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COLLUSION DETECTION IN PUBLIC PROCUREMENT WITH LIMITED INFORMATION

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Abstract

Public procurement data sets usually lack detailed data that are needed to implement existing methods. We design a method to identify and test for bid rigging in procurement auctions with limited information. The method can be applied to limited data sets using standard econometric tools and software. We implement the methodology to a unique data set about all Turkish public procurement auctions in years 2005-2012, numbering 565,297. We uncover the structure of collusive behavior in Turkish public procurement auctions. We find that collusion significantly increases procurement costs and decreases procurement efficiency.

JEL Classifications: C36; D44; H57

Keywords: Collusion Detection; Public Procurement Auctions; Competition

ملخص

عادة ما تفتقر مجموعات بيانات المشتريات العامة إلى البيانات المفصلة اللازمة لتنفيذ الأساليب القائمة. نقوم بتصميم طريقة لتحديد واختبار تزوير العطاءات في مزادات المشتريات بمعلومات محدودة. ويمكن تطبيق هذه الطريقة على مجموعات البيانات المحدودة باستخدام الأدوات القياسية الاقتصادية والبرمجيات. ونقوم بتطبيق المنهجية على مجموعة بيانات فريدة عن جميع مزادات المشتريات العامة التركية في السنوات 2005-2012، وعددها 565،297. نكتشف بنية السلوك التواطئي في مزادات المشتريات العامة التركية. ونجد أن التواطؤ يزيد كثيرا من تكاليف المشتريات ويقلل من كفاءة المشتريات.

1. Introduction

Governments allocate significant resources to deter collusion in public procurement (PP) auctions. Collusive agreements among firms aim to limit competition and artificially increase procurement prices above the competitive level. To prosecute and, by so doing, deter future collusion, tools are needed to detect collusive behavior. All the existing methods require either the knowledge of all submitted bids (Bajari and Ye, 2003), the complete bidding history or characteristics of individual firms, or prior knowledge about potential colluders (Porter and Zona, 1999). Although governments might benefit substantially by detecting and deterring collusion in PP auctions, policy makers are facing many challenges to implement these methods. Most importantly, detailed information required to implement these methodologies is not available especially in developing countries. The available data sets for many countries including Chile, Mexico, Turkey and the European Union only contain information about the outcomes of the PP process namely winning bids and number of bidders.

This paper aims to fill this need by proposing a collusion detection methodology that does not require the complete bidding history or detailed prior information about potential colluders. Additionally, we intend to elaborate a method that is easy to execute and flexible enough to be implemented to a wide range of data sets with limited information. Collusion detection tools can increase PP efficiency and improve government budget deficits if policy makers can use them to identify potential colluders. Accordingly, we deliberately refrain from structural auction models that require complex theoretical derivations and use different sets of assumptions that might differ across countries. We hope that policy makers would be able to implement the methodology developed in this paper to limited data sets using standard econometric tools and software. After presenting the theoretical background and details of the new methodology, we implement it to a unique data set about Turkish PP auctions to study the structure of collusive behavior and its impact on auction outcomes in Turkey.

We first present the theoretical background of the bidding behavior of a bidding ring based on the independent private values auction model. Krishna (2010) shows that a bidding ring can be modeled using a two-step procedure. In the first step, the bidding ring members conduct a pre-auction knockout auction among ring members. They determine who will represent the ring in the auction and submit the winning bid among ring members. In the second stage, the other ring members submit phony bids to form an illusion of competition. Hence, the member of the ring can win the procurement with a higher price and higher profits. This argument indicates that the winning bid would be significantly higher compared to a procurement auction with competitive bidding. In a reduced-form econometric setting, the effect of bid-rigging mentioned above is captured by the relationship between winning bid and number of bidders. Ohashi (2009) states that “ In the presence of collusion among bidders, we certainly do not expect the (number of bidders variable) to negatively effect the bids.” (page 276) Using this argument, we design a collusion detection methodology by calculating the coefficient of number of bidders for each auction. We develop and estimate a varying coefficient model of winning bids to gauge auction-specific coefficients. We use these auction-specific coefficients to rank collusive behavior in each auction. Finally, we use this new method to empirically examine Turkish PP auctions.

The Public Procurement Authority of Turkey (PPAT) registers outcomes of all PP auctions by law. The PPAT publicly provides a data set that contains information about ***all*** PP auctions conducted in years 2005-2012, numbering 565,297. The total value of procurement in this period is over 300 billion US Dollars. There are no studies that examine collusion in Turkish PP auctions although a comprehensive and rich data set is officially available. Similar to many publicly available PP data sets, the PPAT data set lacks information about all submitted bids. Instead, it contains variables about the auction outcome such as the winning bid and number of bidders. Implementation of the new method shows that more than 30% of auctions are susceptible to collusion in Turkish PP auctions. We find that there is a positive and significant relationship between the new collusion measure and procurement costs. This result suggests that the new measure successfully ranks auctions with respect to the level of collusive behavior.

The PPAT data set covers auctions from different sectors, economic regions and government institutions. Existing studies in the literature examine very limited data sets. For example, Porter and Zona (1993) analyzes 116 paving contracts awarded by the New York State Department of Transportation and Bajari and Ye (2003) studies 441 seal coating contracts in Minnesota, North Dakota and South Dakota. We contribute to the literature by investigating collusive behavior in the entire universe of PP auctions of a middle-income country.

The remainder of this paper is organized as follows. Section 2 summarizes the existing collusion detection methods and publicly available data sets that can not be examined using these methods. Section 3 describes the theoretical structure of bid-rigging behavior and limited competition. Section 4 presents the new collusion measure and estimation methodology. Section 5 displays the empirical analysis of collusion in Turkish PP auctions and section 6 concludes the paper.

2. Existing Collusion Detection Methods in the Literature

We categorize the existing methods with respect to the information required to implement the methodology. They mainly employ two types of information: (1) Detailed information about bidders, their bids and identity of the winning bidder. (2) Detailed information about suspected or prosecuted collusion cases from civil lawsuits. Additionally, studies such as Brosig and Reiss (2007) conduct experiments and test theoretical implications of collusion using experimental data.

2.1 Bid-level data

Many studies use specialized data sets such as the California Department of Transportation (Caltrans) and Construction Market Data. These data sets contain information about all the submitted bids for specific construction projects such as pavement and road construction. Bajari and Ye (2003) develop a methodology by identifying the properties of bidding behavior that would always hold under competition. Their methodology involves estimating a pricing equation for each firm and testing whether independence and exchangeability hold for various (or all) subsets of firms. Thus, bids of each firms and information about the factors that determine the cost of each firm should be known to enable implementation of this methodology. Aryal and Gabrielli (2013) use the methods of Bajari and Ye (2003) to identify bidders who could potentially collude. Then, they derive the underlying cost associated with each bidder. Statistical comparison of bidders' cost structure is used to determine collusion. Ishii (2009) and Padhi and Mohaptra (2011) start their study with a graphical analysis of potential clusters of bids. They argue that clusters with higher relative winning bids and low variance of submitted bids are caused by collusion.

2.2 Data about prosecuted collusion cases

An alternative way of collusion detection is comparing the bidding behavior of firms with the known cases of collusive bidding behavior. Porter and Zona (1999) use this approach to examine the procurement process in Ohio school milk auctions. Some of the firms were charged for collusion and confessed to rigging bids. They conduct a regression analysis with bids of defendants in the collusion case and control group of firms that were not named as dependants. They argue that behavior of a firm is consistent with collusion if it differs from that of the competitive group. Similarly, Banerji and Meenakshi (2004) have prior information that three largest buyers may be colluding in wheat markets in Northern India. They design four different competition models (models with alternative collusion characteristics) and calculate the likelihood of each model by using the data. They analyze whether the likelihood functions of the collusive or competitive models are higher.

Abrantes-Metz et al. (2006) examine the structural change in the variance of Defense Personnel Support Center procurement auction data. The Antitrust Division of the US Department of Justice prosecuted several firms for rigging the bids for supplying seafood. The authors conclude that the standard deviation of the bids and procurement price are significantly lower during collusion and increases dramatically after the collusive firms are prosecuted. Similarly, Bolotova et al. (2008) implement ARCH and GARCH models to analyze the structural change in the first two moments of the price distribution after collusion was detected by the US Government in citric acid and lysine cartels. Huschelrath and Veith (2014) examine the German cement market using information about the firms charged by the German Federal Cartel Office for bid rigging. Conley and Decarolis (2016) use data about prosecuted collusion cases to develop statistical tests to detect coordinated entry and bidding choices. They also employ information about "common ownership and management, formation of temporary bidding consortia and exchange of subcontracts" to define the links of bidding firms to convicted firms. Table 1 summarizes the collusion detection methods and characteristics of the data sets used in the literature.

Table 1 presents that all of the existing studies use collusion detection methods that require detailed information about all submitted bids, location and cost structure of all firms or information about prosecuted firms in previous legal cases. Additionally, these studies examine concentrated data sets limited to one sector in a specific location. For example, Bajari and Ye (2003) analyze 495 seal coating projects with 11 main firms; Porter and Zona (1993) 116 auctions for state highway construction projects; Banerji and Meenakshi (2004) 421 auctions in wholesale wheat markets on Northern India in April and May 1999; Ishii (2009) 175 auctions on compensation consulting work in Naha City, Japan; Aryal and Gabrielli (2013) 2,152 highway maintenance contracts awarded by California Department of Transportation; and Conley and Decarolis (2016) 1,304 roadwork auctions between years 2005 and 2010.

However, there are more comprehensive data sets that potentially contain valuable information about PP auctions in advanced and emerging countries. For example, the Tenders Electronic Daily (TED) data set of the European Union (EU) encompasses data about outcomes of more than 4 million public purchases by 33 EU member and affiliated countries for years 2006-2015.[1] Table 2 below lists a subset of publicly available data sets about PP outcomes. All of these data sets contain information only about the outcomes of auctions (winning bids, number of bidders, etc.). Hence, collusive behavior in these countries cannot be examined using existing methods although these rich data sets carry valuable information.

In Sections 3 and 4, we lay out the theoretical background of collusive behavior and propose an easy-to-implement estimation methodology to study collusive behavior in PP auctions using limited information. We examine the structure and effects of collusion in the Turkish public procurement auctions by using the PPAT data set in Section 5.

3. Theoretical Presentation of Bid Rigging Behavior

In this section, we use well-established theoretical results to present a simple model of bid rigging behavior. The model provides the theoretical fundamentals of the new collusion detection methodology. We follow the model specification of Krishna (2010). Specifically, we assume that the bidding ring conducts a preauction knockout (PAKT). The winner of the PAKT represents the bidding ring at the main auction. As stated by Krishna (2010), the PAKT ensures that the collusive behavior of the bidding ring is efficient. This two-stage mechanism is

[1] The TED data set contains a subset of public procurement. For most of the cases, registration at the TED is voluntary. Hence, the TED data set does not evenly represent EU countries. For example, the data set contains 1,202,192 observations for France and 997,957 observations for Poland but only 39,635 for Germany.

efficient because the ring member with the lowest cost submits the winning bid (lowest bid among the ring members) in the procurement auction. As stated by Marshall and Marx (2012), the bidding ring gains profits by suppressing their rivalry by "elimination of meaningful bids by all colluding bidders except for the ring bidder".

As stated by Hendricks et al. (2014) the major task of the rings is the coordination of the bids submitted by the ring members. The two-stage mechanism solves the coordination problem by selecting the most efficient ring member as the primary bidder and making the other ring members to submit intentionally losing bids. The primary bidder is selected through PAKT. Hendricks et al. (2014) mentions that "This technique ... makes collusion more difficult to detect by antitrust authorities using statistical methods."

Many prosecuted bidding-rings used the PAKT. Asker (2010) describes the internal organization of a bidding ring operated in auctions of collectible stamps in New York auction houses from the late 1970s until July 1997. The ring used an internal "knockout" auction to coordinate bidding. Marshall and Marx (2012) present an early example of bid rigging in sealed-bid procurement auctions. Major U.S. cast-iron pipe manufacturers met prior to auctions and held a knockout in which the highest bidding ring member was selected to bid at the procurement. Following the arguments stated above, we design a bidding-ring mechanism that involves two steps: (1) PAKT among ring members; (2) first-price sealed bid procurement auction.

3.1 First-price PAKT

We assume that there are R members of the bidding ring. Before submitting bids at the procurement auction, the ring members conduct a first-price PAKT and submit their bids which is an offer to pay all other members of the ring. The winner of the PAKT represents the ring and the other ring members submit phony losing bids. Proposition 11 of Krishna (2010) (page 167) indicates that "symmetric equilibrium strategies in a first-price sealed-bid PAKT" is

$$\beta_i(c_i) = \frac{1}{R} E\left[Y_1^{(N)} \mid Y_1^{(N)} > c_i\right] \tag{1}$$

where c_i is the cost of the bidder i and Y_1 is the lowest of independently drawn costs of $R-1$ opposing bidders. Equation (1) states that it is optimal for a ring member to truthfully submit a bid consistent with her cost. Accordingly, the ring member with the lowest cost would earn the right to represent the ring in the main auction.

3.2 Main procurement auction

The bidding ring suppresses competition to generate profits for its members. Since only $N-R$ effective bids are submitted instead of N bids, the procurement price is higher compared to the case of no ring. Only the winner of the PAKT submits a serious bid according to her cost. Other ring members submit phony bids. We assume that the main procurement auction is a sealed-bid first-price auction within the independent private value paradigm. This is the case for most government procurement auctions.[2]

Each bidder submits a sealed bid of b_i and the payoff of bidder *i* is

$$\pi(b_i) = (b_i - c_i) Pr(win/b_i) \tag{2}$$

[2] For example, more than 63% of the Turkish public procurement and 83% of European Union procurement are conducted using the "open-procedure" that is first-price auctions. The other procurement methods are negotiation, restricted auction and direct purchase. In this paper, we focus on collusion in first-price auctions.

The first part of equation (2) is the payoff to winning the auction with bid, b_i and the second part is the probability that the bid, b_i, would win the auction. $c_i \in [\underline{c}, \bar{c}]$ is the cost of bidder *i*. The probability can be presented as the following:

$$Pr(win/b_i) = \{1 - F_C[\beta^{-1}(b_i)]\}^{(N-1)} \tag{3}$$

where F_C is the cumulative probability distribution function of cost parameter, c_i and β^{-1} is the equilibrium bid function. The Bayes-Nash equilibrium of this common structure is well-known as presented in Milgrom and Weber (1982) and Krishna (2010). The Bayes-Nash, equilibrium-bid function is

$$\beta_i = c_i + \frac{\int_{\underline{c}}^{\bar{c}} [1 - F_C(u)]^{(N-1)} du}{[1 - F_C(c_i)]^{(N-1)}} \tag{4}$$

Equation (4) states that bidder *i* submits a bid that is equal to her cost plus a positive rent component. The rent component decreases as *N* increases. The equilibrium bid approaches to the cost of the bidder as the level of competition rises. If we assume that F_C is an exponential distribution, we can get a simpler presentation of the relationship between the number of bidders and the equilibrium bid as the following.

$$\beta_i = c_i + \frac{1}{\lambda(N-1)} \tag{5}$$

The serious bidder of the bidding ring is facing $N - R$ effective bids instead of N -1. Hence, its equilibrium bid is significantly higher than that of the competitive case. Specifically, equation (5) becomes

$$\beta_i^w = c_i + \frac{1}{\lambda(N-R)} \tag{6}$$

The equilibrium bid of the serious bidder of the bidding ring, β_i^w, is larger than her bid under competition, β_i. Instead of bidding β_i, the serious bidder of the ring bids a significantly higher amount, β_i^w since she knows that she is facing just $(N-R)$ competitors instead of $(N-1)$. The "honest" bidders that do not belong to the ring submit bids closer to their costs as if they are facing $(N-1)$ competitors. Accordingly, when a non-ring member wins the contract, she earns significantly lower profits. On the contrary, when the serious bidder of the bidding-ring wins the contract, she earns significantly higher profits as if she is facing just $(N-R)$ competitors. Consequently, equation 4-6 present the relationship between the winning big (procurement price) and the competitive environment characterized by total number of bidders, N and total number of bidding ring members, R. In the next section, we design a new collusion measure using this relationship.

4. New Collusive Behavior Measure and Estimation Methodology

The major challenge of collusion detection in auctions is that the bidding-ring is not observable by its nature. However, we can use the theoretical arguments presented in Section 3 to scrutinize the unobservable ring members. Although the number of ring members, R, is not observable, many data sets contain detailed information about winning bid (contract price), β, and total number of bidders, N. Therefore, we implement an identification strategy that utilizes the relationship presented in equations 4-6 and the information we have about the winning bid and total number of bidders to extrapolate the number of bid-rigging members.

Bajari and Ye (2003) employs a similar identification strategy. They use observed bids of all firms to construct statistical conditions for competitive bidding. Then, they examine whether the observed bid distribution satisfies the statistical conditions for competition. They detect collusion if conditional independence and exchangeability conditions are not satisfied. Compared to Bajari and Ye (2003), the methodology we propose has two major advantages. First, the methodology does not require information about all submitted bids. Hence, it can be implemented to a wide range of data sets that contain information only about contract price. Second, we obtain a continuous measure of collusion. We can order auctions according to the severity of collusive behavior.

We start by presenting the relationship between the winning bid and number of bidders. We follow the empirical auction literature (e.g. Porter and Zona, 1993; Pesendorfer, 2000; Bajari and Ye, 2003; Iimi, 2006 and Asker, 2010) and present the relationship between the number of bidders and winning bids as a reduced form regression equation as follows

$$ln(b_a) = N_a\psi + Z_a^{'}\theta + M_a^{'}\alpha + \varepsilon_a \quad (7)$$

where b_a is the winning bid at auction a. Z_a is a vector of auction-specific variables and M_a contains the variables that measure the macroeconomic conditions. Equation 6 states that when the winning bid is submitted by the serious bidder of the bidding ring, the procurement price is significantly higher compared to a non-ring auction. Ohashi (2009) considers the case where all bidders are ring members and states that the relationship between the number of bidders and winning bid would not be negative under collusion. Accordingly, when a bidding ring participates and wins an auction, equation 7 can be written as follows

$$ln(b_a) = (N_a - R_a)\psi + Z_a^{'}\theta + M_a^{'}\alpha + \varepsilon_a \quad (8)$$

or

$$ln(b_a) = N_a\psi^c(R_a) + Z_a^{'}\theta + M_a^{'}\alpha + \varepsilon_a$$

where $\psi^c(R_a)$ is the coefficient of the number of bidders variable in the presence of collusion by the bidding ring. Its value changes with respect to the number of bidding ring members in auction a, R_a. Equation 8 states that when phony bids are submitted by the ring members, the relationship between the number of bidders and the winning bid would be significantly different. As expressed by Ohashi (2009), this difference is gauged by the coefficient of number of bidders, $\psi^c(R_a)$. Specifically, $\psi^c(R_a)$ might be positive or its magnitude might be smaller than the non-collusive coefficient, ψ, in the presence of bid-rigging.

The theoretical arguments described in section 3 and equation 8 indicate that the existence and level of collusion can be measured using the changes in the coefficient of number of bidders. Consequently, we develop a new collusion-detection methodology by calculating and analyzing the coefficient of the number of bidders variable for each auction. The auction-specific coefficients can be calculated using varying coefficient models based on state-space representation. In other words, we extend equation 8 by defining a new auction specific coefficient, ψ_a, for each auction a. $N_a\psi_a$ is equal to $N_a\psi^c(R_a)$ which is equal to $(N_a - R_a)\psi$.

We consider the case that half of the bidders are ring members to illustrate the intuition behind our estimation strategy. Hence, R_a in auction a is equal to $N2$ and N_a is equal to N . Then,

$$N_a\psi_a = (N_a - R_a)\psi$$

$$N\psi_a = (N - \frac{N}{2})\psi = N\frac{\psi}{2}$$

$$\psi_a = \frac{\psi}{2}$$

When there is no collusion, R_a is equal to zero. Accordingly, the coefficient ψ_a is ψ. This simple example demonstrates that ψ_a decreases as number of ring members increases and collusion becomes more severe.

We transform equation 8 with auction-specific coefficient, ψ_a as follows

$$ln(b_a) = N_a\psi_a + Z_a^{'}\theta + M_a^{'}\alpha + \varepsilon_a \quad (9)$$

ψ_a in equation 9 potentially can take different values for each auction a. In other words, the relationship between the winning bid and number of bidders can be different for each auction. As described above, the source of this variation is collusive behavior by bidding rings.

We control for procurement specific characteristics using the information available at the PPAT data set, $Z_a^{'}$, when estimating ψ_a. These variables are estimated cost (engineer's estimate), location, sector, whether the cost is above the threshold, procuring government institution dummy variables, year dummy variables and whether the electronic auction system is used. Among these control variables, estimated cost variable provides essential information about procurement heterogeneity. Bajari and Ye (2003) shows that "the engineer's estimate is a useful control for project costs." (page 979)[3] Additionally, we control for macroeconomic conditions using $M_a^{'}$ that might affect procurement conditions. To be able to get robust results, we implement both instrumental variable (IV) GMM and the heteroskedasticity-based identification approach developed by Lewbel (2012) (HB) in section 5. Lewbel (2012) states that the HB methodology provides an unbiased and consistent estimate of the parameters when the regression model contains endogenous or mismeasured regressors, or when the model suffers from the omitted-variable bias. Finally, we follow Bajari and Ye (2003) and use an alternative dependent variable to take care of potential heteroskedasticity problem: "the ratio of winning bid and the ... engineer's estimate". (page 981)

4.1 Varying coefficient model

It has been long recognized in economics and finance literature that the coefficients of the regression equation might not be constant. The workhorse in estimating that type regression equations is the varying coefficient model. The model estimates the dynamic pattern of regression coefficients by designing a state-space model. The state-space model consists of unobserved "state" variables and observed variables which are related to the state equations. State equations are inferred using the information in observed variables. In our case, the auction-specific coefficient of number of bidders is an unobserved state variable. The state-space representation that consists of the state and observation equations present the structure of auction-specific coefficients and observed auction characteristics: winning bid, number of bidders, sector, estimated cost, etc.

State equation:

$$\psi_{a+1} = f\psi_a + v_{a+1} \quad (10)$$

[3] Bajari and Ye (2003) examines 441 auctions and engineer's estimate is available for 139 projects.

Observation equation:

$$ln(b_a) = N_a \psi_a + Z_a^{'} \theta + M_a^{'} \alpha + \varepsilon_a \qquad (11)$$

The parameters of the system of equations 10 and 11 can be estimated using maximum likelihood. The Extended Kalman filtering algorithm provides the distribution of $ln(b_a)$ conditional on its previous values. It is Gaussian assuming that ψ_a, v_a and ε_a are Gaussian. A forward recursion using the Kalman filter provides expressions for the mean and variance of the distribution. Then, the parameters that maximizes the likelihood function can be calculated. Accordingly, we can form an inference about the value of ψ_a based on the complete data set. This Kalman smoothing methodology provides the estimated values of the state variable, ψ_a. Hence, we calculate the coefficient of the number of bidders variable for each auction a, ψ_a, using Kalman smoothing. Maximum likelihood estimation of the state-space parameters and Kalman smoothing are well-established methods used extensively in economics and finance literature. Therefore, we do not provide the details here and refer to the excellent presentation of Hamilton (1994) Chapter 14.

5. Collusion in Turkish Public Procurement Auctions

In this section, we implement the new collusion detection methodology to the PPAT data set by estimating the varying coefficient model of equation 11. First, we extend the data set of Onur et al (2012)[4] and estimate equation 7 with the unvarying number of bidders coefficient, ψ. Then, we estimate the varying coefficient, ψ_a, and study the structure of collusion in Turkish public procurement. Finally, we conduct empirical analyses to examine the impact of collusion on the efficiency of public procurement. We start with the description of the data set.

5.1 Data description

The PPAT data set used in this study contains data about all government procurement auctions from 2005 to 2012. The Turkish Public Procurement Law (Law no 4734) enacted in 2003 makes it mandatory that all procuring government agencies register the procurement outcomes at the PPAT. Accordingly, the PPAT governs the integrity of the data set. The major variables of interest are the winning bid (WINBID) and number of bidders (N). Additionally, the PPAT data set includes the estimated cost (ESTIMATE)[5] and additional variables about the characteristics of the auction and product. We use them as control variables. The PP law requires collection of only the value of the winning bid and number of bidders. When an institution registers its procurement request at the PPAT, the PPAT determines the estimated cost by consulting experts as dictated by the Public Procurement Law Article 9.[6] Auctioned products are categorized as construction, services and goods. We also construct dummy variables for these product types.

We use additional control variables to consider the effects of auction and product characteristics. Firstly, we construct the ABOVE THRESHOLD dummy variable. The PPAT determines a threshold value for various types of procurement auctions according to the rules specified by the legislation and announced to the public. The auction rules vary depending on the estimated cost (ESTIMATE) for a specific auction being above or below the threshold value. After collecting the published threshold values, we assign the value of 1 to the ABOVE THRESHOLD dummy variable if the ESTIMATE is above the threshold value, and 0

[4] They examine a narrower data set of 86,085 auction in years 2004-2006.

[5] The Public Procurement Law Article 9 describes how the estimated cost is calculated by the contracting authority. The Law can be accessed at http://www2.ihale.gov.tr/english/4734_English.pdf

[6] The law can be accessed at http://www2.ihale.gov.tr/english/4734_English.pdf

otherwise. The ABOVE THRESHOLD variable has significant practical implications. When the estimated cost is above the threshold value, the institutions have the option to offer price advantages to domestic bidders whereas if the estimate is below the threshold value, then no price advantage can be offered.

In addition, we group the auctions into regional dummies depending on which stimulus region the city is located in. The Turkish Government provides financial support to investors that invest in less-developed regions. The Ministry of Development identifies six stimulus regions according to the economic development of those regions. The first region is the most developed and the sixth region is the least developed one. Firms that invest in Region 1 are not eligible for any financial support. Whereas firms invest in Region 6 can get tax refunds, financial support for employment and can be eligible for rent-free land. These regional variables are important since some regions could attract more/less participants because of their geographical location, their economic development and the amount of government benefits offered. Finally, we include macroeconomic variables to control for the impact of macroeconomic conditions of the economy on the participation of firms and the procurement costs. We use inflation, industrial production and central bank policy rate as macroeconomic control variables. We retrieve these variables from International Financial Statistics of the IMF. We present the summary statistics of the variables in Table 3.

One of the interesting features of Table 3 is the ratio of winning bid and estimated cost. We find that on average the contract price is 85% of the estimated cost. The variance of the ratio is very high and ranges from 0.24 to 1.45. Collusive behavior is the prime suspect for this high variation and contract prices that are well above the estimated cost. We conduct several empirical analysis in the next sections to examine the effect of collusion on procurement price and the ratio.

5.2 Procurement price and competition

We first focus on the stable relationship between the winning bid and number of bidders by estimating the regression specification presented in equation 7. We first use the GMM IV methodology to estimate the coefficients of equation 7 following Onur et al (2012). Studies like Estache and Iimi (2010) argue that there might be factors that simultaneously affect the participation decisions of bidders and the winning bid. This might cause the number of bidder dummy variable to be endogenously determined. We search for valid instrumental variables and implement GMM IV to deal with potential endogeneity of number of bidders variable. To obtain robust estimates, we also use an alternative IV methodology. HB methodology developed by Lewbel (2012) identifies structural parameters when valid instrumental variables do not exist. HB uses the heteroskedasticity of the errors to achieve identification through observing a vector of regressor variables uncorrelated with the covariance of heteroskedastic errors. Lewbel (2012) states that this approach may be applied when external instrumental variables are not available since the method constructs instruments as functions of the model's data. Table 4 displays the GMM IV and HB estimation of equation 7 with alternative dependent variables: log procurement price and ratio of procurement price and estimated cost.

We employ BIG CITY and GENERALBUDGET as instrumental variables in the GMM estimation. Onur et al. (2012) shows that BIGCITY is an important determinant of the number of bidders in Turkish public procurement auctions. We classify a city in which the auctions took place as a BIG CITY if the population is greater than or equal to one million. Furthermore, the PPAT data set contains information about the source of the procurement budget. The GENERALBUDGET dummy variable takes the value 1 if the auction is conducted under the general or the annexed budget. Alternatively, the contracting authority might operate under its own budget if it is a state economic enterprise or partly owned by public administrations. The threshold values and procurement details are different for the auctions not covered by the general budget. We conduct negative binomial regression analysis where the dependent variable is the number of bidders to examine the relationship between these two variables and the number of bidders. Table A.1 in the Appendix displays results of the count data regression analysis. We conclude that besides other control variables, these variables are significant determinants of number of bidders. Additionally, they are naturally exogenous. Accordingly, they are good candidates to be valid instrumental variables.

We conduct statistical tests to assess the validity of BIG CITY and GENERALBUDGET as instrumental variables. The Hansen *J* statistic of the test of overidentifying restriction has a joint null hypothesis that the instruments are valid in the sense that they are uncorrelated with the error term. The *J* statistics is 0.57 with a p-value of 0.45 when the dependent variable is logarithm of procurement price and 0.15 with a p-value of 0.70 when the dependent variable is the ratio of procurement price and estimated cost. Accordingly, we statistically accept the null hypothesis that BIGCITY and GENERALBUDGET are valid instruments. Furthermore, we implement the HB methodology to examine the robustness of GMM IV results to alternative regression methodologies and selection of instrumental variables. We do not select the IVs in the HB. Instead, the method builds valid IVs (uncorrelated with the error term) using the heteroskedasticity structure of the error terms. Accordingly, we can observe how the results hold when alternative IVs are implemented using the HB.

Table 4 shows that the number of bidders variable is significant with a negative coefficient in all regression specifications. Accordingly, we conclude that competition is an integral component of procurement costs since the coefficient of number of bidders is significant and negative. This result suggests that bidding rings can generate profits by limiting competition in PP auctions. In the next section, we calculate the collusion measure and study bid-rigging behavior in Turkish PP auctions.

5.3 Auction-specific coefficients as a collusion detection tool

In section 4, we argue that auction-specific ψ_a can be used to measure the level of collusion in PP auctions. In this section, we estimate auction-specific ψ_a for each auction a by using the state-space model and maximum likelihood estimation described in Section 4.1. Figure 1 below displays the estimated coefficients for each auction. Figure 1 provides a compact presentation of the collusion measure, ψ_a, for all auctions. Figure 1 shows that the coefficient of the number of bidders variable, ψ_a, differs substantially across auctions. We present the histogram of ψ_a below.

Figure 2 displays that a considerable number of auctions have positive or zero ψ_a. Theoretical arguments indicate that these auctions are more likely to be subject of collusive behavior. The collusion measure serves as a proxy for a bidding-ring member winning a PP auction. Hence, one can use this measure to order the level of collusive behavior in an auction.[7] Theoretical findings of equations 5 and 6 suggest that auctions with higher levels of the measure would have significantly higher levels of winning bids after controlling for all auction characteristics. We empirically test this argument by estimating the following regression equation using GMM IV and HB.

$$ln(b_a) = \psi_a \lambda + N_a \gamma + Z_a^{'} \theta + M_a^{'} \alpha + \varepsilon_a \qquad (12)$$

λ gauges the impact of collusive behavior on the auction outcome. Equation 6 indicates that λ would be significant and positive showing that the winning bid increases as collusion

[7] We would like to note that the only unerring method to detect collusion is through confessions of ring members and legal prosecution. Our measure provides policy-makers and researchers a tool to rank auctions with respect to level of competition and potential collusive behavior in those auctions.

becomes more severe. Table 5 displays the estimated coefficients of equation 12. We implement alternative regression specifications and alternative IV estimation methods to obtain robust results. First regression specification uses the log winning bid as the dependent variable and uses log estimated cost as an explanatory variable. Alternatively, we use the ratio of the winning bid and estimated cost as the dependent variable. We use GMM IV with BIG CITY and GENERALBUDGET as instrumental variables and the HB methodology.

The collusion measure variable is significant with a positive sign in all regression specifications. All of the other control variables have the expected signs. Accordingly, Table 5 shows that the collusion measure correctly identifies inefficient auctions with higher values of procurement prices. Figure 3 below presents procurement efficiency measured by the ratio and the collusion measure of 565,297 auctions. The fitted regression lines stresses the significant positive relationship between the ratio and collusion measure.

5.4 Collusion measure and auction characteristics

The new collusion measure allows us to rank auctions with respect to the severity of collusive behavior in Turkish PP auctions. In this section, we examine the relationship between major auction characteristics and the collusion measure in detail. First, we divide the collusion measure into 100 percentiles and calculate average auction characteristics for the corresponding percentile. Namely, we calculate the average ratio of winning bid and estimated cost, number of bidders and estimated cost for each percentile.

Table 5 displays the significant positive relationship between the ratio of procurement price and estimated cost and the collusion measure. Figure 4 below validates this result graphically. The last percentile of figure 4 presents an interesting feature. Average collusion measure is 0.12 and average ratio is is 1.11 in the last percentile. Average ratio is above 1 for the 99th and 100th percentiles. Average collusion measure is 0.09 and 0.12 for these percentiles. Accordingly, the right-hand tail of the collusion measure graph identifies auctions with extremely high procurement prices. Similarly, most efficient auctions with ratios as low as 0.36 are associated with the left-hand tail of the collusion measure.

Additionally, we conduct a simple threshold regression analysis to determine collusion measure threshold levels that are associated with lower efficiency levels. Accordingly, we implement the Threshold Regression (TR) model described in Hansen (2000) and Yu and Phillips (2014). The TR model splits the sample according to the realized value of some observed threshold variable, q. The indicators $1(q \le \tau)$ and $1(q > \tau)$ define two regimes in terms of the value of q relative to a threshold point given by the parameter τ. We calculate the structural change in the constant term, c, in terms of the threshold value of collusion measure. The constant term measures the average value of the dependent variable, ratio of procurement price and estimated cost. We implement the TR methodology to determine the threshold value of collusion measure and the change in average ratio measured by the constant term, c. Particularly, we estimate the following TR model:

$$ratio_a = c1(q \le \tau)\beta + c1(q > \tau)\beta + \varepsilon_a \quad (13)$$

Where q is the collusion measure of an auction. Yu and Phillips (2014) state that the parameters of the TR model are identified in case of endogeneity and can be estimated consistently. Consequently, we estimate the parameters of equation (2) including the threshold value using nonlinear least squares approaches.[8] Table 6 below displays the TR results for ratio.

[8] Bai and Perron (2003) state that estimation of the threshold and breakpoint models are fundamentally equivalent. Threshold regressions can be thought of as breakpoint least squares regressions with data reordered with respect to the threshold variable.

Table 6 concludes that when the collusion measure is below -0.11 average ratio is 0.6. The ratio increases dramatically when the measure becomes positive. The ratio is 0.98 when the measure is larger than 0.03. As presented by Asker (2010), the winning ring member makes side-payments to other ring members that submit intentionally losing bids. When the number of members of the ring increases, the amount of profit should be sufficiently large to be able to pay all ring-members. In this case, we might observe a positive relationship between number of bidders and procurement price, the collusion measure. Figure 5 below supports this argument by displaying the collusion measure and number of bidders.

There is a negative relationship between the collusion measure and number of bidders when the the measure is negative. At the left-hand tail there are competitive auctions with high number of bidders. The relationship becomes positive when the collusion measure is larger than zero. This finding supports the argument that a rise in the number of bidding-ring members increases the total amount of side-payments. In the extreme case of $N_a = R_a$ where all bids are submitted by ring members, we expect that the collusion measure would be strictly positive and it would increase as number of ring member rises. Figure 5 displays this phenomenon.

Figure 6 presents the relationship between the collusion measure and estimated cost of an auction. The average estimated cost dramatically increases when the collusion measure becomes positive. Extreme values of the collusion measure at the right-hand side of the graph coincide with very high average estimated costs up to 150 million Turkish Liras (50 million US Dollars). This result indicates that collusive behavior becomes severe in auctions with very high estimated costs. This is caused by the fact that potential profits of the bidding-ring is higher for large tenders. To sum up, we provide additional information about the collusion measure and major auction characteristics in this section. Figures 4-6 and Table 6 present that the collusion measure is associated with significant anomalies in auction characteristics.

6. Conclusion

We propose an alternative collusion detection methodology that can be implemented to data sets with limited information. Many available data sets about PP contain information only about the outcomes of PP auctions, that is the winning bid. Starting from theoretical arguments about bid-rigging behavior, we argue that the auction-specific coefficient of number of bidders can be used as a collusion measure. Since bidding rings limit competition, the level of competition measured as the number of bidders would have a significantly lower effect compared to competitive auctions. The effect will diminish further as the collusion becomes more severe. We estimate the collusion measure using the data about Turkish PP auctions. We find that the measure varies substantially across 565,297 public procurement auctions for the years 2005-2012. We conduct further empirical analysis which displays the positive relationship between procurement cost and the measure. This result shows that inefficient auctions that are susceptible to collusion can be ranked and identified using the measure.

We believe that policy-makers can use this easy-to-implement methodology to examine data sets with limited information. Specifically, collusion and efficiency in many publicly available data sets such as, the TED data set about EU procurement and CompraNet procurement data set of Mexico, can be analyzed using this new measure. Usually, more than 100,000 procurement auctions are conducted annually in a single developing country. It is impossible for authorities to analyze each auction in detail. Policy-makers can use the measure developed in this paper to rank auctions with respect to their susceptibility to bid-rigging and allocate more resources to examine auctions with very high collusion-measure values. Additionally, common properties of auctions with high levels of the collusion measure can be examined to identify auctions with higher probability of bid-rigging. Authorities can pay more attention to auctions with those common properties. To sum up, we hope that policy-makers would find this tool helpful and use it to improve PP efficiency by identifying auctions with limited competition.

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Figure 1: Number of Bidder Coefficient Estimates

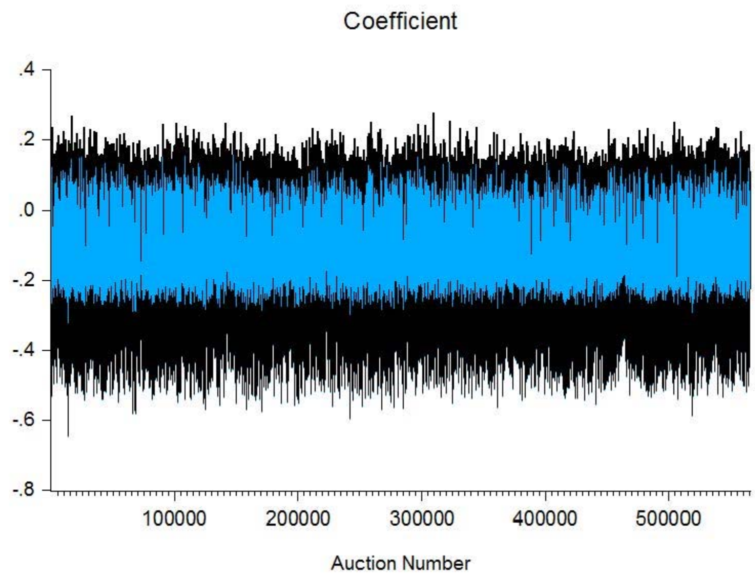


Figure 2: Histogram of Collusion Measure

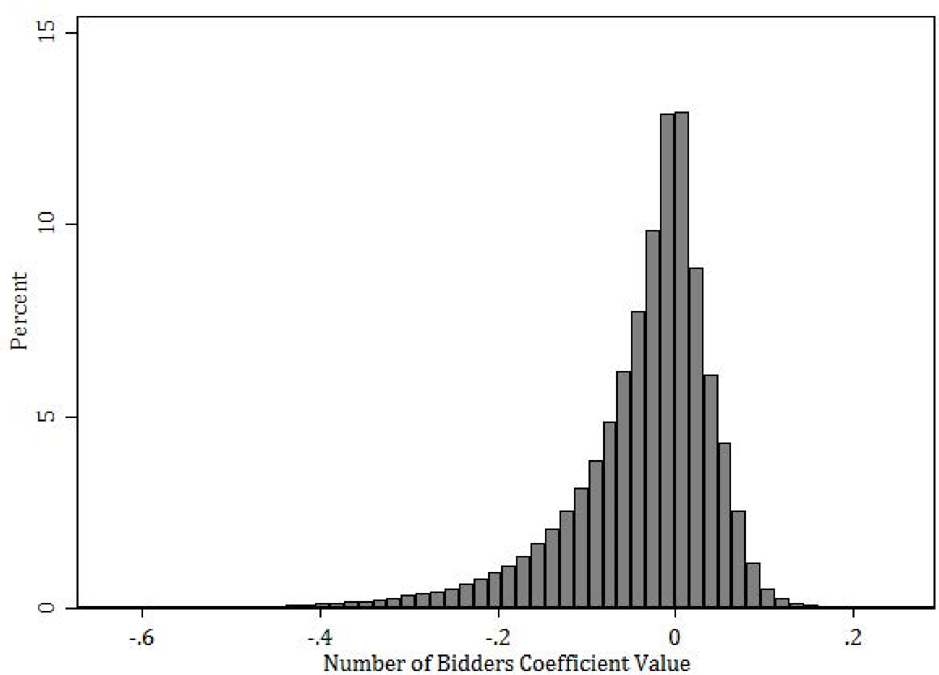
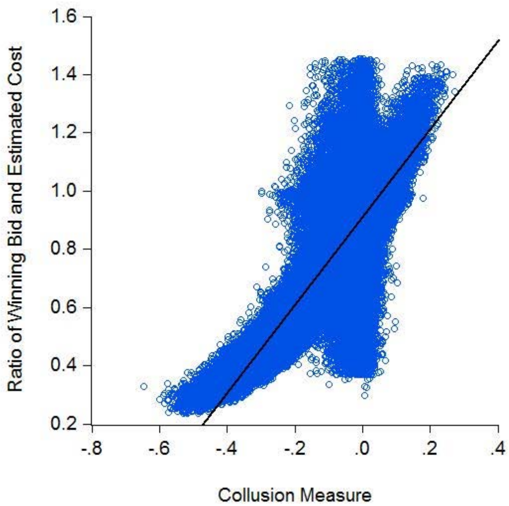
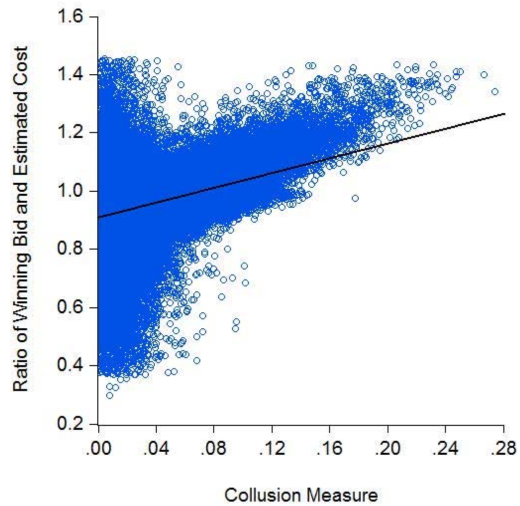


Figure 3: Collusion Measure and Auction Efficiency



All Auctions



Auctions with Positive Collusion Measure

Figure 4: Collusion Measure and Ratio of Price and Estimated Cost

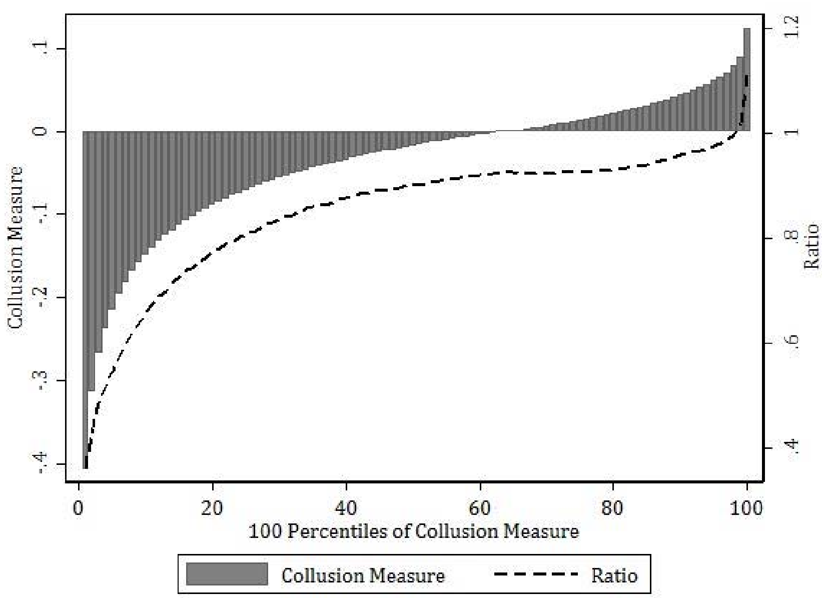


Figure 5: Collusion Measure and Number of Bidders

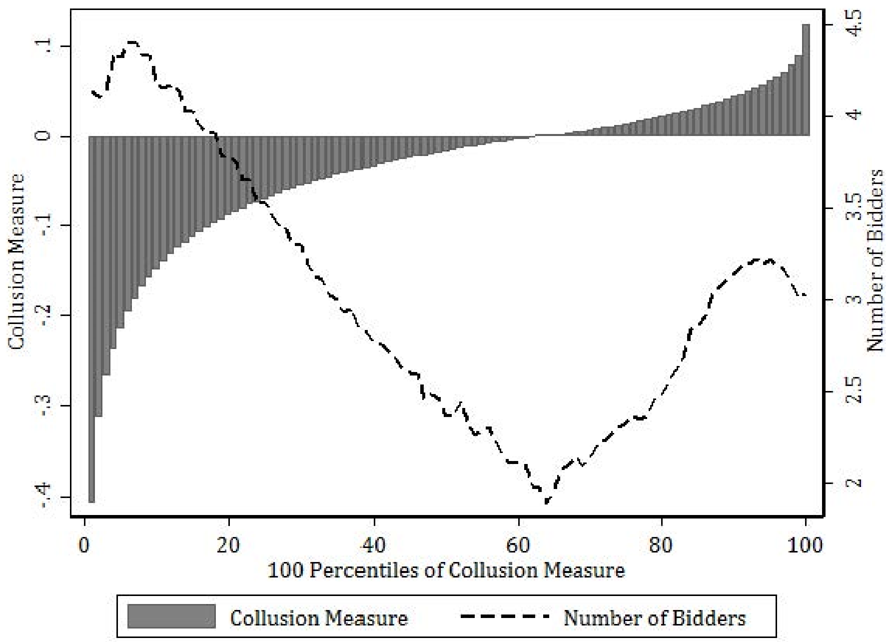


Figure 6: Collusion Measure and Estimated Cost

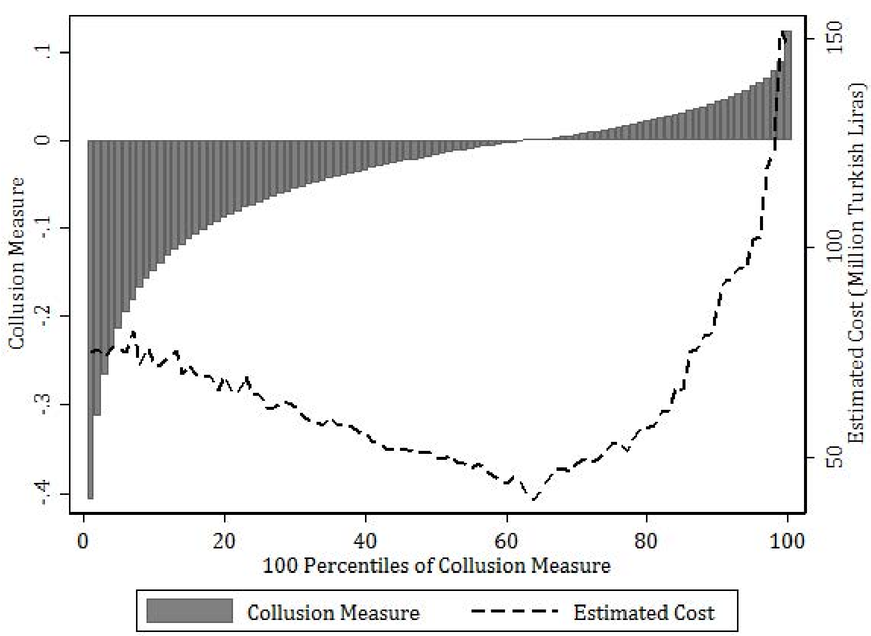


Table 1: Existing Methods for Collusion Detection in Auctions

Reference	Method	Data Set	Data Characteristics
Porter and Zona (1993,1999)	Determine a competitive control group and compare the bidding behavior of other bidders with respect to competition.	Ohio State school milk procurement data.	- Detailed information about all submitted bids. - Identification information of firms prosecuted in the collusion case. - Detailed information about location and cost of firms.
Bajari and Ye (2003)	Theoretical derivation of collusive bidding behavior and empirical analysis to examine whether bidding behavior is consistent with theoretical collusive behavior.	Construction Market Data. Public and private road construction projects in Minnesota, North Dakota and South Dakota	- Detailed information about all submitted bids. - Detailed information about structure and cost of construction projects.
Banerji and Meenakshi (2004)	Comparison of likelihood functions of collusive and competitive models.	Wholesale markets for Wheat in Northern Ireland	- Detailed information about all submitted bids. - Identification information of firms that are suspected for bid rigging.
Abrantes-Metz et al. (2006)	Examine structural change in variance after prosecution of collusion by US Department of Justice	Defense Personnel Support Center bid level data	- Detailed information about all submitted bids. - Identification information of firms prosecuted in the collusion case.
Bolotova et al. (2008)	ARCH and GARCH to examine structural change in mean and variance after prosecution of collusion by US Government	Data from federal class-action suit documents	- Identification information of firms prosecuted in the collusion case. - Time-series price data.
Ishii (2009)	Graphical representation of correlation between variance of bids and relative procurement price	Naha City, Japan, compensation consulting works.	- Detailed information about all submitted bids. - Detailed information about firm size.
Aryal and Gabrielli (2013)	Implement Bajari and Ye (2013) to identify potential bid ring members. Estimate costs under collusion and competition.	California Department of Transportation	- Detailed information about all submitted bids. - Detailed information about structure and cost of construction projects.
Hüschelrath and Veith (2014)	Empirical comparison of bidding behavior of competitive firms and firms charged by the German Federal Cartel Office for bid rigging	Cartel Damage Claims and German Federal Statistical Office	- Identification information of firms that are suspected for bid rigging. - Procurement price data.
Conley and Decarolis (2016)	Statistical tests to compare collusive and competitive participation and bidding behavior using prosecuted collusion cases.	Roadwork contract auctions conducted by Italian public administrations.	- Detailed information about all submitted bids. - Identification information of firms prosecuted in the collusion case. -Information about ownership and management, bidding consortia and exchange of subcontracts.

Table 2: Datasets with Limited Information About Public Procurement Contracts

The datasets listed below are publicly available and contain detailed information about the outcomes of public procurement processes.

Country	Dataset Name	Data Source
European Union	OpenTED – Contract Awards	Tenders Electronic Daily. Available at https://data.europa.eu/euodp/en/data/dataset/ted-csv
Canada	Buyandsell.gc.ca - Tenders Data	Buyandsell.gc.ca. Available at https://buyandsell.gc.ca/procurement-data/tenders/download-tenders-data
Chile	ChileCompra – Contracting	MercadoPublico.cl. Available at https://www.mercadopublico.cl/Home
Korea	KONEPS - Contracts	Korea On-line E-Procurement System. Available at http://www.g2b.go.kr:8060/jsp/out/index.jsp
Mexico	CompraNet	CompraNet. Available at https://sites.google.com/site/cnetuc/contrataciones
Moldova	Date.gov.md - Public Procurement	Date.gov.md. Available at http://date.gov.md/ckan/dataset/4978-aviz-publicitar-privind-atribuirea-contractelor-de-achizitii-publice
Nepal	Nepal Open Contract Data	Government of Nepal. Available at https://aiddata.github.io/opencontracts/
Turkey	Public Procurement Data Set	Public Procurement Authority. Available by official submission to the Public Procurement Authority. Data after implementation of the E-procurement system (2010) can be purchased from private data collection companies like ekap.co.
United States	Checkbook – Contracts	Checkbook NYC. Available at http://www.checkbooknyc.com/data-feeds
Uruguay	ACCE - Awards	Compras Estatales. Available at https://www.comprasestatales.gub.uy/

Table 3: Summary Statistics of the Variables

	Mean	Standard Deviation	Minimum	Maximum
Winning Bid (WINBID)	454,091.3	8,063,788	1.95	4.30e+09
Estimated Cost (ESTIMATE)	560,406.4	9,294,096	1.97	4.30e+09
Ratio[9]	0.85	0.16	0.24	1.45
Number of Bidders (N)	3	2.47	1	20
AUCTYPE: Services	197,808 (34.99%) among 565,297 auctions			
AUCTYPE: Goods	236,238 (41.79%) among 565,297 auctions			
AUCTYPE: Construction	131,252 (23.22%) among 565,297 auctions			
Stimulus Region 1	149,066 (26.4%) auctions conducted in this region.			
Stimulus Region 2	89,328 (15.8%) auctions conducted in this region.			
Stimulus Region 3	89,328 (15.8%) auctions conducted in this region.			
Stimulus Region 4	85,179 (15.1%) auctions conducted in this region.			
Stimulus Region 5	65,403 (11.6%) auctions conducted in this region.			
Above Threshold	36,417 (6.4%) auctions are above threshold.			
Year Dummy Variables	Dummy variables for years 2005-2012.			

[9] Ratio of winning bid and estimated cost.

Table 4: Determinants of Procurement Price

	Dependent Variable			
	Log Procurement Price (Winning Bid)		Ratio	
Variable	GMM	HB	GMM	HB
Log Number of Bidders	-0.14	-0.05	-0.10	-0.06
	(10.27)**	(20.06)**	(19.14)**	(29.70)**
Log Estimated Cost	1.00	0.99		
	(454.04)**	(2,306.12)**		
Above Threshold	0.03	0.03	0.01	-0.00
	(14.38)**	(24.39)**	(5.87)**	(2.15)*
Electronic Auction	0.01	0.03	0.01	0.02
	(3.35)**	(16.86)**	(5.71)**	(12.18)**
AUCTYPE: Goods	-0.05	-0.06	-0.04	-0.05
	(34.04)**	(86.43)**	(50.30)**	(86.49)**
AUCTYPE: Construction	-0.02	-0.06	-0.03	-0.06
	(2.60)**	(44.53)**	(8.21)**	(37.64)**
Stimulus Region 2	0.01	0.01	0.01	0.01
	(12.02)**	(12.52)**	(10.85)**	(19.85)**
Stimulus Region 3	0.01	0.01	0.01	0.01
	(5.39)**	(10.70)**	(5.08)**	(17.55)**
Stimulus Region 4	0.01	0.01	0.01	0.02
	(14.67)**	(16.22)**	(12.35)**	(24.29)**
Stimulus Region 5	0.03	0.03	0.02	0.03
	(31.13)**	(30.46)**	(23.98)**	(37.43)**
Stimulus Region 6	0.04	0.03	0.03	0.03
	(17.30)**	(26.61)**	(40.14)**	(40.67)**
Inflation	0.00	0.00	0.00	0.00
	(11.84)**	(10.46)**	(9.97)**	(7.36)**
Central Bank Rate	0.00	0.00	0.00	0.00
	(0.89)	(5.22)**	(1.56)	(5.68)**
Industrial growth	0.00	0.00	0.00	0.00
	(9.53)**	(8.01)**	(9.15)**	(8.15)**
Constant	-0.10	-0.01	0.92	0.89
	(7.00)**	(2.13)*	(221.15)**	(334.11)**
Number of observations	565,297	565,297	565,297	565,297

Notes: * $p<0.05$; ** $p<0.01$. Year and institution dummy variables are not presented. Heteroscedasticity-robust z statistics are presented in parentheses.

Table 5: Impact of Collusion on Auction Outcomes

	Dependent Variable			
	Log Procurement Price (Winning Bid)		Ratio	
Variable	GMM	HB	GMM	HB
Collusion Measure	2.02	2.13	1.38	1.60
	(138.28)**	(890.38)**	(228.12)**	(609.30)**
Log Number of Bidders	-0.07	-0.05	-0.07	0.00
	(8.85)**	(44.41)**	(23.86)**	(0.92)
Log Estimated Cost	0.99	0.99		
	(803.89)**	(4,583.17)**		
Above Threshold	0.03	0.03	0.00	-0.03
	(34.27)**	(76.45)**	(0.60)	(38.90)**
Electronic Auction	-0.01	-0.01	-0.02	-0.00
	(8.11)**	(15.93)**	(17.30)**	(1.54)
AUCTYPE: Goods	0.01	0.01	0.01	0.02
	(27.81)**	(44.08)**	(25.42)**	(61.76)**
AUCTYPE: Construction	0.01	0.01	0.01	0.03
	(15.12)**	(31.45)**	(14.65)**	(57.70)**
Stimulus Region 2	0.01	0.02	0.01	0.03
	(29.86)**	(49.66)**	(25.98)**	(68.57)**
Stimulus Region 3	0.02	0.03	0.02	0.03
	(50.68)**	(81.97)**	(40.46)**	(89.43)**
Stimulus Region 4	0.02	0.02	0.02	0.02
	(16.19)**	(60.79)**	(55.83)**	(65.16)**
Stimulus Region 5	-0.05	-0.05	-0.04	-0.05
	(65.46)**	(192.32)**	(83.56)**	(188.96)**
Stimulus Region 6	-0.06	-0.08	-0.05	-0.11
	(16.16)**	(120.54)**	(23.68)**	(107.77)**
Inflation	0.00	0.00	0.00	-0.00
	(15.55)**	(22.79)**	(9.60)**	(1.45)
Central Bank Rate	-0.00	0.00	-0.00	0.00
	(0.24)	(4.43)**	(0.13)	(15.60)**
Industrial growth	0.00	0.00	0.00	0.00
	(5.05)**	(9.96)**	(5.49)**	(3.40)**
Constant	0.08	0.08	0.97	0.93
	(9.56)**	(38.97)**	(422.59)**	(664.13)**
Number of observations	565,297	565,297	565,297	565,297

Notes: * *p*<0.05; ** *p*<0.01. Year and institution dummy variables not presented. Heteroscedasticity-robust z statistics are presented in parentheses.

Table 6: Threshold Regression Analysis of Ratio of Procurement Price and Estimated Cost

Threshold	Constant (Average Ratio)
Collusion Measure <-0.11	0.6
	(0.013)
-0.11<=Collusion Measure<-0.04	0.81
	(0.01)
-0.04<=Collusion Measure<-0.03	0.92
	(0.007)
0.03<=Collusion Measure	0.98
	(0.013)

Note: Standard errors are presented in parentheses.

Appendix

Table A1: Determinants of Number of Bidders Negative-Binomial and Poisson Regression Analysis

	Negative Binomial	Poisson
BIGCITY	0.05	0.05
	(18.88)**	(18.30)**
GENERALBUDGET	-0.17	-0.15
	(9.02)**	(7.90)**
Log Estimated Cost	0.18	0.17
	(235.52)**	(226.39)**
Above Threshold	-0.12	-0.12
	(26.77)**	(27.78)**
Electronic Auction	-0.28	-0.28
	(42.94)**	(42.81)**
AUCTYPE: Goods	0.06	0.04
	(24.60)**	(19.09)**
AUCTYPE: Construction	0.49	0.48
	(186.53)**	(179.35)**
Stimulus Region 2	0.00	0.00
	(0.48)	(1.06)
Stimulus Region 3	-0.03	-0.03
	(8.26)**	(7.41)**
Stimulus Region 4	0.02	0.03
	(6.40)**	(7.11)**
Stimulus Region 5	0.03	0.03
	(8.19)**	(8.31)**
Stimulus Region 6	0.21	0.20
	(57.06)**	(55.39)**
Inflation	0.00	0.00
	(3.93)**	(3.45)**
Central Bank Rate	-0.01	-0.01
	(14.48)**	(13.65)**
Industrial growth	0.00	0.00
	(4.63)**	(4.83)**
Constant	-0.73	-0.67
	(30.69)**	(28.13)**
Number of Observations	565,297	565,297

Notes: Year and institution dummy variables are not presented. Robust z statistics in parentheses. ** indicates significance at 1% level, * indicates significance at 5% level.