars in $2011-2017$. If I interpret this estimate as causal, eliminating collusion in simultaneous bidding form in procurement auctions would have saved around 0.16 billion U.S. dollars over 6.5 years. However, the estimated damages may be lower due to the effect of other factors that are out of the scope of this study.

This study shows that information on the timing of bids can help to detect collusion between firms in auctions. Collecting bid timestamps and applying methods based on them should become a part of auction monitoring for violating anti-monopoly laws. Then collusion between firms would become even more complicated and encourage a more competitive environment. Therefore, government losses caused by collusion would also decline.

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Appendices

1 Figures

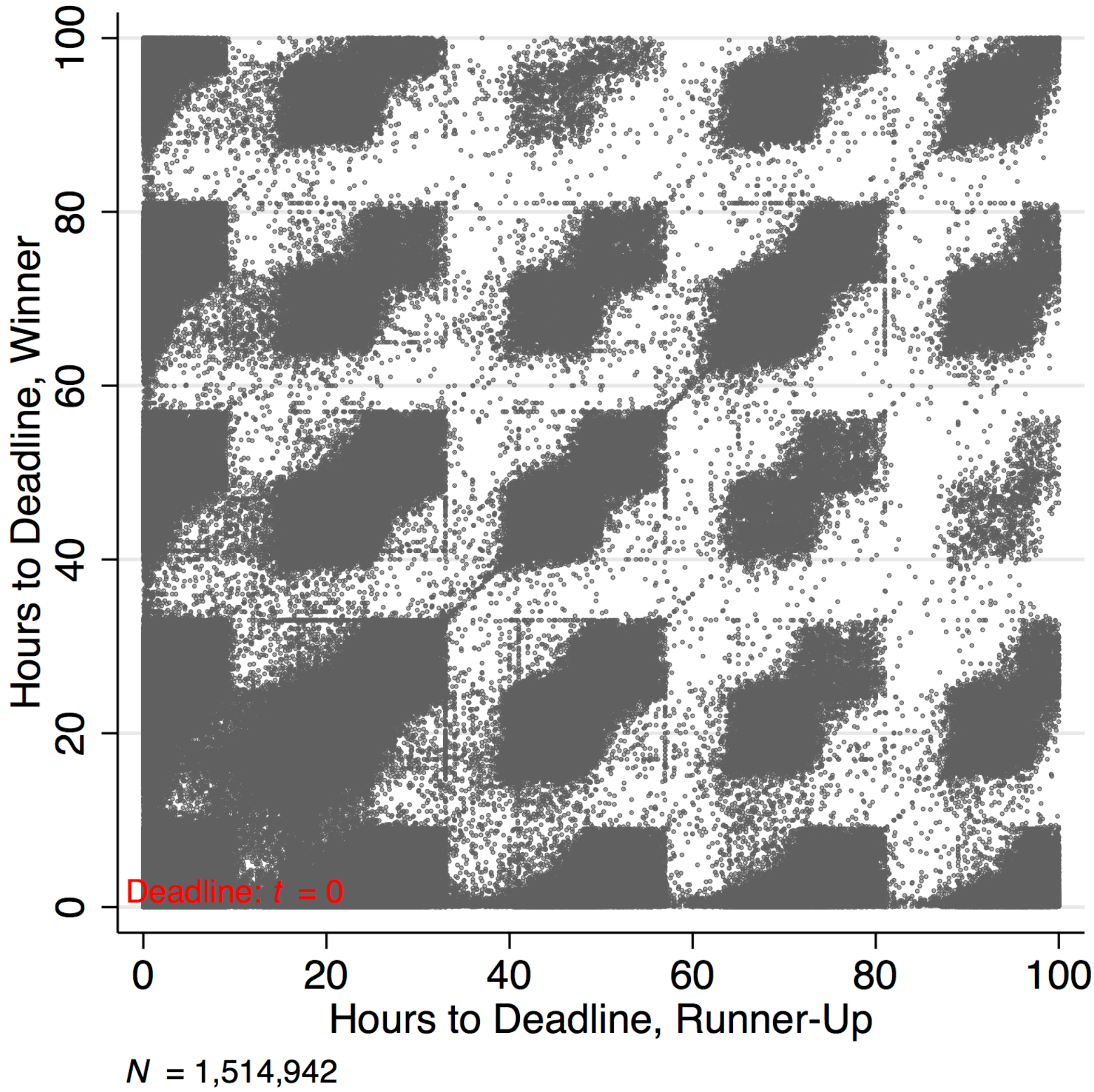

Figure 1: Winners and Runners-Up Bidding Time, Auctions All Deadlines
Note: The figure shows the relationship between winners and runners-up bidding time in hours to the deadline. Auctions with all deadlines.

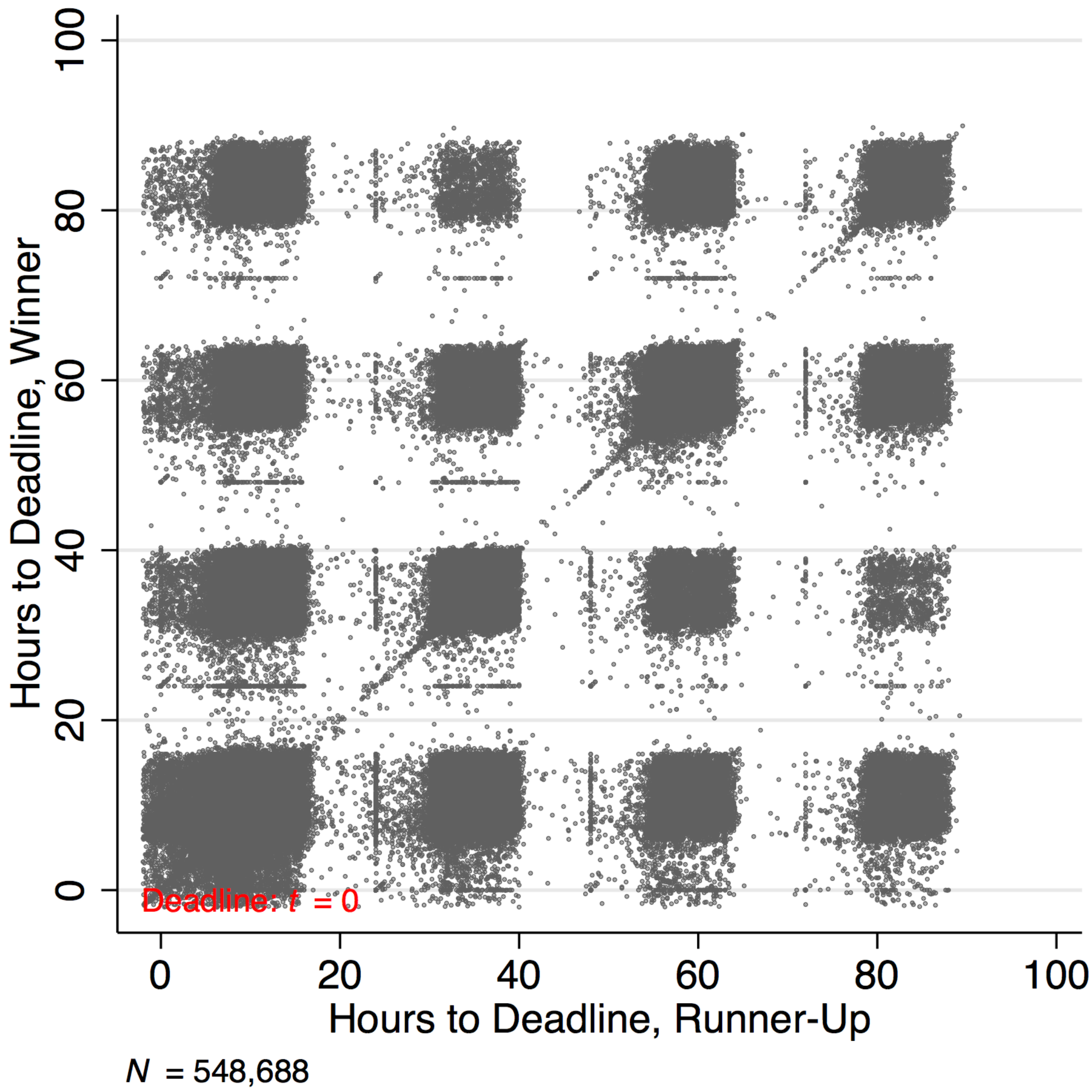

Figure 2: Winners and Runners-Up Normalized Bidding Time, Auctions All Deadlines
Note: The figure shows the relationship between winners and runners-up bidding time in hours to the deadline. All points are normalized by the time of the deadline.

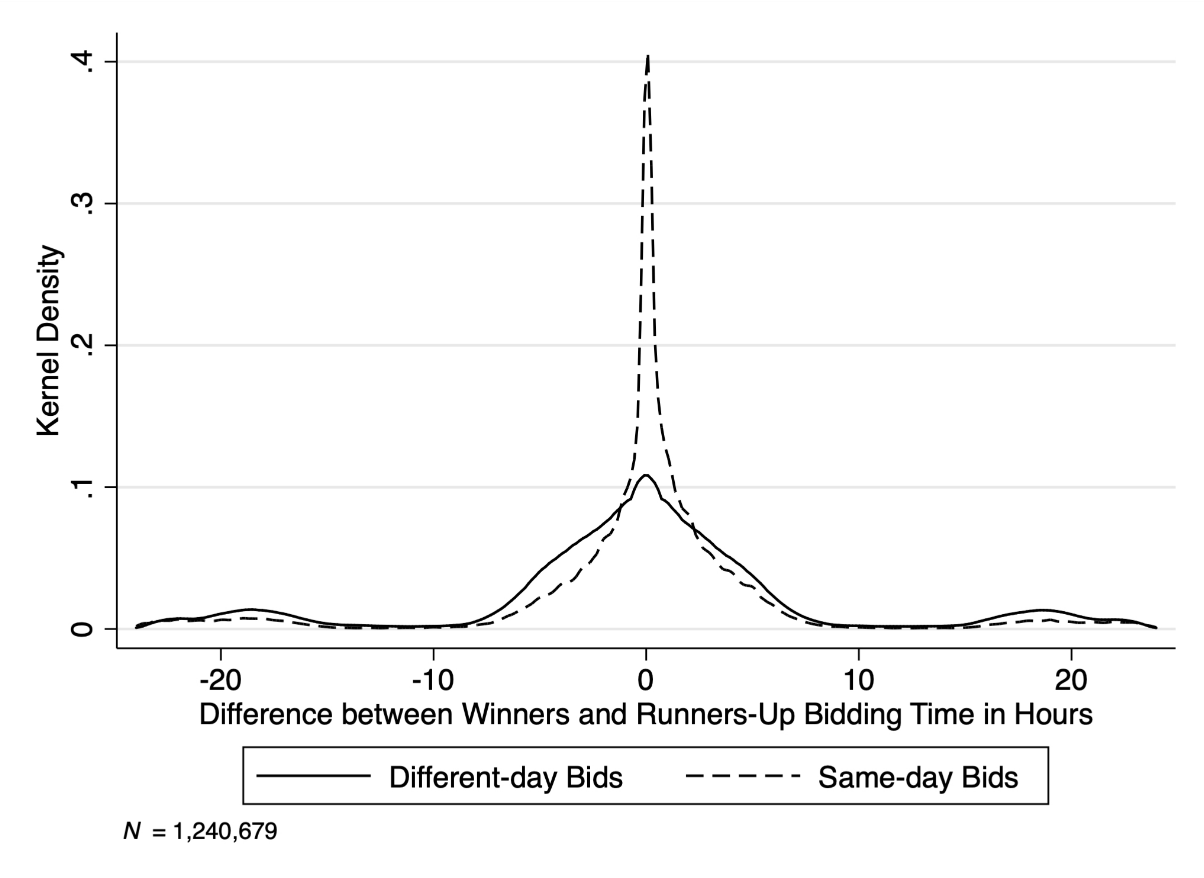

Figure 3: Difference between Bidding Time in Hours of Winners, Runners-Up, and Third-Best Bidders

Note: The figure shows the distribution of the difference in hours of bids submitted by winners, runners-up, and third-best bidders on the same and different days.

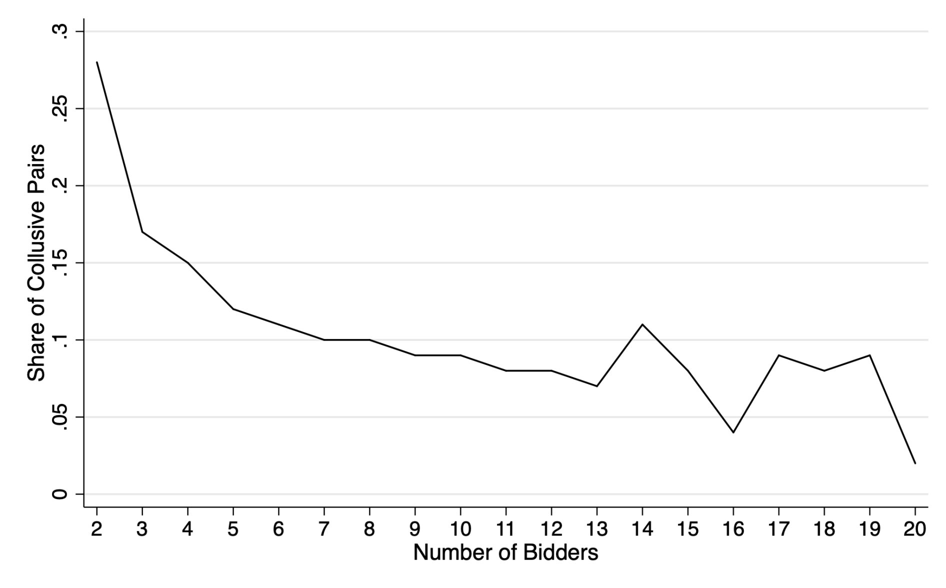

Figure 4: Share of Collusive Consecutive Bid Pairs Depending on Number of Bidders in Main Data

Note: The figure illustrates the share of collusive consecutive bid pairs depending on the number of bidders in auctions. In K-bidder auctions, the number of consecutive bis pairs is $K-1$. 15-minute band. 5-hour cutoff.

2 Share of Collusive Pairs: Sample Analog

This proof focuses only on two-bidder auctions or, similarly, on one pair of bids. However, this proof is relevant for K-bidder auctions and may be generalized to N bid pairs. Each auction has index i. I firstly define the difference in bidding time in hours between two bidders as $w^i = |h^i_k - h^i_j|$ and the difference in bidding days as $d^i = |d^i_k - d^i_j|$. The former is a continuous variable, while the latter is discrete.

The scope of collusion is defined as ν and is obtained from the regression of $1\{w^i \leq \epsilon\}$ on $1\{d^i = 0\}$, assuming a bandwidth ϵ being fixed and close in magnitude to 0. Then, the slope estimate is equal to

$$\hat{\beta}_1 = \frac{\frac{1}{N_i}\sum_i 1\{w^i \leq \epsilon\} \cdot (1\{d^i = 0\} - \overline{1\{d^i = 0\}})}{\frac{1}{N_i}\sum_i 1\{d^i = 0\} \cdot (1\{d^i = 0\} - \overline{1\{d^i = 0\}})},$$

which is the sample equivalent of

$$\frac{\mathbb{P}\Big[w^i \leq \epsilon \cap d^i = 0\Big] - \mathbb{P}\Big[w^i \leq \epsilon\Big] \cdot \mathbb{P}\Big[d^i = 0\Big]}{\mathbb{P}\Big[d^i = 0\Big] \cdot \Big(1 - \mathbb{P}\Big[d^i = 0\Big]\Big)}$$

Applying Bayes rule to the equation above, the ratio can be modified to the following:

$$\frac{\mathbb{P}\Big[w^i \leq \epsilon | d^i = 0\Big]\mathbb{P}\Big[d^i = 0\Big] - \mathbb{P}\Big[w^i \leq \epsilon\Big] \cdot \mathbb{P}\Big[d^i = 0\Big]}{\mathbb{P}\Big[d^i = 0\Big] \cdot \Big(1 - \mathbb{P}\Big[d^i = 0\Big]\Big)} =$$

$$\frac{\mathbb{P}\Big[w^i \leq \epsilon | d^i = 0\Big] - \mathbb{P}\Big[w^i \leq \epsilon\Big]}{1 - \mathbb{P}\Big[d^i = 0\Big]} =$$

$$\frac{\mathbb{P}\Big[w^i \leq \epsilon | d^i = 0\Big] - \Big(\mathbb{P}\Big[w^i \leq \epsilon | d^i = 0\Big] \cdot \mathbb{P}\Big[d^i = 0\Big] + \mathbb{P}\Big[w^i \leq \epsilon | d^i \neq 0\Big] \cdot \mathbb{P}\Big[d^i \neq 0\Big]\Big)}{1 - \mathbb{P}\Big[d^i = 0\Big]} =$$

$$\mathbb{P}\Big[w^i \leq \epsilon | d^i = 0\Big] - \mathbb{P}\Big[w^i \leq \epsilon | d^i \neq 0\Big]$$

By Slutsky's theorem, the estimate β_1 converges to

$$\hat{\beta}_1 \xrightarrow{p} \mathbb{P}\Big[w^i \leq \epsilon | d^i = 0\Big] - \mathbb{P}\Big[w^i \leq \epsilon | d^i \neq 0\Big]$$

The constant estimate in the regression of $1\{w^i \leq \epsilon\}$ on $1\{d^i = 0\}$ is the following:

$$\hat{\beta}_0 = \frac{1}{N_i}\sum_i 1\{w^i \leq \epsilon\} - \hat{\beta}_1 \cdot \frac{1}{N_i}\sum_i 1\{d^i = 0\}.$$

The constant term is the sample analog of the following:

$$\mathbb{P}\Big[w^i \leq \epsilon\Big] - \Big(\mathbb{P}\Big[w^i \leq \epsilon | d^i = 0\Big] - \mathbb{P}\Big[w^i \leq \epsilon | d^i \neq 0\Big]\Big) \cdot \mathbb{P}\Big[d^i = 0\Big].$$

Using Bayes rule again, the equation can be rearranged to the following:

$$\Big(\mathbb{P}\Big[w^i \leq \epsilon | d^i = 0\Big] \cdot \mathbb{P}\Big[d^i = 0\Big] + \mathbb{P}\Big[w^i \leq \epsilon | d^i \neq 0\Big] \cdot \mathbb{P}\Big[d^i \neq 0\Big]\Big) -$$

$$\Big(\mathbb{P}\Big[w^i \leq \epsilon | d^i = 0\Big] - \mathbb{P}\Big[w^i \leq \epsilon | d^i \neq 0\Big]\Big) \cdot \mathbb{P}\Big[d^i = 0\Big] =$$

$$\mathbb{P}\Big[w^i \leq \epsilon | d^i \neq 0\Big] \cdot \Big(\mathbb{P}\Big[d^i = 0\Big] + \mathbb{P}\Big[d^i \neq 0\Big]\Big) =$$

$$\mathbb{P}\Big[w^i \leq \epsilon | d^i \neq 0\Big]$$

Again by Slutsky's theorem, the estimate β_0 converges to

$$\hat{\beta}_0 \xrightarrow{p} \mathbb{P}\Big[w^i \leq \epsilon | d^i \neq 0\Big].$$

Therefore, by Slutsky's theorem, the measure of collusion is

$$\hat{\nu} = \frac{\hat{\beta}_1}{1 - \hat{\beta}_0}.$$

3 Regression Results

Table 1: Collusion Measure: Varying Number of Bidders in Pharmaceutical Industry, Winner — Runner-Up Pairs, 5-hour Cutoff

Dependent variable: Simultaneous Bidding	(1) 2 Bidders	(2) 3 Bidders	(3) 4 Bidders	(4) 5 Bidders	(5) 6 Bidders	(6) 7 Bidders	(7) 8 Bidders
				Panel A: 30-minute Interval			
Same-Day Bids	0.221***	0.070***	0.074***	0.072***	0.072***	0.093***	0.070**
	(0.004)	(0.006)	(0.008)	(0.011)	(0.017)	(0.027)	(0.035)
Constant	0.078***	0.066***	0.054***	0.047***	0.047***	0.049***	0.049**
	(0.002)	(0.004)	(0.005)	(0.007)	(0.009)	(0.015)	(0.021)
Share $\hat{\nu}$	0.24	0.08	0.08	0.08	0.08	0.10	0.07
Observations	36,767	9,966	4,586	2,242	1,030	460	238
				Panel B: 60-minute Interval			
Same-Day Bids	0.276***	0.111***	0.102***	0.101***	0.103***	0.112***	0.088**
	(0.004)	(0.007)	(0.010)	(0.015)	(0.022)	(0.032)	(0.045)
Constant	0.122***	0.112***	0.094***	0.093***	0.096***	0.092***	0.097***
	(0.003)	(0.005)	(0.006)	(0.009)	(0.013)	(0.020)	(0.029)
Share $\hat{\nu}$	0.31	0.12	0.11	0.11	0.11	0.12	0.10
Observations	36,767	9,966	4,586	2,242	1,030	460	238

Notes: The table shows the estimated share of collusive bid pairs for auctions in which different numbers of bidders participate. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.
* p<0.1, ** p<0.05, *** p<0.01.

Table 2: Collusion Measure: Varying Number of Bidders in Pharmaceutical Industry, Winner — Runner-Up Pairs, 12-hour Cutoff

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Simultaneous Bidding	2 Bidders	3 Bidders	4 Bidders	5 Bidders	6 Bidders	7 Bidders	8 Bidders
				Panel A: 30-minute Interval			
Same-Day Bids	0.202***	0.051***	0.052***	0.054***	0.049**	0.076**	0.046
	(0.004)	(0.007)	(0.010)	(0.013)	(0.021)	(0.032)	(0.041)
Constant	0.085***	0.074***	0.060***	0.049***	0.065***	0.054**	0.053*
	(0.003)	(0.005)	(0.007)	(0.009)	(0.014)	(0.021)	(0.030)
Share $\hat{\nu}$	0.22	0.05	0.06	0.06	0.05	0.08	0.05
Observations	29,803	7,612	3,398	1,613	732	320	169
				Panel B: 60-minute Interval			
Same-Day Bids	0.250***	0.082***	0.078***	0.053***	0.068**	0.080**	0.029
	(0.005)	(0.008)	(0.012)	(0.017)	(0.027)	(0.040)	(0.055)
Constant	0.131***	0.124***	0.102***	0.107***	0.123***	0.107***	0.123***
	(0.003)	(0.006)	(0.008)	(0.013)	(0.019)	(0.029)	(0.044)
Share $\hat{\nu}$	0.29	0.09	0.09	0.06	0.08	0.09	0.03
Observations	29,803	7,612	3,398	1,613	732	320	169

Notes: The table shows the estimated share of collusive bid pairs for auctions in which different numbers of bidders participate. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.

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

Table 3: Collusion Measure: Varying Number of Bidders in Pharmaceutical Industry Auctions, Winner — Runner-Up and Third-Best Bidder Pairs, 5-hour Cutoff

Dependent variable: Simultaneous Bidding	(1) 3 Bidders	(2) 4 Bidders	(3) 5 Bidders	(4) 6 Bidders	(5) 7 Bidders	(6) 8 Bidders	(7) 9 Bidders	(8) 10 Bidders
Panel A: 30-minute Interval								
Same-Day Bids	0.074***	0.045***	0.041***	0.041***	0.044***	0.045**	0.046	0.040
	(0.003)	(0.005)	(0.006)	(0.009)	(0.014)	(0.020)	(0.031)	(0.047)
Constant	0.066***	0.060***	0.055***	0.049***	0.056***	0.055***	0.057***	0.060**
	(0.002)	(0.003)	(0.004)	(0.005)	(0.009)	(0.012)	(0.018)	(0.026)
Share $\hat{\nu}$	0.08	0.05	0.04	0.04	0.05	0.05	0.05	0.04
Observations	29,898	13,758	6,726	3,090	1,380	714	321	144
Panel B: 60-minute Interval								
Same-Day Bids	0.104***	0.060***	0.056***	0.058***	0.045**	0.050**	0.039	0.033
	(0.004)	(0.006)	(0.008)	(0.012)	(0.018)	(0.025)	(0.035)	(0.052)
Constant	0.113***	0.106***	0.099***	0.101***	0.110***	0.101***	0.091***	0.083***
	(0.003)	(0.004)	(0.005)	(0.007)	(0.012)	(0.016)	(0.022)	(0.030)
Share $\hat{\nu}$	0.12	0.07	0.06	0.06	0.05	0.06	0.04	0.04
Observations	29,898	13,758	6,726	3,090	1,380	714	321	144

Notes: The table shows the estimated share of collusive bid pairs for auctions in which different numbers of bidders participate. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors. * p<0.1, ** p<0.05, *** p<0.01.

Table 4: Collusion Measure: Varying Number of Bidders in Pharmaceutical Industry Auctions, Winner — Runner-Up and Third-Best Bidder Pairs, 12-hour Cutoff

Dependent variable: Simultaneous Bidding	(1) 3 Bidders	(2) 4 Bidders	(3) 5 Bidders	(4) 6 Bidders	(5) 7 Bidders	(6) 8 Bidders	(7) 9 Bidders	(8) 10 Bidders
				Panel A: 30-minute Interval, 12-hour Cutoff				
Same-Day Bids	0.075***	0.045***	0.034***	0.040***	0.049***	0.047**	0.068*	0.065
	(0.004)	(0.006)	(0.008)	(0.011)	(0.018)	(0.024)	(0.035)	(0.054)
Constant	0.067***	0.062***	0.058***	0.054***	0.058***	0.054***	0.044**	0.053*
	(0.002)	(0.003)	(0.005)	(0.007)	(0.011)	(0.014)	(0.018)	(0.030)
Share $\hat{\nu}$	0.08	0.05	0.04	0.04	0.05	0.05	0.07	0.07
Observations	22,836	10,194	4,839	2,196	960	507	243	108
				Panel B: 60-minute Interval, 12-hour Cutoff				
Same-Day Bids	0.105***	0.065***	0.049***	0.071***	0.060***	0.042	0.083**	0.067
	(0.005)	(0.007)	(0.010)	(0.015)	(0.022)	(0.030)	(0.041)	(0.059)
Constant	0.116***	0.109***	0.103***	0.104***	0.106***	0.108***	0.066***	0.070**
	(0.003)	(0.004)	(0.006)	(0.009)	(0.014)	(0.019)	(0.021)	(0.034)
Share $\hat{\nu}$	0.12	0.07	0.05	0.08	0.07	0.05	0.09	0.07
Observations	22,836	10,194	4,839	2,196	960	507	243	108

Notes: The table shows the estimated share of collusive bid pairs for auctions in which different numbers of bidders participate. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors. * p<0.1, ** p<0.05, *** p<0.01.

Table 5: Collusion Measure: Varying Number of Bidders in Pharmaceutical Industry Auctions, Winner — Runner-Up and Third Bidder Pairs, 5-hour Cutoff , Fixed Effects

Dependent variable: Simultaneous Bidding	(1) 3 Bidders	(2) 4 Bidders	(3) 5 Bidders	(4) 6 Bidders	(5) 7 Bidders	(6) 8 Bidders	(7) 9 Bidders	(8) 10 Bidders
Panel A: 30-minute Interval								
Same-Day Bids	0.099***	0.060***	0.046***	0.047***	0.039***	0.040***	0.040***	0.038***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)	(0.007)	(0.010)	(0.014)
Constant	0.063***	0.059***	0.059***	0.056***	0.059***	0.060***	0.051***	0.062***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)	(0.007)
Public Body FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	317,544	125,988	59,286	29,691	15,699	8,271	4,692	2,520
Panel B: 60-minute Interval								
Same-Day Bids	0.119***	0.076***	0.059***	0.056***	0.053***	0.052***	0.036***	0.035**
	(0.001)	(0.002)	(0.003)	(0.005)	(0.007)	(0.009)	(0.012)	(0.017)
Constant	0.115***	0.109***	0.108***	0.106***	0.107***	0.108***	0.103***	0.111***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)	(0.009)
Public Body FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	317,544	125,988	59,286	29,691	15,699	8,271	4,692	2,520

Notes: The table shows the estimated share of collusive bid pairs for auctions in which different numbers of bidders participate. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors. * p<0.1, ** p<0.05, *** p<0.01.

Table 6: Collusion Measure: Varying Number of Bidders in Pharmaceutical Industry with Fixed Effects, Winner — Runner-Up and Third Bidder Pairs, 12-hour Cutoff , Fixed Effects

Dependent variable: Simultaneous Bidding	(1) 3 Bidders	(2) 4 Bidders	(3) 5 Bidders	(4) 6 Bidders	(5) 7 Bidders	(6) 8 Bidders	(7) 9 Bidders	(8) 10 Bidders
Panel A: 30-minute Interval, 12-hour Cutoff								
Same-Day Bids	0.102***	0.064***	0.053***	0.048***	0.047***	0.047***	0.046***	0.069***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.006)	(0.009)	(0.011)	(0.017)
Constant	0.063***	0.061***	0.058***	0.057***	0.059***	0.059***	0.052***	0.052***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)	(0.006)	(0.008)
Public Body FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	259,995	101,331	47,487	23,643	12,627	6,525	3,684	1,959
Panel B: 60-minute Interval, 12-hour Cutoff								
Same-Day Bids	0.123***	0.081***	0.067***	0.064***	0.061***	0.056***	0.037***	0.071***
	(0.002)	(0.003)	(0.004)	(0.005)	(0.008)	(0.011)	(0.014)	(0.020)
Constant	0.116***	0.111***	0.110***	0.108***	0.108***	0.110***	0.107***	0.102***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)	(0.006)	(0.007)	(0.010)
Public Body FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	259,995	101,331	47,487	23,643	12,627	6,525	3,684	1,959

Notes: The table shows the estimated share of collusive bid pairs for auctions in which different numbers of bidders participate. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors. * p<0.1, ** p<0.05, *** p<0.01.

Table 7: Collusion Measure: Varying Number of Bidders in Pharmaceutical Industry, Consecutive Pairs (Each Bidder is Paired with up to Four Closest in Price Bidders), K-Bidder Auctions, 30-minute Interval, 5-hour Cutoff

Dependent variable: Simultaneous Bidding	(1) 2 Bidders	(2) 3 Bidders	(3) 4 Bidders	(4) 5 Bidders	(5) 6 Bidders	(6) 7 Bidders	(7) 8 Bidders	(8) 9 Bidders	(9) 10 Bidders	(10) 11 Bidders	(11) 12 Bidders
Same-Day Bids	0.188***	0.085***	0.058***	0.046***	0.053***	0.052***	0.062***	0.052***	0.053*	0.053**	0.018
	(0.005)	(0.006)	(0.005)	(0.005)	(0.007)	(0.009)	(0.013)	(0.017)	(0.028)	(0.027)	(0.050)
Constant	0.125***	0.098***	0.070***	0.062***	0.052***	0.050***	0.055***	0.057***	0.093***	0.056***	0.077**
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.006)	(0.009)	(0.011)	(0.018)	(0.017)	(0.033)
Share $\hat{\nu}$	0.22	0.09	0.06	0.05	0.06	0.05	0.07	0.06	0.06	0.06	0.02
Observations	22,596	13,593	15,710	10,750	6,068	3,480	1,802	1,079	515	414	128

Notes: The table shows the estimated share of collusive bid pairs for auctions with different numbers of participants. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.
* p<0.1, ** p<0.05, *** p<0.01.

Table 8: Collusion Measure: Varying Number of Bidders in Main Data, Winner — Runner-Up Bid Pairs, 5-hour Cutoff

Dependent variable: Simultaneous Bidding	(1) 2 Bidders	(2) 3 Bidders	(3) 4 Bidders	(4) 5 Bidders	(5) 6 Bidders	(6) 7 Bidders	(7) 8 Bidders	(8) 9 Bidders	(9) 10 Bidders	(10) 11 Bidders
Panel A: 30-minute Interval										
Same-Day Bids	0.204***	0.081***	0.072***	0.059***	0.055***	0.061***	0.055***	0.043***	0.060***	0.042*
	(0.001)	(0.002)	(0.003)	(0.004)	(0.006)	(0.008)	(0.011)	(0.014)	(0.020)	(0.022)
Constant	0.069***	0.064***	0.059***	0.062***	0.060***	0.059***	0.062***	0.060***	0.052***	0.038***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)	(0.006)	(0.008)	(0.010)	(0.011)
Share $\hat{\nu}$	0.22	0.09	0.08	0.06	0.06	0.07	0.06	0.05	0.06	0.04
Observations	391,469	105,848	41,996	19,762	9,897	5,233	2,757	1,564	840	524
Panel B: 60-minute Interval										
Same-Day Bids	0.251***	0.107***	0.094***	0.080***	0.079***	0.078***	0.064***	0.038**	0.055**	0.015
	(0.001)	(0.002)	(0.004)	(0.005)	(0.007)	(0.010)	(0.014)	(0.018)	(0.025)	(0.029)
Constant	0.117***	0.116***	0.110***	0.112***	0.108***	0.112***	0.119***	0.125***	0.110***	0.112***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)	(0.006)	(0.008)	(0.011)	(0.014)	(0.018)
Share $\hat{\nu}$	0.28	0.12	0.11	0.09	0.09	0.09	0.07	0.04	0.06	0.02
Observations	391,469	105,848	41,996	19,762	9,897	5,233	2,757	1,564	840	524

Notes: The table shows the estimated share of collusive bid pairs for auctions in which different numbers of bidders participate. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.
* p<0.1, ** p<0.05, *** p<0.01.

Table 9: Collusion Measure: Varying Number of Bidders in Main Data, Winner — Runner-Up Bid Pairs, 12-hour Cutoff

Dependent variable: Simultaneous Bidding	(1) 2 Bidders	(2) 3 Bidders	(3) 4 Bidders	(4) 5 Bidders	(5) 6 Bidders	(6) 7 Bidders	(7) 8 Bidders	(8) 9 Bidders	(9) 10 Bidders	(10) 11 Bidders
Panel A: 30-minute Interval										
Same-Day Bids	0.204***	0.081***	0.072***	0.059***	0.055***	0.061***	0.055***	0.043***	0.060***	0.042*
	(0.001)	(0.002)	(0.003)	(0.004)	(0.006)	(0.008)	(0.011)	(0.014)	(0.020)	(0.022)
Constant	0.069***	0.064***	0.059***	0.062***	0.060***	0.059***	0.062***	0.060***	0.052***	0.038***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)	(0.006)	(0.008)	(0.010)	(0.011)
Share $\hat{\nu}$	0.22	0.09	0.08	0.06	0.06	0.07	0.06	0.05	0.06	0.04
Observations	391,469	105,848	41,996	19,762	9,897	5,233	2,757	1,564	840	524
Panel B: 60-minute Interval										
Same-Day Bids	0.251***	0.107***	0.094***	0.080***	0.079***	0.078***	0.064***	0.038**	0.055**	0.015
	(0.001)	(0.002)	(0.004)	(0.005)	(0.007)	(0.010)	(0.014)	(0.018)	(0.025)	(0.029)
Constant	0.117***	0.116***	0.110***	0.112***	0.108***	0.112***	0.119***	0.125***	0.110***	0.112***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)	(0.006)	(0.008)	(0.011)	(0.014)	(0.018)
Share $\hat{\nu}$	0.28	0.12	0.11	0.09	0.09	0.09	0.07	0.04	0.06	0.02
Observations	391,469	105,848	41,996	19,762	9,897	5,233	2,757	1,564	840	524

Notes: The table shows the estimated share of collusive bid pairs for auctions in which different numbers of bidders participate. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.
* p<0.1, ** p<0.05, *** p<0.01.

Table 10: Collusion Measure: Varying Number of Bidders in Main Data, Winner — Runner-Up and Third Bidder Pairs, 5-hour Cutoff

Dependent variable: Simultaneous Bidding	(1) 3 Bidders	(2) 4 Bidders	(3) 5 Bidders	(4) 6 Bidders	(5) 7 Bidders	(6) 8 Bidders	(7) 9 Bidders	(8) 10 Bidders	(9) 11 Bidders	(10) 12 Bidders
Panel A: 30-minute Interval										
Same-Day Bids	0.098***	0.057***	0.044***	0.046***	0.039***	0.044***	0.031***	0.038***	0.030**	0.029
	(0.001)	(0.002)	(0.002)	(0.003)	(0.005)	(0.006)	(0.008)	(0.012)	(0.014)	(0.019)
Constant	0.064***	0.061***	0.059***	0.056***	0.059***	0.059***	0.055***	0.062***	0.059***	0.050***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)	(0.006)	(0.007)	(0.009)
Share $\hat{\nu}$	0.10	0.06	0.05	0.05	0.04	0.05	0.03	0.04	0.03	0.03
Observations	317,544	125,988	59,286	29,691	15,699	8,271	4,692	2,520	1,572	843
Panel B: 60-minute Interval										
Same-Day Bids	0.120***	0.074***	0.057***	0.060***	0.054***	0.056***	0.041***	0.030**	0.026	0.030
	(0.001)	(0.002)	(0.003)	(0.004)	(0.006)	(0.008)	(0.010)	(0.014)	(0.018)	(0.023)
Constant	0.114***	0.109***	0.109***	0.104***	0.107***	0.107***	0.101***	0.113***	0.117***	0.088***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)	(0.006)	(0.008)	(0.010)	(0.012)
Share $\hat{\nu}$	0.14	0.08	0.06	0.07	0.06	0.06	0.05	0.03	0.03	0.03
Observations	317,544	125,988	59,286	29,691	15,699	8,271	4,692	2,520	1,572	843

Notes: The table shows the estimated share of collusive bid pairs for auctions in which different numbers of bidders participate. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.
* p<0.1, ** p<0.05, *** p<0.01.

Table 11: Collusion Measure: Varying Number of Bidders in Main Data, Winner — Runner-Up and Third Bidder Pairs, 12-hour Cutoff

Dependent variable: Simultaneous Bidding	(1) 3 Bidders	(2) 4 Bidders	(3) 5 Bidders	(4) 6 Bidders	(5) 7 Bidders	(6) 8 Bidders	(7) 9 Bidders	(8) 10 Bidders	(9) 11 Bidders	(10) 12 Bidders
Panel A: 30-minute Interval, 12-hour Cutoff										
Same-Day Bids	0.101***	0.060***	0.048***	0.045***	0.043***	0.049***	0.036***	0.059***	0.034**	0.038*
	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)	(0.007)	(0.009)	(0.014)	(0.016)	(0.022)
Constant	0.064***	0.062***	0.061***	0.058***	0.060***	0.058***	0.056***	0.055***	0.061***	0.056***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)	(0.008)	(0.011)
Share $\hat{\nu}$	0.11	0.06	0.05	0.05	0.05	0.05	0.04	0.06	0.04	0.04
Observations	259,995	101,331	47,487	23,643	12,627	6,525	3,684	1,959	1,275	681
Panel B: 60-minute Interval, 12-hour Cutoff										
Same-Day Bids	0.123***	0.078***	0.060***	0.063***	0.056***	0.058***	0.046***	0.045***	0.020	0.043*
	(0.002)	(0.002)	(0.003)	(0.005)	(0.006)	(0.009)	(0.012)	(0.016)	(0.020)	(0.026)
Constant	0.116***	0.112***	0.112***	0.108***	0.110***	0.109***	0.103***	0.111***	0.119***	0.089***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.005)	(0.006)	(0.009)	(0.011)	(0.014)
Share $\hat{\nu}$	0.14	0.09	0.07	0.07	0.06	0.07	0.05	0.05	0.02	0.05
Observations	259,995	101,331	47,487	23,643	12,627	6,525	3,684	1,959	1,275	681

Notes: The table shows the estimated share of collusive bid pairs for auctions in which different numbers of bidders participate. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 12: Varying Number of Bidders in Main Data, Winner — Runner-Up and Third Bidder Pairs, 5-hour Cutoff, Fixed Effects

Dependent variable: Simultaneous Bidding	(1) 3 Bidders	(2) 4 Bidders	(3) 5 Bidders	(4) 6 Bidders	(5) 7 Bidders	(6) 8 Bidders	(7) 9 Bidders	(8) 10 Bidders	(9) 11 Bidders	(10) 12 Bidders
Panel A: 30-minute Interval										
Same-Day Bids	0.098***	0.060***	0.047***	0.047***	0.040***	0.041***	0.039***	0.039***	0.019	0.013
	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)	(0.007)	(0.010)	(0.015)	(0.018)	(0.024)
Constant	0.063***	0.059***	0.058***	0.056***	0.059***	0.060***	0.052***	0.062***	0.062***	0.056***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)	(0.007)	(0.009)	(0.011)
Industry FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Public Body FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	317544.00	125988.00	59286.00	29691.00	15699.00	8271.00	4692.00	2520.00	1572.00	843.00
Panel B: 60-minute Interval										
Same-Day Bids	0.119***	0.076***	0.060***	0.057***	0.054***	0.052***	0.034***	0.033*	0.019	0.010
	(0.001)	(0.002)	(0.003)	(0.005)	(0.007)	(0.009)	(0.012)	(0.017)	(0.023)	(0.030)
Constant	0.115***	0.109***	0.108***	0.105***	0.106***	0.108***	0.104***	0.112***	0.119***	0.095***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)	(0.009)	(0.012)	(0.014)
Industry FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Public Body FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	317,544	125,988	59,286	29,691	15,699	8,271	4,692	2,520	1,572	843

Notes: The table shows the estimated share of collusive bid pairs for auctions in which different numbers of bidders participate. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 13: Varying Number of Bidders in Main Data, Winner — Runner-Up and Third Bidder Pairs, 12-hour Cutoff, Fixed Effects

Dependent variable: Simultaneous Bidding	(1) 3 Bidders	(2) 4 Bidders	(3) 5 Bidders	(4) 6 Bidders	(5) 7 Bidders	(6) 8 Bidders	(7) 9 Bidders	(8) 10 Bidders	(9) 11 Bidders	(10) 12 Bidders
Panel A: 30-minute Interval, 12-hour Cutoff										
Same-Day Bids	0.102***	0.064***	0.054***	0.049***	0.048***	0.048***	0.044***	0.068***	0.022	0.026
	(0.001)	(0.002)	(0.003)	(0.004)	(0.006)	(0.009)	(0.011)	(0.017)	(0.021)	(0.029)
Constant	0.064***	0.061***	0.058***	0.057***	0.058***	0.059***	0.053***	0.052***	0.065***	0.060***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.005)	(0.006)	(0.008)	(0.010)	(0.014)
Industry FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Public Body FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	259,995	101,331	47,487	23,643	12,627	6,525	3,684	1,959	1,275	681
Panel B: 60-minute Interval, 12-hour Cutoff										
Same-Day Bids	0.122***	0.081***	0.068***	0.064***	0.062***	0.057***	0.035**	0.067***	0.012	0.035
	(0.002)	(0.003)	(0.004)	(0.005)	(0.008)	(0.011)	(0.014)	(0.021)	(0.026)	(0.035)
Constant	0.116***	0.111***	0.109***	0.107***	0.107***	0.110***	0.107***	0.103***	0.121***	0.092***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)	(0.006)	(0.007)	(0.010)	(0.013)	(0.017)
Industry FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Public Body FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	259,995	101,331	47,487	23,643	12,627	6,525	3,684	1,959	1,275	681

Notes: The table shows the estimated share of collusive bid pairs for auctions in which different numbers of bidders participate. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.
* p<0.1, ** p<0.05, *** p<0.01.

Table 14: Collusion Measure: Varying Number of Bidders in Main Data, $K-1$ Consecutive Pairs, K-Bidder Auctions, 30-minute Interval, 5-hour Cutoff

Dependent variable: Simultaneous Bidding	(1) 2 Bidders	(2) 3 Bidders	(3) 4 Bidders	(4) 5 Bidders	(5) 6 Bidders	(6) 7 Bidders	(7) 8 Bidders	(8) 9 Bidders	(9) 10 Bidders
Same-Day Bids	0.251***	0.154***	0.129***	0.107***	0.095***	0.086***	0.089***	0.077***	0.081***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)	(0.006)	(0.008)
Constant	0.117***	0.118***	0.112***	0.112***	0.110***	0.108***	0.108***	0.103***	0.108***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Share $\hat{\nu}$	0.28	0.17	0.15	0.12	0.11	0.10	0.10	0.09	0.09
Observations	391,469	225,020	139,052	88,847	55,702	35,474	21,736	14,057	8,571

Dependent variable: Simultaneous Bidding	(10) 11 Bidders	(11) 12 Bidders	(12) 13 Bidders	(13) 14 Bidders	(14) 15 Bidders	(15) 16 Bidders	(16) 17 Bidders	(17) 18 Bidders	(18) 19 Bidders	(19) 20 Bidders
Same-Day Bids	0.075***	0.070***	0.059***	0.096***	0.076***	0.039	0.078**	0.069	0.075	0.019
	(0.010)	(0.012)	(0.015)	(0.019)	(0.023)	(0.026)	(0.036)	(0.044)	(0.046)	(0.064)
Constant	0.106***	0.099***	0.099***	0.095***	0.098***	0.106***	0.110***	0.128***	0.132***	0.148***
	(0.005)	(0.006)	(0.008)	(0.009)	(0.012)	(0.015)	(0.019)	(0.026)	(0.026)	(0.033)
Share $\hat{\nu}$	0.08	0.08	0.07	0.11	0.08	0.04	0.09	0.08	0.09	0.02
Observations	5,697	3,514	2,152	1,590	960	692	429	294	290	163

Notes: The table shows the estimated share of collusive bid pairs for auctions in which different numbers of bidders participate. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.
* p<0.1, ** p<0.05, *** p<0.01.

Table 15: Collusion Measure: Varying Number of Bidders in Main Data, Four Closest-in-Price Bid Pairs, 30-minute Interval, 5-hour Cutoff

Dependent variable: Simultaneous Bidding	(1) 2 Bidders	(2) 3 Bidders	(3) 4 Bidders	(4) 5 Bidders	(5) 6 Bidders	(6) 7 Bidders	(7) 8 Bidders	(8) 9 Bidders	(9) 10 Bidders	(10) 11 Bidders
Same-Day Bids	0.193***	0.117***	0.089***	0.071***	0.064***	0.058***	0.058***	0.055***	0.055***	0.060***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.006)	(0.007)
Constant	0.102***	0.091***	0.065***	0.062***	0.061***	0.059***	0.060***	0.056***	0.065***	0.053***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Share $\hat{\nu}$	0.21	0.13	0.10	0.08	0.07	0.06	0.06	0.06	0.06	0.06
Observations	233,354	139,072	142,684	97,126	62,270	40,851	25,093	16,192	9,910	6,708

Dependent variable: Simultaneous Bidding	(11) 12 Bidders	(12) 13 Bidders	(13) 14 Bidders	(14) 15 Bidders	(15) 16 Bidders	(16) 17 Bidders	(17) 18 Bidders	(18) 19 Bidders	(19) 20 Bidders	(20) $\leq$ 20 Bidders
Same-Day Bids	0.056***	0.051***	0.035***	0.061***	0.038**	0.034	0.056*	0.045	0.021	0.124***
	(0.009)	(0.012)	(0.013)	(0.017)	(0.019)	(0.026)	(0.031)	(0.035)	(0.047)	(0.001)
Constant	0.055***	0.057***	0.061***	0.054***	0.053***	0.067***	0.055***	0.065***	0.081***	0.070***
	(0.005)	(0.006)	(0.008)	(0.008)	(0.010)	(0.015)	(0.017)	(0.019)	(0.026)	(0.000)
Share $\hat{\nu}$	0.06	0.05	0.04	0.06	0.04	0.04	0.06	0.05	0.02	0.13
Observations	4,150	2,425	1,715	1,205	804	480	336	286	170	924,391

Notes: The table shows the estimated share of collusive bid pairs of four closest-in-price bidders for auctions in which different numbers of bidders participate. Column (20) presents the results for all auctions with $K \leq 20$ bidders. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.

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

Table 16: Normalized Prices: Winner and Runner-Up Bids, Two-Bidder Auctions

	(1)	(2)
Dependent variable:	Winning Bid	Bid Difference
	Panel A: 10-minute Interval	
Same-Day Bids	0.02***	-0.01***
	(0.00)	(0.00)
10-min Interval	0.01***	-0.00***
	(0.00)	(0.00)
Same-Day Bids × 10-min Interval	0.03***	-0.01***
	(0.00)	(0.00)
Constant	0.88***	0.05***
	(0.00)	(0.00)
Price Change $\hat{\delta}$ (%)	6.91%	-41.70%
R^2	0.015	0.006
Observations	389,923	389,923
	Panel B: 30-minute Interval	
Same-Day Bids	0.02***	-0.01***
	(0.00)	(0.00)
30-min Interval	-0.01***	0.00**
	(0.00)	(0.00)
Same-Day Bids × 30-min Interval	0.05***	-0.02***
	(0.00)	(0.00)
Constant	0.88***	0.05***
	(0.00)	(0.00)
Price Change $\hat{\delta}$ (%)	6.55%	-39.55%
R^2	0.020	0.008
Observations	389,923	389,923
	Panel C: 60-minute Interval	
Same-Day Bids	0.01***	-0.00***
	(0.00)	(0.00)
60-min Interval	-0.01***	0.00***
	(0.00)	(0.00)
Same-Day Bids × 60-min Interval	0.05***	-0.02***
	(0.00)	(0.00)
Constant	0.88***	0.05***
	(0.00)	(0.00)
Price Change $\hat{\delta}$ (%)	5.99%	-36.48%
R^2	0.022	0.008
Observations	389,923	389,923

Notes: The table shows the estimated change in prices in % caused by collusion in two-bidder auctions. Winning Bid is the bid of a winner. Bid Difference is the difference between winner and runner-up bids. The cutoff is 5 hours before the auction ends. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.
* p<0.1, ** p<0.05, *** p<0.01.

Table 17: Prices: Winner and Runner-Up Bids, Two-Bidder Auctions

	(1)	(2)
Dependent variable:	Winning Bid	Bid Difference
	Panel A: 10-minute Interval	
Same-Day Bids	-7849.50***	-1581.00***
	(500.15)	(57.58)
10-min Interval	15479.35***	-370.77*
	(1889.77)	(224.25)
Same-Day Bids × 10-min Interval	-2662.03	-1144.59***
	(2123.81)	(239.60)
Constant	183010.04***	8093.40***
	(359.65)	(43.85)
Price Change $\hat{\delta}$ (%)	2.71%	-38.26%
R^2	0.001	0.003
Observations	389,923	389,923
	Panel B: 30-minute Interval	
Same-Day Bids	-9922.76***	-1266.35***
	(526.01)	(61.24)
30-min Interval	3625.68**	381.73**
	(1409.18)	(175.99)
Same-Day Bids × 30-min Interval	8853.93***	-2115.69***
	(1589.58)	(188.56)
Constant	183367.03***	8052.37***
	(365.71)	(44.43)
Price Change $\hat{\delta}$ (%)	1.39%	-37.26%
R^2	0.001	0.004
Observations	389,923	389,923
	Panel C: 60-minute Interval	
Same-Day Bids	-11047.20***	-1082.76***
	(551.98)	(64.45)
60-min Interval	158.74	493.16***
	(1102.58)	(139.24)
Same-Day Bids × 60-min Interval	11536.84***	-2195.94***
	(1293.75)	(154.24)
Constant	183599.85***	8021.28***
	(375.67)	(45.47)
Price Change $\hat{\delta}$ (%)	0.35%	-34.73%
R^2	0.001	0.004
Observations	389,923	389,923

Notes: The table shows the estimated change in prices in % caused by collusion in two-bidder auctions. Winning Bid is the bid of a winner. Bid Difference is the difference between winner and runner-up bids. The cutoff is 5 hours before the auction ends. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.
* p<0.1, ** p<0.05, *** p<0.01.

Table 18: Log-Prices: Winner and Runner-Up Bids, Two-Bidder Auctions

	(1)	(2)
Dependent variable:	Winning Bid	Bid Difference
	Panel A: 10-minute Interval	
Same-Day Bids	-0.04***	-0.01***
	(0.00)	(0.00)
10-min Interval	0.08***	-0.00***
	(0.01)	(0.00)
Same-Day Bids × 10-min Interval	0.03*	-0.01***
	(0.02)	(0.00)
Constant	11.60***	0.07***
	(0.00)	(0.00)
Price Change $\hat{\delta}$ (%)	7.33%	-3.08%
R^2	0.001	0.005
Observations	389,923	389,923
	Panel B: 30-minute Interval	
Same-Day Bids	-0.05***	-0.01***
	(0.00)	(0.00)
30-min Interval	0.01	0.00**
	(0.01)	(0.00)
Same-Day Bids × 30-min Interval	0.09***	-0.02***
	(0.01)	(0.00)
Constant	11.60***	0.07***
	(0.00)	(0.00)
Price Change $\hat{\delta}$ (%)	4.83%	-2.91%
R^2	0.001	0.007
Observations	389,923	389,923
	Panel C: 60-minute Interval	
Same-Day Bids	-0.06***	-0.01***
	(0.00)	(0.00)
60-min Interval	-0.01	0.00***
	(0.01)	(0.00)
Same-Day Bids × 60-min Interval	0.10***	-0.02***
	(0.01)	(0.00)
Constant	11.61***	0.07***
	(0.00)	(0.00)
Price Change $\hat{\delta}$ (%)	3.29%	-2.65%
R^2	0.001	0.007
Observations	389,923	389,923

Notes: The table shows the estimated change in prices in % caused by collusion in two-bidder auctions. Winning Bid is the bid of a winner. Bid Difference is the difference between winner and runner-up bids. The cutoff is 5 hours before the auction ends. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.
* p<0.1, ** p<0.05, *** p<0.01.

Table 19: Normalized Prices: Winner and Runner-Up Bids, K-Bidder Auctions

	(1)	(2)
Dependent variable:	Winning Bid	Bid Difference
	Panel A: 10-minute Interval	
Same-Day Bids	0.027***	-0.007***
	(0.000)	(0.000)
10-min Interval	0.023***	-0.004***
	(0.002)	(0.001)
Same-Day Bids × 10-min Interval	0.040***	-0.010***
	(0.002)	(0.001)
Constant	0.820***	0.054***
	(0.000)	(0.000)
Price Change $\hat{\delta}$ (%)	10.93%	-38.48%
R^2	0.016	0.004
Observations	578,543	578,543
	Panel B: 30-minute Interval	
Same-Day Bids	0.018***	-0.005***
	(0.001)	(0.000)
30-min Interval	0.001	0.001**
	(0.001)	(0.001)
Same-Day Bids × 30-min Interval	0.064***	-0.016***
	(0.001)	(0.001)
Constant	0.821***	0.054***
	(0.000)	(0.000)
Price Change $\hat{\delta}$ (%)	10.14%	-35.67%
R^2	0.022	0.006
Observations	578,543	578,543
	Panel C: 60-minute Interval	
Same-Day Bids	0.013***	-0.004***
	(0.001)	(0.000)
60-min Interval	-0.004***	0.002***
	(0.001)	(0.000)
Same-Day Bids × 60-min Interval	0.066***	-0.016***
	(0.001)	(0.001)
Constant	0.822***	0.054***
	(0.000)	(0.000)
Price Change $\hat{\delta}$ (%)	9.08%	-32.18%
R^2	0.023	0.006
Observations	578,543	578,543

Notes: The table shows the estimated change in prices in % caused by collusion in K-bidder auctions. Winning Bid is the bid of a winner. Bid Difference is the difference between winner and runner-up bids. The cutoff is 5 hours before the auction ends. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.
* p<0.1, ** p<0.05, *** p<0.01.

Table 20: Prices: Winner and Runner-Up Bids, K-Bidder Auctions

	(1)	(2)
Dependent variable:	Winning Bid	Bid Difference
	Panel A: 10-minute Interval	
Same-Day Bids	-5254.719***	-1407.330***
	(386.802)	(49.651)
10-min Interval	16648.083***	-532.665***
	(1549.540)	(195.053)
Same-Day Bids × 10-min Interval	-1001.362	-1399.709***
	(1772.802)	(211.240)
Constant	171344.839***	8946.636***
	(271.719)	(36.817)
Price Change $\hat{\delta}$ (%)	6.06%	-37.33%
R^2	0.001	0.003
Observations	578,543	578,543
	Panel B: 30-minute Interval	
Same-Day Bids	-7385.015***	-1108.586***
	(403.825)	(52.411)
30-min Interval	4626.379***	287.343*
	(1091.992)	(146.854)
Same-Day Bids × 30-min Interval	10787.203***	-2323.854***
	(1262.630)	(160.236)
Constant	171611.643***	8909.031***
	(276.635)	(37.387)
Price Change $\hat{\delta}$ (%)	4.68%	-35.30%
R^2	0.001	0.003
Observations	578,543	578,543
	Panel C: 60-minute Interval	
Same-Day Bids	-8508.123***	-938.996***
	(421.791)	(55.020)
60-min Interval	1382.078	357.219***
	(842.345)	(114.470)
Same-Day Bids × 60-min Interval	12803.301***	-2289.697***
	(1016.039)	(129.855)
Constant	171760.671***	8886.896***
	(284.314)	(38.374)
Price Change $\hat{\delta}$ (%)	3.31%	-32.31%
R^2	0.001	0.003
Observations	578,543	578,543

Notes: The table shows the estimated change in prices in % caused by collusion in K-bidder auctions. Winning Bid is the bid of a winner. Bid Difference is the difference between winner and runner-up bids. The cutoff is 5 hours before the auction ends. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.
* p<0.1, ** p<0.05, *** p<0.01.

Table 21: Log-Prices: Winner and Runner-Up Bids, K-Bidder Auctions

Dependent variable:	(1) Winning Bid	(2) Bid Difference
	Panel A: 10-minute Interval	
Same-Day Bids	-0.021***	-0.011***
	(0.003)	(0.000)
10-min Interval	0.082***	-0.006***
	(0.012)	(0.001)
Same-Day Bids × 10-min Interval	0.028**	-0.016***
	(0.014)	(0.002)
Constant	11.550***	0.076***
	(0.002)	(0.000)
Price Change $\hat{\delta}$ (%)	8.90%	-3.33%
R^2	0.001	0.004
Observations	578,543	578,543
	Panel B: 30-minute Interval	
Same-Day Bids	-0.034***	-0.008***
	(0.003)	(0.000)
30-min Interval	0.015*	0.002*
	(0.009)	(0.001)
Same-Day Bids × 30-min Interval	0.087***	-0.025***
	(0.010)	(0.001)
Constant	11.552***	0.076***
	(0.002)	(0.000)
Price Change $\hat{\delta}$ (%)	6.80%	-3.09%
R^2	0.001	0.005
Observations	578,543	578,543
	Panel C: 60-minute Interval	
Same-Day Bids	-0.042***	-0.006***
	(0.004)	(0.000)
60-min Interval	-0.001	0.003***
	(0.007)	(0.001)
Same-Day Bids × 60-min Interval	0.094***	-0.025***
	(0.008)	(0.001)
Constant	11.553***	0.075***
	(0.002)	(0.000)
Price Change $\hat{\delta}$ (%)	5.12%	-2.76%
R^2	0.001	0.005
Observations	578,543	578,543

Notes: The table shows the estimated change in prices in % caused by collusion in K-bidder auctions. Winning Bid is the bid of a winner. Bid Difference is the difference between winner and runner-up bids. The cutoff is 5 hours before the auction ends. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.
* p<0.1, ** p<0.05, *** p<0.01.

Table 22: Normalized Prices: Winner and Runner-Up Bids, K-Bidder Auctions

	(1)	(2)	(3)	(4)
Dependent variable:	Winning Bid			
	Panel A: 10-minute Interval			
Same-Day Bids	0.027***	0.027***	0.030***	0.027***
	(0.000)	(0.000)	(0.000)	(0.000)
10-min Interval	0.023***	0.013***	0.008***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
Same-Day Bids × 10-min Interval	0.040***	0.048***	0.069***	0.062***
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.820***	0.814***	0.818***	0.797***
	(0.000)	(0.031)	(0.000)	(0.040)
Industry and Region FEs		✓		✓
Public Body FEs			✓	✓
Price Change $\hat{\delta}$ (%)	10.93%	10.74%	12.97%	12.14%
R^2	0.016	0.134	0.233	0.293
Observations	578,545	578,545	578,545	578,545
	Panel B: 30-minute Interval			
Same-Day Bids	0.018***	0.019***	0.021***	0.019***
	(0.001)	(0.000)	(0.000)	(0.000)
30-min Interval	0.001	-0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Same-Day Bids × 30-min Interval	0.064***	0.063***	0.075***	0.069***
	(0.001)	(0.001)	(0.002)	(0.001)
Constant	0.821***	0.818***	0.818***	0.802***
	(0.000)	(0.031)	(0.000)	(0.040)
Industry and Region FEs		✓		✓
Public Body FEs			✓	✓
Price Change $\hat{\delta}$ (%)	10.14%	9.93%	11.61%	10.88%
R^2	0.022	0.139	0.238	0.298
Observations	578,545	578,545	578,545	578,545
	Panel C: 60-minute Interval			
Same-Day Bids	0.013***	0.014***	0.017***	0.015***
	(0.001)	(0.000)	(0.001)	(0.000)
60-min Interval	-0.004***	-0.003***	-0.003***	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Same-Day Bids × 60-min Interval	0.066***	0.062***	0.070***	0.064***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.822***	0.821***	0.819***	0.806***
	(0.000)	(0.031)	(0.000)	(0.040)
Industry and Region FEs		✓		✓
Public Body FEs			✓	✓
Price Change $\hat{\delta}$ (%)	9.08%	8.85%	10.24%	9.52%
R^2	0.023	0.140	0.238	0.298
Observations	578,545	578,545	578,545	578,545

Notes: The table shows the estimated change in prices in % caused by collusion in K-bidder auctions. Winning Bid is the bid of a winner. Bid Difference is the difference between winner and runner-up bids. The cutoff is 5 hours before the auction ends. Regressions include different sets of control variables. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.
* p<0.1, ** p<0.05, *** p<0.01.

Table 23: Normalized Prices: Winner and Runner-Up Bids, K-Bidder Auctions

	(1)	(2)	(3)	(4)
Dependent variable:	Bid Difference			
	Panel A: 10-minute Interval			
Same-Day Bids	-0.007***	-0.007***	-0.007***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.000)
10-min Interval	-0.004***	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Same-Day Bids × 10-min Interval	-0.010***	-0.014***	-0.021***	-0.020***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.054***	0.089***	0.055***	0.093***
	(0.000)	(0.023)	(0.000)	(0.020)
Industry and Region FEs		✓		✓
Public Body FEs			✓	✓
Price Change $\hat{\delta}$ (%)	-38.48%	-24.36%	-51.73%	-28.70%
R^2	0.004	0.051	0.157	0.177
Observations	578,545	578,545	578,545	578,545
	Panel B: 30-minute Interval			
Same-Day Bids	-0.005***	-0.005***	-0.005***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
30-min Interval	0.001**	0.002***	0.001*	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Same-Day Bids × 30-min Interval	-0.016***	-0.016***	-0.021***	-0.019***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.054***	0.088***	0.055***	0.092***
	(0.000)	(0.023)	(0.000)	(0.020)
Industry and Region FEs		✓		✓
Public Body FEs			✓	✓
Price Change $\hat{\delta}$ (%)	-35.68%	-22.32%	-44.73%	-25.17%
R^2	0.006	0.052	0.158	0.179
Observations	578,545	578,545	578,545	578,545
	Panel C: 60-minute Interval			
Same-Day Bids	-0.004***	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
60-min Interval	0.002***	0.002***	0.001**	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
Same-Day Bids × 60-min Interval	-0.016***	-0.015***	-0.018***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.054***	0.088***	0.055***	0.091***
	(0.000)	(0.023)	(0.000)	(0.020)
Industry and Region FEs		✓		✓
Public Body FEs			✓	✓
Price Change $\hat{\delta}$ (%)	-32.19%	-20.08%	-39.15%	-22.22%
R^2	0.006	0.053	0.158	0.179
Observations	578,545	578,545	578,545	578,545

Notes: The table shows the estimated change in prices in % caused by collusion in K-bidder auctions. Winning Bid is the bid of a winner. Bid Difference is the difference between winner and runner-up bids. The cutoff is 5 hours before the auction ends. Regressions include different sets of control variables. Each observation is a pair of bids. The reported values in parentheses represent robust standard errors.
* p<0.1, ** p<0.05, *** p<0.01.

Table 24: Percentage Change in Bid Gaps Caused by Collusion in 24 Largest Industries

Industry	% Change in Bid Differences	% Change in Prices
Inorganic substances	−56.28	15.24
Special equipment	−51.38	14.09
Pharmaceutical substances	−45.42	10.99
Electronic equipment	−39.96	8.68
Publish and print services	−39.93	13.75
Plastic and rubber products	−39.23	12.15
Petroleum products	−35.77	2.42
Computer and software services	−35.02	8.30
Furniture	−34.44	8.89
Processed food	−33.63	7.97
Agricultural products	−32.63	8.82
Fabrics	−31.69	11.11
Electric equipment	−31.16	8.42
Other technical services	−28.82	22.00
State services	−28.25	15.24
Building construction	−27.94	8.52
Repair services	−27.63	12.49
General equipment	−26.94	8.98
Metal production	−26.65	7.16
Other construction	−25.52	7.53
General equipment repair and service	−25.23	10.71
Civil engineering construction	−22.21	5.75
Paper and paper products	−21.08	6.56
Health services	−14.3	9.13

Notes: The table shows the estimates for the changes in bid difference between normalized prices of winners and runners-up in K-bidder auctions. The estimates are based on regressions of absolute difference in winner and runner-up bids without control variables.