Collusion Detection in Public Procurement with Limited Information

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Abstract

We design a method to identify and test for bid rigging in procurement auctions with limited information. Public procurement data sets usually lack detailed data that are needed to implement existing methods. We develop a varying-coefficient model to estimate the auction-specific coefficient of competition and use the coefficient as the collusion measure. The method can be implemented 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 565,298. We find that collusion significantly increases procurement costs and decreases procurement efficiency in Turkey.

JEL Codes: C36; D44; H57

Keywords: Collusion Detection; Public Procurement Auctions; Competition

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1 Introduction

Governments allocate significant resources to deter collusion in public procurement 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 public procurement (PP) auctions, policy makers are facing many challenges to implement these methodologies. 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 developing a collusion detection methodology that does not require the complete bidding history or detailed prior information about potential colluders. Additionally, we would like to devise 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 by 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 models. 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 to determine the member who would 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. Accordingly, the member of the bid ring can win the procurement price 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 coefficient of 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 an unobserved components 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 detailed information about ***all*** PP auctions conducted in years 2005-2012, numbering 565,298. The total value of procurement in this period is over three hundred 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. We conduct an empirical analysis using the new method and examine collusion in Turkish PP auctions. We find that there is a positive and significant relationship between the new collusion measure and procurement costs as indicated by theoretical arguments. This result suggests that the new measure successfully ranks auctions with respect to the level of collusive behavior.

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

As stated by Harrington, Jr. (2008) current empirical methods for detecting collusion review four major questions:

1. Is firm behavior inconsistent with competition?
2. Is there a structural break in bidding behavior?
3. Does the behavior of suspected colluding firms differ from that of compet-

itive firms?

4. Does a collusive model fit the data better than a competitive model?

Current methods examine the existence and effects of collusion in auctions by studying these questions. We categorize these methods with respect to the information used to implement the methodology. The existing collusion detection methods 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 detailed 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 the results of 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 the behavior of firms 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 about here.)

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. 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 four million public purchases by thirty-three EU member and affiliated countries for years 2006-2015.[1] Similarly, the PPAT data

[1] The TED data set contains a subset of public procurement. For most of the cases,

set covers the entire universe of PP auctions for the years 2005-2012, 565,298 auctions. The PPAT data set encompasses *all* public procurement auctions conducted for an extended period of time by the entire set of government agencies. These unique features of the data set allows us to conduct detailed analysis of the structure and effect of collusion in a middle-income country, namely Turkey. 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. 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.

(Table 2 about here.)

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 public procurement auctions. Then, 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 present a simple model of bid rigging behavior to provide the theoretical fundamentals of the new collusion detection methodology. We

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 observation for Poland but only 39,635 for Germany.

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 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." 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, the mechanism of the bidding ring 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

$$\beta(c) = \frac{1}{N} E\left[Y_1^{(N)} / Y_1^{(N)} > c\right] \tag{1}$$

where c is the cost of the bidder and Y_1 is the lowest of $N-1$ independently drawn cost values. 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 $N - R + 1$ 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. For example, more than 63% of the Turkish public procurement and 83% of European Union procurement are through the "open-procedure" that is first-price auctions. The other procurement methods are negotiation, restricted auction and direct purchase.

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

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

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. $c_i \in [\underline{c}, \overline{c}]$ is the cost of bidder i. The probability can be presented as the following:

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

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 second rent component decreases as N decreases. 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 $N - R + 1$ effective bids instead of (N-1). Hence, its equilibrium bid is significantly higher than that of the competitive case. Specifically, equation (5) becomes

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

The equilibrium bid of the serious bidder of the bidding ring, β_i^w, is larger than her bid under competition, β_i.

4 New Collusive Behavior Measure and Estimation Methodology

Section 3 presents the theoretical background for the new collusion detection measure. Equations 5 and 6 show that when the winning bidder is a ring-member, she would submit a higher bid as if she was facing lower number of competitors, that is $(N - R + 1)$ compared to $(N - 1)$. We follow the empirical auction literature (e.g. Porter and Zona, 1993; 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

$$ln(b_t) = \psi N_t + Z_t^{'}\theta + M_t^{'}\alpha + \varepsilon_t \tag{7}$$

where b_t is the winning bid at auction t.[2] Z_t is a vector of auction-specific variables and M_t denotes the variables that measure the macroeconomic conditions. Equation 6 states that when the winning bid is submitted by the primary bidders 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

[2]The PPAT data set includes data about the date and time of the auction. The auctions are sorted with respect to date and time.

a bidding ring participates in the auction, equation 7 can be written as follows

$$ln(b_t) = \psi(N_t - R_t) + Z_t^{'}\theta + M_t^{'}\alpha + \varepsilon_t \quad (8)$$

or

$$ln(b_t) = \psi^c(R_t)N_t + Z_t^{'}\theta + M_t^{'}\alpha + \varepsilon_t$$

where $\psi^c(R_t)$ 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, R_t. 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, N_t. Specifically, ψ^c 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. Equation 8 can be transformed with auction-specific coefficients as follows

$$ln(b_t) = \psi_t N_t + Z_t^{'}\theta + M_t^{'}\alpha + \varepsilon_t \quad (9)$$

ψ_t in equation 9 is the auction-specific coefficient with potentially different values for each auction t.

4.1 Varying Coefficient Model

The varying coefficient model considers that the coefficients of the regression equation might not be constant. The model estimates the dynamic pattern of regression coefficients by designing a state-space model. We assume that the auction-specific coefficient of number of bidders is an unobserved state variable. The state-space representation consists of the state and observation equations.

State equation:

$$\psi_{t+1} = f\psi_t + v_{t+1} \tag{10}$$

Observation equation:

$$ln(b_t) = \psi_t N_t + Z_t^{'}\theta + M_t^{'}\alpha + \varepsilon_t \tag{11}$$

Equations 10 and 11 form the state-space representation. The Kalman filtering algorithm provides the distribution of $ln(b_t)$ conditional on its previous values. It is Gaussian assuming that ψ_t, v_t and ε_t are Gaussian. A forward recursion using the Kalman filter provides expressions for the mean and variance of the distribution. Then, the parameters of the state-space model can be estimated using maximum likelihood. We can form an inference about the value of ψ_t based on the complete data set. This Kalman smoothing methodology provides the estimated values of the state variable, ψ_t. Hence, we calculate the coefficient of the number of bidders variable for each auction t, ψ_t, using Kalman smoothing. Maximum likelihood estimation of the state-space parameters and Kalman smoothing are well-established methods used extensively in the 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 estimate equation 7 with the unvarying number of bidders coefficient, ψ. Then, we estimate the varying coefficient, ψ_t, 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 major variables stated in the theoretical arguments of section 3 are the winning bid (WINBID) and number of bidders (N). Additionally, the PPAT data set includes the estimated cost (ESTIMATE)[3] and additional variables about the characteristics of the auction and product. We use some of these variables 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.[4] 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

[3] 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

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

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 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.

(Table 3 about here.)

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 use OLS and GMM instrumental variable regression (IV) methods to estimate the coefficients of equation 7. 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. Some of the features of the Turkish public procurement system makes it easier for firms to obtain or make an educated guess about the number of potential bidders. First, firms are required to obtain official documents before the auction by paying a fee and auction participants usually observe the number of firms that obtain pre-auction documents. Second, during the bid submission process, firms are able to observe the firms that submit bids and correct their bids before submitting. Accordingly, it is unlikely that the number of bidders is endogenous in Turkish public procurement auctions. Regardless of these arguments, we conduct an IV regression estimation to obtain robust results. We search for valid instrumental variables and conduct a GMM IV in addition to OLS. Table 4 displays the OLS and GMM IV estimation of equation 7. We calculate heteroscedasticity-robust standard errors for both OLS and GMM IV.

(Table 4 about here.)

We employ BIG CITY and GENERALBUDGET as instrumental variables in the GMM estimation. Onur et al. (2012) show 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. The GENERALBUDGET dummy variable takes the value one 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. 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. Table 4 shows that we accept the null hypothesis that BIGCITY and GENERALBUDGET are valid instruments. Then we conduct a C statistic test to examine whether the instrumented variable, number of bidders (N_t), is exogenous. We accept the null hypothesis that N_t is exogenous. We also note that the coefficient of N_t is similar in both OLS and GMM estimations. Table 4 displays the coefficients of equation 7. We conclude that competition is an integral component of procurement costs since the coefficient of number of bidders is significant and negative. This result confirms that bidding rings can generate profits by limiting competition in PP auctions.

To have a better understanding of the relationship between the winning bid and number of bidders, we conduct a quantile regression analysis. Quantile regression estimates the parameters of an equation expressing a quantile of the conditional distribution of the dependent variable. The method allows for the effects of the explanatory variables to vary over different quantiles. This method allows us to examine whether the coefficient of number of bidders vary across auctions and whether this variation is important for procurement efficiency. We estimate nine quantiles from 0.1 to 0.9. Figure 1 displays the main result of the quantile regression analysis. It shows the coefficient of number of bidders variable for each quantile and the 95% confidence intervals.[5] Figure 1 below displays the change in the coefficient of number of bidders, ψ, with respect to the winning bid.

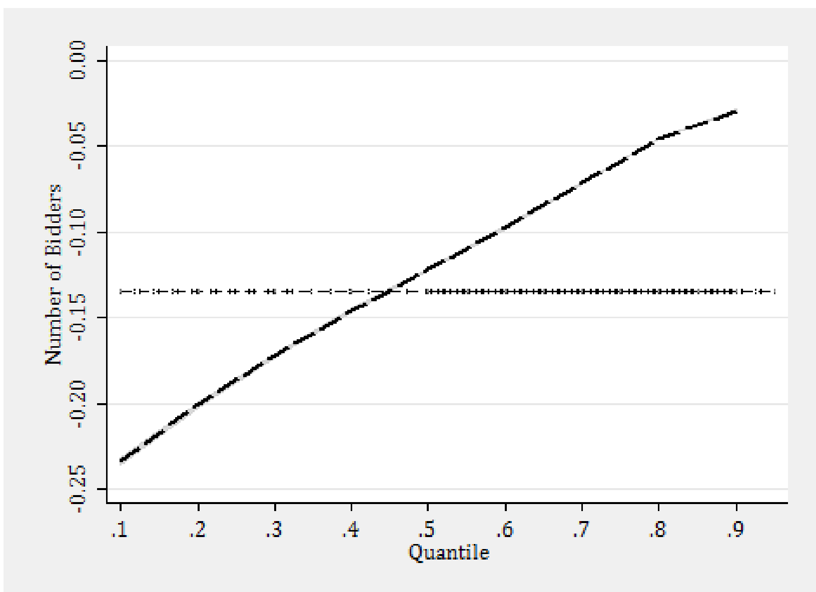

Figure 1: Quantile regression coefficients of number of bidders

Figure 1 presents the change in the coefficient of number of bidders with respect to the winning bid conditional on the estimated cost. Figure 1 suggests that the dynamics presented in the theoretical arguments of equations 5 and

[5] The tables that contain the coefficients and statistics are not presented in the paper. The tables are available from the author upon request.

6 might be confirmed empirically. We further investigate this argument by calculating the varying coefficients of the number of bidders variable, ψ_t, for each auction.

5.3 Auction-Specific Coefficients as a Collusion Detection Tool

In section 4, we argue that auction-specific ψ_t can be used to measure the level of collusion in PP auctions. In this section, we estimate auction-specific ψ_t for each auction t by using the state-space model and maximum likelihood estimation described in Section 4.1. Figure 2 below displays the estimated coefficients for each auction.

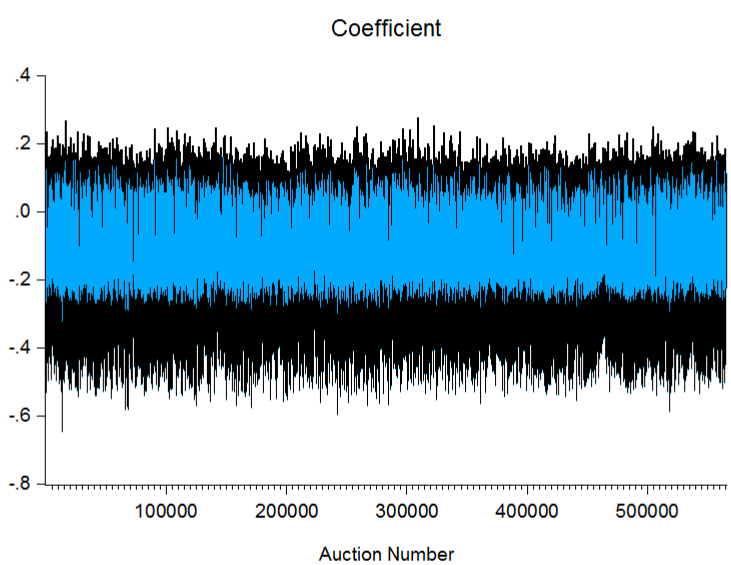

Figure 2: Number of bidder coefficient estimates

Figure 2 shows that the coefficient of the number of bidders variable, ψ_t, differs substantially among auctions. We present the histogram of ψ_t below.

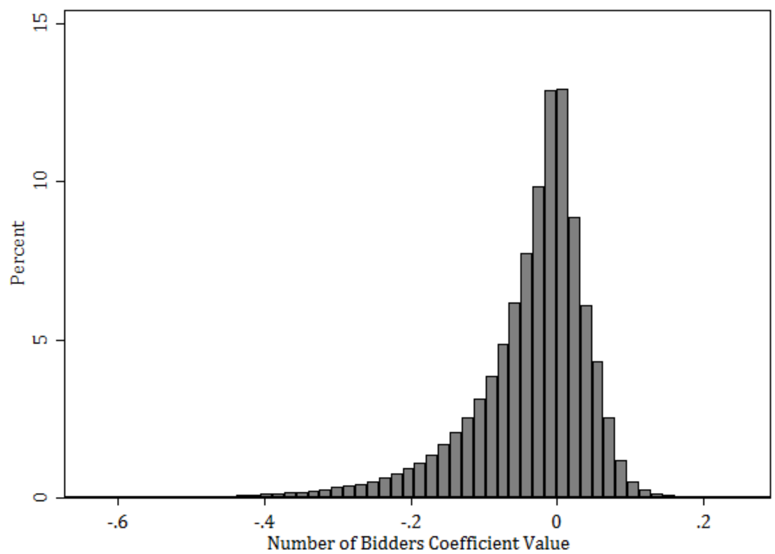

Figure 3: Histogram of Number of bidder coefficients

Figures 2 and 3 show the high-degree of variation in the coefficient of number of bidders across auctions. As suggested by the theoretical arguments of Section 4 and Ohashi (2009), this variation might be caused by collusive bidding behavior. Accordingly, we use the auction-specific number of bidders coefficient as our collusive-behavior measure. This 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.[6] 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

[6]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.

characteristics. We empirically test this argument by estimating the following regression equation by using OLS and GMM IV.

$$ln(b_t) = \lambda\psi_t + \gamma N_t + Z_t^{'}\theta + M_t^{'}\alpha + \varepsilon_t \tag{12}$$

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 becomes more severe. Table 5 displays the estimated coefficients of equation 12.

(Table 5 about here.)

Table 5 presents the expected positive and significant relationship between the collusion measure and the winning bid. We use an alternative regression specification by constructing a dummy variable that is 1 if the number of bidders coefficient is equal to 0 or positive. Both the continuous collusion measure and the positive measure dummy variable have significant positive coefficients. Accordingly, Table 5 shows that the collusion measure correctly identifies inefficient auctions with higher values of winning bids.

5.4 Determinants of the Collusion Measure

In this section, we conduct further empirical analysis to identify the factors that cause the changes in the collusion measure, the coefficient of number of bidders. The continuous nature of the collusion measure allows us to rank auctions with respect to suspected collusive behavior and conduct regression analysis to examine the determinants of the measure. We examine the following auction characteristics on the level of the collusion measure: level of competition (number of bidders), whether the estimated cost is above the threshold determined by the PPA, sector and stimulus regions . Table 6 displays the OLS and probit regression analysis where the dependent variables are the collusion measure and the positive measure dummy variable.

(Table 6 about here.)

Table 6 allows us to examine the factors that make an auction more prone to collusive bidding. We find that the level of competition has a negative and significant impact on collusion. Auctions with higher level of competition (number of bidders) experience lower levels of collusive behavior. In addition, auctions with higher estimated costs where the above threshold dummy variable is positive have higher collusive bidding. In other words, auctions with higher procurement prices attract collusive behavior. This finding is consistent with rent-seeking by bidding rings. We find that goods and construction auctions have higher levels of collusion measure compared to services. An interesting result is the impact of region on collusive behavior. We find that the least developed region with highest government economic subsidies experience higher levels of collusion. This might be caused by the fact that expected profit is higher in those auctions because of the economic incentives provided by the government.

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 data 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 the 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. Using data about the outcome of auctions, a policy-maker or a researcher can calculate this new measure using standard econometric tools and software without the need for complex theoretical derivations.

We estimate the collusion measure using the data about Turkish PP auctions. We find that the measure varies substantially across 565,298 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. Finally, we find that the collusion measure decreases when the number of bidders increase and the measure is higher for auctions with high estimated costs. 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 data of procurement in 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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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
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.			

Table 4
Determinants of Winning Bid: OLS and GMM IV

Variable	OLS	GMM
Log Number of Bidders	-0.13	-0.15
	(304.28)**	(20.61)**
Log Estimated Cost	1.00	1.00
	(4,721.23)**	(849.60)**
Above Threshold	0.03	0.03
	(19.18)**	
Electronic Auction	0.01	
	(6.90)**	(16.65)**
AUCTYPE: Goods	-0.05	-0.05
	(77.61)**	(51.24)**
AUCTYPE: Construction	-0.02	-0.01
	(24.38)**	(3.55)**
Stimulus Region 2	0.01	0.01
	(12.16)**	(12.04)**
Stimulus Region 3	0.01	0.01
	(6.66)**	(5.72)**
Stimulus Region 4	0.01	0.01
	(15.17)**	(14.84)**
Stimulus Region 5	0.03	0.03
	(31.18)**	(31.13)**
Stimulus Region 6	0.04	0.04
	(44.82)**	(29.06)**
Inflation	0.00	0.00
	(12.09)**	(12.48)**
Central Bank Rate	0.00	-0.00
	(1.14)	(0.92)
Industrial growth	0.00	0.00
	(9.74)**	(8.86)**
Constant	-0.09	-0.10
	(25.34)**	(11.65)**
Number of observations	565,297	565,298
Instrumental Variables		BIGCITY
		GENERALBUDGET
Hansen J statistic		0.57
		(p-value: 0.45)
GMM C statistic		0.01
Ho: variables are exogenous		(p-value: 0.92)

Notes: * p<0.05; ** p<0.01. Year dummy variables not presented. Logarithm of winning bid is used as the dependent variable. Heteroscedasticity-robust standard errors are estimated

Table 5
Impact of Collusion on Auction Outcomes
Determinants of Winning Bid: OLS and GMM IV

Variable	OLS	OLS	GMM	GMM
Collusion Measure	2.02		2.02	
	(1,295.93)**		(138.28)**	
Positive Measure		0.19		0.18
		(438.63)**		(116.82)**
Log Number of Bidders	-0.06	-0.12	-0.07	-0.14
	(241.72)**	(297.44)**	(8.85)**	(12.34)**
Log Estimated Cost	0.99	0.99	0.99	1.00
	(8,867.10)**	(5,273.65)**	(803.89)**	(505.16)**
Above Threshold	0.03	0.03	0.03	0.03
	(52.81)**	(26.61)**	(34.27)**	(17.91)**
Electronic Auction	-0.01	-0.01	-0.01	-0.01
	(14.22)**	(4.31)**	(8.11)**	(3.96)**
AUCTYPE: Goods	0.01	0.01	0.01	0.01
	(28.40)**	(14.93)**	(27.81)**	(14.44)**
AUCTYPE: Construction	0.01	0.01	0.01	0.01
	(19.38)**	(9.19)**	(15.12)**	(6.36)**
Stimulus 2	0.01	0.01	0.01	0.01
	(31.56)**	(18.58)**	(29.86)**	(17.35)**
Stimulus 3	0.02	0.03	0.02	0.03
	(50.58)**	(34.88)**	(50.68)**	(34.53)**
Stimulus 4	0.02	0.03	0.02	0.03
	(48.85)**	(36.71)**	(16.19)**	(15.26)**
Stimulus 5	-0.05	-0.05	-0.05	-0.05
	(140.88)**	(88.34)**	(65.46)**	(37.96)**
Stimulus 6	-0.07	-0.03	-0.06	-0.01
	(184.24)**	(39.46)**	(16.16)**	(2.23)*
Inflation	0.00	0.00	0.00	0.00
	(16.03)**	(9.73)**	(15.55)**	(9.86)**
CB Rate	-0.00	0.00	-0.00	-0.00
	(0.04)	(1.19)	(0.24)	(0.12)
Industrial growth	0.00	0.00	0.00	0.00
	(5.12)**	(6.37)**	(5.05)**	(6.65)**
Constant	0.08	-0.10	0.08	-0.12
	(40.90)**	(30.23)**	(9.56)**	(10.42)**
Number of observations	565,297	565,297	565,297	565,297

Table 6
Determinants of Collusion Measure

	Dependent Variable	
	Collusion Measure	Positive Collusion Measure
Log Number of Bidders	-0.03	-0.15
	(193.06)**	(59.80)**
Above Threshold	0.02	0.17
	(32.06)**	(23.52)**
Electronic Auction	0.01	0.28
	(18.83)**	(24.42)**
AUCTYPE: Goods	0.00	0.05
	(4.22)**	(11.70)**
AUCTYPE: Construction	0.03	0.16
	(81.34)**	(31.44)**
Stimulus Region 2	-0.00	-0.05
	(12.21)**	(10.38)**
Stimulus Region 3	-0.01	-0.07
	(16.08)**	(13.43)**
Stimulus Region 4	-0.00	-0.07
	(12.72)**	(12.43)**
Stimulus Region 5	-0.00	-0.05
	(5.84)**	(8.66)**
Stimulus Region 6	0.01	0.13
	(16.18)**	(21.07)**
Constant	-0.02	-0.25
	(43.83)**	(38.66)**
R^2	0.07	565,297
N	565,297	-0.25

Notes: * p<0.05; ** p<0.01. Year dummy variables not presented. Heteroscedasticity-robust standard errors are estimated

Appendix

Table A.1

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

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