Bid Manipulation in Open Procurement Auctions

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Abstract

Public procurement is a vital process for every economy and, no doubt, corruption is a long-standing problem. Policymakers often view transparency as a panacea for collusion and corruption in procurement. Following these recommendations, many countries have opted for the use of open electronic tenders which use transparent bidding mechanisms. But, paradoxically, collusion between procurement officials and bidders still seems to be a key to winning a contract. According to international business surveys, more than 30% of firms that have participated in procurement believe that corruption has prevented them from winning. One of the possible explanations is that transparency causes unscrupulous procurement officials to find new avenues of corruption.

I examine whether auctioneers abuse bid evaluation in an open electronic auction to give an unfair advantage to favored bidders. First, I formulate a new theoretical model for low-bid auctions with a corruption agreement between an auctioneer and a bidder, as realized through bid manipulation. The theoretical model contributes several new and pertinent features to existing auction models. In the model, favored bidders are aware that some competitors may be eliminated by an auctioneer at the post-bidding phase; they incorporate this knowledge and overstate procurement costs and bid higher to increase rents from procurement awards. As a result, this equilibrium response inflates the average prices of procurement. I also propose a method for model identification using data inconsistencies in auction documentation (the information on bids is often not reported). The proposed auction model can be used in other conditions where similar incentives for bid manipulation exists.

I then estimate this model using a novel dataset on public procurements to evaluate the welfare loss and rents resulting from corruption. For the model application, I have collected a large dataset containing over 2 million procurement purchases from the Russian Federation, where corruption is a known problem. I start with fixed-effects regression analysis which documents that non-reported bids are associated with 41.5–37% higher procurement prices; and although participation is considerably higher in potentially rigged auctions, the actual number of admitted bidders is 23% lower. I apply the English auction model to winning bids of auctions in which at least one bid has not been reported by an auctioneer, to empirically test for the presence of non-competitive bidding behavior. The statistical tests show that the predicted cost distribution is different from the actual distribution, thus rejecting the hypothesis of competitive bidding. After that, using the first-order conditions of the optimal bid in the model with bid manipulation, I develop a non-parametric two-stage estimator to confirm that the bidding behavior of favored firms is described according to the reduced-form facts. The statistical tests no longer reject the hypotheses of equivalence between the predicted versus actual cost distribution. In fact, the estimates show that an auction model with bid manipulation provides a 54–99% better fit than a standard English auction model in auctions with non-reported bids in 20 studied markets.

Keywords: corruption, procurement, English auction, bid manipulation, bid evaluation

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Chapter 1

Introduction

Public procurement is a government activity highly vulnerable to corruption because of the large amounts of money involved, its complexity and delegation, and close interactions between public and private sectors. International business surveys indicate that 34% of firms that have participated in a public procurement bidding process say corruption prevented them from winning; among the most frequent reasons they name are red tape and tailor-made selection criteria (Flash Eurobarometer 428: Businesses' attitudes towards corruption, 2015). To promote effective oversight of procurement allocation and reduce fraud and corruption, many countries have opted for the use of open electronic tenders. Procurement is a complex process and the impacts of open electronic procedures on each of its stages are not entirely understood (Lewis-Faupel et al., 2016). Although e-procurement may mitigate corruption and access to information at the bidding stage, it may also shift corruption to other, less transparent stages that occur both before and after the bidding.

Using data inconsistencies in open electronic procurement auctions in Russia (the information on bids is often not reported), I examine whether auctioneers abuse bid evaluation to give an unfair advantage to favored bidders. I then propose an auction model with bid manipulation at the evaluations stage to describe the environment of auctions with non-reported bids. A key feature of the data is that the model performance is verified using information from auctions where all bids were reported. This model can then be used to answer policy questions about public organizations' welfare losses due to bid manipulation and winners' gains due to misallocation.

The Russian procurement system provides a useful test case to study corruption in procurement, for several reasons. First, due to historical conditions, government procurement plays an important role in the Russian economy. It is a multi-billion and diverse sector that accounts for approximately 10% of annual GDP. Second, the new Federal Procurement Law, which governs the reporting of information, was enacted in January 2014. Under the new law, it is obligatory to conduct all purchases using electronic tenders and to provide public access to the procurement data. Third, corruption in procurement is a well-known problem in Russia. For example, the National Procurement Transparency Ranking estimates the annual loss due to overstated procurement prices to be about $7B.

To build my dataset, I have collected auction announcements, bidding and placement protocols, and bid evaluation reports (stored in the procurement database by Centralized Procurement Systems) for each procurement auction held between January 1 and December 31 2014. The dataset contains almost

2M data entries and covers auction-level and bidder-level information, such as procurement mechanisms, information about the procurer and vendor, and auction outcomes.

In a bid manipulation scheme, an auctioneer can increase the probability that a favored bidder will win by unfairly disqualifying the bidder's competitors during evaluation. Thus, the favored bidder can adjust the bidding strategy accordingly. By cross-checking the auction documentation, I have found that nearly one-fifth of auction protocols information on bids is missing. This is suspicious; with bid manipulation, the auctioneer responsible for the entire procurement process can conceal the unfairly rejected bids and discourage complaints.

The empirical analysis begins by exploring the non-reported bids in connection with procurement outcomes. Because auctions may differ in the number of observed and unobserved characteristics, I employ fixed-effects regression to control for any bid preferences programs and the size of entry fees, as well as the effects invariant by region and quarter of the year. The reduced form analysis highlights two facts: i) the non-reported bids are strongly positively correlated with procurement prices and the 39% higher prices in auctions with non-reported bids are not explained by observed characteristics; ii) although more bidders on average participate in auctions with non-reported bids, 24-18% fewer bids are accepted by auctioneers.

Non-reported bids do not always imply corruption agreements; they may also result from auctioneer incompetence. To disentangle these two reasons, I use a standard English auction model. In line with empirical auctions literature, any open electronic auction with a known price increment is strategically equivalent to an English auction. Thus, the value distribution can be identified using the data on winning bids only. The idea behind this exercise is that if non-reported bids are consequences of auctioneers' lack of effort rather than a sign of fraud, the non-reported bids should be random and the patterns of winning bids should be indistinguishable from competitive behavior.

I examine the winning bid data for a group of auctions in which all bids are observed and the estimated English auction model is generally consistent with a competitive bidding scenario. When I apply the same English auction model to a sample of auctions in which at least one bid has not been reported by an auctioneer, I observe that the predicted cost distribution lies significantly to the right of the actual distribution of costs, thus disproving the hypotheses of a competitive bidding model.

To explain the observed differences between auctions with and without non-reported bids, I propose an alternative auction model with bid manipulation. In the model, favored bidders are aware that some competitors may be eliminated by an auctioneer at the post-bidding phase; they incorporate this knowledge into their objective function. The favored bidder thus has an incentive to overstate procurement costs and bid higher to increase rents from procurement awards. As a result, this equilibrium response inflates the average prices of procurement. This is consistent with the reduced-form facts about auctions with non-reported bids. I restrict the analysis to the bidding behavior of winners; using the first-order conditions of the optimal bid, I propose a non-parametric estimation strategy based on the approach pioneered by Guerre, Perrigne and Vuong (2000). The statistical tests no longer reject the hypotheses of equivalence between the predicted versus actual cost distribution. In fact, in auctions with non-reported bids, the observed difference between the cost distribution from data and the cost distribution predicted by the model with bid manipulation is reduced by at least 59% and by 99% in 60% of cases.

Having shown that the model-predicted cost distribution fits the cost distribution from the data, the estimates are used to explore counterfactual simulations of the model that address two aspects of corruption influence in the procurement market. First, I quantify the distribution of rents to winners in rigged auctions. Second, I explore the losses to procurers' welfare. In an open electronic auction, the contract is allocated to the most efficient bidder because everyone bids up to their own costs and the winner benefits from private information about his own costs. This information rent is not reflected in the award price of a contract. In contrast, under bid manipulation, a winner receives additional gains from blowing up his costs; this rent is included in the procurement price. The results highlight that corruption rents are large, ranging on average between 1.3% and 41% of award prices, depending on the type of product procured. The model also allows for explicit quantification of the expected costs of bid manipulation for a procurer. These are the potentially avoidable costs that a procurer should consider when forming a procurement budget. An analysis of procurement costs suggests that, due to corruption, government procurers should expect to pay up to 4.6% more on average across different product categories.

This paper makes several contributions to the existing literature. To the best of my knowledge, it is the first paper that considers how corruption at the post-bidding stage affects the strategic behavior of bidders. It introduces a new channel of corruption—bid manipulation—into the existing theoretical and empirical auction models. The unique feature of the collected dataset is that it has both competitive and rigged auctions. This allows for model validation. Moreover, the model framework proposed in this paper is applicable to a wide range of auction data with suspected bid manipulation because it does not require that corruption be revealed (by an anti-trust investigation, for example). The identification is based exclusively on the auctioneers' bid evaluation decisions and the winners' bids.

The rest of this dissertation proceeds as follows. Chapter 2 reviews the relevant literature. Chapter 3 describes the institutional details and necessarily details about the auction procedure and corruption mechanism. Chapter 4 discusses the data collection procedure and presents reduced-form evidence of non-competitive behavior, based on the data. In chapter 5, I present the theory of bidding with bid manipulation. Chapter 6 outlines identification and estimation for a version of the model with exogenous entry. In Chapter 7, I discuss the results of the estimation and the model performance. I then quantify the additional gains for a corrupt firm and the additional losses for a procurer in chapter 8. Chapter 9 concludes the research findings and outlines directions for future work.

Chapter 2

Related Literature

In in this chapter, I review the most relevant empirical literature on corruption in government procurement in general first. Then I will briefly discuss several empirical studies which are related to corruption in procurement auctions specifically. And after that I will describe the existing theoretical models of auctions with corruption.

2.1 Review of Empirical Literature

This project is most closely related to the empirical literature on corruption in public procurement. Despite the severity of the problem, there are very few empirical studies on how corruption affects procurement outcomes. Bandiera, Prat and Valletti (2009) have studied public procurement prices as they relate to the efficiency of procurement officials in Italy. They report that up to 2% of GDP could be saved if most procurement officers would pay the same price as the most frugal officers. Mironov and Zhuravskaya (2016) investigates local governments' procurement in Russia and conclude that, due to inefficient allocation of contracts to less productive favored firms, local governments lose 4% of their procurement revenue. Palguta and Pertold (2017) finds that procurement auctioneers manipulate the reserve price to influence the procurement procedure, which leads to 5.9–8.9% higher prices in Czech procurement. Decarolis et al. (2020) study delegation in Italian public procurement and its effects on corruption using restricted access information on firms owners and public servants suspected of corruption. They find out that corrupt firms are more likely to win in auctions which involve subjective or negotiated choice criteria. A number of papers are using procurement data to detect and assess corruption (see, for example, Di Tella and Schargrodsky, 2003; Ferraz and Finan, 2008; Coviello and Gagliarducci, 2017). My paper complements this strand of literature by providing empirical evidence of corruption at the bid evaluation stage. Specifically, I develop a fully structural econometric model designed to be implemented using actual data with possible corruption at the bid evaluation stage as part of the equilibrium and to demonstrate that the model is non-parametrically identified by commonly available observables at open electronic auctions.

Structural empirical auction models of corruption are rather scarce. A notable example is Cai, Henderson and Zhang (2013), which finds evidence of price manipulation by auctioneers to favor less transparent procurement procedures in Chinese urban land markets. Another example is Huang (2017), which investigates quality manipulation by the auctioneer in scoring procurement auctions for server room construction projects in China. The author finds that corruption distorts behavior of the favored bidder and causes it to bid more aggressively. Auriol (2006) takes a calibration approach to quantify corruption in public procurement. Unlike these papers, I empirically study bid manipulation by auctioneers in open outcry procurement auctions.

This paper is also related to the studies of electronic procurement and electronic bidding as technological means to deter corruption and improve procurement outcomes. In Lewis-Faupel et al. (2016) the authors compare the effects of introducing electronic procurement on procurement outcomes in India and Indonesia. They do not find any effect on procurement prices, but argue that e-procurement has lowered participation costs and increased quality of procurement projects. Kochanova, Hasnain and Larson (2020) uses cross-country survey to measure impact of e-procurement on competition. They report that introduction of electronic tenders improves applications, but also increased the probability of paying a bribe to secure a procurement contact in developed countries. Banerjee et al. (2020) takes an experimental approach to explore the effects of e-invoicing on public programs expenditures in India. The study reveals the long-lasting decrease in workfare program (MGNREGS) expenditures as well as improved monitoring and lower leakages. In this paper I emphasize the importance of information reporting and auctioneers discretion in electronic procurement auctions: free public access to electronic recordings of auctions procedures is helpful for detecting and deterring fraudulent behavior and measuring its magnitude.

Finally, this paper is more broadly connected to a growing body of work which examines procurement market. A group of papers empirically analyzes the advantages and disadvantages of different award mechanisms (for example, open vs. sealed-bid auction, average-bid vs. first-price auction, etc.) (Athey, Levin and Seira, 2011; Decarolis, 2018). Another group of paper is concentrated on impact of various policy regimes and procurement regulations (Decarolis, 2014; Athey, Coey and Levin, 2013; Krasnokutskaya and Seim, 2011; De Silva, Kosmopoulou and Lamarche, 2009). This paper suggest that, holding other rules fixed, an important aspect of effective procurement is integrity of participants and procurement officials.

2.2 Review of Theoretical Literature

This paper also extends the literature on theoretical models of corruption in auctions. The previous literature on auction models with corruption agreements between an auctioneer and bidders can be divided into three groups according to a corruption mechanism under study. One group of papers focuses on bid leakage. In these papers an auctioneer allows his preferred bidder to adjust the bid after observing information on competing bids. In Compte, Lambert-Mogiliansky and Verdier (2005) the authors consider a first-price procurement auction in which an auctioneer allows his favored bidder to re-adjust its bid in exchange of a bride. They show that corruption provides auction participates with a sustainable implicit collusion mechanism where everyone competes in bribes for a chance to re-submit the initial bid. Burguet and Perry (2009) propose a three-stage bid leakage auction model. During the first stage an auctioneer grants right-of-first-refusal to a preferred bidder. At the third stage the authors examine how such an agreement modifies a first-price and open clock auction mechanisms. They conclude that if this kind of corruption occurs, the auction is not effective. Arozamena and Weinschelbaum (2009) investigate how leakage of bid information to a favored bidder alters behavior of non-favored bidders in first-price auctions. The theoretical results point out that for a class of logconcave cost distributions, the non-favored participants bid more aggressively in presence of corruption.

In the papers reviewed in the previous paragraph, there is only one favored bidder. Yet it may be advantageous for the auctioneer to form a corruption agreement with more than one bidder. This form of corruption if often referred to as "bid orchestration". In a bid orchestration scenario, the corrupt auctioneer plays a role of a cartel manger and benefits from bid coordination or market allocation by members of a collusive ring. In Lambert-Mogiliansky and Sonin (2006) the dishonest auctioneer extracts rents from abusing his power to allow the bidders simultaneously re-adjust their bids in first-price multi-object auction. The authors show that corruption enables a sustainable collusion agreement even in absence of repeated interactions.

The third group of papers concentrates on corruption mechanisms of manipulating quality in procurement auctions. For example, Celentani and Ganuza (2002) consider a first-score procurement auction where the corrupt auctioneer may adjust quality of the procured product to favor one of bidders. They point out that corruption, as opposed to a generally perceived view, may lead to an increase in the number of potential bidders and thus overall competition in procurement market. Burguet and Che (2004) explore the same mechanism in relation to efficiency, quality distortion and contract allocation. Burguet (2017) characterizes how the optimal procurement mechanism in presence of manipulation of quality assessment procedures and bribing competition. In contrast, Huang and Xia (2019) examine a scoring and minimum quality procurement auction with an exogenously formed corruption agreement. In a unique contribution, I develop a new theoretical auction model that involves a dishonest auctioneer reducing competition during bid evaluation to favor a preferred bidder.

Chapter 3

Background

In this chapter, I summarize pertinent information on the institutional background in Russia, the auction procedure, and the bid manipulation mechanism.

3.1 Procurement in Russia

There are several important stages of development in the procurement system in the Russian Federation. The first attempts to provide unified guidance for government agencies about procurement procedures were made in 2005. They resulted in the first Federal Procurement Law, enacted on January 1st, 2006. The electronic procurement was introduced in 2011 and the Centralized Procurement System was created. The purpose of this system is twofold: to ease search and access to public procurement tenders and contracts and minimize opportunities for corruption and other procurement fraud. This system also collects, processes, and stores all procurement data. In 2014, the Federal Procurement Law was modified, introducing several important changes. First, it required that public access be provided to all procurement data. This made the entire database on public procurement available for free through the Centralized Procurement System. Second, the new law mandated that all procurement purchases above RUB 35K (about \$ 1K) should be made through an open electronic auction. This has eliminated any remaining manual procurement. It also means that data on all public procurement purchases in the country since 2014 are contained in a single source—the Centralized Procurement System. Third, the new Federal Procurement Law significantly broadens the responsibilities of the procurement officers who act as auctioneers in electronic auctions.

It is difficult to determine the exact size of the public procurement sector in Russia because the Federal Statistical Agencies do not provide this data, although (as in many other post-Soviet countries) government procurement is still a large part of the economy. The volume of procurement requests placed in 2014 totals RUB 7,517.11B[1], which constitutes about 9.5% of the country's GPD in 2014 prices. Almost 300K public organizations in 2014 placed 2.7M procurement requests, resulting in the award of 2.5M contracts with an average savings of 8.2% off the initial procurement price. Among regions where the number of procurement purchases was the largest are Moscow and Moscow Oblast, St. Petersburg, and Krasnodar Krai. The latter can be attributed to the fact that the City of Sochi, situated in Krasnodar Krai, hosted the XXII Olympic Winter Games in 2014. The two biggest regions (Krasnoyarsk Krai and the Republic of Sakha) accounted for 3.3% of the total procurement

[1]Statistics available from the Centralized Procurement System webpage `https://zakupki.gov.ru/epz/main/public/home.html#statAnchor` (in Russian only)

volume. The size of the Russian procurement sector and its diversity and data availability, as well as the history of corruption, makes it an ideal case for this study.

3.2 Open Electronic Procurement Auction

I concentrate on open electronic procurement auctions conducted between January 1st and December 31st, 2014. A procurement auction is run by a procurement officer. A procurement officer is an external and internal expert or an organization's employee who received advanced training in procurement. An officer begins a purchase by placing a public announcement in one of the eligible online platforms. An auction platform is a website that enables an auction algorithm and communication between auctioneers and bidders and between auctioneers and the Centralized Procurement System. Since July 10, 2010 all auctions have been conducted through one of the five designated online platforms[2].

To participate in an auction, a firm must be qualified[3], accredited with the online platform holding the auction[4], and submit the bid security deposit[5]. A firm also must prepare a formal application consisting of two parts. The

[2]Approximately 1.5 million of procurement purchases each year is conducted through the undesignated electronic platforms. These are governed by the Federal Law 223-FZ and apply less strict regulations.

[3]This implies that a firm is not bankrupt, is not sanctioned under administrative law, does no have any substantial unpaid taxes, is not in the registry of the suppliers who have committed violations of procurement rules during the last two years, does not have a conflict of interests and is not an off-shore entity.

[4]The accreditation is with an auction platform is free and valid for 3 years.

[5]The amount of a bid security deposit varies between 0.5 and 5% of the maximum price of the lot (for contracts above RUB3 million) and 1% of maximum price for contracts below RUB3 million.

first part describes the good or service that they are offering to fulfill the procurement order. The second part contains information on the firm itself (tax ID, name, address, owner, bank information and other relevant details). Until the winner of the auction is determined, the list of firms who submitted their applications is available only to the auctioneer and the online platform holding the auction.

An auction proceeds to the bidding stage if at least two qualified participants have submitted their applications. The eligible firms (anonymous at the bidding stage) are each assigned a participant number. All participants log in to the online platform and participate in a low-bid open English auction. Any participant making a bid must lower the current bid by a fixed amount (0.5-5% of the reserve price). Because the auction is open, the information on the bid, the time entered, and the participant number is immediately visible to all auction participants. However, the exit decision of a participant is not observed by other bidders straight away. On the contrary, bidders may re-join the auction at any point after the current bid was made within the ten-minute time limit.[6] The auction continues until ten minutes have passed since the most recent qualifying bid.

An hour after the auction is completed, the auctioneer receives the ten best

[6]The possibility to exit and rejoin the auction creates an issue of within-auction bid dynamics. To deal with it, I adopt an approach similar to that of other paper on electronic auctions (see, in particular, Bajari and Ye (2003) or Hickman, Hubbard and Paarsch (2017)). This approach divides auction time into two periods. During the initial period bidders test the waters and submit bids which convey little or no information about their true costs or the likely award price. Thus bidders disregard these bids and will formulate their strategy at the beginning of the final period ignoring the previous bid dynamics. Bidders do this by incrementally decreasing their bids by a predetermined amount up to the level of their optimal bid. In other words, only the last bid submitted by each bidder matters.

offers. These contain the identifying information for the auction participants, but do not allow for the bidders to be linked to the specific bids they submitted during the auction. The auctioneer has three business days to evaluate each bidder's proposals and credentials.

The auctioneer must select the lowest bidder to award the procurement contract. The winner is paid the second-lowest bid plus a fixed price decrement. However, if the lowest bidder is not qualified by the auctioneer, then the second lowest bidder will be considered a winner[7] and the contract will be drawn at the price equal to its own bid. If there are no approved participants, either because none of the firms submitted bids or because all bidders were deemed unqualified, the procurement order is canceled.

3.3 Corruption and Bid Evaluation

There are numerous opportunities for an auctioneer to achieve personal gain from delegation at any stage of the procurement process; many of these opportunities arise outside of the bidding itself. This type of corruption implies rather simply reducing or eliminating competition. A bidder cannot lose if it is the only one in the game. One of the most widespread methods for eliminating competition in a procurement auction at the post-bidding phase involves unfair rejection of qualified bids. An auctioneer approaches a potential bidder and offers to adjust the bidding results in the bidder's favor. Manipulation of bids may involve very broad and vague or, alternatively, detailed specifi-

[7] In a case, the second lowest bidder is also disqualified, the contract is awarded to the third lowest and so forth.

cations for the procurement project. A dishonest auctioneer may destroy or manipulate documentation to disqualify a rival's bid during bid evaluation.

Because this type of corruption reduces competition in auctions and involves an agreement between an auctioneer and a bidder, it is often referred to as collusion between an auctioneer and a bidder. Assuming that both an auctioneer and a favored bidder stand to benefit from this corruption agreement by eliminating some (or all) rival bidders, the probability of selecting a favored bidder will increase and a dishonest auctioneer may also enjoy higher returns than under an open and truly competitive auction. This method of limiting competition in an auction is rather effective, as well as difficult and costly to detect. At the same time, this method cannot guarantee that all of the non-favored bidders will be disqualified.

Below I discuss several real anti-trust cases taken place in Russia to illustrate how bid manipulation works in practice. In the first example a procurer has placed a work order for gas pipeline construction and one of the criteria in the technical specifications required to use only yellow or orange pipes. This specification considerably increased the procurement price. Regular black pipes of the same quality cost 60-80% less. It also allowed the auctioneer to eliminate all the potential suppliers but one. This participant offered black pipes with a thin yellow stripe and was awarded a contract for RUB 37 million. My second example is a road construction project for a RUB 10 million contract in a medium-size town. The job specification includes a general description of the works and the total volume (500 sq. meters of road surface) but it lacks details (e.g. street addresses and what kind of work is required in each street). For comparison, costs of surfacing a single section of a road are much lower than costs of repairing of 200 pot-holes in distant parts of a town. Vague and incomplete specifications have allowed the auctioneer to disqualify most of potential suppliers in this case. The third example is an example of aligning specifications to that of a particular supplier. A regional administrative body has placed a RUB 1.7 million purchase order for a truck. The product description includes a very detailed vehicle configuration (up to a heater brand, number of audio speakers and trim design). These detailed description intended to match a favored supplier and left no space for alternative offers. These examples highlight that while in general it is possible to completely eliminate competitors using bid manipulation, neither an auctioneer nor a favored bidder can be certain: in the second example only some of the bidders were disqualified.

Reducing competition by disqualifying bids at the bid evaluation stage is not endemic to Russia; unfortunately, it is a quite commonly discussed abuse of power that occurs in procurements all over the world. In its recent report "Preventing Corruption in Public Procurement", the OECD identified corruption opportunities arising at the bid evaluation stage as a major risk to integrity in procurement.

Chapter 4

Data

A primary obstacle to empirical research on collusion and corruption is that — by their nature — these are illegal activities that do not show up in data. In empirical auction literature, researchers instead rely on so-called validation samples to determine data irregularities, which helps identify auctions with suspected collusion and construct formal econometric tests. A validation sample is a subset of auctions in which collusion has been made observable by an anti-trust investigation.

One of the most famous examples Bajari and Ye (2003) uses data on seal-coating construction auctions in which some of the major participants had been convicted of bid-rigging; this shows that correlated bids are indicative of cartel behavior. Another example, Conley and Decarolis (2016), documents that, in average bid auctions, unusually high/low bids from a group of firms that frequently participate together are indicative of bid coordination by firms with shills or by a bidding ring.

In this chapter, I describe the process of data collection, delineate data irregularities, and provide reduced-form evidence that these irregularities signal non-competitive behavior.

4.1 Data Collection, Sample Selection and Non-reported Bids

All of the information on procurements is stored at the ftp-server of the Centralized Procurement System in the form of open data with free public access[1]. New data are uploaded daily during regular maintenance hours and contain documentation on all procurement stages, such as announcements, auction protocols, and contracts, that happen during the day.

To create my dataset, I have downloaded reports on procurement notifications, bidding, and bid evaluation protocols, as well as placement reports for all of the procurements conducted through an open electronic auction procedure between January 1st and December 31st, 2014. If any changes are made to a report, the database contains two versions of the report with the same identification number. In such cases, I downloaded the most recent report. Reports are recorded in the form of structured xml-documents. The structure of a report is fairly standardized for a given procurement procedure and report type. This allows for the extraction of large volumes of data in a relatively short time, as the whole parsing process can be automated.

I began with a sample of over 2 million data entries. I filtered the sample

[1] Accessible at `ftp://ftp.zakupki.gov.ru/`. Last accessed on 06/08/2020.

based on several criteria: (i) a single contract for a single item procured; (ii) only one winner. During the period of study, there were 1.25M such auctions placed in five platforms. Table A.1 in appendix A reports the numbers and percentages of auctions by platform. I only utilize auctions from the three largest platforms, which together constitute 93.5% of all procurement purchases conducted through an open electronic procedure.

Procurement notifications contain information on a procurement procedure, the object of procurement, reserve price, procurer, procurement officer, and any preference programs that apply. Bidding protocols provide details on the first and last bids of every auction participant, along with a timestamp. Empirically, almost all first bids represent a minimal starting bid of 0.5% below the reserve price and fall far away from the final price. This pattern is consistent with the previous assertion that bidders submit very high meaningless bids early on and then covert to their optimal strategy later on.

After auction completion, a procurement officer reviews each bidder and decides whether a bid satisfies the auction specifications. This decision is recorded in a bid evaluation report along with the participating firm's name.

4.1.1 Non-reported Bids

In order to find corruption indicators in my data, I cross-check (Banerjee, Hanna and Mullainathan (2012)) bid evaluation reports submitted by auctioneers against other bidding documents. Even though the reports do not have detailed data on the amount of each bid, this allows me to compare how many auction participants have submitted bids to how many bids were evaluated by auctioneers.

Although procurement officers are required by federal law to make all auction information available to the public, a comparison of the bidding results with bid evaluation protocols suggests that the number of bids reported by an officer to the system does not coincide with the number of bidders who participated in the auctions. Figure 4.1 depicts a histogram of the number of participating bidders versus the number of reported bids. It is evident that the two distributions do not coincide. In fact, 15.5% of all auctions in the sample show non-reported bids.

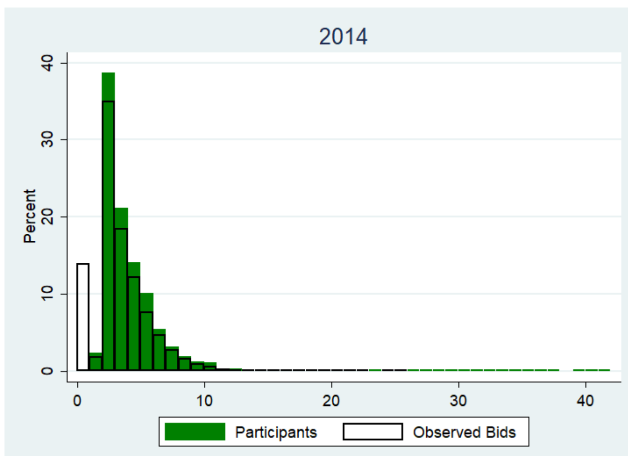

Figure 4.1: Distribution of the number of participated bidders and reported bids - all data

This pattern in the data persists across different auction platforms and can be attributed to discrepancies in information reporting regulations between them. Figure 4.2 shows the distribution of observed and reported bids across five online auction platforms.

Figure 4.2 shows that bid underreporting occurs in platforms two and four

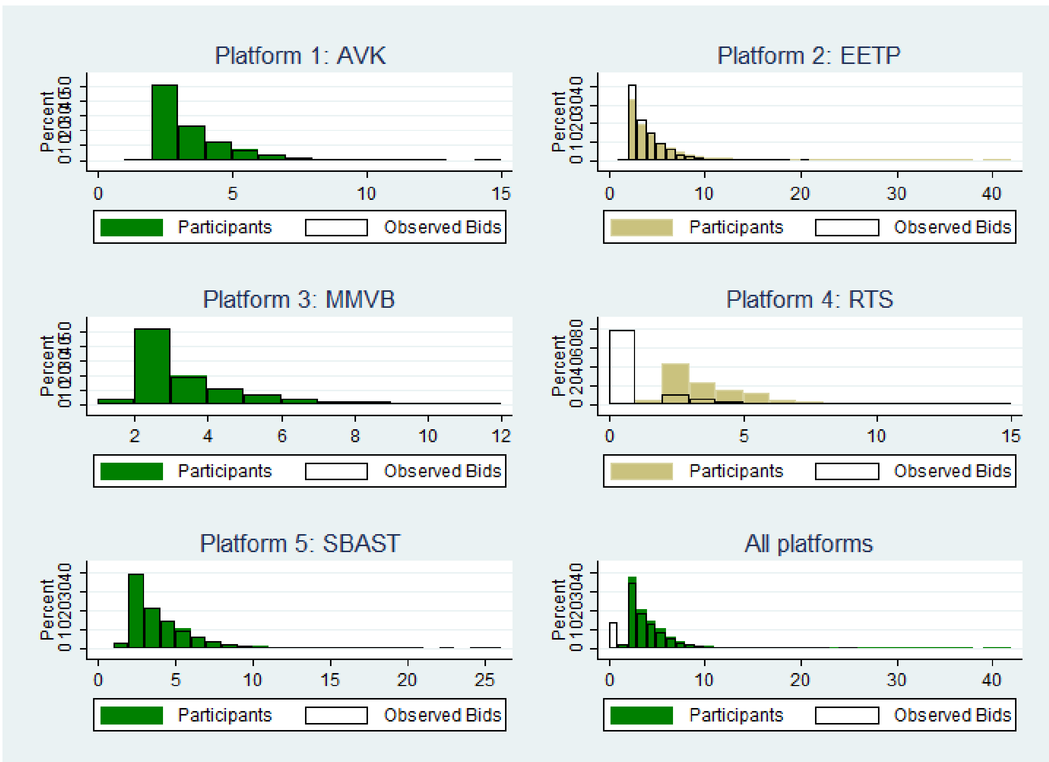

Figure 4.2: Distribution of reported bids vs. total submitted bids by auction platform

(in yellow), while other platforms do not show any significant number of non-reported bids. Platform 5 is the oldest and most widely used online auction platform for procurement(56% of all auctions in 2014). It is owned by the biggest bank in the CIS region. It is also considered the most secure and technologically advanced platform: the interface is fully integrated with the Centralized Procurement System and all auction results are automatically uploaded into the System. The other platforms, however, require auctioneers to enter auction results manually into protocol forms provided by the Centralized Procurement System. This feature of these platforms allows auctioneers to manipulate bid information for their own benefit.

To fill in the non-reported bids, I supplement my dataset with placement reports, which record the name of the firm with which the contract has been signed and the amount of the award. Using procurement contract placement results, I can restore the price of procurement for 60.3% of auctions. All of the reports can be merged using a unique procurement identifier.

Later in this section, I show why non-reported bids—and other patterns visible in the data —indicate bid manipulation. I investigate what this implies about procurement costs and the competitiveness of auctions in the sample. I also formulate data-driven tests of non-competitive behavior. For these purposes, I have limited the sample to include only auctions with at least two participants. I have only kept product categories in which a sufficient number of auctions have at least one non-reported bid. The final dataset contains 151K entries and 52K unique auctions in 20 product categories. Both of the limitations are necessary to perform an empirical analysis. First, an auction only occurs if there are least two bidders. Second, I need a homogeneous sample of the auctions for the same product to be sufficiently large to provide sufficient power for model estimation.

4.2 Data Description

My data contain 5,799 auctions with non-reported bids and 31K auctions in which I observe all bids. Contracts involve procurement of various products that can be broadly divided into three categories: goods, services, and pharmaceuticals. The three largest product categories include security services, drugs for cancer treatment, and computerized system maintenance services (see table A.2 in Appendix A for details).

Table 4.1 presents summary statistics for the key outcomes of interests at both the auction and bidder levels. The average initial or maximum reserve price for a contract is approximately \$21K (RUB 751K); the average award price is 11.7% lower (approximately \$19K). This 11.7% constitutes savings for local and federal governments from running an auction. The procurement contracts vary considerably in size. The median winning bid is \$2.2K (RUB 77K), with a standard deviation of almost \$100K. Such huge variation prevents aggregation of procurements for different products. The analysis must be between auctions for the same good, service, or work. The table also indicates that the entry rate into auctions is quite low. Each auction averages 4 potential participants and 3 actual bidders. The reported number of bids on average is even lower—about 2.4 bids.

Dependent variable	Mean	Median	SD	5 %-tile	95 %-tile	Obs
	Unit of observation: auction					
Initial price per unit, RUB	751,012	95,657	3,665,723	68.3	2,779,728	37,396
Award price per unit, RUB	662,416	76,554	3,506,804	47.369	2,399,760	37,396
Potential bidders	3.631	3	2.667	2	8	37,396
Bidders	2.803	2	1.835	2	5	37,396
Admitted bids	2.587	2	1.150	1	5	37,396
Reported bids	2.468	2	1.239	1	5	37,396
Reported admitted bids	2.419	2	1.201	1	5	37,396
	Unit of observation: bidder					
Bid per unit, RUB	644,475	77,113	3,075,887	47.83	2,411,880	92,301
Reported admitted bid per unit, RUB	634,101	76,075	2,913,857	47.81	2,386,069	90,464

Note. - Conversion rate: 35RUB/1USD.

Table 4.1: Descriptive statistics for main outcomes of interest in original units of measurement

In Table 4.2, the same outcomes have been standardized by the average value among auctions without non-reported bids:

$$Y_{tj}^S = \frac{Y_{tj}}{\overline{Y}_{\text{all reported}}}$$

where Y_{tj} is an outcome for auction $t = \{1, \ldots, T\}$ in sample $j = \{\text{non-reported}, \text{all reported}\}$ and $\overline{Y}_{\text{all reported}} = \frac{\sum_{t=1}^{T} Y_{t,\text{all reported}}}{T}$ is an average value for an outcome in the sample of auctions in which all bids have been reported. Subscript 'non-reported' then stands for the type of auctions with non-reported bids. This has been done to highlight the differences in outcomes between the two samples.

The first entry in the table reads, "on average, the reserve price is 8.6% higher than an average reserve price in the auctions without non-reported bids." The difference in award prices between two kinds of auctions is even more pronounced—14%. While the number of auction participants is only 10% below the average, the number of reported bids is almost 20% below the average.

Standardized variable	Mean	Median	SD	5 %-tile	95 %-tile	Obs
	Unit of observation: auction					
Initial price per unit	1.086	0.138	5.299	0.0001	4.018	37,396
Award price per unit	1.138	0.132	6.026	0.00008	4.124	37,396
Potential bidders	0.881	0.728	0.647	0.485	1.941	37,396
Bidders	0.905	0.646	0.592	0.646	1.614	37,396
Admitted bids	0.856	0.662	0.381	0.331	1.654	37,396
Reported bids	0.797	0.646	0.400	0.323	1.614	37,396
Reported admitted bids	0.801	0.662	0.397	0.331	1.655	37,396
	Unit of observation: bidder					
Bid per unit	1.062	0.127	5.070	0.00008	3.976	92,301
Reported admitted bid per unit	1.057	0.127	4.858	0.00008	3.978	90,464

Table 4.2: Descriptive statistics for the primary outcomes of interest, normalized by the average outcome among auctions in which all bids are reported

To further investigate whether these higher-than-averages prices can be attributed to missing bids, I regress each auction outcome on a constant and a dummy indicator of non-reported bids. The auctions in the dataset also differ on several observed characteristics, such as place of contract performance, contract duration, size of bid and contract security deposits, and whether an auction is subject to any bid preference or domestic producer program. To control for these differences, I use the fixed-effects regression:

$$Y_t = \alpha + \beta Non - reported_t \tag{4.1}$$

$$+ \sum_{m=1}^{M} \delta_m X_{mt} \tag{4.2}$$

$$+ \gamma_{region} + \gamma_{quarter} + \gamma_{product} + \varepsilon_t \tag{4.3}$$

Here, Y_t is an outcome in auction t; $Non - reported_t$ is a dummy that equals 1 if an auction t has at least one non-reported bid; X_m is a vector of observed auction characteristics—bid and contract deposit, share of auctions set aside for small businesses and domestic producers; and γ_{region}, $\gamma_{quarter}$, $\gamma_{product}$ are region, quarter, and product fixed effect.

In equation 4.1, the coefficient α is the average across auctions without non-reported bids. The coefficient β, reported in the first column of table 4.3, is interpreted as "an outcome in auctions with non-reported bids is $\beta \times 100\%$ higher than an average in auctions without non-reported bids if $\beta > 0$. And, if $\beta < 0$ then the outcome is $-\beta \times 100\%$ lower than an average among auction in which all bids are reported. Even columns report the results that are conditional on the vector of controls, as in equation 4.2. Odd columns in table 4.3 also add fixed-effects as controls, as in equation 4.3. Conditional results do not have the same clear interpretation as in regression 4.1, but do yield several important observations. First, the procurement prices are approximately 37% higher in auctions in which some bids were not reported.

Dependent variable	β							
	Unit of observation: auction							
Initial price per unit	0.447***	0.428***	0.481***	0.414***	0.442***	0.376***	0.504***	0.389***
	(0.113)	(0.121)	(0.136)	(0.146)	(0.139)	(0.150)	(0.137)	(0.150)
Award price per unit	0.415***	0.377***	0.458***	0.371**	0.419***	0.334**	0.493***	0.366**
	(0.129)	(0.139)	(0.156)	(0.169)	(0.160)	(0.174)	(0.157)	(0.174)
Potential bidders	0.331***	0.376***	0.356***	0.401***	0.356***	0.401***	0.34***	0.373***
	(0.013)	(0.015)	(0.013)	(0.016)	(0.013)	(0.016)	(0.012)	(0.014)
Bidders	0.462***	0.517***	0.521***	0.579***	0.515***	0.572***	0.509***	0.554***
	(0.015)	(0.018)	(0.016)	(0.019)	(0.016)	(0.019)	(0.015)	(0.017)
Admitted bids	0.117***	0.127***	0.13***	0.14***	0.131***	0.141***	0.125***	0.131***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)
Reported bids	-0.235***	-0.203***	-0.189***	-0.158***	-0.192***	-0.161***	-0.197***	-0.172***
	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.006)	(0.007)
Reported admitted bids	-0.24***	-0.207***	-0.196***	-0.164***	-0.198***	-0.167***	-0.205***	-0.178***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)
	Unit of observation: bidder							
Bid per unit	0.535***	0.34***	0.397***	0.319***	0.314***	0.23***	0.315***	0.177*
	(0.076)	(0.079)	(0.083)	(0.089)	(0.086)	(0.094)	(0.086)	(0.095)
Reported admitted bid per unit	0.493***	0.29***	0.347***	0.258***	0.261***	0.167**	0.268***	0.118
	(0.065)	(0.068)	(0.066)	(0.072)	(0.067)	(0.074)	(0.066)	(0.073)
Covariates								
Bid deposit, %	No	Yes	No	Yes	No	Yes	No	Yes
Contract deposit, %	No	Yes	No	Yes	No	Yes	No	Yes
Set aside	No	Yes	No	Yes	No	Yes	No	Yes
Domestic preference	No	Yes	No	Yes	No	Yes	No	Yes
Fixed Effects								
Region FEs	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FEs	No	No	No	No	Yes	Yes	Yes	Yes
Product FEs	No	No	No	No	No	No	Yes	Yes

Note. - Robust standard errors in parentheses.

*, **, *** denote the significance at 10-, 5-, and 1-% levels, accordingly.

Table 4.3: Difference in means of auction outcomes between samples of auctions with and without non-reported bids: fixed-effects regression

Second, even if I control for relevant observed auction characteristics and fixed-in-time variables, the difference in prices and number of bidders remains large and statistically significant and preserves its sign. Third, the comparison of the coefficients between columns in table 4.3 suggests that, after controlling for the auction-level covariates—even though competition is twice as great—the prices in procurement purchases with non-reported bids are higher by 38.5%. The higher prices under higher competition in auctions with non-reported bids themselves do not allow for drawing any conclusions about the presence of corruption or distinguish between corrupted or simply inefficient auctioneers. This is the topic of the next section.

4.3 Descriptive Evidence for Non-competitive Behavior

In this section, I argue that patterns in the data are not explained by a non-collusive bidding model. The presence of non-reported bids itself does not imply the presence of dishonest behavior. There are two potential explanations to non-reported bids. One is that auctioneers intentionally conceal information on bids in situations in which the winning bid is not the lowest possible bid; this is consistent with the corruption scenario. Another explanation is that auctioneers are lax in their duties to report information to the Centralized Procurement System. Procurement officers simply may not exert sufficient effort to comply with the requirements of the new federal law, which does not prescribe any significant punishment or penalties for compliance failure and is hardly enforceable. Comparing the cost distribution of auctions with all bids observed to that of auctions with non-reported bids helps determine which explanation is more applicable.

In the competitive English auction, the winning bid is not observed; instead, the researcher observes the second-lowest bid (in other words, the award price). In the bid manipulation scenario, the goal of the auctioneer is to exclude all bidders that have bid lower than the favored bidder during bid evaluation. For example, if the result of this unfair disqualification is that only one of the bidders with lower costs has been eliminated, than the lowest opponent's bid will increase from second-lowest to third-lowest. Thus, it is not possible for a researcher to observe what the winning bid represents in cases in which some bids are not reported. However, these differences are statistically testable.

Athey and Haile (2002) have shown that—in a single-unit English auction with risk-neutral bidders, independent private values, and an absence of collusion—the underlying value distribution can be recovered using the observed winning bids only. Then, assuming that the observed bid is actually the second-lowest bid, the underlying cost distribution is non-parametrically identified. When there is no bid manipulation, using the winning bid distribution should yield the same cost distribution estimates in both samples (except for statistical error). Hence the assumption:

Assumption 1. *Using winning bids from auctions in which all bids are observed and from auctions with non-reported bids should result in the same predicted cost distribution if non-reported bids are random and both types of auctions are competitive.*

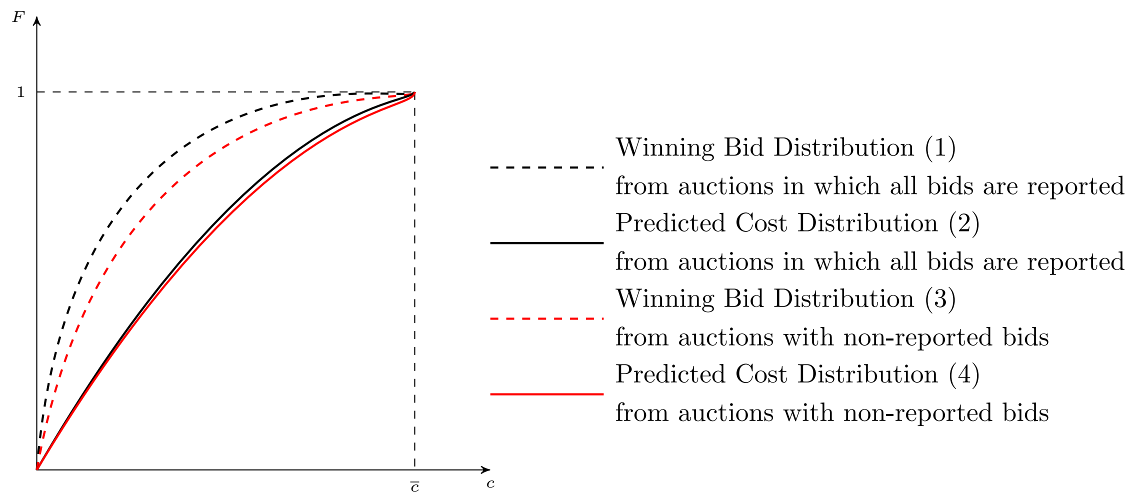

Figure 4.3: Illustration of winning bid and predicted cost distributions when Assumption 1 is satisfied

Assumption 1 is the main identification assumption. Under this assumption, auctions in which all bids observed are free of corruption and bids submitted in these auctions can be used to infer the true cost distribution of firms and to validate and simulate competitive outcomes in auctions with non-reported bids.

Figure 4.3 illustrates Assumption 1. In the figure, the black dashed line represents the distribution of winning bids in auctions without non-reported bids. The black solid line is the distribution of costs from the same auctions. This distribution can be predicted by applying the English auction model to the corresponding winning bids distribution as described below. In the absence of bid manipulation under assumption 1, this cost distribution also can be obtained directly from data using all observed bids from auctions in which all bids are reported. Thus cost distribution (2) is also a true empirical cost distribution. The winning bid distribution from auctions with non-reported

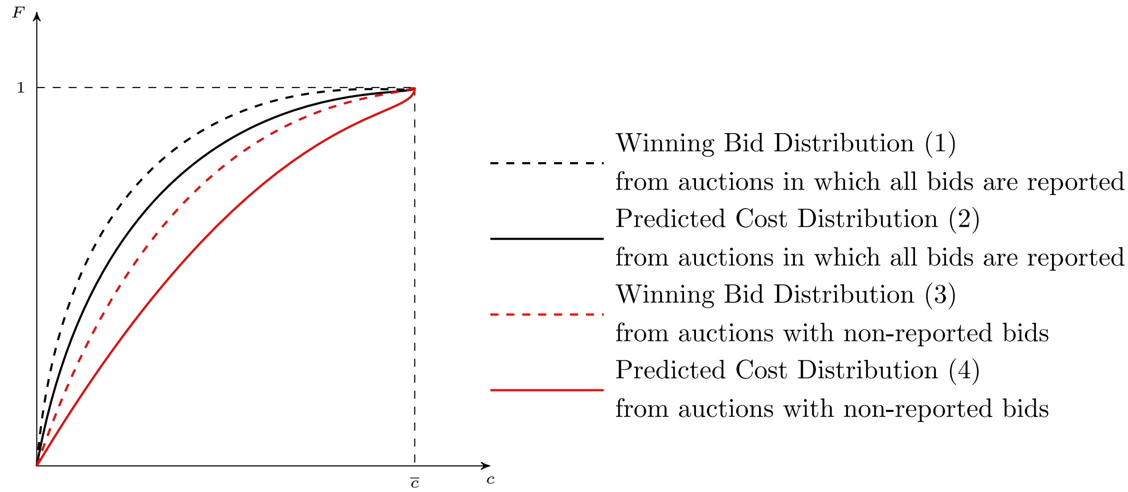

Figure 4.4: Illustration of winning bids and cost distributions when assumption 1 is violated

bids is pictured by a red dashed line. The solid red line is the cost distribution predicted from these winning bids using an English auction. If the black cost distribution (2) matches the red cost distribution then assumption 1 is satisfied.

When there is corruption, the winning bid in the sample of auctions where only a fraction of bids is reported is not the second-lowest bid, with a large probability. In this case, the two estimated cost distributions in the two samples will be statistically different. Figure 4.4 illustration this situation. In the figure, the predicted red cost distribution (4) from auctions with non-reported bids under a competitive English auction assumption does not match the true cost distribution (2). This happens when the non-reported bids are not random, assumption 1 is violated and the data do not fit a competitive English auction format.

Next I present an empirical test for assumption 1. Consider an environment where n risk-neutral bidders compete for a single procurement contract in a low-bid, open English auction with a public reserve price and a fixed price decrement Δ. Each bidder independently draws a private cost for the procurement from a commonly known distribution $F_C(c)$ that is twice continuously differentiable with a strictly positive on $[\underline{c}, \overline{c}]$ density $f_C(c)$. c represents costs of procurement to a bidder and $\xi(c)$ is an equilibrium bidding function. Let $c^{n-1:n-1} = \min\{c_1, c_2, \cdots, c_{n-1}\}$ be the lowest cost value among $n-1$ opponents and the *cdf* of $c^{n-1:n-1}$ be $F^{n-1:n-1}(c) = (1 - F(c))^{n-1}$ with the *pdf* $f^{n-1:n-1}(c) = (n-1)f(c)(1 - F(c))^{n-2}$.

In this framework, the Bayesian Nash equilibrium is to bid one's own costs; hence, the cost distribution of the winner $F^*(c)$ is identified from the observed winning bids immediately, via the following equation:

$$F^*(c) = F^{n-1:n}(\xi(c) - \Delta) \tag{4.4}$$

where $F^{n-1:n}(\cdot)$ corresponds to the distribution of the second-lowest bids. In an electronic procurement auction, a winning bid is the second-lowest bid plus price decrement, which is equivalent to the drop-out price of the highest value bidder in an English auction. Thus, an electronic procurement auction is strategically equivalent to the second-price auction [2].

If the winning bids from $t = \{1, 2, \cdots, T\}$ auctions are observed, the of $F^{n-1:n}(c)$ is estimated as using an empirical distribution function or more-

[2]The assumption that an e-auction can be modeled as SPA aligns with previous literature (see, for example, Haile and Tamer (2003) and Bajari and Hortaçsu (2004). The important difference that allows for point identification is that, in my case, the price decrement rules are well-defined and explicit (see, Hickman, Hubbard and Paarsch (2017) for details).

complex KDE methods. To account for the correlation between the winning bids and several observed auction characteristics (as discussed in the previous section), I use a smoothing conditional density estimator proposed by Li and Racine (2008):

$$\hat{F}(c^{n-1:n}|n, X) = \frac{\frac{1}{T}\sum_{t=1}^{T}\Phi\left(\frac{c^{n-1:n}-c_t^{n-1:n}}{h}\right)\nu^{|n-n_t|}K(X, X_t)}{\frac{1}{T}\sum_{t=1}^{T}\nu^{|n-n_t|}K(X, X_t)} \tag{4.5}$$

where $\Phi(\cdot)$ is a standard normal CDF; $\nu(\cdot)$ is a discrete kernel function for a number of bidders; and $K(\cdot)$ is a generalized mixed-data product kernel for each $X = x$ in the vector of observed auction differences. The estimator in 4.5 is preferred in this case due to its flexibility in accounting for both a mix of discrete and continuous covariates in X and ordered and unordered datatypes.

The knowledge of a single-order statistic is sufficient to uniquely determine the underlying distribution. In fact, the distribution of a second-lowest order statistic $F^{n-1:n}(c)$ from an *iid* sample of n from a distribution $F(c)$ is as follows:

$$\begin{aligned} F^{n-1:n}(c) &= \frac{n!}{n-2!}\int_0^{F(c)} t(1-t)^{(n-2)}dt \\ &= n(1-(1-F(c)^{(n-1)})) - (n-1)(1-(1-F(c)^{n})) \end{aligned} \tag{4.6}$$

Let $\hat{\mathbf{F}}^{n-1:n} = \{\hat{F}^{n-1:n}(c_1 \leq c), \cdots, \hat{F}^{n-1:n}(c_T \leq c)\}$ be the $1 \times T$ vector of the empirical frequencies, estimated using equation 4.5. Denote the RHS of equation 4.6 as $g_t(n_t; F(c_t \leq c))$ for each observed auction $t \in [1, T]$. I then define a minimum-distance estimator as an optimizer of the following objective function:

$$\hat{\mathbf{F}} = arg\min_{F}\left\{[\hat{\mathbf{F}}^{n-1:n} - \mathbf{g}(n;F)]'[\hat{\mathbf{F}}^{n-1:n} - \mathbf{g}(n;F)]\right\} \qquad (4.7)$$

In other words, the estimate of $\hat{F}$ is chosen to bring the empirical frequencies of the winning bid as close as possible to the frequencies of theoretical distribution in equation 4.6, given the number of participants n.

Assuming that there is no corruption in an auction and that the reported bid is the actual second-lowest bid, the distribution of costs estimated using a sample of auctions in which all bids are reported and the distribution of costs estimated using sample with missing data should coincide. However, if an auctioneer has been dishonest and misused the loopholes in the information-reporting regulations to conceal that some of the valid bids have been unfairly disqualified, the distribution of cost recovered using winning bids from the sample with non-reported bids should be below the distribution from the sample in which all bids are properly noted. Furthermore, the distance between two distributions increases as the reported winning bid moves away from the second-lowest bid.

The resulting estimated cost densities are shown in Figure 4.5 for 20 different products described in previous sections. The solid lines represent CDFs conditional on the full vector of observed auction characteristics. The vector of relevant auction characteristics includes the size of the bid and the contract security deposit and whether an auction is a set-aside or is subject to the domestic producer preference program. The dashed line includes only the number of bidders as a control; the dashed-dotted line includes time and region fixed effects. As expected, Figure 4.5 indicates that two densities do not coincide and that the differences increase as I control for auction characteristics.

To formally test the hypothesis that both empirical densities have been generated by a competitive English auction model, I apply two statistical tests. I denote frequencies estimated using bid data from the subsample of auctions where all bids are observed as $F^{data}(c)$; frequencies estimated using the English auction from the subsample of auctions with non-reported bids are denoted as $F^{Eng}(c)$. Assessing for the presence of non-competitive behavior tests the following hypotheses:

$$\begin{aligned} \mathrm{H}_0 &: F(c)^{data} = F(c)^{Eng} \; \forall c \in [\underline{c}, \overline{c}] \\ \mathrm{H}_A &: F(c)^{data} \geq F(c)^{Eng} \; \exists c \in [\underline{c}, \overline{c}] \end{aligned} \tag{4.8}$$

The one-sided Kolmogorov-Smirnov (KS) test considers the maximum distance as an evaluation criterion and also specifies the direction of stochastic dominance. The two-sided Anderson-Darling (AD) test is a more precise modification that uses the same criterion as the KS test but puts more weight on the tails of distribution. The results of the two tests, shown in Table 4.4, reject the null hypothesis of the equivalence between two distributions and confirm that the cost distribution of auctions with missing bids lies to the right. This alleviates a common problem with statistical tests as a collusion-detection de-

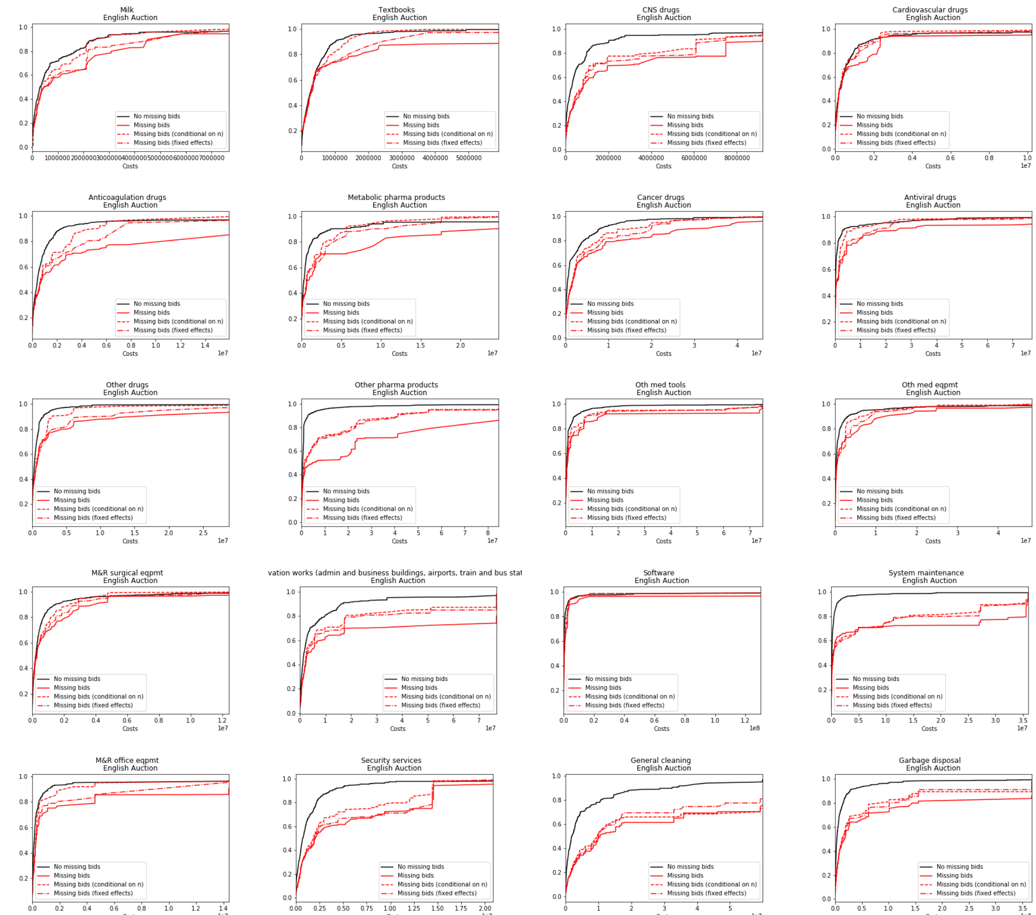

Figure 4.5: Estimated cost distributions using the English auction assumption

Product	KS Statistic	KS Bootstrap p-value	AD Statistic	AD p-value
Milk	0.208	0.0000	20.1033	0.0010
Textbooks	0.228	0.0000	70.3998	0.0010
CNS drugs	0.244	0.0000	26.1464	0.0010
Cardiovascular drugs	0.163	0.0007	7.0490	0.0010
Anticoagulation drugs	0.281	0.0000	32.3650	0.0010
Metabolic products	0.266	0.0011	4.1771	0.0069
Cancer drugs	0.140	0.0000	23.4604	0.0010
Antiviral drugs	0.267	0.0000	3.4072	0.0135
Miscellaneous drugs	0.130	0.0005	5.0339	0.0034
Pharmaceutical products	0.505	0.0000	176.0656	0.0010
Medical tools	0.250	0.0000	42.7332	0.0010
Medical equipment	0.270	0.0000	11.1031	0.0010
Surgical equipment	0.086	0.0000	10.1640	0.0010
Renovation work	0.271	0.0000	35.6973	0.0010
Software	0.227	0.0000	14.8442	0.0010
System maintenance	0.222	0.0000	14.2957	0.0010
Office equipment	0.164	0.0016	7.2894	0.0010
Security services	0.183	0.0000	37.4222	0.0010
General cleaning	0.425	0.0000	168.9339	0.0010
Garbage disposal	0.427	0.0000	64.9708	0.0010

Note. – The bootstrap K-S statistic and p-value has been computed using 10,000 samples.

Table 4.4: Results of the one-sided Kolmogorov-Smirnov test and the two-sided Anderson-Darling test

vice. When the test does not reject the null, it provides evidence that the data rationalize the competitive model. When the test rejects the competitive model, it cannot specify whether the reason is collusion or model misspecification. The one-sided test finds that the firms in auctions with non-reported bids actually bid more conservatively—not more aggressively—across all product categories. This indicates the presence of non-competitive behavior.

4.4 Alternative Sources of Non-reported Bids

As with any other method of measuring corruption, my method does not allow to argue with certainty that non-reported bids resulted from bid manipulation by auctioneers. In this section, I discuss alternative sources of non-reported bids and show that non-reported are not a simple mismeasurement in the or just a sign of auctioneers incompetence.

Non-admitted Bids. These non-reported bids cannot be explained by the fact that auctioneers do not report disqualified bids. Figure 4.6 compares the distribution of admitted bidders to the distribution of observed bids. It is evident from the figure 4.6 that—even accounting for disqualified bids—the number of reported bids is lower than the number of bids submitted by auction participants.

Revised Auctions. Under certain conditions, the auction results can be revised at any stage of the procurement procedure. Non-reported bids can reflect bids withdrawn by the participants in response to changes in the procurement procedure. Figure 4.7 compares the distribution of revised auctions

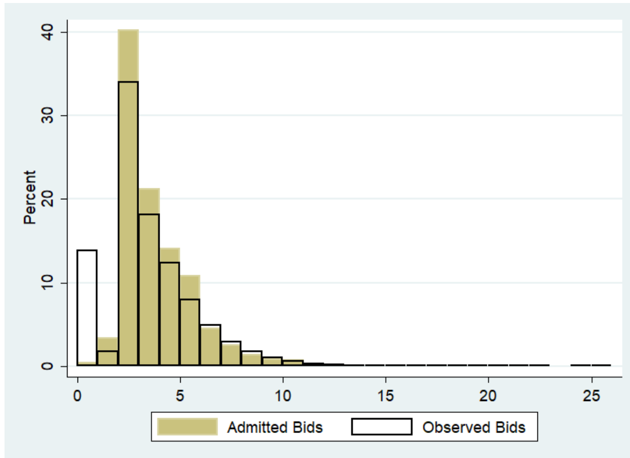

Figure 4.6: The distribution of the number of admitted bids vs number of reported bids

to the distribution of auctions with non-reported bids. This shows that only a very small proportion of non-reported bids can be explained by the fact they were recalled.

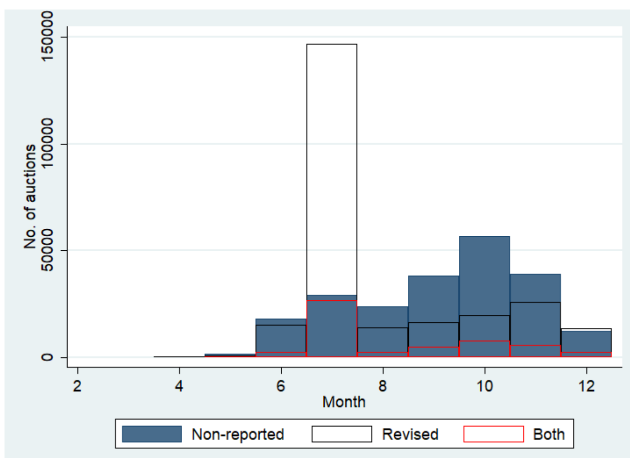

Figure 4.7: The number of revised auctions vs number of auction with no-reported bids per month

Poorest Quality. In open electronic procurements auctioneers have a simple task of choosing the bidder offering the lowest price. Despite that auctioneers

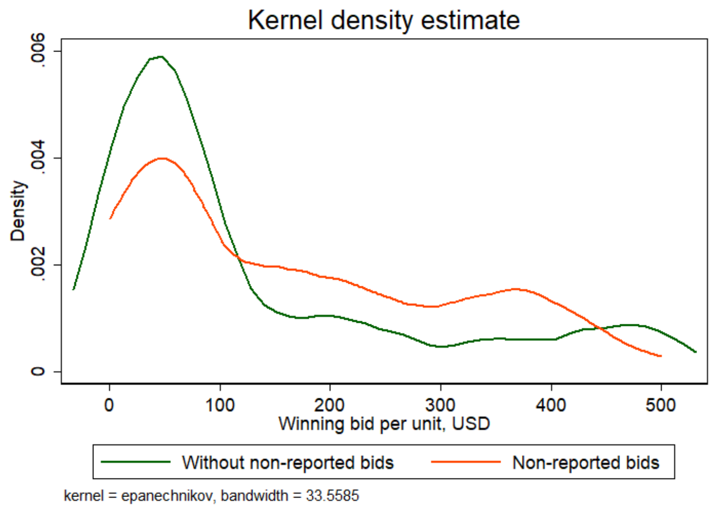

Figure 4.8: Comparison of winning bid distributions from auctions with non-reported bids and from auctions in which the lowest bid was disqualified

may be concerned about the quality of the cheapest product or service. Then auctioneers will be reluctant to accept the lowest offer and will disqualify such bids. Such disqualification may also result in higher procurement prices. However, if it is true the same pattern should be observed in both auction samples. Figure 4.8 plots the distribution of award prices from competitive auctions (auctions without non-reported bids) in which the lowest bid was disqualified and the distribution of award prices from auctions with non-reported bids. Notice that the winning bid distribution of potentially rigged auctions is derived using only auctions in which a fraction of bids is reported in order to make the samples of two types of auctions more comparable.

In figure 4.8 the winning bid distribution from auctions with non-reported bids (red distribution) is skewed to the right and prices are significantly higher than in auctions without non-reported bids even though the lowest bid was rejected (black distribution). This disproves that higher award prices in auctions with non-reported bids can be attributed to the auctioneer disqualifying the lowest bids out of concern for poor quality.

Chapter 5

Procurement Auction with Bid Manipulation

In this chapter, I present an auction model of bid manipulation and demonstrate that the equilibrium of a favored bidder is characterized by a cutoff strategy.

5.1 Motivation

The goal of this section is to formalize a theoretical method of bids underreporting and formulate an applied auction model with a corruption agreement between an auctioneer and a bidder which describes behavior of agents in the auctions with non-reported bids: (i) favored bidders bid less aggressively; (ii) probability to win of a favored bidder is increased by eliminating its competitors ex post; (iii) higher equilibrium procurement prices.

Then if the cost distribution predicted from auctions with non-reported

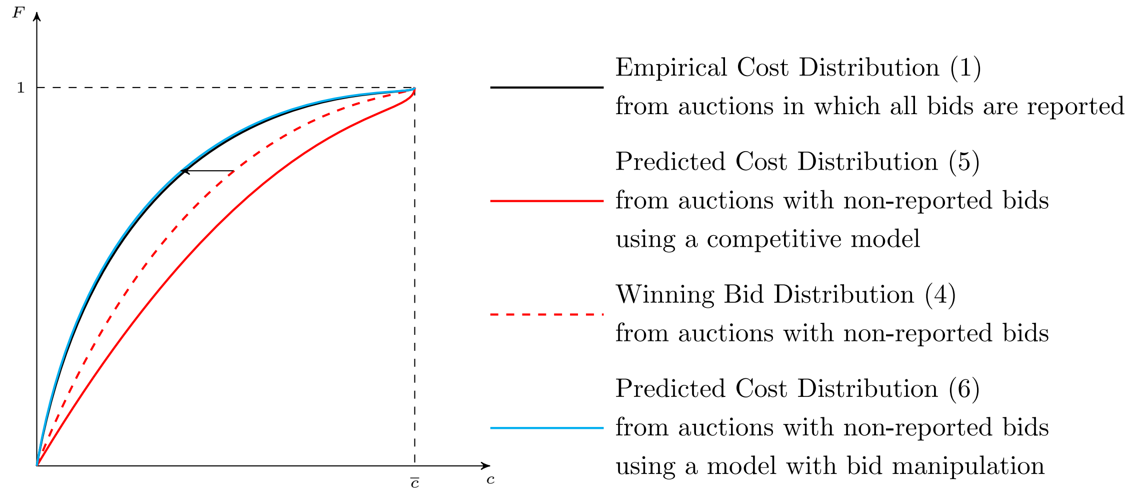

Figure 5.1: Illustration: Performance of Model of Auction Adjusted for Bid Manipulation

bids adjusted for bid manipulation matches the empirical cost distribution estimated from auctions in which all bids are observed, the model accurately reflects the procurement environment with corruption at the bid evaluation stage. This is illustrated in figure 5.1. The black distribution (1) as before represents the underlying true cost distribution predicted using all observed bids from auctions in which all bids are reported. The same as previously the dashed red line is the award price distribution from auctions with non-reported bids and the red solid curve (5) is the cost distribution estimated using these winning bids from a competitive English auction model. The blue curve represents the cost distribution predicted by a model adjusted for bid manipulation from prices in auctions with non-reported bids. Then if the the predicted blue costs distribution (6) coincides with the underlying black cost distribution (1) as in the figure above, an auctions with bid manipulation is a more applicable way to model auctions with non-reported bids.

5.2 Settings

There are n risk-neutral firms competing for a single procurement contract in a low-bid English auction with a publicly announced maximum reserve price r and price decrement Δ. Price decrement $\Delta \in [0.005r, 0.05r]$ refers to the maximum amount by which an auction bid must be decreased each time the current lowest bid is reduced [1]. There is one favored bidder i in an auction and $j \in [1, n-1]$ other bidders. The costs of the procurement c_i to a bidder i and the remaining $n-1$ bidders — c_j — are private and independent across bidders. These are drawn from the same costs distribution $F(c)$, which is common knowledge.

The following standard IPV framework assumption about the structure of a common cost distribution are maintained throughout:

Assumption 2. *The cost values c_i and c_j are drawn independently across bidders from the same distribution with continuous CDF $F(c)$; the random variable C has a positive bounded support $[\underline{c}, \overline{c}]$.*

I make two assumptions regarding the behavior of auction participants in an auction with bid manipulation. First, I assume that the corruption relationship between an auctioneer and the favored bidder is formed exogenously. Therefore, in this paper, the question of how an auctioneer chooses a favored bidder is not addressed. Second, at the bid evaluation stage, the auctioneer has the instruments to reject other bids after the auction is completed and only rejects bids below the favored one.

[1] I henceforth drop Δ to ease the notation, as this does not affect the subsequent analysis.

Based on interviews with representatives of firms who frequently participate in procurement auctions and with procurement officers who run auctions, I have gained valuable insights into the behavior of auction participants and the mechanisms for manipulating bids. In particular, the interviewees have emphasized that, even if auction participants suspect or know of an agreement between an auctioneer and another bidder, they do not respond strategically and do not modify their bidding behavior from optimal bidding for an English auction. This is motivated by the idea that honestly bidding their costs still provides the best chance to win. To be consistent with these facts, I propose the following:

Proposition 1. *Other j bidders follow the optimal bidding strategy of an English auction and bid down to their cost value c_j.*

This proposition is rather intuitive. Consider a situation in which the bidder j is currently a winner of an auction. If they bid below their own costs, they will lose money. If they are not the current winner, they may increase their chances of winning the auction by bidding below their costs—but then the award will not cover expenses. What about bidding above own costs? If the bidder j is the winner and bids above their costs, they may simply lose the winning position. If they are not the winner, would they improve their position by bidding above their costs? The answer remains "no". Assuming that the bidder j is currently the second-lowest bidder, if j increases its bid, they may move to the third-lowest position. Now, if the bidder below j is a favored bidder, than j loses for sure. If the bidder below j is not a favored bidder, than j may win if the auctioneer disqualifies the two bidders below it but does not manage to disqualify j. Because it is generally more difficult to eliminate two bidders than one, the chances that j will win inevitably drop. Thus, bidding truthfully is the dominant strategy for non-favored bidders here.

5.3 Equilibrium

I now examine the auction from the perspective of a favored bidder i.

5.3.1 2 bidders

First, I consider a case in which there is exactly one favored bidder i and one other bidder: $j = 1$. A favored bidder i knows that, at the bid evaluation stage, the other bidder will be eliminated by the auctioneer with a probability of $\rho \in [0, 1]$. i adjusts its bidding strategy accordingly. Suppose that the favored bidder's equilibrium bid is a strictly increasing and differentiable function $\xi_i(c_i)$ of its procurement costs c_i.

The favored firm i, which draws a cost value c_i, will win a contract against the non-favored firm j in one of the two events: either j bids higher or j bids lower and is eliminated by the auctioneer. In the former case, a favored bidder's payoff is equal to the difference between his and his opponent's expected costs. In the latter case, it will receive the difference between its bid and its costs.

Hence, favored bidder i, whose true costs are $c_i \leq r$, wants to maximize its expected payoff $\pi_i(c_i)$ by the choice of $p = \xi_i(c_i)$, whereas the other bidder adopts an optimal bidding strategy $\xi_i(c_j) = c_j$:

$$\max_{p<r} \mathbb{P}[p < c_j](\mathbb{E}[c_j|p < c_j] - c_i) + \rho\mathbb{P}[p > c_j](p - c_i) \tag{5.1}$$

where the probability that favored bidder i bids below its opponent $\mathbb{P}[p < c_j] = 1 - F(p)$ and $\mathbb{P}[p > c_j] = F(p)$ correspondingly, and the expectation $\mathbb{E}[c_j|p < c_j] = \frac{\int_p^r \tilde{c}f(\tilde{c})d\tilde{c}}{1-F(p)}$.

If the $\xi_i(c_i)$ is indeed an equilibrium, then $\pi(c_i)$ should be maximized, where $\xi_i(c_i) = p$. Thus, the bidding equilibrium is uniquely characterized by the following first-order condition:

$$c_i f(p) - pf(p) + \rho F(p) + \rho(p - c_i)F(p) = 0 \tag{5.2}$$

Solving the equation 5.2 for p, the optimal strategy for the favored bidder is to drop out at:

$$p = c_i + \frac{\rho}{1-\rho}\frac{F(p)}{f(p)} \tag{5.3}$$

In other words, the equilibrium bid consists of the bidder's own costs and a markup that depends on the bid distribution and can be interpreted as a favored bidder's rent. It follows immediately from 5.3 that, under bid manipulation, the equilibrium bid is higher than it would be in the case of a non-rigged English auction, by the amount $\frac{\rho}{1-\rho}\frac{F(p)}{f(p)}$.

5.3.2 n bidders

I now generalize the model to the case of one favored bidder and the $n-1$ competing bidders who bid truthfully.

To increase its chances to win, the favored bidder may choose to undercut some of the participants if its costs allow. I define the number of bidders that the favored bidder undercuts as $n-m$. Then, the auctioneer must eliminate the $m \in [1, n-1]$ opponents who bid lower than the favored bidder. A 2-bidder case shows that the probability that the auctioneer successfully eliminates one bidder who bids below the favored one is ρ. The probability that the auctioneer eliminates m out of $n-1$ bidders who bid below the favored bidder can thus be written as $\mathbb{P}[m; n-1, \rho]$.

In an auction with collusion between an auctioneer and a bidder, two scenarios determine the price of procurement. In the first scenario, the favored bidder has submitted the lowest bid and receives the lowest losing bid. In the second scenario, the favored bidder wins if all the bidders below it will be disqualified by the auctioneer during bid evaluation; it then receives its own bid.

To derive the equilibrium bidding strategy, let $\min_{j=1}^{n-1}\{c_j\} = \min\{c_1, c_2, \ldots, c_{n-1}\}$ be the minimum among bidder i's opponents and let $\max_{k=1}^{m}\{c_k\} = \max\{c_1, c_2, \ldots, c_m\}$ denote the maximum bid among bidder i's opponents who bid below him. The favored bidder's optimization problem can then be expressed:

$$\max_{p<r} \Pi =$$

$$\max_{p<r} \Big[\mathbb{E}\Big(\min\{c_j\}_{j=1}^{n-1} | p < \min\{c_j\}_{j=1}^{n-1}\Big) - c_i\Big]\mathbb{P}[p < \min\{c_j\}_{j=1}^{n-1}]$$
$$+ \sum_{m \subset n-1}^{n-1} (p - c_i)\mathbb{P}[p > \max\{c_k\}_{k=1}^{m}]\mathbb{P}[p < \min\{c_j\}_{j=1}^{n-1-m}]\mathbb{P}[m; n-1, \rho] \tag{5.4}$$

The first term in the sum above represents a favored bidder winning an auction without the auctioneer's help—that is, when bidder i's bid p is lower than the other $n-1$ bids. The second term corresponds to the favored bidder winning the auction given that all m bids below its bid p have been unfairly rejected by the auctioneer.

Given that costs are distributed independently and identically—and that the equilibrium bid function $p = \xi_i(c_i)$ with the inverse $\xi_i^{-1}(p) = c_i$ —we can express the winning probability in the first case as $\mathbb{P}[p < \min\{c_j\}_{j=1}^{n-1}] = (1 - F(p))^{(n-1)} \equiv F^*(p)$ with a density $f^*(p) = (n-1)(1 - F(p)^{n-2} f(p))$.

The conditional expectation in the first sum term of expression (5.4) then becomes:

$$\mathbb{E}\Big(\min\{c_j\}_{j=1}^{n-1} | p < \min\{c_j\}_{j=1}^{n-1}\Big) = \frac{\int_p^r \tilde{c} d(1 - F(\tilde{c}))^{n-1})}{(1 - F(p))^{(n-1)}}$$

The joint probability of the second event is

$$G^*(p) \equiv$$
$$\sum_{m \subset n-1}^{n-1} \mathbb{P}[m; n-1, \rho]\mathbb{P}[p > \max\{c_k\}_{k=1}^{m}]\mathbb{P}[p < \min\{c_j\}_{j=1}^{n-1-m}]$$
$$= \sum_{m \subset n-1}^{n-1} \mathbb{P}[m; n-1, \rho] F(p)^m (1 - F(p))^{(n-1-m)} \tag{5.5}$$

and $g^*(p) = \frac{\partial G^*}{\partial p}$ is its density.

To reduce clutter, it is helpful to use $F^*(p)$ and $G^*(p)$ to denote the winning probabilities in either case.

Differentiating with respect to p yields the first-order condition:

$$(p - c_i) f^*(p) = G^*(p) + (p - c_i) g^*(p) \tag{5.6}$$

where the *LHS* can be interpreted as a marginal payoff from winning honestly (that is, the favored bidder is also the most efficient one) and the *RHS* is the marginal payoff from being corrupt.

Rearranging the equation (5.6), the optimal bid for a favored bidder is as follows:

$$p = c_i + \frac{G^*(p)}{f^*(p) - g^*(p)} \tag{5.7}$$

Applying the definition of F^* and G^* and their corresponding *pdf*s yields the following:

$$p = c_i + \frac{\sum_{m\subset n-1}^{n-1} \mathbb{P}[m, n-1] F(p)^m (1 - F(p))^{n-m-1}}{(n-1)(1-F(p))^{(n-2)} f(p) - \sum_{m\subset n-1}^{n-1} \mathbb{P}[\cdot] f(p) F(p)^m (1-F(p))^{(n-m-1)} \left(\frac{m}{F(p)} - \frac{n-m-1}{1-F(p)}\right)} \tag{5.8}$$

When the number of non-colluding bidders is greater than 1[2] , the equilibrium bidding strategy of a favored bidder depends on the total number of bidders in the auction, as well as on the number of bidders that must be eliminated by the auctioneer for the favored bidder to win. Notice that the second term in the last expression is positive as long as $\frac{m}{n-1} < F(p)$ is in the denominator. In other words, the favored bidder receives a positive rent as long as the proportion of bidders to be eliminated is less than the ex-ante probability that any bidder j has lower costs. Negative rent would imply that the bidder bids below its own costs. Since it is never optimal to bid below own costs, such instances are interpreted to mean that the winner has won by bidding all

[2]Notice that when there are only two bidders, $n = 2$ amd $m = 1$ and the sum term in equation (5.7):

$$\begin{aligned}
&\mathbb{P}[1, n-1, \rho] F(p)(1-F(p))^{n-2} + \\
&+ \mathbb{P}[2, n-1, \rho] F(p)^2 (1-F(p))^{n-3} + \\
&+ \ldots + \\
&+ \mathbb{P}[n-2, n-1, \rho] F(p)^{n-2}(1-F(p)) + \\
&+ \mathbb{P}[n-1, n-1, \rho] F(p)^{n-1}
\end{aligned}$$

reduces to $\rho F(p)$, where $\mathbb{P}[1, 1, \rho] = \rho$. The probability that p is the lowest bid $(1 - F(p))^{n-1} = \prod_{j\in n-1}^{n-1}(1 - F(p))$ is equal to $1 - F(p)$ when there are only 2 bidders, as well as when the expected minimum among competing bids is simply the expected bid of the other bidder. Then the optimization problem in (5.7) reduces to the following:

$$\int_p^r \tilde{c} f(\tilde{c}) d\tilde{c} - c_i(1 - F(p))) + (p - c_i)\rho F(p)$$

which is equivalent to the optimization problem in the 2-bidder case in expression (5.1).

the way down to its value.

5.4 Existence and Uniqueness

This section describes the existence and uniqueness of equilibrium in the auction with bid manipulation in cases of two and multiple bidders.

Let $\psi(p)$ denote an inverse function of a bidding strategy $p = \xi(c_i)$. Then the optimization problem for two bidders in 5.1 can be rewritten as:

$$\int_{\psi(p)}^{r} \tilde{c} f(\tilde{c}) d\tilde{c} - c_i(1 - F(\psi(p))) + (p - c_i)\rho F(p) \tag{5.9}$$

Taking a derivative with respect to p, by the Leibniz rule this expression becomes:

$$(c_i - p) f(\psi(p))\psi^{'}(p) - \rho F(\psi(p)) - \rho(p - c_i) f(\psi(p))\psi^{'}(p) = 0 \tag{5.10}$$

Given the boundary condition condition $\xi(r) = r$, the optimal inverse-bid function of the favored bidder is described by the differential equation:

$$\frac{d\xi^{-1}(p)}{dp} = \frac{\rho F(\xi^{-1}(p))}{(1 - \rho)(p - c_i) f(\xi^{-1}(p))} \tag{5.11}$$

Note that the derivative in 5.11 exists everywhere as the *RHS* is defined continuous function since p is an increasing function of c. In fact using the inverse function theorem, re-arranging and multi-plying both parts by an integrating factor $\mu = F^{\frac{\rho-1}{\rho}}$, the equilibrium bidding strategy for the case of two bidders can be re-written as:

$$Const + F^{\frac{\rho-1}{\rho}}\xi(c) = \int_{\xi^{-1}(p)}^{r} c_i \frac{d}{dc}(F^{\frac{\rho-1}{\rho}dc}) \tag{5.12}$$

The expression in 5.12 is not particularly helpful for empirical research because it does not have a closed-form solution, however, it can be used to show that the 2-bidder equilibrium is unique. First, note that the right boundary condition on the bidding function along with the inverse bid function equivalent $\xi^{-1}(r) = r$ makes $F^{\frac{\rho-1}{\rho}}(r) = \Pr[c_i < r]^{\frac{\rho-1}{\rho}} = 1$. The left boundary condition implies $\xi(\underline{c}) = \underline{c}$. Since any bid below $\underline{c}$ will be sub-optimal and a bidder may increase its bid by some small amount and still win an auction: $F(\underline{c}) = \Pr[c_i < \underline{c}] = 0$. Then using the integration by parts, at the left boundary equation in 5.12 has only one unique solution where $Const = 0$.

Similarly, in the case of n bidders the FOC in 5.6 can be re-written:

$$(c_i - p)f^*(\psi(p))\psi^{'}(p) + G^*(\psi(p)) + (p - c_i)g^*(\psi(p))\psi^{'}(p) = 0 \tag{5.13}$$

And the equilibrium bidding function is represented by the following differential equation:

$$\psi^{'}(p) = \frac{d\xi^{-1}(p)}{p} = \frac{G^*(\psi(p))}{(f^*(\psi(p)) - g^*(\psi(p)))(p - c_i)} \tag{5.14}$$

where G^*, g^* and f^* are defined as before (note that in equilibrium $\psi(p) = \xi^{-1}(p) = c_i$).

Because by definition density $f(c)$ is continuous, the denominator of the expression in 5.14 is never zero and the derivative of the RHS with respect to $\psi(p)$ is defined and continuous everywhere, so by the existence and uniqueness theorems of differential equations we can conclude that the solution to this equation exists on $[\underline{c}, \overline{c}]$ and is unique.

Chapter 6

Estimation and Identification

In this chapter, I demonstrate that the model for an auction with bid manipulation is identified under several assumptions. I then propose an estimation strategy based on winning bid data. Before presenting the details of the estimation approach and counterfactual results, the next section discusses practical issues in selecting the sample of auctions used for estimation.

6.1 Practical Considerations

The principal challenges in applying the previously described model to data are twofold. First, corruption is an illicit activity that is not directly observed by a researcher. Furthermore, the exact corruption mechanism is unknown. For the purposes of model estimation, I assume that the auction is rigged if some bids have not been reported; thus, the winner is the favored bidder. Second, for a subsample of the auctions with non-reported bids, only winning bids are accessible. One way to circumvent the this issue would be to restrict the sample to the subset of potentially rigged auctions in which the auctioneers reported bids partially. Unfortunately this option is not appealing because in presence of non-reported bids it unclear whether the reported bids are ordered statistics. Thus they cannot be used to infer underlying costs, as they do not necessarily map to a firm's true cost.

In the preferred sample I utilize the winners' bids from both subsamples: with no reported bids and with partially reported bids. An advantage of this approach is that the sample size allows for the cost distribution to be estimated non-parametrically. A drawback of this approach is that it does not recover the specific cost distribution for rigged auctions. Instead, it computes an upper bound on such costs. This approach also assumes that the distribution of bidders' costs in auctions without non-reported bids (competitive auctions) is the same as the one in auctions with non-reported bids (rigged auctions).

6.2 Empirical Strategy

For a sample of T auctions in the same product category, winning bids are observed $\{p_t^*\}_{t=1}^T$ along with the number of actual participants n_t. Denote $G^*(p)$ the distribution of winning bids in auctions suspicious for bid manipulation and the distributions of bids in equilibrium $F_P(p)$; their respective densities are denoted by lower-case letters. Similarly, the distribution of costs is $F_C(c)$ and its *pdf* - $f_C(c)$. For the time being, I consider entry to be exogenous and the number of bidders to be fixed n.

The first step in the estimation process is to obtain the winning bid distribution. The distribution $\hat{G}(p_t^*)$ is estimated non-parametrically, given the observed winning bids p_t^*, similarly to Section 4.3.

The additional parameter of the model that must be estimated is the probability that a bid is rejected by the auctioneer during bids evaluation. To recover this parameter, I am using the observed auctioneers' decisions regarding bid suitability to auction specifications. In auction t, each bid p_{kt}, $k = 1, \ldots, m$ below that of the favored bidder's is rejected with an identical probability ρ_{kt}. For estimation, I specify a logit functional form:

$$\rho_{kt}(\mathbf{x}) = \frac{\exp(\sum_{l=1}^{L} \alpha_l X_{lt})}{1 + \exp(\sum_{l=1}^{L} \alpha_l X_{lt})} \tag{6.1}$$

where X controls for the auctioneer's identity and the winner's rank. The parameter vector α is estimated by the NLS procedure using the observed bid evaluation decisions. The estimated probabilities from equation 6.1 are reported in Figure B.1 in the appendix A for 20 products. The figures demonstrate that the total number of non-reported bids increases with the probability that any single bid in an auction is disqualified.

Unlike the bidding process, the bid evaluation process remains opaque and entails a great deal of randomness for an auctioneer. Success in eliminating a bid at the bid evaluation stage depends only partially on the auctioneer's craftiness and knowledge of procurement law. A firm whose bid has been disqualified has an opportunity to submit a complaint to an anti-trust service. If the anti-trust services find the complaint valid, the auction results will be reviewed. If the complaint is discarded, the firm that believes it has been unfairly disqualified also may appeal to the higher authorities. For this reason, even the most capable auctioneer cannot guarantee that all (if any) of the non-favored bidders will be disqualified. Because the auctioneer does not fully control the elimination process, I make the assumption that any firm's disqualification probability is independent of the probability that other non-favored bidders are disqualified. Thus, the auctioneer's belief about the chances of eliminating the non-favored bidders can be described by binomial distribution:

$$\mathbb{P}[m; n-1, \rho] = \begin{pmatrix} n-1 \\ m \end{pmatrix} \rho^m (1-\rho)^{n-m-1}. \tag{6.2}$$

where $\begin{pmatrix} n-1 \\ m \end{pmatrix} = \frac{(n-1)!}{m!(n-1-m)!}$ is a binomial coefficient and ρ is the probability of successful bid elimination.

Figure 6.1 plots predicted probabilities over frequently observed pairings of the number of bidders in an auction and the number of non-reported bids, along with the shares observed in the data. This shows that the disqualification probability decreases as the number of bids that must be disqualified increases. It also indicates that the predicted probabilities tend to be overestimated for small numbers of rejected bids and underestimated for higher numbers of rejected bids, although it stays within a standard deviation of the average in the data. Table 6.1 shows the average disqualification probabilities by a product. The average probability of disqualifying any number of unfavored bids is 61%. In general, the average probability of disqualification does not vary significantly from product to product.

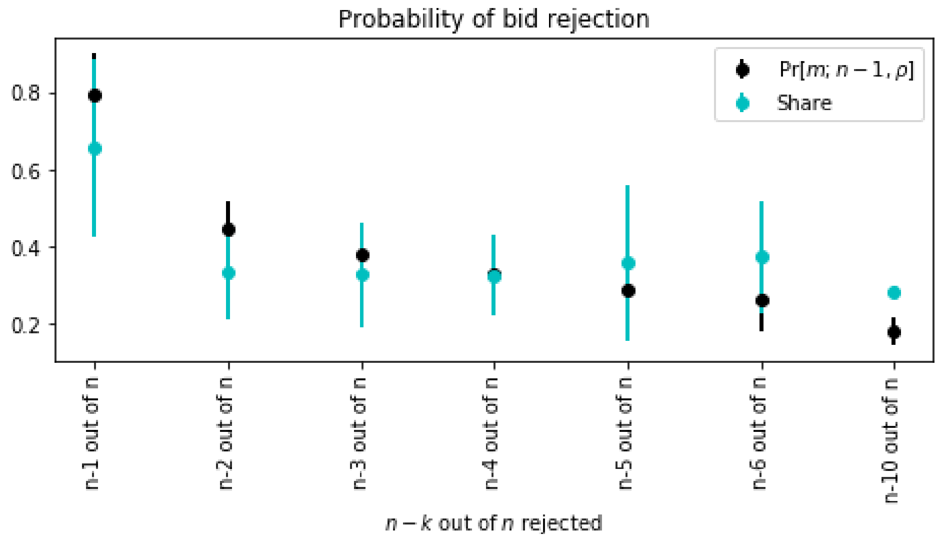

Figure 6.1: Estimated probabilities of bid disqualification $\mathbb{P}[m; n-1, \rho]$ over some of the most frequently observed combinations of the number of bidders and the number of missing bids

Taking the estimated rejection probability parameters and combining them with the distribution of winning bids estimated in the first step, I use the definition of $G(p_t^*)$ in (5.5) to recover the distribution of equilibrium bids, conditional on (n, X). The bid distribution $\hat{F}_P(p_t|n, X)$ is estimated via a simple GNLS method. Figure B.2 in appendix A depicts the resulting bid distributions graphically versus the underlying bid distributions estimated using all bids. The graphs suggest that the estimated CDF fits the data well, except for some products, for which it overstates the probability of drawing very low costs. I use these CDFs to recover the underlying cost distribution.

In the last step, given the first-order conditions in Section 5.3.2, I construct a GPV (Guerre, Perrigne, and Vuong, 2000)-style two-stage estimator. The

Product	Mean	SD	Max	Min
Milk	0.6422	0.2068	0.9420	0.1355
Textbooks	0.7502	0.0572	0.9335	0.4238
CNS drugs	0.6299	0.2019	0.9999	0.1869
Cardiovascular drugs	0.6643	0.2019	0.9559	0.2100
Anticoagulation drugs	0.6353	0.1826	0.9507	0.1944
Metabolic products	0.6371	0.1850	0.9949	0.3107
Cancer drugs	0.6775	0.2055	1.0000	0.0735
Antiviral drugs	0.6840	0.1734	0.9486	0.2430
Miscellaneous drugs	0.6987	0.1594	0.9223	0.1958
Pharmaceutical products	0.4372	0.1399	0.8407	0.0626
Medical tools	0.6119	0.1913	0.9623	0.1900
Medical equipment	0.7186	0.1538	0.9513	0.2421
Surgical equipment	0.7253	0.1514	0.9657	0.3456
Renovation work	0.5803	0.2308	0.9661	0.0000
Software	0.6128	0.1991	0.9355	0.0501
System maintenance	0.6472	0.1870	0.9443	0.0815
Office equipment	0.5926	0.2077	0.9248	0.1790
Security services	0.5407	0.2119	0.9158	0.0283
General cleaning	0.3436	0.1296	0.8954	0.0003
Garbage disposal	0.4773	0.1671	0.9209	0.1904

Table 6.1: Estimated bid disqualification probabilities $\mathbb{P}[m; n-1, \rho]$ averaged by product category

advantage of this technique is that it does not require solving for an equilibrium bid as a function of cost distribution — the cost distribution is identified and estimable from bid data alone. To obtain this, I substitute the estimated distributions and their corresponding *pdf*s into expression (5.7):

$$\hat{c}_t = p_t - \frac{\hat{G}(p_t)}{\hat{f}_P(p_t) - \hat{g}(p_t)} \tag{6.3}$$

Along with maintaining the original Guerre, Perrigne and Vuong (2000) assumptions, which ensure that the regularity conditions of the model are satisfied, Condition 2 of Theorem 1 in Guerre, Perrigne and Vuong (2000) imposes the log-concavity of the bid distribution $F_P(p_t)$. This assumption ensures that the RHS of the equilibrium bid expression in (5.7) is increasing more slowly than the LHS. This property is illustrated in Figure 6.2 for the case of 2 and n bidders for the frequently used empirical auction literature distributions. Given n_t and m_t for a log-concave distribution, the equilibrium bid function $\xi(c_t)$ is monotonically increasing; thus, the observed bid distribution $F_P(p)$ rationalizes the cost distribution $F_C(c)$.

Given the pseudo-value estimates $\hat{c}_t$ from (6.3), the private costs distribution can be recovered using KD estimation, such that $\hat{F}_C(c) = \frac{1}{T}\sum_{t=1}^{t} \mathbb{I}|\hat{c}_t < c|$ and $\hat{f}_C(c) = \frac{1}{Th}\sum_{t=1}^{t} K\left(\frac{c-\hat{c}_t}{h}\right)$, where h is an optimally chosen Scott bandwidth and $K(\cdot)$ is a Gaussian kernel function.

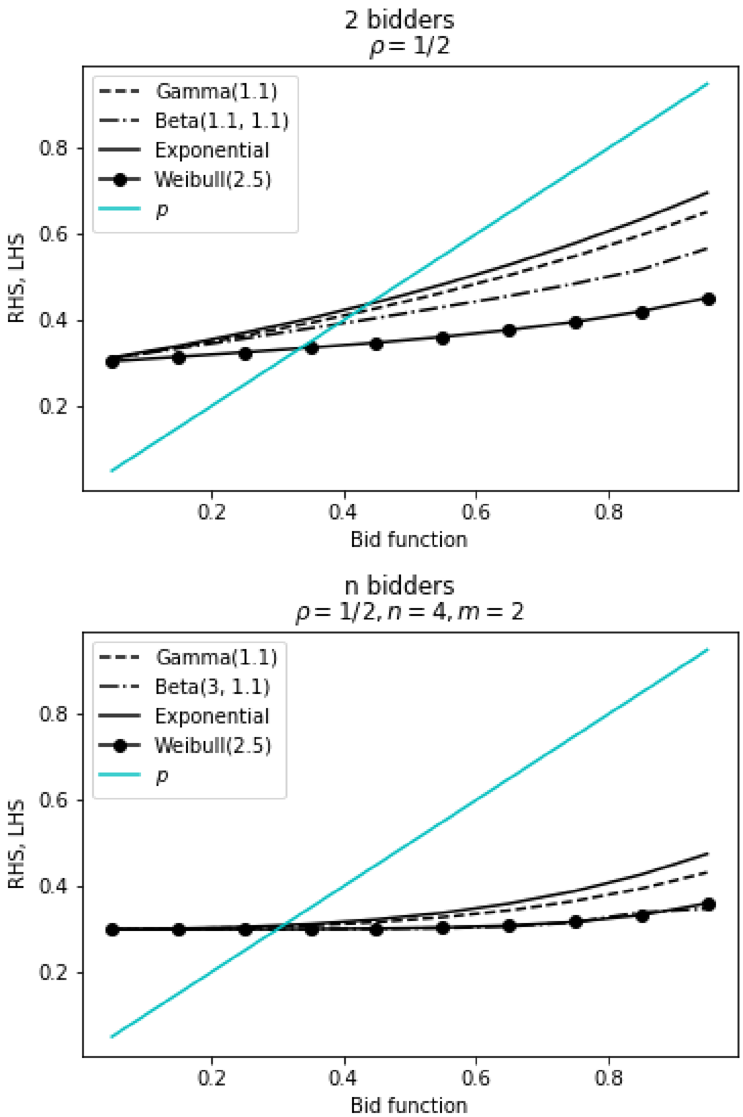

Figure 6.2: The illustration of single-crossing condition for several log-concave distributions

Chapter 7

Results

7.1 Model Fit

Before quantifying the auction outcomes, Figure 7.1 presents the results in graphical form. Each figure displays the estimated distribution from which firms draw their procurement costs for a particular product. Figure 7.1 compares the results of the corruption model estimates (blue line) to the results obtained from a competitive English model (in red) and the actual cost distribution obtained from bid data (black line). Visually, the cost distribution generated by the auction model with corruption approximates the underlying cost distribution rather well—the blue line lies close to the black one.

Table 7.1 reports the results of the comparison of the cost distribution generated by the model with corruption and the cost distribution from data. In contrast to the results presented in Table 4.4 Section 4.3, the p-values of the two-sided Kolmogorov-Smirnov test are high and do not reject[1] the null hy-

[1] Although graphical results show no difference, the statistical test results in Table 7.1

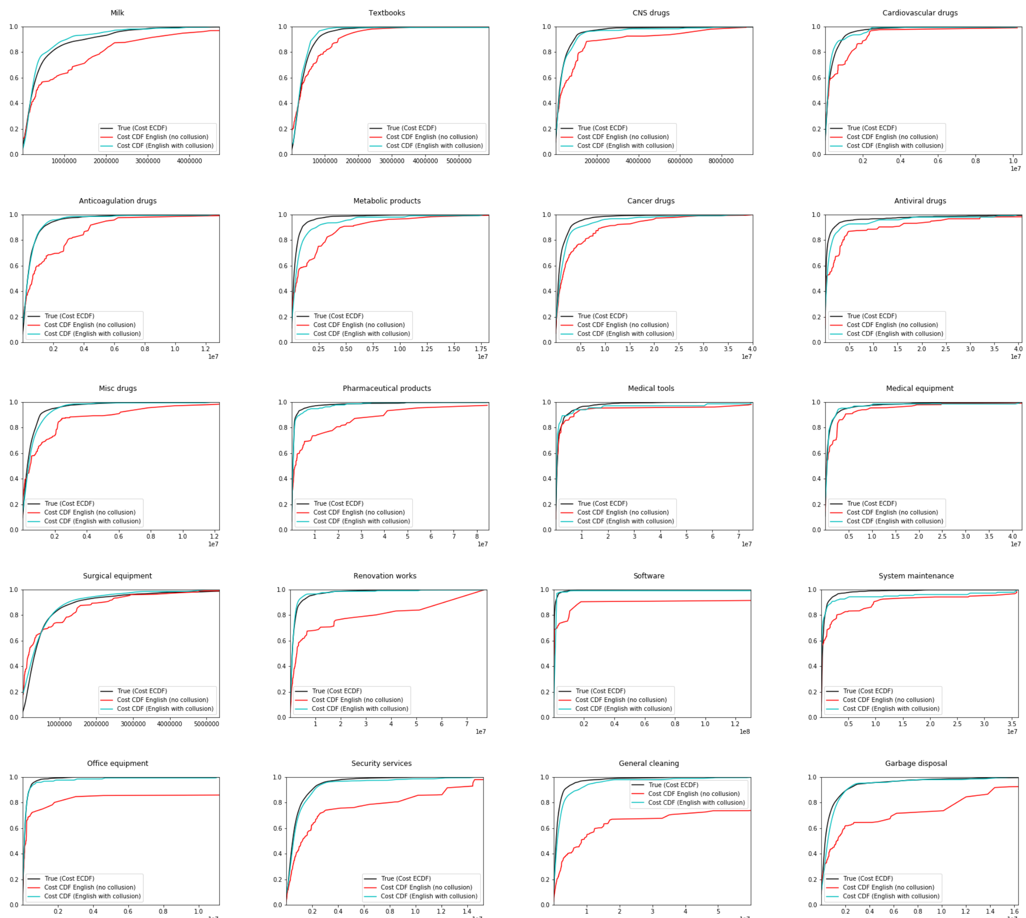

Figure 7.1: Estimated cost distributions $\hat{F}_C(c_t|n, X)$ versus the estimated cost distribution using a competitive English auction model

pothesis that the predicted cost distribution comes from the same distribution as the empirical cost distribution observed in the data. This confirms that the auction model with corruption at the bid evaluation stage aptly explains agents' behavior in auctions with non-reported bids.

Product	KS Statistic	KS Bootstrap p-value
Milk	0.05	0.982
Textbooks	0.17	0.012
CNS drugs	0.052	0.94
Cardiovascular drugs	0.071	0.809
Anticoagulation drugs	0.061	0.89
Metabolic products	0.115	0.401
Cancer drugs	0.1	0.179
Antiviral drugs	0.128	0.175
Miscellaneous drugs	0.109	0.265
Pharmaceuticals products	0.063	0.783
Medical tools	0.058	0.969
Medical equipment	0.124	0.513
Surgical equipment	0.085	0.864
Renovation work	0.052	0.886
Software	0.07	0.594
System maintenance	0.116	0.373
Office equipment	0.044	0.997
Security services	0.045	0.892
General cleaning	0.023	1
Garbage disposal	0.025	1

Notes. - Bootstrap p-value computed based on 10000 samples.

Table 7.1: Goodness-of-fit Kolmogorov-Smirnov test: results of comparing the predicted cost distribution to the actual empirical distribution of costs

In addition to Table 7.1, Figure B.3 in appendix A plots the estimated empirical distributions along with Kolmogorov confidence bounds, computed as in Hollander et al. (2015). These bounds can be interpreted as follows: if a distribution falls into the Kolmogorov confidence bound of another empirical

suggest that the difference between the predicted and empirical cost distributions from the data remains marginally significant for the product category "Textbooks" at a 5% level. This results from the over-sensitivity of the KS test in the middle of the distribution, because the estimates for these product categories are less precise than those for other categories. For precision of the estimated cost distribution, refer to Figure B.4 in appendix **??**

distribution, these distributions are generated by the same CDF. Figure B.3 supports the conclusions from Table 7.1 — the predicted cost distributions lay within the bounds.

Figure B.4 in the appendix plots the estimated cost distributions with 95% and 5% confidence bounds and actual data. Although—in some instances—the auction with corruption at the bid evaluation stage does not provide a perfect fit for the middle of the distributions, the figure shows that the results are significant at the 5% level in 20 studied markets.

Figure 7.1 also suggests that the model with collusion between an auctioneer and a bidder outperforms a competitive auction model in every market. Unlike the cost distribution approximated using a competitive English model (plotted in red)—which lies below the actual cost distribution and significantly overestimates the procurement costs—the cost distribution generated by the auction with corruption fits the actual cost data.

To quantitatively assess the model's goodness-of-fit, I use the Cramer-von Mises criterion (Anderson (1962), Darling (1957)). This criterion uses the area between the two empirical distributions for evaluating the goodness-of-fit. Specifically, a smaller area between a model-predicted distribution and a distribution from the data indicates better model performance. In Table 7.2 , the first column contains the standardized area between the empirical cost CDF from the data and the cost CDF estimated using the competitive auction model. The second column computes the same area, but between the empirical cost CDF from the data and the cost CDF estimated from a model with corruption.

Product	CvM Statistic (before)	CvM Statistic (after)	-Improvement\+Deterioration, %
Milk	3.3809	0.0179	-99.4693
Textbooks	10.0546	1.1788	-88.2762
CNS drugs	4.3730	0.0157	-99.6406
Cardiovascular drugs	1.1446	0.0676	-94.0919
Anticoagulation drugs	5.2430	0.0911	-98.2634
Metabolic products	0.8110	0.0993	-87.7509
Cancer drugs	3.4677	0.3785	-89.0864
Antiviral drugs	0.6992	0.1627	-76.7316
Miscellaneous drugs	0.6880	0.2752	-59.9987
Pharmaceuticals products	26.7227	0.0655	-99.7548
Medical tools	5.3442	0.0943	-98.2346
Medical equipment	1.6341	0.3617	-77.8648
Surgical equipment	1.6478	0.0517	-96.8633
Renovation work	5.7566	0.0335	-99.4179
Software	2.2623	0.6507	-71.2366
System maintenance	1.9274	0.2619	-86.4121
Office equipment	1.1610	0.0181	-98.4421
Security services	5.5949	0.0122	-99.7822
General cleaning	24.7762	0.0051	-99.9796
Garbage disposal	10.3014	0.0271	-99.7370

Table 7.2: Cramer-von Mises criterion for the costs distribution predicted by a competitive model (column 'before') and predicted by the model with corruption (column 'after'), compared to the empirical cost distribution observed in the data.

As the table shows, the model with corruption provides a several-times better fit than the competitive model. The last column in Table 7.2 shows the percentage improvement in model fit compared to the base case of a competitive English model. In 12 product markets, the percentage improvement is almost 100%. Even in markets where the KS tests do not find statistically insignificant differences, the improvement in model fit is not less than 80%.

The graphical results of the final test of goodness-of-fit are presented in Figure 7.2. The purpose of the test is to evaluate whether the cost distribution generated by the corruption model lies within the 5% variation bounds of the underlying cost distribution from the data. As the figure shows, although the predicted cost distribution slightly overestimates the probability in the middle for a few markets, it generally fits well in the tight bounds.

Overall, the cost distributions generated by the auction with bid manipulation at the bid evaluation stage are significantly better in predicting the procurement cost in auctions with non-reported bids than those generated from a standard English auction; the former provide a good enough fit to perform policy evaluations.

7.2 Model Validation: Expected Costs of Procurement

Given the estimated primitives, the model with corruption makes predictions about auction outcomes, such as the expected costs of procurement. Assuming that the cost distribution estimated using all of the observed bids correctly

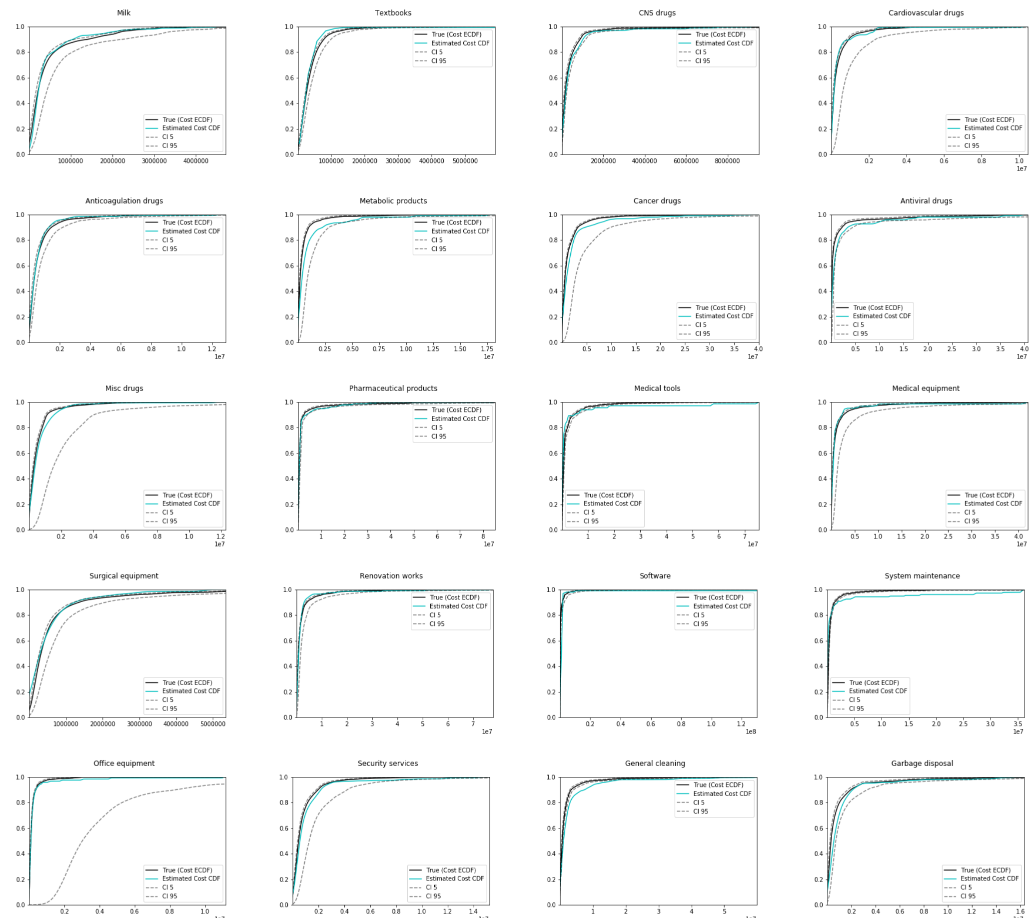

Figure 7.2: Estimated cost distributions $\hat{F}_C(c_t|n, X)$ (blue) along with the empirical cost distribution from the data (black) and its 5% confidence bounds

reflects the reality without corruption, these quantities are observed in the data. In this section, I validate the model by comparing the model-generated procurement costs to the data-generated procurement costs.

In a standard English auction with a symmetric and independent private-value environment and a known number of bidders, the expected costs of procurement are equal to the expected second-lowest bid:

$$\mathbb{E}[c^{n-1:n}|c_i < c^{n-1:n}] = \int_{\underline{c}}^{\overline{c}} \tilde{c} d(1 - F(\tilde{c}))^{n-1}, \tag{7.1}$$

where $c^{n-1:n}$ is the second-lowest cost value.

Given the number of bidders n, the expected cost of procurement can be computed using either the empirical distribution of costs from the data $F_n(c)$ or by using the distribution of cost predicted by the model with corruption $\hat{F}_C(c)$[2].

In order to make these calculations, I take the observed vector of the number of bidders n and — for each value of this vector—randomly draw n bids from the data-generated cost distribution $F_n(c)$. I record the second-lowest bid to compute the distribution $(1 - F(c))^{n-1}$ and the integral in 7.1. I repeat these steps using the model-generated cost distribution $\hat{F}_C(c)$ to approximate the procurement costs predicted by the auction with bid manipulation. The integral in 7.1 is evaluated using Simpson's rule.

Figure 7.3 depicts two expected procurement costs observed in the data (in grey) and the hypothetical outcomes without corruption, computed using the

[2]Note that this is the cost of procurement net of corruption cost, which is computed in the next section. In other words, these are the expected costs of procurement purchases if auctions with non-reported bids were truly competitive.

cost distribution predicted by the model with bid manipulation (in blue) for 20 product categories. The results are presented in thousands of US dollars.

Comparing the first and second bars in the figure illustrates that the auction outcomes predicted by the model with corruption from auctions with non-reported bids are sufficiently similar to the outcomes generated in the data: the largest difference between the predicted costs of procurement and actual costs in the data does not exceed 8% of the observed procurement costs for auctions of metabolic pharmacological products (insulin). In percent of actual costs, the lowest difference in predicted costs is observed in general cleaning auctions (0.8%) and in the medical tools category (0.56%).

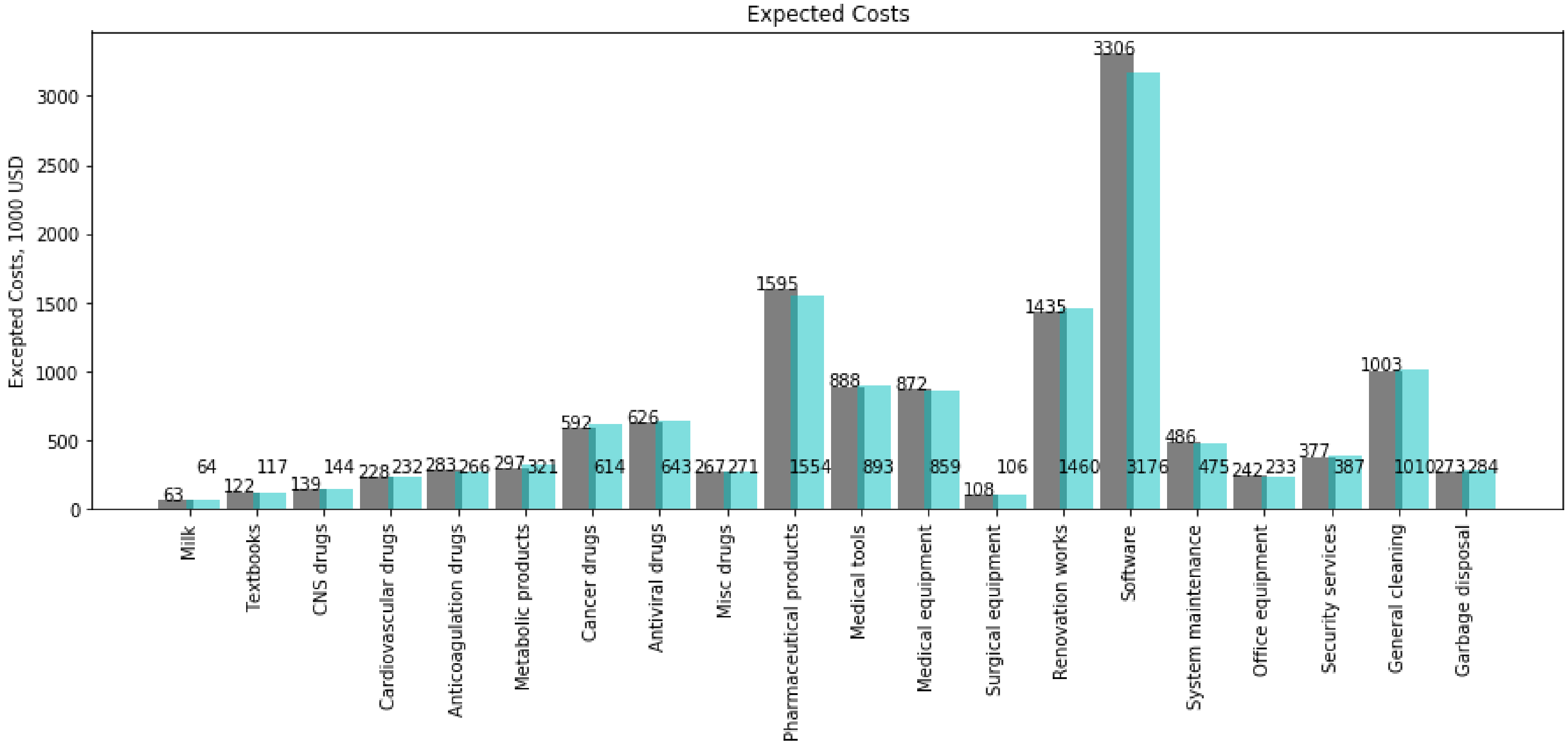

Figure 7.3: Simulated costs of procurement averaged by product in $$$USD

Chapter 8

Quantifications and Counterfactuals

8.1 Rent Comparison

In this subsection, I explore winners' rents arising from bid manipulation in comparison with winners' rents arising from private information in a standard (non-rigged) English auction.

In an auction in which an auctioneer and a bidder are in a corruption agreement and non-favored bids are rejected at the bid evaluation stage, the favored bidder receives an additional gain from bidding above the actual costs of providing a good or service. I define the corruption rent in auction t as:

$$R_t = P_t - \hat{C}_t \tag{8.1}$$

where P_t is the observed award price in auction t, and C_t is the predicted costs

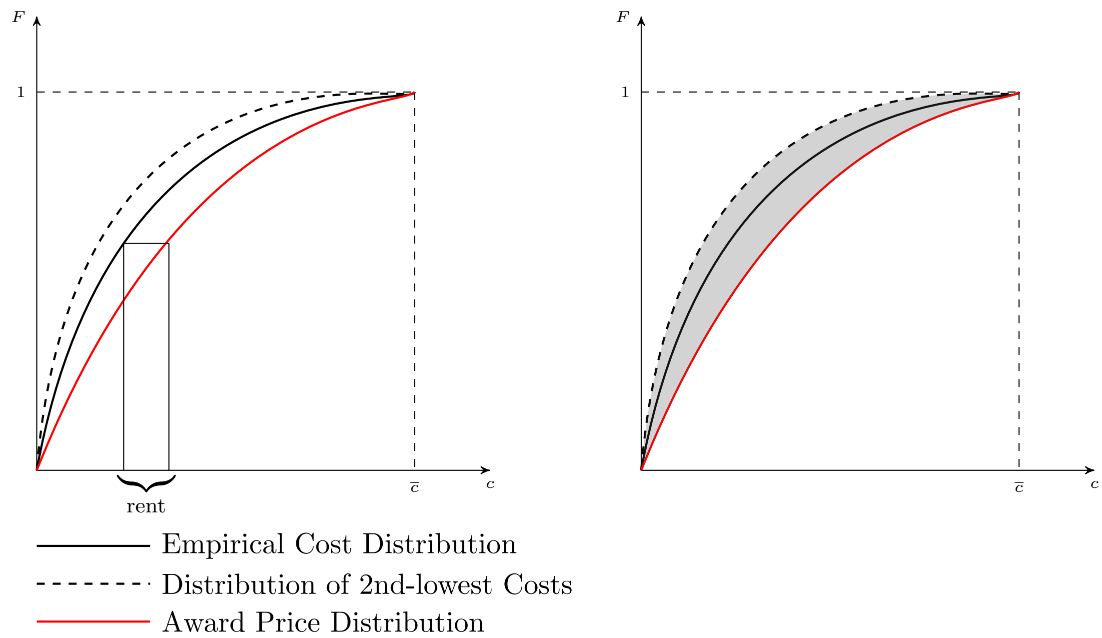

Figure 8.1: Corruption Rent and Welfare Loss: Illustration

for the winner.

This quantity is illustrated graphically in the left panel of Figure 8.1. Holding the probability constant, the favored bidder's rent is the difference between the award price of procurement and its actual costs.

Using the cost distribution predicted by the corruption auction model, along with the model fundamentals (distribution of the winning bids and the number of bidders), I evaluate the distribution of corruption rents in each of 20 product categories. The average corruption rents are presented below in column (3) of Table 8.1 in $$$USD.

The estimated average gain of a corrupted bidder is quite low in categories that are generally considered unattractive for corruption, such as general cleaning contracts, computer system maintenance services, or dairy products. On average, the rent amount does not exceed $20K in categories that are relatively unprofitable for corruption. On the contrary, the highest rent above $200K is observed in the software, medical equipment, and pharmaceuticals categories.

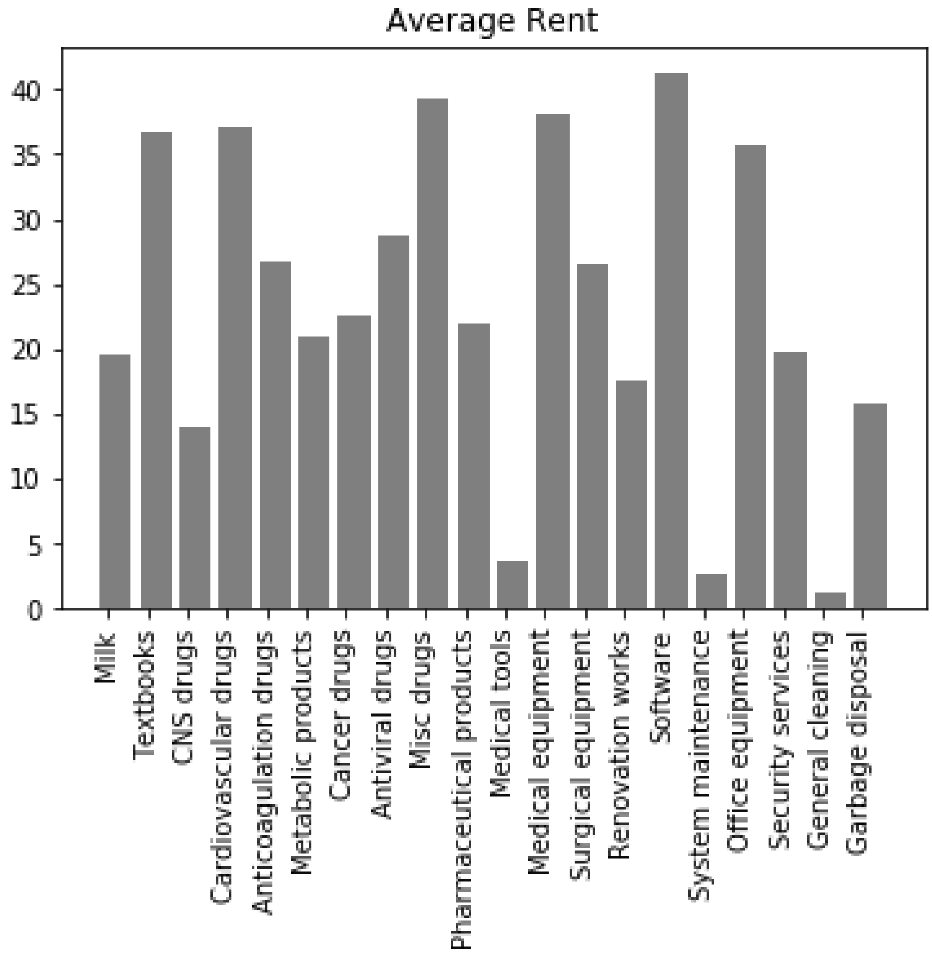

Figure 8.2: Average rent in percentage of award price

Figure 8.2 depicts the average rent as percentage of the average award price in each category. In percentage presentation the average rent varies from 1.3% of price in general cleaning to 41% in software purchases. If averaged across all product categories, favored bidders' rent constitutes 23.5% of the award price.

Though the amount of gain for a firm may not seem particularly high in some product markets, the rent in relation to the award price in such markets may constitute up to 35% of the final price of procurement. These costs can be partially avoided if each firm in an auction bids down to its cost value and a contract is alocated to the most effective firm.

The English auction with independent and private value frameworks is efficient in that the contract is awarded to the bidder with the lowest costs. In this case, winners receive additional gains due to the private information on their actual costs of supplying a procurement. This information rent in auction t is defined as:

$$IR_t = C_t^{n-1:n-1} - C_t^{n-1:n} \tag{8.2}$$

where $C^{n-1:n}$ is lowest among n bidders' costs of providing a procured good or service; $C^{n-1:n-1}$ is the second-lowest cost value, which is equivalent to the award price in an English auction.

The computation of information rent is more challenging than the computation for corruption rent, due to two primary complications. First, in the auctions with non-reported bids, the costs are never directly observed. Second, in English auctions, winners' costs are not revealed. The predicted cost distribution along with the observed number of auction participants is needed to simulate the distribution of winners' costs and to compute the information rent.

To calculate the information rent, I first simulate the cost for each of n bidders by randomly drawing n cost values from the estimated distribution of pseudo costs. Secondly, I collect the lowest private cost valuation and the second-lowest cost to compute a simulated value for IR. The results of this exercise are presented in Figure A.3. The averages are described in columns (1) and (2) of Table 8.1. Table A.3 in the appendix also summarizes information and corruption rents at several quantities of the winner distribution.

Product	Losing bid	Information rent	Corruption rent
Milk	57.538	26.497	16.251
Textbooks	487.601	236.263	33.192
CNS drugs	112.808	53.158	10.482
Cardiovascular drugs	130.785	57.352	87.043
Anticoagulation drugs	167.083	86.072	41.438
Metabolic products	226.891	107.033	67.300
Cancer drugs	531.129	245.281	166.168
Antiviral drugs	633.000	289.986	190.402
Miscellaneous drugs	173.918	80.728	110.587
Pharmaceutical products	972.890	404.982	224.475
Medical tools	1059.787	469.511	32.896
Medical equipment	615.640	277.191	234.411
Surgical equipment	86.600	39.900	25.611
Renovation work	686.786	333.402	119.533
Software	3603.531	1815.021	197.480
System maintenance	564.107	250.198	0.668
Office equipment	123.303	60.147	24.807
Security services	157.501	73.219	52.749
General cleaning	461.381	210.036	6.354
Garbage disposal	182.540	82.664	42.518

Table 8.1: Simulated average corruption and information rents and the lowest losing bids

Figure A.3 shows that, on average, a favored firm enjoys nearly the same

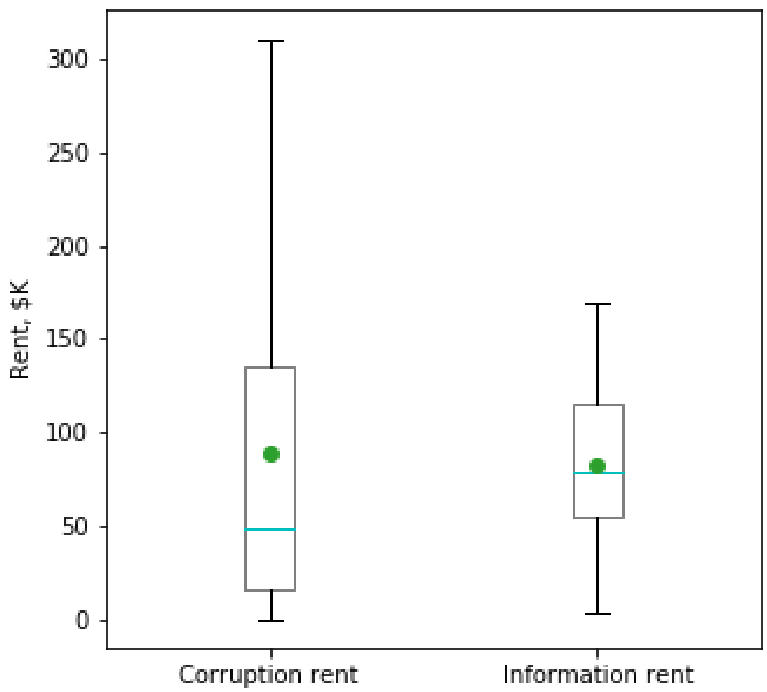

Figure 8.3: Distribution of corruption and information rents pooled together across all products

Note. - Green dots represent the mean values and blues lines are the medians. The upper and lower ends of the box correspond to the 25th and 75th percentiles, respectively; the upper and lower whiskers represent the 10th and 90th percentiles, respectively.

rent as a result of bid manipulation as a winner on a competitive open procurement auction. However, the information rent is also much less dispersed than the corruption rent: the median value of information rent is close to the average. The information rent varies in the range from 37% to 52% of the second-lowest bid. This can be interpreted as follows: if an auction is competitive, the most efficient firm can supply a procurement almost 2x cheaper than the second-most efficient firm.

Although the counterfactual award price remains lower on average than the award price from auctions with bid manipulation: \$186,870 vs. \$269,944, the information rent exceeds the corruption rent in many instances. Not surprisingly, in procurements of products not particularly attractive for corruption, the winners' information rents are several times higher than the corruption rents. For example, for procurement of cleaning contacts, the corruption rent is only around \$6K while the information rent is around \$200K. In procurements that attract a lot of money, such as medical equipment, the information rent is similar to the corruption rent, or even lower.

8.2 Expected Costs of Procurement

This section outlines the computation for expected costs of a procurement purchase in the presence of collusion between an auctioneer and a bidder. I compare this cost to the costs obtained in a competitive English auction under the assumption that the estimated model accurately reflects the procurement environment with corruption at the bid evaluation stage.

The expected procurer's costs are equal to the expected payment made by an auction winner. In cases of bid manipulation, this payment consists of the expected second-lowest bid and the expected bid in case the favored bidder is not the lowest bidder:

$$\int_{p}^{r} \tilde{c} d(1-F(\tilde{c}))^{n-1} + p \sum_{m \subset n-1}^{n-1} \mathbb{P}[m; n-1, \rho](1-F(p))^{(n-m-1)} F(p)^{m} \quad (8.3)$$

For convenient representation, I am using the envelope approach to characterize the expected costs. According to the Envelope Theorem, in equilibrium $p = \xi(c_i)$, the equation (8.3) is equal:

$$\begin{aligned}
&c_i(1-F(p))^{n-1} + c_i \sum_{m \subset n-1}^{n-1} \mathbb{P}[m; n-1, \rho](1-F(p))^{(n-m-1)} F(p)^{m} \\
&+ \int_{c_i}^{r} (1-F(\xi(\tilde{c})))d\tilde{c} + \sum_{m \subset n-1}^{n-1} \int_{c_i}^{r} \mathbb{P}[m; n-1, \rho] F(\xi(\tilde{c}))^{m}(1-F(\xi(\tilde{c})))^{n-m-1} d\tilde{c} \\
&= \int_{c_i}^{r} \tilde{c} d(1-F(\xi(\tilde{c})))^{n-1} + \sum_{m \subset n-1}^{n-1} \int_{c_i}^{r} \tilde{c} \mathbb{P}[m; n-1, \rho](1-F(\xi(\tilde{c})))^{(n-m-1)} F(\xi(\tilde{c}))^{m} d\tilde{c}
\end{aligned} \quad (8.4)$$

where the last expression follows from integration by parts.

The first term in the sum (8.4) corresponds to the expected costs of procurement in an English auction in the absence of corruption; it is equal to the expected second-lowest bid. The second term can be interpreted as representing the additional procurement costs due to collusion between the auctioneer and one of the bidders. Therefore, I have shown that the expected costs in the auction with bid manipulation are higher than in a competitive English auction by exactly the amount of the second term in expression (8.4). Notably, this expression should be negative, as it represents costs.

In the right panel of Figure 8.1, the costs due to corruption are pictured as a gray shaded region. Graphically, the expected corruption costs are the difference in areas above the distribution of procurement prices in the honest and rigged auction.

Table 8.2 reports the estimated costs of procurement in auctions with non-reported bids for a range of product categories. The first two columns reflect the estimated costs of procurement purchases and corruption costs in thousands of the original currency and in USD. Notice that column (4) replicates the results in Figure 7.1. The last column presents the percentage of the total expected procurement costs to the additional costs due to collusion between an auctioneer and a bidder.

The amount of corruption losses varies greatly across different product types. On average, the procurers overpay about 4.6% for the same product because of corruption.

Lastly, using back on the envelope calculations, I extrapolate the findings on the universe of procurement contacts in 2014. I find that the total welfare loss due to bid manipulation is \$ 2B 703M (RUB 94B 606M). This is the expected increase in procurement costs for public organizations. These welfare losses should be considered when local and federal governments and public organizations are planning their procurement purchases and drafting the yearly budgets.

Product	Expected Costs, 1000RUB	Corruption Costs, 1000RUB	Expected Costs, 1000RUB	Corruption Costs, 1000RUB	Percent of Total
Milk	2198.532	289.987	62.815	8.285	11.653
Textbooks	4099.281	230.166	117.122	6.576	5.316
CNS drugs	4977.708	284.208	142.220	8.120	5.401
Cardiovascular drugs	8087.976	504.015	231.085	14.400	5.866
Anticoagulation drugs	9809.116	370.370	280.260	10.582	3.638
Metabolic products	11214.648	413.943	320.419	11.827	3.560
Cancer drugs	21113.599	1725.457	603.246	49.299	7.555
Antiviral drugs	22712.021	1371.546	648.915	39.187	5.695
Miscellaneous drugs	9802.033	449.086	280.058	12.831	4.381
Pharmaceutical products	56624.073	2620.359	1617.831	74.867	4.423
Medical tools	31021.282	1228.449	886.322	35.099	3.809
Medical equipment	33100.693	838.162	945.734	23.947	2.470
Surgical equipment	3541.626	453.683	101.189	12.962	11.355
Renovation work	51315.173	1664.115	1466.148	47.546	3.141
Software	116752.613	146.462	3335.789	4.185	0.125
System maintenance	16372.850	2791.135	467.796	79.747	14.564
Office equipment	7979.699	130.634	227.991	3.732	1.611
Security services	13473.337	769.750	384.952	21.993	5.404
General cleaning	33666.222	3954.442	961.892	112.984	10.511
Garbage disposal	10000.618	1313.311	285.732	37.523	11.608

Table 8.2: Predicted expected costs of procurement in the presence of corruption

Chapter 9

Conclusion

Despite notable improvements in data availability and scientific methods for studying corruption in the procurement sector, this problem remains difficult to model. This paper advances an understanding of the corruption problem through an auction model for collusion between an auctioneer and a bidder, as realized through bid manipulation. In the model, a favored bidder enjoys a higher chance of winning and gaining additional rents because the auctioneer may disqualify its rivals at the bid evaluation stage.

I have found evidence that non-reported bids in bid evaluation reports indicate corruption in an auction. Furthermore, I demonstrate that these patterns can be rationalized by a model. From the procurer's perspective, I demonstrate that corruption at the bid evaluation stage can cause considerable losses. In some categories of products, public organizations overpay by more than 14% as a result of corruption. A favored bidder may increase its gains from a procurement award by up to 41.2% of the award price in auctions for products that are especially lucrative for corruption, such as computer software or medical equipment. My model also points out that corruption is especially pronounced in the procurement of medical services and equipment and drug procurement.

However, the results, should be interpreted with caution due to several limitations that may affect the estimates and subsequent analysis. Importantly, this model considers the number of bidders in an auction as fixed and does not allow for endogenous entry, although many recent studies have pointed out the importance of selective entry into the auction (see, for example, Roberts and Sweeting (2013) and Gentry and Li (2014)). I expect that the line of comparison between auctions with and without non-reported bids may be affected by the positive selection of corrupt firms into the former category. In other words, the observed difference in prices may be explained by the fact that only inefficient firms that are in a corruption agreement with an auctioneer participate in certain auctions and do not show up in others because they *a priori* do not have a chance to win honestly.

A future improvement may also involve modeling an auctioneer's choice of the favored bidder. While corruption at the bid evaluation stage involves interaction between two agents, the auction model describes only the behavior of a favored bidder. To conduct policy/counterfactual experiments examining auctioneers, I suggest extending the model and introducing an auctioneer. A possible avenue for proceeding is to incorporate the estimated auction rents into the auctioneer's utility.

In short, this paper provides evidence of how an auctioneer and a bidder may benefit from corruption in open procurement auctions through abuse of the bid evaluation process. The data introduced in this paper can be used to advance research in this area.

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Appendices

Appendix A

Additional Tables

Platform	Obs	%	Cum. %
1: ETP AVK	39,237	3.1	3.1
2: ETP EETP	245,165	19.54	22.66
3: ETP MMVB	42,841	3.41	26.08
4: ETP RTS	249,944	19.92	46.00
5: ETP SBAST	677,643	54.00	100.0
Total	1,254,830	100.0	

Table A.1: Distribution of auctions across Federal online auction platforms

Product	All reported	Non-reported	% of Total
Anticoagulation drugs	1,364	269	4.367
Antiviral drugs	1,239	288	4.083
CNS drugs	1,467	258	4.613
Cancer drugs	2,268	582	7.621
Cardiovascular drugs	964	261	3.276
Garbage disposal	1,271	254	4.078
General cleaning	1,333	343	4.482
M&R office equipment	1,070	181	3.345
M&R surgical equipment	1,668	214	5.033
Metabolic products	1,000	223	3.270
Milk	944	223	3.121
Medical equipment	1,117	225	3.589
Medical tools	1,899	206	5.629
Misc drugs	1,712	342	5.493
Pharmasutical products	1,721	277	5.343
Renovation works	1,748	306	5.493
Security services	2,552	458	8.049
Software	2,224	305	6.763
System maintenance	2,423	225	7.081
Textbooks	1,613	359	5.273
Total	31,597	5,799	37,396

Table A.2: Frequency table of auctions where all bid are reported (column 1) and auction with non-reported bids (column 2) by product category

Product	Variable	10th %-tile	25th %-tile	Median	75th %-tile	90th %-tile
Milk	2nd lowest bid	4711	5191	5990	6539	6859
	Information rent	761	923	1191	1626	1895
	Corruption rent	121	128	203	500	669
Textbooks	2nd lowest bid	11545	15467	22003	28540	33646
	Information rent	8046	11662	17962	28961	35580
	Corruption rent	2783	2920	3148	3376	3513
CNS drugs	2nd lowest bid	9626	9626	9857	11625	12686
	Information rent	492	1230	2417	3301	3831
	Corruption rent	211	215	222	229	233
Cardiovascular drugs	2nd lowest bid	6758	8747	12062	13551	14214
	Information rent	5467	6018	6934	7873	8440
	Corruption rent	609	637	683	729	766
Anticoagulation drugs	2nd lowest bid	10039	10858	12222	13585	14404
	Information rent	1963	2468	3310	5001	6161
	Corruption rent	79	106	152	198	225
Metabolic products	2nd lowest bid	10389	14123	20345	24832	24832
	Information rent	9978	9978	9978	10289	11006
	Corruption rent	1459	1859	2526	3193	3678
Cancer drugs	2nd lowest bid	47655	50117	50663	59693	67077
	Information rent	3151	3151	10948	20603	24649
	Corruption rent	1602	2428	3590	4367	4704
Antiviral drugs	2nd lowest bid	17821	20768	25679	30590	33537
	Information rent	7450	9570	12832	12832	12832
	Corruption rent	633	1216	2187	3159	3742
Misc drugs	2nd lowest bid	15523	16735	18756	20508	20508
	Information rent	2419	3258	3872	4006	4664
	Corruption rent	504	991	1802	2613	3087
Pharmaceutical products	2nd lowest bid	19942	46363	69557	69557	72995
	Information rent	34722	34722	37326	42895	45288
	Corruption rent	2224	2413	2729	3158	3475
Medical tools	2nd lowest bid	76340	84901	99169	104808	104808
	Information rent	30480	30480	30480	34215	38011
	Corruption rent	1914	2045	2264	2483	2615
Medical equipment	2nd lowest bid	22394	22394	22394	25673	30185
	Information rent	2433	6082	12164	21327	29384
	Corruption rent	3057	3753	4913	6073	6769
Surgical equipment	2nd lowest bid	2579	3248	4364	5480	6149
	Information rent	1004	1278	1735	1929	1929
	Corruption rent	851	894	966	1039	1082
Renovation works	2nd lowest bid	32574	32574	35672	41425	41425
	Information rent	1539	3849	5723	5797	7498
	Corruption rent	2752	3026	3483	3939	4213
Software	2nd lowest bid	329540	353318	377606	377606	422093
	Information rent	3059	3059	17201	54362	63238
	Corruption rent	8454	9125	10244	11362	12033
System maintenance	2nd lowest bid	26828	31247	38613	41212	41212
	Information rent	11557	11557	11557	15072	18403
	Corruption rent	164	165	166	167	168
Office equipment	2nd lowest bid	7207	7801	8792	9351	9351
	Information rent	2151	2151	2151	2684	3447
	Corruption rent	484	606	810	1013	1135
Security services	2nd lowest bid	8321	8321	9574	10098	10098
	Information rent	182	456	536	536	574
	Corruption rent	174	429	810	1052	1237
General cleaning	2nd lowest bid	19479	21306	22127	27734	35041
	Information rent	1351	1351	5303	9024	10006
	Corruption rent	127	132	140	149	154
Garbage disposal	2nd lowest bid	10223	10223	10528	12588	13823
	Information rent	340	850	1725	2761	3383
	Corruption rent	178	261	413	622	747

Table A.3: Distribution of information and corruption rents

Appendix B

Additional Figures

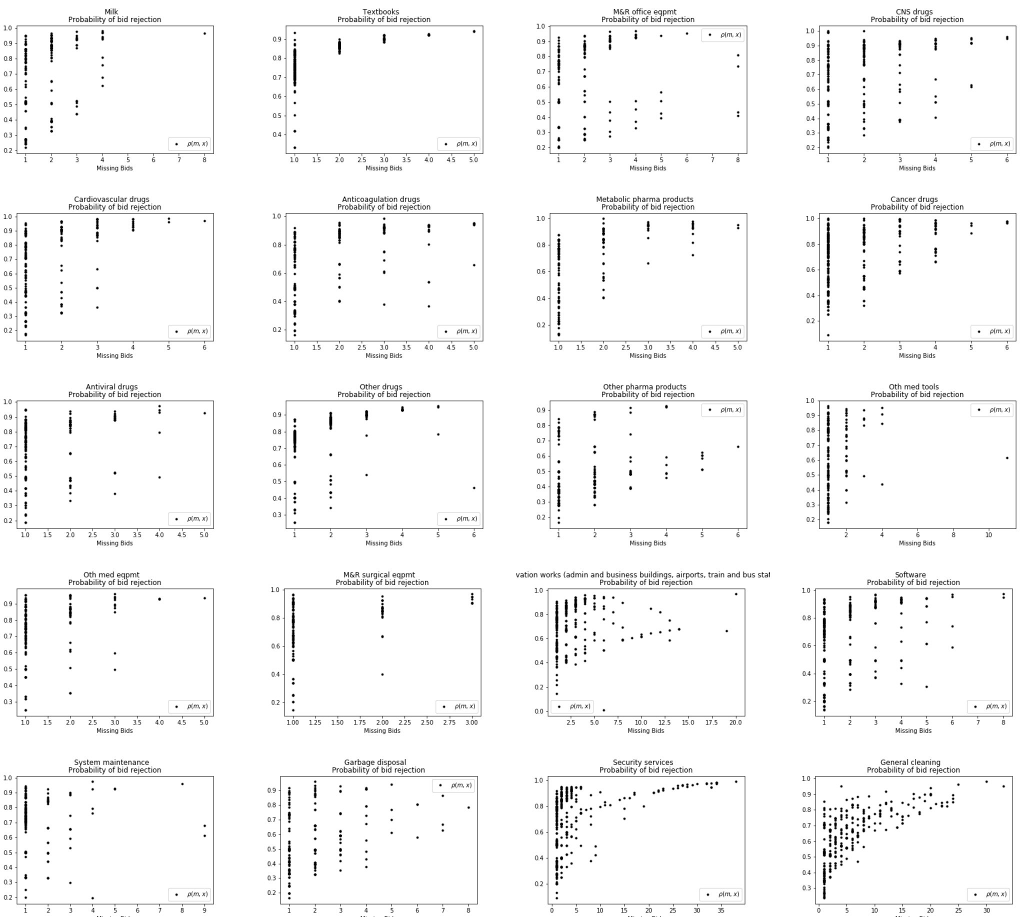

Figure B.1: Estimated probabilities of bid disqualification ρ_t

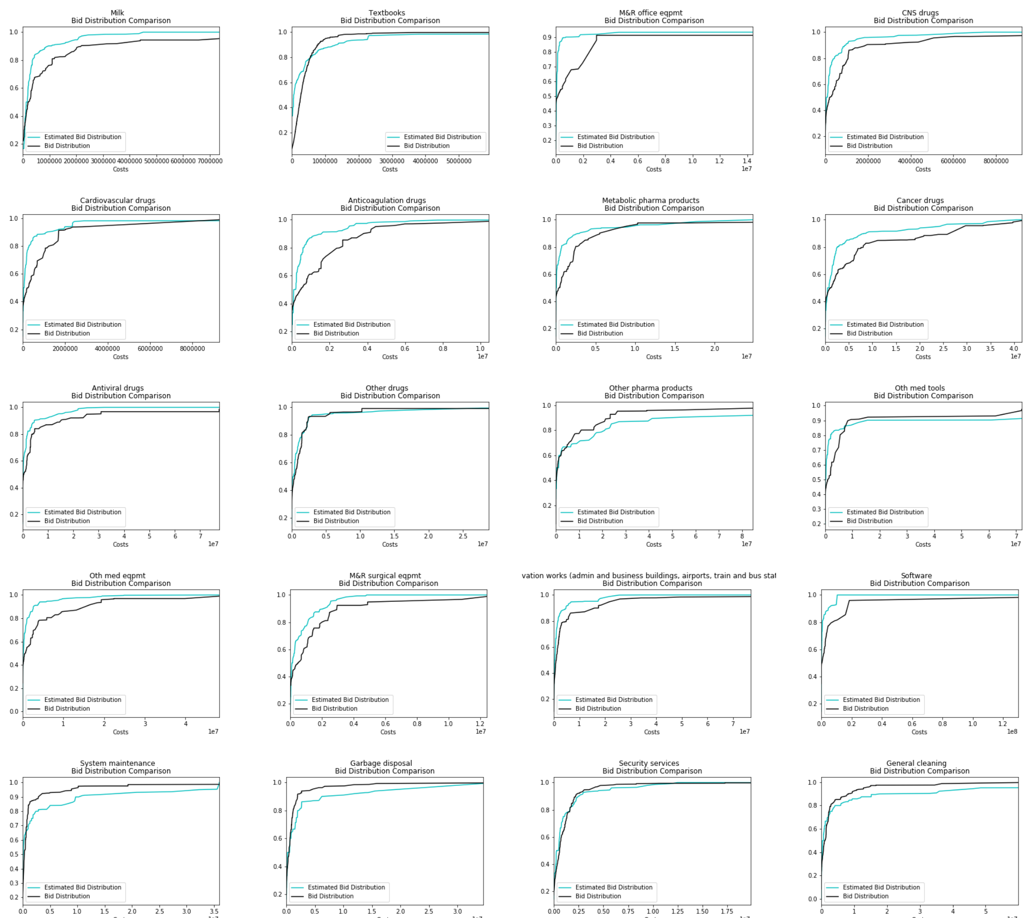

Figure B.2: Estimated bid distributions $\hat{F}_P(p_t|n, X)$

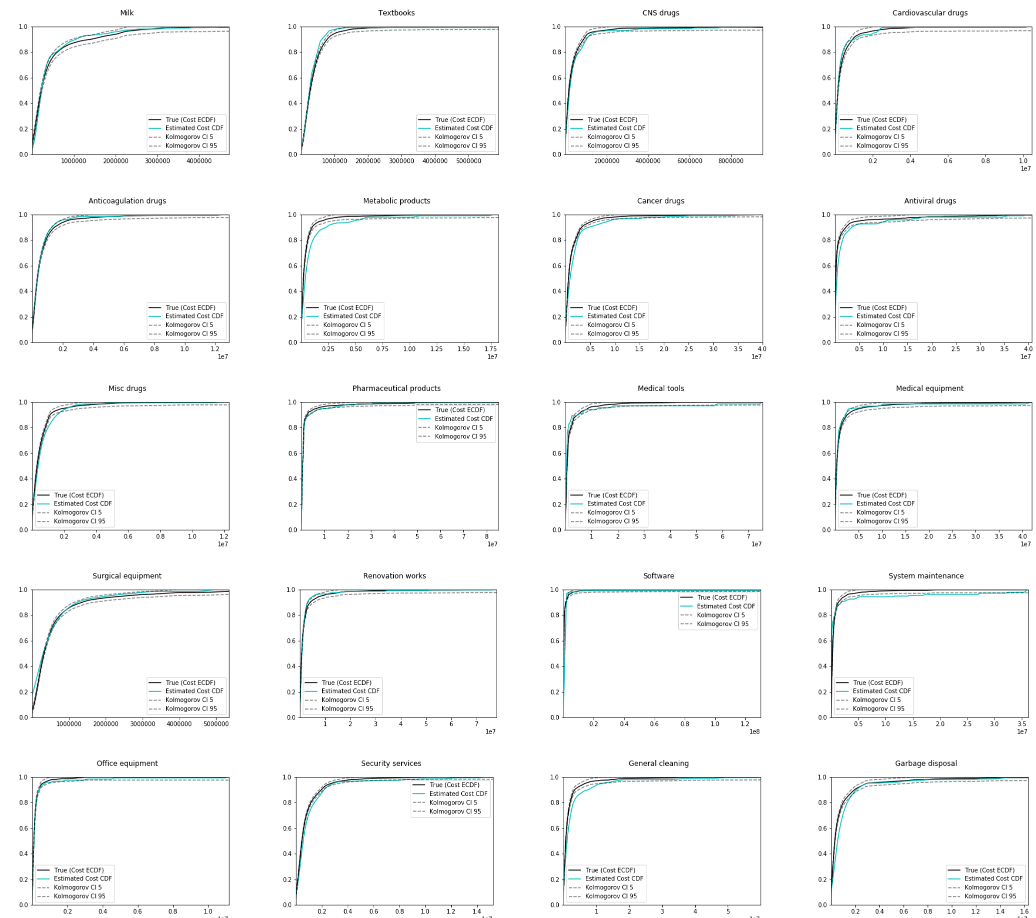

Figure B.3: Estimated cost distributions $\hat{F}_C(c_t|n, X)$ with 5% Kolmogorov confidence bounds

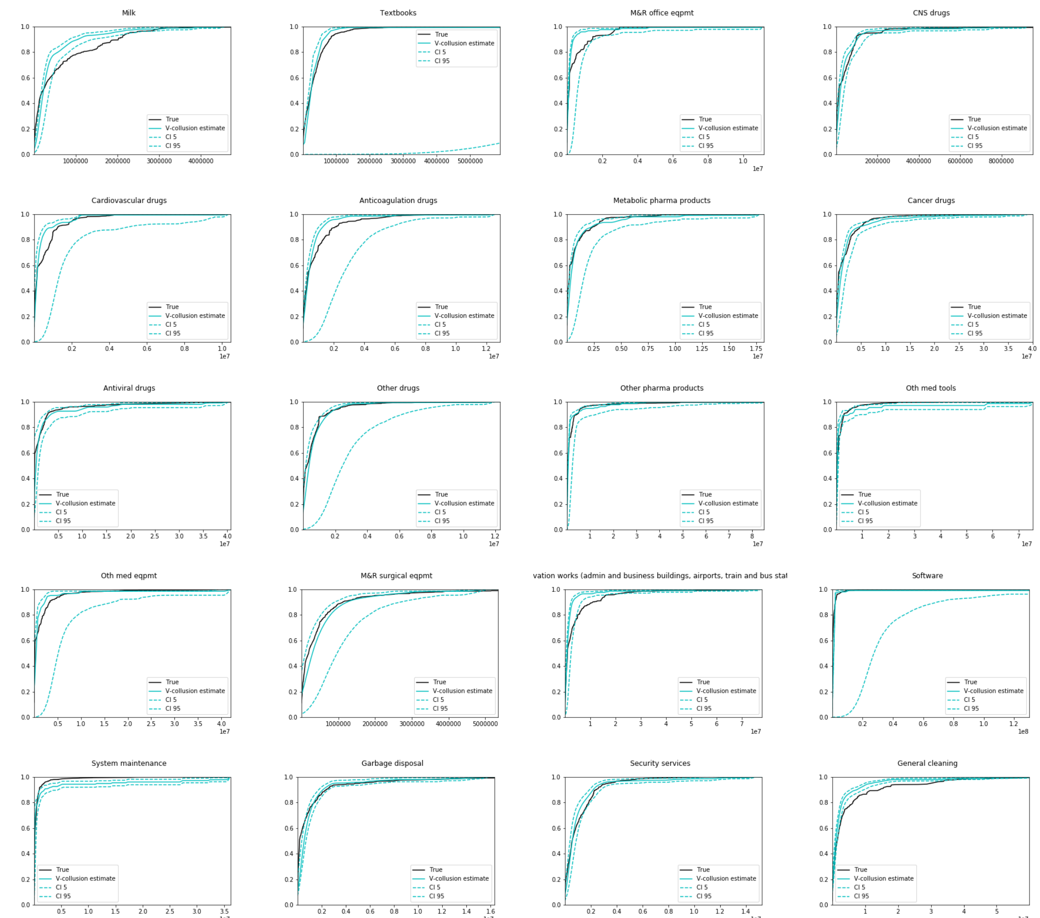

Figure B.4: Estimated cost distributions $\hat{F}_C(c_t|n, X)$ with 5% variation bounds