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**Econometric Tests to Detect
Bid-rigging Cartels:
Does it Work?**

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Abstract

This paper tests how well the method proposed by Bajari and Ye (2003) performs to detect bid-rigging cartels. In the case investigated in this paper, the bid-rigging cartel rigged all contracts during the collusive period, and all firms participated to the bid-rigging cartel. The two econometric tests constructed by Bajari and Ye (2003) produce a high number of false negative results: the tests do not reject the null hypothesis of competition, although they should have rejected it. A robustness analysis replicates the econometric tests on two different sub-samples, composed solely by cover bids. On the first sub-sample, both tests produce again a high number of false negative results. However, on the second sub-sample, one test performs better to detect the bid-rigging cartel. The paper interprets these results, discusses alternative methods, and concludes with recommendations for competition agencies.

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Disclaimer

All views contained in this paper are solely those of the author and cannot be attributed to the Swiss Competition Commission or its Secretariat.

1 Introduction

Bid-rigging cartels are a pervasive and a persistent problem as attested by the numerous case prosecuted by competition agencies around the world.¹ Switzerland is not an exception.² At the international level, the OECD have dealt several times with this problematic.³ Fighting against these harmful and inefficient practices should be one of the top priorities for competition agencies. If leniency programs are surely an important tool to enforce law for competition agencies, they may also have limits. Competition agencies should be more reactive, if not pro-active to deter and to destabilize bid-rigging cartels.⁴ But, in order to react, competition agencies need an appropriate detection method. Does such a method exist to detect bid-rigging cartels? And if so, is it an appropriate instrument for competition agencies?

To study this question, researchers first need to have data from previous bid-rigging cases in order to differentiate competition from collusion. It is only with perfect prior information on collusion that researchers are able to gauge the reliability of a detection method. Yet, we use in this paper data drawn from a previous case in Switzerland, the Ticino's bid-rigging cartel.⁵ In this case, the bid-rigging cartel rigged all contracts during the collusive period, and all firms participated to the bid-rigging cartel, without exception. Hence, the Ticino case represents an interesting laboratory to perform experiments and to evaluate detection methods. But, which method should we evaluate?

The paper of *Bajari and Ye* (2003) is a seminal paper for methods to detect bid-rigging cartels. Based on a first-sealed bid asymmetric procurement model, they formalize a method to detect and to screen bid-rigging cartels in an *ex ante* analysis.⁶ Different papers try to replicate the method

¹See, OECD, *Ex officio Cartel Investigations and the Use of Screens to Detect Cartels* (2013), (<http://www.oecd.org/daf/competition/exofficio-cartel-investigation-2013.pdf>), and the *Report on implementing the OECD Recommendation* (2016) (<http://www.oecd.org/daf/competition/Fighting-bid-rigging-in-public-procurement-report-2016.pdf>)

²See *Strassenbeläge Tessin* (LPC 2008/1, pp. 85-112), *Elektroinstallationsbetriebe Bern* (LPC 2009/2, pp. 196-222), *Wettbewerbsabreden im Strassen- und Tiefbau im Kanton Aargau* (LPC 2012/2, pp. 270-425), *Wettbewerbsabreden im Strassen- und Tiefbau im Kanton Zürich* (LPC 2013/4, pp. 524-652) and *Tunnelreinigung* (LPC 2015/2, pp. 193-245). Furthermore, Swiss Competition Commission (COMCO) investigates still three cases at the beginning of 2016.

³See, OECD, *the Guidelines for Fighting Bid-rigging in Public Procurement* (2009), *the Recommendation on Fighting Bid-rigging in Public Procurement* (2012), and the *Report on implementing the OECD Recommendation* (2016) Documents are available at the OECD homepage (<http://www.oecd.org/daf/competition/fightingbidrigginginpublicprocurement.htm>).

⁴See, OECD, *Ex officio Cartel Investigations and the Use of Screens to Detect Cartels* (2013)

⁵See *Strassenbeläge Tessin* (LPC 2008/1, pp. 85-112)

⁶An *ex ante* analysis is an analysis carried out, before the opening of an investigation. (See *Imhof et al.*, 2015, for an *ex ante* analysis.)

proposed by *Bajari and Ye* (2003) but they do not have reliable information on collusion, as we do. Because they are not able to discriminate clearly between collusion and competition, none of them can evaluate exactly how well any detection method performs. In this paper, we aim to fill this lack of empirical validation, and we replicate the detection method proposed by *Bajari and Ye* (2003) on the Ticino case. Because we have a perfect knowledge of collusion and competition, we can evaluate, if it is an appropriate instrument for competition agencies to use in an *ex ante* screening analysis.

First, we estimate the reduced-form of the bid function following *Bajari and Ye* (2003). We find that the estimates of the bid function for the cartel period are consistent with a competitive market. This result suggests that the cartel somehow manages to imitate competition. Then, we apply the two econometric tests proposed by *Bajari and Ye* (2003) on a pairwise base: each test considers solely two firms, called hereafter a pair of firms, or solely a pair.

The first test, the conditional independence test, checks if the bids are independent conditional on some observable covariates. The null hypothesis of competition stipulates that the residues of firm i , drawn from the estimation of the bid function, are uncorrelated with the residues of firm j . The alternative hypothesis of collusion assumes that bids are not independent: the residuals are correlated between colluding firms. In our case, the test does not reject the null hypothesis of competition for 89% of the pairs of firms at 5% risk level, albeit we implement the conditional independence test for the cartel period. Hence, the conditional independence test produces too many false negative results because it should have rejected the null hypothesis of competition in favour of the alternative hypothesis of collusion. In other words, we should find correlation between the residues of firms for the cartel period but we do not: bids are independent for most of the pairs.

The second test, called the exchangeability of the bids, examines if firms react in the same way considering their own costs. To put it differently, if we permute the costs of firm i with the costs of firm j , then firm i should submit the same bids as firm j . Formally, the null hypothesis of competition specifies that the estimated coefficients of firm i do not differ from those of firm j . If the estimated coefficients are not identical across firms, this may be indicative of collusion. In our case, we find again too many false negative results for the cartel period: 68% of the pairs pass the test at 5% risk

level. Therefore, a lot of pairs of firms react in the same way, when their own costs change: firms seem to behave competitively during the cartel period.

Finally, we check the robustness of these false negative results by implementing both tests on two different sub-samples. Cover bids may be less informative than the winning bids because they are, by definition, fake bids: costs should less explain the cover bids than the winning bids. Therefore, if we implement the tests only on cover bids, we should find more rejection. For the first sub-sample, we consider only the pairwise observation, when firm i and firm j do not win the contract, respectively when they both submit simultaneously a cover bid. Hence, the first sub-sample contains solely covers bids, excluding all winning bids.⁷ We call this first sub-sample, the *indirect cover bids* sample, because neither firm i nor firm j wins the contract, but they both submit a cover bid in favour of a third firm. For this *indirect cover bids* sample, we do not find better results neither for the conditional independence test nor for the exchangeability test: both tests produce yet again a high number of false negative results.

For the second sub-sample, we consider solely the pairwise observation, where firm i wins the contract and firm j submits a cover bid, or the inverse. We call this sub-sample the *direct cover bids* sample, because firm i wins the contract whereas firm j submits a cover bid; respectively firm j submits a intentional higher bid than firm i . Note also that the second sub-sample contains all pairwise observation excluded in the first sample, so that the addition of the two sub-samples is the whole sample. We implement only the conditional independence test. In contrast to all the previous tests, we find a higher number of rejection: 69% of the pairs fail the test. This result is the first result supporting the existence of the Ticino bid-rigging cartel; It suggests that the conditional independence test is appropriate to detect bilateral agreements.

We discuss the results obtained, and we conclude that the failure of one test should be sufficient to classify a pair of firms as candidate for further investigation. Moreover, the tests suggest that competition agencies should envisage to initiate a deeper investigation, if half of the pairs, or more, fail one of the two tests proposed by *Bajari and Ye (2003)*. Then, we compare the method of Bajari

⁷Note that all winning bids are the lowest submitted bids for each contract during the cartel period.

with another method, based on simple statistical screens to detect bid-rigging cartels, proposed by *Imhof et al.* (2015). We find that simple statistical screens are less data intensive and produce better results for the Ticino case: we clearly observe the impact of collusion on the distribution of the bids, and we find significantly fewer false negative results for the cartel period. We present also the strengths of both methods, and how we could combine them to use each method strength.

This paper is related to the papers of *Porter and Zona* (1993, 1999) and *Pesendorfer* (2000). They estimate the reduced-form of the bid function based on costs to illustrate the effects of bid-rigging practices. Using information drawn from previous cases, these authors demonstrate, first that colluding bidders do not fit basic economical logic: their bids are not related to their own costs. Second, estimates for colluding bidders differ significantly from estimates for competitive bidders. However, it is not possible to apply the method developed by these authors in an *ex ante* analysis; they aim to proof the anti-competitive effects of bid rigging, and for that purpose they need prior information on collusion. In contrast to these authors, we do not intend to demonstrate *ex post* the effects of a bid-rigging cartel in this paper; we want to test in a natural experiment, if and how well the method proposed by *Bajari and Ye* (2003) would have detected the Ticino bid-rigging cartel in an *ex ante* analysis.

Three papers apply the method developed by *Bajari and Ye* (2003). First, *Jakobsson* (2007) applies only the test for the conditional independence to a Swedish database with prior information using the spearman rank correlation as non parametric test. She finds that about 50% of the pairs fail the test. Second, *Chotibhongs and Arditi* (2012a,b) implement both tests and find evidence of collusion for a group of 6 firms. Three of these six firms are involved in bid-rigging cases or bid frauds. Third, *Aryal and Gabrielli* (2013) assume that costs under competition must first-order stochastically dominate costs under collusion, because collusion increases firm mark-up. Therefore costs under competition must be higher than costs under collusion. Then, considering four potential colluding bidders identified with the tests proposed by *Bajari and Ye* (2003), they test the first order stochastic dominance with costs recovered under a competitive model against costs estimated with a collusive model; they find no evidence for collusion. The estimation of the bid function is also related to the

estimation of structural models for competition and collusion (see *Baldwin et al.*, 1997; *Banerji and Meenakshi*, 2004).

However, all these papers contrast strongly with very few papers using simple screens to detect bid-rigging cartels (see *Feinstein et al.*, 1985; *Imhof et al.*, 2015; *Imhof*, 2017).

Section 2 introduces the asymmetric first-price procurement model. Section 3 recapitulates briefly the case of the bid-rigging cartel in Ticino and the data used. Section 4 presents the estimation for the reduced-form of the bid function. Section 5 implements the tests for the conditional independence and for the exchangeability of the bids. Section 6 proposes a robustness analysis by implementing the tests on two different sub-samples. Finally, section 7 discusses in details the results of the papers. Section 8 concludes.

2 The Model

In this section, we introduce the asymmetrical procurement auction model drawn from *Bajari and Ye* (2003). Using the properties derived from the equilibrium, established by the literature on asymmetrical auctions, they demonstrate that a set of specific conditions has to hold for a competitive model. Based on these conditions, they formulate the tests for the conditional independence and for the exchangeability of the bids. Then, recapitulating *Bajari and Ye* (2003)'s model allow us to describe more precisely the conditions underlining the two tests, applied in the next sections.

Bajari and Ye (2003) consider a procurement auction model with N risk-neutral firms competing for a contract to build a single indivisible public work contract. Firms have independent cost estimates, respectively, firm i knows its own cost estimate (c_i) but not its competitors' (c_{-i}). Cost estimates c_i are drawn from a cumulative distribution function $F_i(c_i)$ with the associated probability density function $f_i(c_i)$. Both $F_i(c_i)$ and $f_i(c_i)$ are common knowledge among all competitive firms participating to the auction.

They further assume first that for all i , the distribution of costs $F_i(c_i)$ has the support $[\underline{c}, \bar{c}]$ and that the associated probability density function $f_i(c_i)$ is continuously differentiable. Second, for all i , $f_i(c_i)$ is positive on its support $[\underline{c}, \bar{c}]$.

The strategy function of firm i is a function $B_i(c_i)$ which is assumed to be strictly increasing and differentiable on the support of c_i for all i . We also suppose that its inverse bid function $\phi_i(b_i)$ is strictly increasing and differentiable on the support of the bids. Then, given costs, cost function, bids and strategic bidding function, *Bajari and Ye* (2003) express the expected profit function for firm i as the probability of winning given the strategic bidding functions of competitors j times a certain mark-up, captured by the difference between the bid and the costs. The expected profit function $\pi_i(\cdot)$ for firm i can be written as

$$\pi_i(b_i, c_i; B_{-i}) = (b_i - c_i)\Psi_i(b_i), \quad (1)$$

where

$$\Psi_i(b_i) = \prod_{j \neq i} [1 - F_j(\phi_j(b_i))] \quad (2)$$

is the probability of firm i to win the contract, i. e. to submit the lowest bid considering competitors' costs and competitors' inverse bid functions, which can be expressed by $Pr(c_j > \phi_j(b_i))$.

The equilibrium in pure strategies is a Bayes-Nash equilibrium, where the strategic function $B_i(c_i)$ maximizes the profit function in b_i for all i and c_i in its support. First-order condition is given by the following equation:

$$\frac{\partial}{\partial b_i} \pi_i(b_i, c_i; B_{-i}) = (b_i - c_i)\Psi_i'(b_i) + \Psi_i(b_i) = 0, \quad (3)$$

where $\Psi_i(b_i)$ is given by 2.

Rearranging the first-order condition, they formulate the following differential equation for all i :

$$c_i = b_i - \frac{1}{\sum_{j \neq i} \frac{f_j(\phi_j(b_i))\phi_j'(b_i)}{1 - F_j(\phi_j(b_i))}}. \quad (4)$$

Lebrun (1996) and *Maskin and Riley* (2000b) demonstrate that there exists an equilibrium in pure strategies, and the equilibrium bid function is strictly monotone and differentiable. The uniqueness of this equilibrium has been equally shown in the literature (see *Maskin and Riley*, 2000a,b; *Lebrun*, 1996, 2002).

After identifying the model, *Bajari and Ye* (2003) derived five conditions to be satisfied in equilibrium by the distribution of bids $G_i(b; z)$, where z is a set of observable covariates. Three conditions

are classic and imply that first the support of each distribution $G_i(b; z)$ is identical for all i . Second, the equilibrium bid function must be strictly monotone. Third, boundary conditions for the bid function have to hold in equilibrium.

Because of the model specification, they impose two additional conditions. From these two additional conditions, *Bajari and Ye* (2003) derive the two econometric tests to diagnose collusion. First, firm i 's bid and firm j 's bid are independently distributed conditioned on a set of covariates z observable to all firms. Conditional independence can be expressed with the following equation:

$$G(b_1, \dots, b_N; z) = \prod_{i=1}^N G_i(b_i; z). \quad (5)$$

Testing this equation directly with limited data is not a simple empirical implementation. However, we estimate the distribution of the bids in the next sections, by regressing a set of covariates z on the bids. Then, we test if the residuals, obtained from the estimated regression, are correlated across firms. If residuals are uncorrelated, then the distribution of the bids are independent conditional on the observable covariates used.

The second condition added by *Bajari and Ye* (2003) postulates that the distribution of bids is exchangeable in equilibrium. For any π and any index i , the following equality holds:

$$G_i(b; z_1, z_2, \dots, z_N) = G_{\pi(i)}(b; z_{\pi(1)}, z_{\pi(2)}, \dots, z_{\pi(N)}). \quad (6)$$

This equation implies that if we permute the costs of firm i by π , then the bids of firm i should also be permuted by π . Concretely, we test if the estimated coefficients of firm i from the estimated regression do not differ from those of firm j . In section 4, we model the bid function with cost variables as covariates z to explain the submitted bids. Then, we present the test procedures in section 5.

These five conditions allow *Bajari and Ye* (2003) to formalize the two following theorems. First, if the distribution of bids $G_i(b; z)$ for all i is generated from a Bayes-Nash equilibrium, then the set of five conditions identified must hold. Second, if the distribution of bids $G_i(b; z)$ satisfies the five conditions, then it is possible to construct the distribution of costs $F_i(b | z_i)$ that uniquely rationalizes the observed bids $G_i(b; z)$ in equilibrium. Therefore, the following equation estimates the cost for

firm i given observables covariates z in equilibrium.

$$c_i = b_i - \frac{1}{\sum_{j \neq i} \frac{g_j(b;z)}{1-G_j(b;z)}}. \quad (7)$$

Equilibrium assumes competition, and we can recover the costs of all firms i with equation 7, if all firms i do not collude. If firms collude, we cannot recover the costs with equation 7. However, it is still possible to reformulate equation 7 when collusion occurs. For example, equation 8 proposes to rationalize the lowest bid submitted from the cartel, denoted c , and the bids of non-cartel firms, denoted i . C depicts the cartel subset.

$$c_c = b_c - \frac{1}{\sum_{j \neq i, j \notin C} \frac{g_j(b;z)}{1-G_j(b;z)}}. \quad (8)$$

If we consider equation 8 closer, we need non-cartel firms i to rationalize the costs for the lowest bid submitted from the cartel. Without non-cartel firms i , the denominator of equation 8 would be unfixed, and it would be impossible to recover the costs of the lowest bid submitted from the cartel. With our data, we face such a problem, because all bids for the cartel period are rigged: we do not have non-cartel firms i , because all firms participated to the bid-rigging cartel. This may question the relevance of the model used. However, as section 6 shows, the set of covariates z explains the distribution of the cover bids (excluding the lowest bids from the cartel). Therefore, cover bids have still some informative value.

3 The Ticino's bid-rigging cartel

The Ticino cartel has existed since the 50s.⁸ However, since the mid 90s, collusion has not been so easily sustainable as it used to. Competition pressure, within cartel members, started to grow up, and reached its peak in intensity in the year 1998. In fact, the growing competitive behaviour and the risk of bankruptcy motivated cartel members to settle down an agreement at the end of 1998. They applied this agreement called the convention⁹ from 1999 to April 2005, date to which the new

⁸Ticino is a Canton in Switzerland, which is comparable to a State.

⁹In Italian: *la convenzione*

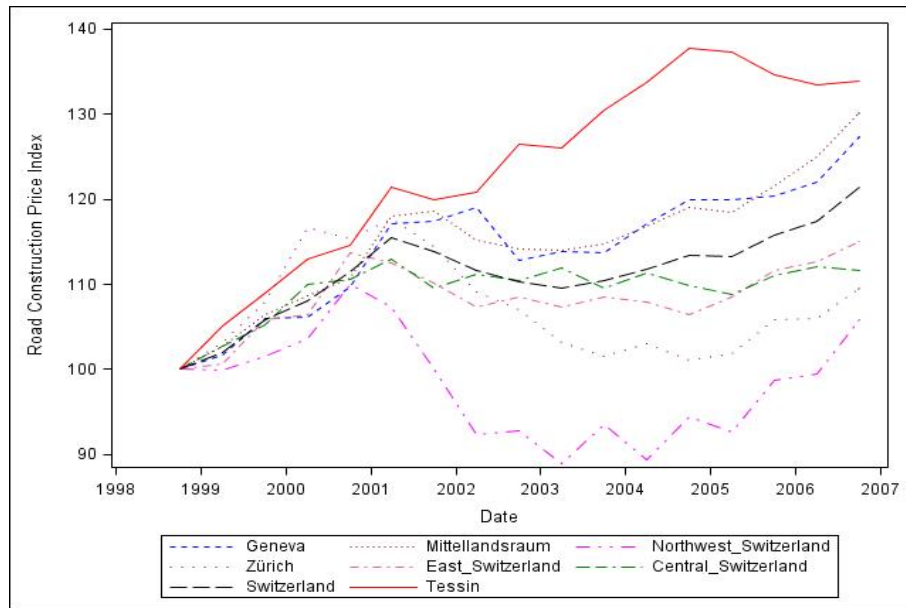


Figure 1: Evolution of the Price Index for Road Construction

revision of the Cartel Act in Switzerland entered in force with direct sanctions.¹⁰ During this period, called hereafter the cartel period, all firms active in the road construction sector participated to the cartel, and they rigged all contracts for road construction without exception. Therefore, the Ticino cartel is certainly one of the most severe bid-rigging cartel, also called all-inclusive cartel because all firms participated to rig every contract. It is also an excellent case to study collusion and to test how well detection methods perform.

Close to the end of the cartel, local politicians went to COMCO because they began to suspect prices to be exaggerated. COMCO investigated the prices for road construction, and found that the price index for road construction was significantly higher in Ticino. In fact, as the price index for the rest of Switzerland decreased, the price index for Ticino continued rising in 2002, as depicted on figure 1.¹¹ Finally, the bid-rigging cartel denounced itself in order to benefit immunity until April 2005.

The cartel convention was a written document, and instituted weekly mandatory meeting, at which all firms active in the road construction sector participated. The cartel convention sanctioned absence to these meetings without valid and legitimate reasons, and punished absent firms by pos-

¹⁰For COMCO decision, see Strassenbeläge Tessin (LPC 2008-1, pp. 85-112)

¹¹Source: Swiss Federal Statistical Office.

sible loss of future contracts. In practice, it is unknown if such punishment took effectively place. In each meeting, firms had to announce every new construction contract from public procurement authorities as every other private construction contract above 20'000 CHF. During these meetings, firms discussed contract allocation among them and the bids to submit.

The cartel convention defined different criteria to allocate new construction contracts. As first criterion, the free capacity of a participant firm was preponderant in the allocation mechanism. Second, the location of the contract work played also a crucial role in the allocation mechanism among participants, especially for contracts below 500'000 CHF. Third, firms considered also the specialization of the participants to allocate contracts. Fourth, the convention privileged participants first invited by private actors to estimate a quotation considering the other criteria.¹² The final decision of contract allocation was adopted by a majority. In case of divergence, firms vote in secret, except firms involved in litigation.

The Ticino bid rigging cartel never used side-payments, and is therefore a weak cartel (see *McAfee and McMillan*, 1992, for the definition of a weak and a strong cartel). Following *Pesendorfer* (2000), two elements allow a weak cartel to achieve efficiency as a strong cartel. First, there must be a lot of contracts to allocate every year within the cartel members. As we can see from table 2, the high number of contracts meets this first condition, with a total of 175 public contracts for the years 1999 to 2004.

Second, a Ranking Mechanism, as described by *Pesendorfer* (2000), should allocate contract among cartel members. In the Ticino cartel, the cartel convention played the role of the Ranking Mechanism described by *Pesendorfer* (2000). It forced cartel members to reveal their true preferences, systematically controlled by the allocation criteria of the cartel convention, in order to avoid adverse selection problem. In fact, the cartel convention on its own searched to determine the bidder with the lowest cost for a specific contract in order to maximize the *ex ante* payoff of the cartel.

After allocating contracts between cartel members, firms discussed prices. For public contracts,

¹²Estimating a quotation causes costs which are not recoverable if another firm wins the contract. To avoid such sunk costs, the convention stipulated that the firm who first announced a private contract had the priority on this contract. It fostered also the announcement of contracts because private contracts are more difficult to observe than public contracts.

all involved firms had to calculate their bids before the meeting. The cartel member, chosen considering all criteria, revealed his price. All participants discussed then the revealed price, and they determined together the best price to submit for the designated winner and the cover bids. Involved participants could not renounce to submit a bid in public tenders; the convention made them submit a bid, respectively a cover bid.

COMCO did not investigate how the cartel members determined the price for the designated winner. However, it is likely that they should have used a rule or any other mechanism to determine relatively quickly the price for the designated winner. In fact, without such a rule, discussions about price could linger too much. One rule could be the following one: the designated winner revealed his price and if the price was not exaggerated, he could submit the bid to this revealed price. Another rule could be that every member revealed their prices and then they calculated the arithmetic mean of all prices; the price of the designated winner could be this arithmetic mean.

If other cartel members had calculated a cheaper bid than the one determined in the discussion, they inflated their bids by some factor to ensure that the designated cartel member would win the contract. The convention stipulates that submitted cover bids should be calculated and justifiable for each position on the bidding documentation provided by procurement agencies. Moreover, cover bids should be high enough relative to the winning bid so that they would not be considered by procurement agencies ensuring the rewarding of the contract to the designated winner.

At the end of the cartel, prices dropped significantly: they were suddenly 25%-30% cheaper than engineer estimates¹³. It is interesting to note that engineers progressively endogenized the higher cartel price, as proposed by *Harrington and Chen* (2006). Thus, this observation is an indication to use with caution engineer estimates to normalize the bids to obtain the dependent variable for econometric estimations.

COMCO condemned all involved firms rendering the decision in 2007 but did not pronounce sanctions against them because the involved firms ceased illegal conducts before April 2005, date to which the revised Federal Act on Cartels entered in force with a sanction regime after a transition

¹³See decision Strassenbeläge Tessin, LPC 2008-1, p. 103

phase from 2004.¹⁴ Because the Ticino road construction cartel was discovered before this date and because the cartel stopped illicit infringements before the final transitory date of April 2005, COMCO did not sanction the involved firms. If they had been sanctioned, they would have paid a roughly CHF 30 mio penalty.

COMCO defined the relevant market as the market for road construction and pavement in Canton Ticino with an upstream market for asphalt pavement material, which plays a strategic role on the road construction and pavement industry. Asphalt pavement material constitutes of 95% of aggregates and 5% of asphalt or bitumen and is a crucial input for covering and pavement works. It has to be heated at a mixing plant in order to be mixed and transported quickly to the contract location to cover the road before getting cold. Market specialists say that the duration of asphalt once mixed is comprised between one hour and one hour and half; it is then possible to be operational in a radius of 50-80 km from the production mixing plant.

Because its importance in pavement works and the necessity to transport it heated, pavement material is typically a strategic input. This influences the market structure: firms try to integrate vertically their production process by owning an asphalt mixing plant (see table 9 in Appendix, firm 3, 4, 5 and 6). Because the infrastructure for an asphalt mixing plant is important and expensive, small and local road construction firms try to join their effort in vertical integration by owning commonly asphalt production plants. In our case, twelve road construction firms own the two biggest asphalt production plants with a capacity of 80% of the overall asphalt production market in Ticino.

This cross-ownership on the upstream market conditions the downstream market structure and put serious entry barriers for new competitors because the convention included a clause foreclosing the road construction market: it was forbidden to sell asphalt or other inputs for road construction to third firm not involved in the convention.¹⁵ Then, the costs to enter the market were prohibitive because any new entrant should build its own mixing plant. Second, the disciplinary effect of mixing plants was real and enormous. Defecting to the cartel, respectively not taking part to the convention could have raised important difficulties for a single firm considering that asphalt may account for

¹⁴Illegal infringements of antitrust laws before 2004 went generally unsanctioned in Switzerland.

¹⁵*Gilo et al.* (2006) show that cross-ownership may sustain collusion.

50% to 80% of the price for pavement works.

3.1 Data

In the rest of this section, we discuss the data for the Ticino case. First, we present some summary statistics. Second, we explain the variables used in the econometric estimation. Specifically, we detail how we construct the variables *distance* and *capacity*. We use these variables as proxies for the firm real costs in order to estimate the reduced-form of the bid function in the following sections. Note also that other proxies exist to determine the bid function of each firm i as, for example, the wage of workers, the cost for capital, the price of intermediary inputs (which play a central role in road construction), the taxes paid by the firm. The frequent use of the capacity and the distance in the bid function may be explained for practical reasons: they are simple to be observed and constructed.

Summary Statistics

Table 4 recapitulates briefly the database for the Ticino case. Altogether, the database contains 334 contracts from 1995 to April 2006. However, we have only the records of the tender opening for 238 contracts mainly from the year 1999 to 2006. Therefore, we can identify 1381 submitted bids mainly for the cartel and post cartel period. The tender process follows a first-sealed bid auction, and the tender opening means that at a fixed date, announced by the procurement procedure, public officials open the sealed bids received from the submitting firms. Then, they write the price for each bid and the name of the bidders on a record. This record allows us to have basic information on the contract and on the firms, like the contract location, bidders' identity and location, prices for each bid.

Table 2 presents the amount of contracts in CHF tendered per year. For the years 1995, 1996 and 2006, we do not have all the contracts publicly tendered. However, we do have all public contracts for the years 1997 to 2005 and we observe important variations of the amount tendered, especially between the years 1997 to 2001. There is a maximal difference of 23 million between the years 1998 and 1999 representing 45% of the maximal amount tendered per year. Major and regular contracts tendered each two years explain these differences.

Table 1: General Descriptive Statistics

Number of tenders	334
Number of submitted bids	2179
Number of tenders with details	238
Number of identified bids	1381
Number of identified bids from individual firm	1100
Number of identified bids from consortia	281
Number of winning bids from individual firms	148
Number of winning bids from consortia	90

Table 2: Tenders per year

Year	Contracts	Amount
1995	7	16'365'378.95
1996	18	15'881'311.40
1997	50	42'929'902.85
1998	36	28'802'066.70
1999	28	51'896'534.75
2000	27	31'479'500.25
2001	24	46'762'575.10
2002	30	38'713'586.60
2003	21	38'985'740.80
2004	45	35'282'493.70
2005	35	20'926'231.70
2006	14	19'079'459.70
Total	334	387'104'782.50

The sample is characterized by a very high degree of frequent interaction among the same firms. In total, we record 24 firms in the sample but only 17 firms regularly submitted bids for covering and pavement works in Ticino. Table 3 describes the number of bids per tenders for the period from 1995 to 2006. The modus is 4 bids, the mean is 6.5 bids and the median is 6 bids. Note that the number of bids does not necessarily equal the number of bidders because of the possibility for firms to build a consortium.¹⁶

Table 3: Bids Distribution

Number of bids	2	3	4	5	6	7	8	9	10	11	12	13	Total
Number of tenders	13	31	53	37	42	44	33	30	18	15	10	8	334

The Bids

In the econometric estimations, we take as dependent variable the natural logarithm of all submitted bids $LN\text{BID}_{it}$ for all firm i and for all contract t . It is worthy to note, that, in contrast to the literature (see *Porter and Zona*, 1993, 1999; *Pesendorfer*, 2000; *Bajari and Ye*, 2003; *Aryal and Gabrielli*, 2013), we do not normalize the bids through the engineer estimates of each contract. First, we possess only a few engineer estimates. Second, engineers endogenized gradually the increase in price, caused by the cartel, exactly as predicted by *Harrington and Chen* (2006). Indeed, after the breakdown of the cartel, prices fell 30% under those engineer estimates. Therefore, we would not recommend to use them in our case. But, because we do not standardize the submitted bids, we estimate the regression in the next section with robust variance clustered by firms to take account for heterogeneity.

The Distance

A larger distance between firms and contract location increases the costs, other things being equal, and a rational firm should submit a higher bid in a distant location and a lower bid in a closer location. Therefore, the *distance* should have a positive impact on the bid function of all firm i .

¹⁶A consortium is a joint bidding or a business combination: two bidders or more submit jointly a bid and execute the contract together if they win.

Usually, the literature confirms this positive relationship.

We use the number of kilometres calculated from Google Map between the contract location and the firm place, which is the location indicated on the official record of the tender opening.¹⁷ Note also that the *distance* changes, if the bid is submitted from the headquarters or from a firm subsidiary. Then, we add 1 for all observations in kilometre to exclude 0 in order to take the logarithmic of the kilometres.¹⁸ The variable *distance* is $LDIST_{it} = \ln(km_{it} + 1)$ for all firm i and for all contract t .

The construction of the *distance* raises some issues. First, some contracts have two different locations. We calculate the distance in kilometres for both locations and compute a simple mean for the value of the *distance* per firm i . Furthermore, some contracts are provided every two years and concern principally maintenance works in a particular region of Canton Ticino. We took then the three most important locations situated in the designated region considering the importance of the road network, and we compute again a simple mean for the *distance*.¹⁹

Second, the address of the firm may not correspond with the exact location of the operation center of the firm. We assume that the firm address, gathered from the official records of the tender opening, corresponds with the nearest operation center for each firm. We cannot verify this information but usually both locations correspond. Third, even if the distance between the operation center and the contract location matters, the distance from the mixing plant to the contract location matters as well. We have no information about the location where firms buy their inputs. Finally, note that the *distance* may capture other effects like proximity to the market or to procurement agencies.

The Capacity of firms

The assumption for the *capacity* is the same for the *distance*: A firm with a full own capacity engaged in current contracts should submit a higher bid (if it submits one at all) compared to a firm with a greater free capacity. A firm with few contracts won should submit aggressive bids to win contracts

¹⁷Note that we also construct a variable for the travelling time based on Google, and we find the same qualitative results for the regression in the next section.

¹⁸Kilometres equal zero if the contract location is in the same place than the firm location.

¹⁹We asked native people from Ticino to determine the three most important locations for the road network in a particular region.

in order to fill its order backlog.

Capacity of firms is usually measured in the literature as the volume of contracts won from the beginning of the year until contract t divided by the volume of contracts won during the entire year. Unfortunately, such a measure of the capacity appears inappropriate for our case, since some contracts last two years and not just one year in our data. Thus, the volume of contracts won by each firm i fluctuate significantly per year. Nevertheless, we attempt to construct the *capacity* for one year, as proposed by the literature, and we find insignificant estimates. We extend the *capacity* on two years, and we find again no significant results. Intuitively, the strong fluctuating income for each firm suggests to calculate the *capacity* in a different way, taking account for the dynamic evolution of the contract volume won per firm.

In this paper, we calculate *capacity* by summing the contracts won for each firm i and for each contract t . The value of the contracts won is discounted for all firms i by 10% for each month except from 15th July to 15th August and from 15th December to 15th January. These periods are known as vacation period for the construction industry and the activity is paused or significantly reduced. This depreciation of 10% represents the amount of work completed by firms for each month. Once we calculate the sum of the discounted value of all contracts won for all firms i , we divide each observation for the *capacity* by the firm average turnover per year as stated in the COMCO decision.²⁰ Consequently, the *capacity* used in the regression varies from 0 to value over 1, because the firm turnover fluctuates strongly over the year. Since we do not know the identity of the bidders before January 1999, we cannot observe the *capacity*. Therefore, we assume that all firms start in January 1999 with a capacity equal to the half of its average turnover per year. The first observation for the capacity variable for all firms i takes the value of 0.5. We denote it CAP_{it} for all firms i at the time of contract t . Note also that we exclude the year 2004 for the cartel period because we do not have precise information about the date for 20% of the contracts. The whole cartel period sample, used in the regression in the next section, contains all tenders from 1999 to 2003.

Another problem rises from the fact that we observe only a portion of the market and not the

²⁰See, Strassenbeläge Tessin (LPC 2008/1, p. 99).

overall market. In fact, firm turnovers, observed in the COMCO decision, constitute about 60% to 80% of the market volume. In order to have a perfect measure of the capacity variable, we should ask firms to give us a list of all contracts completed per year. If such demand is realistic during an investigation, it seems however unrealistic during an *ex ante* analysis. So, if the official records of the tender opening are insufficient to construct the capacity variable, then this restriction may certainly compromise the use of the method proposed by *Bajari and Ye (2003)* during an *ex ante* analysis to screen for collusion. However, as presented in the next section, the capacity variable CAP_{it} provides good and coherent results.

Strategic Interaction Variables

We create two variables to take account for the strategic interaction between firms. The first variable is the minimal distance among rivals, noted $LMDIST_{it}$ for each firm i at contract t . We expect that the minimal distance among rivals affects positively the bid of firm i . The intuition is the following: if firm i knows that all its rivals are very distant from the contract location, it might raise its bid because it assumes that competition softens. The second variable is the minimal used capacity among rivals, noted $MCAP_{it}$ for each firm i at contract t . We expect that the minimal capacity among rivals affects positively the bid of firm i . The intuition is the same as for the minimal distance among rivals. If firm i knows that all potential rivals have full capacity engaged in different contracts, it might raise its bid because competition for the contract will be less fierce.

Consortium

Consortium raises a next concern. Each consortium is a business combination of multiple firms (in general 2 or 3 firms). Usually, a consortium is organized for one contract, but, in our case, we find regularly the same consortia composed by the same set of firms. So, we identify these regular consortia with an identification number as for the individual firms. We give to these regular consortia the identification numbers from 21 to 26. Note also we give the value of 0 for irregular and occasional consortia.

Moreover, we consider uniquely the minimum value of the firms in the consortium to determine the cost variables. This is justified for two reasons: first the convention stipulates this mechanism of the minimum value in order to allocate contracts between different consortia. Second, the purpose of a consortium usually consists of circumventing capacity restrictions or any other disadvantages. Because of this basic economic justification for consortium, the cost variables of the consortium solely take the minimum value of the costs from firms jointed in the consortium. Table 4 provides basic descriptive statistics for the cartel and post cartel period.

Table 4: Summary of Descriptive Statistics

Descriptive Statistics for the Cartel Period					
Variable	Mean	Std. Dev.	Min.	Max.	Obs.
LNBID	13.57	1.12	9.99	15.65	778
LDIST	2.83	1.12	0	4.60	778
CAP	0.54	0.27	0	1.45	778
MLDIST	1.95	1.09	0	4.47	778
MCAP	0.25	0.20	0	1.11	778
Descriptive Statistics for the Post Cartel Period					
Variable	Mean	Std. Dev.	Min.	Max.	Obs.
LNBID	13.12	0.88	11.03	15.04	226
LDIST	2.93	1.12	0	4.58	226
CAP	0.42	0.21	0	1.07	226
MLDIST	2.14	1.21	0	4.42	226
MCAP	0.18	0.13	0	0.68	226

4 Estimating the Bidding Function

As explained in section 2, it is convenient to use a regression analysis in order to test for the conditional independence and for the exchangeability of the bids. The related papers in the literature generally estimate a panel model to analyse the structural relationship between the observable covariates z and the bids (see *Porter and Zona*, 1993, 1999; *Pesendorfer*, 2000; *Bajari and Ye*, 2003; *Jakobsson*, 2007; *Chotibhongs and Arditi*, 2012a,b; *Aryal and Gabrielli*, 2013). Then, we formulate the following panel model:

$$y_{it} = x'_{it}\beta + f'_{it}\alpha + \varepsilon_{it}. \quad (9)$$

In this equation, x_{it} include K estimators, and $f'_{it}\alpha$ capture the individual fixed effects including a constant term, where i is the subscript for firms and t for contracts. y_{it} is the logarithm of the bids, submitted by firm i for contract t .

In our case, the exogenous variables x_{it} are the cost variables presented in the previous section, namely the distance ($LDIST_{it}$), the capacity (CAP_{it}), and the strategic interaction variables ($LMDIST_{it}$ and $MCAP_{it}$). If $LDIST_{it}$ and CAP_{it} vary for all firms i and for all contract t , each $LMDIST_{it}$ and $MCAP_{it}$ solely take two values per contract t . For example, the nearest bidder's $LMDIST_{it}$ takes for contract t the value of the second nearest bidder for contract t , but for all other bidders (excluding the nearest bidder) $LMDIST_{it}$ takes the value of the nearest bidder for contract t . Note also that these cost variables are solely proxies for the firm real costs. Again, because we replicate in this paper the detection method, proposed by *Bajari and Ye* (2003), we consider the functional reduced-form of the bid function and the cost variables as given. Dummies for contracts (α_t) and for firms (γ_i) capture the fixed effects.

Based on these cost variables and fixed effects, we estimate the following panel equation, with robust variance clustered by firms:

$$LNBID_{it} = \beta_0 + \gamma_i + \alpha_t + \beta_1 LDIST_{i,t} + \beta_2 CAP_{i,t} + \beta_3 LMDIST_{i,t} + \beta_4 MCAP_{i,t} + \varepsilon_{it}. \quad (10)$$

Empirical Results

Table 5 reports the estimation of the previous equation for the cartel period and the post cartel period. For the cartel period, we use in the estimation 130 dummies for contracts (α_t), and 23 dummies for firms (γ_i). We have a total of 778 observations and 158 regressors.

The estimated coefficients for the *distance* ($LDIST_{it}$), the *capacity* (CAP_{it}), and the *minimal capacity* ($MCAP_{it}$) used among rivals are positive and significant. These results are coherent with the expected behaviour of firms in a competitive environment. If, all things being equal, $LDIST_{it}$ of firm i increases by 1%, it raises firm i 's bid by 0.79%. The same yields for the firm capacity: if firm i 's CAP_{it} engaged in previous contracts increases, all things being equal, then firm i submits a higher bid. This consistent result also supports the construction of the variable CAP_{it} , discussed in the previous section.

Turning to the strategic interaction variables, we find that the minimal distance among rivals is not significant. However, the minimal used capacity among rivals ($MCAP_{it}$) is significant and has even a stronger positive effect on firm i 's bid than the own used capacity. Intuitively, if firm i knows that the other firms have already a high capacity engaged in other contracts, it submits a higher bid assuming that competition is soften, because the other firms have too much capacity used to bid aggressively. The fixed effects for contracts (α_t) and for firms (γ_i) are also significant. Moreover, we notice that the R^2 is very high. This can be common for a panel model, and also implies that the reduced-form of the bid function explains almost all variation observed in the bids. If we retrieve the fixed effects for contracts (α_t), the $Adj.R^2$ decreases to 0.3534. To sum up, all these results rather depict a behaviour fitting a competitive environment, although the estimations are made for the cartel period.

For the post cartel period, we use a total of 63 regressors including 39 dummies for contracts (α_t), and 19 dummies for firms (γ_i). With 224 observations, we have 3.5 time fewer observations than the cartel period sample. All variables are insignificant in the estimation of equation 10. Moreover, we notice that the standard deviation for all variables is roughly 10 times higher than for the cartel period. This means that the estimators are imprecise, and this phenomenon explains, at least partially,

why the estimators are insignificant. The small sample size and the transition phase, from a cartel to a more competitive equilibrium, may explain this inaccurate estimation. Thus, even if we replicate the econometric tests on the post cartel sample for comparison purpose, we must interpret them with a certain caution. Finally, the R^2 is again very high, although all variables are insignificant. This suggests that the high number of dummies compared to the sample size explains mostly the high R^2 . Again, R^2 shrinks to 0.2922 without the fixed effects for contracts (α_t).

Table 5: OLS Estimation for the Reduced-Form Bid Function

Variable	Cartel Period	Post Cartel Period
C (constant)	13.525*** (0.0159)	12.8866*** (0.1325)
LDIST (own distance)	0.0079*** (0.0025)	0.0258 (0.0212)
CAP (own used capacity)	0.019*** (0.0062)	0.0844 (0.0635)
LMDIST (minimal distance among rivals)	-0.0012 (0.0041)	0.028 (0.0322)
MCAP (minimal used capacity among rivals)	0.0429** (0.0208)	0.2709 (0.2416)
Dummies for contracts	130	39
Dummies for firms	23	19
Sample Size	778	224
$Adj.R^2$	0.9995	0.9852

Where ***, **, * denote significance level at 1, 5, 10 percent level.

5 Testing for collusion

In this section, we implement the tests for the conditional independence and for the exchangeability of the bids. In order to implement these two econometric tests, we estimate the same equation as equation 10 but we allow coefficients to vary across firms i . This is necessary if we want to implement the test of the exchangeability of the bids. All tests presented hereafter are based on the following panel equation:

$$LBID_{it} = \beta_0 + \gamma_i + \alpha_t + \beta_{1,i}LDIST_{i,t} + \beta_{2,i}CAP_{i,t} + \beta_{3,i}LMDIST_{i,t} + \beta_{4,i}MCAP_{i,t} + \epsilon_{it}. \quad (11)$$

Note also that in the rest of this section, we present results not only for a standard risk level of 5%, but also for a risk level of 10%. As explained in the introduction, we might have a problem of false negative results. This means that the tests do not reject the null hypothesis of competition in favour of the alternative hypothesis of collusion, although they should reject it because of the bid-rigging cartel. Then, a simple way to analyse this problem of false negative results is to raise the test risk level at 10%. Because, this implies logically to raise the risk of false positive results, we would not recommend to raise it in other cases, especially in an *ex ante* screening activity. However, our case is special, and because we have a perfect information on the Ticino bid-rigging cartel, we cannot make any mistakes, if we reject the null hypothesis of competition for the cartel period. To sum up, presenting the results for a risk level at 10% allows us to discuss the sensitivity of the tests.

5.1 Test for the Conditional Independence

After estimating the equation 11, we test if the residuals of firms i and j are correlated. If the residuals are uncorrelated between firms i and j , their bids are independent conditional on the observed cost variables and the fixed effects included in the regression. However, if we find that residuals are correlated, bids are not independent: we can reject the null hypothesis of competition, depicted by the Nash equilibrium of the asymmetric procurement model. Formally, the null hypothesis is the following:

$$H_0 : \rho_{ij} = 0, \quad (12)$$

where ρ_{ij} is the Pearson correlation coefficient. We perform the test only if there is at least five pairwise observations for a pair of firms. This means that both firms submit simultaneously a bid for five contracts. If r is the coefficient of correlation calculated from the data and n the number of pairwise observation for each pair (where $n \geq 5$), we apply the following Fisher Z transformation:

$$Z = \frac{1}{2} \ln \frac{1+r}{1-r}, \quad (13)$$

which is approximatively normal with

$$\mu_Z = \frac{1}{2} \ln \frac{1+\rho}{1-\rho} \quad \text{and} \quad \sigma_Z = \frac{1}{\sqrt{n-3}} \quad (14)$$

If we normalize Z in order to obtain the standard normal distribution, we have

$$z = (Z - \mu_Z) \sqrt{n-3}, \quad (15)$$

where $\mu_Z = 0$ under the null hypothesis, i. e. $\rho = 0$. The test statistic is then $Z \sqrt{n-3}$.

For the cartel period, we test 133 pairs presented in table 10 in appendix and we reject the null hypothesis at 5% risk level for 15 pairs, at 10% for 24 pairs. The failure proportion is 11% and 18%, respectively. This result is surprising because it suggests that false negative results are considerable. For the post cartel period, we apply the test on 47 pairs presented in table 11 in appendix; 7 pairs fail the test at 5% risk level, 24 pairs at 10%. The failure proportion is 15% and 21%, respectively. This result is confusing because we find slightly more rejection for the post cartel period than for the cartel period. We would have expected the contrary.

5.2 Test for the Exchangeability

The test for the exchangeability of the bids examines if the coefficients estimated in equation 11 are identical between firms. If they are identical, it means that firms react in the same way based on their own costs. In other words, if we permute the costs of firm i with the costs of firm j , then firm i should submit the same bids as firm j . The null hypothesis of competition specifies that the estimated coefficients of firm i do not differ from those of firm j . Formally, the null hypothesis for the exchangeability of the bids is the following:

$$H_0 = \beta_{ki} = \beta_{kj} \quad \forall i, j, i \neq j, \quad \text{and} \quad \forall k = 1, \dots, 4. \quad (16)$$

The test is implemented with the following F-statistic

$$F = \frac{(SSR_C - SSR_U)/J}{SSR_U/(N - k)}, \quad (17)$$

which has an F-distribution with parameters $(J, N-k)$ under the null hypothesis, where J is the number of constraints, N the sample size and k the number of regressors.

Again, we implement the test solely on pairs of firms, which bid simultaneously at least for five common contracts, respectively with five pairwise observations for each pair. Table 14 in appendix shows the results for 133 pairs. We find that 42 pairs fail the test at 5% risk level and 58 at 10%. The failure proportion is 32% and 44%, respectively. Failures are more important for pairs with fewer observations. The pairs failing the test at 5% have on average 14 pairwise observation, whereas the pairs passing the test have on average 19 pairwise observations.

Then, we test the exchangeability of the bids for the post cartel period. Table 15 in appendix recapitulates the results for 47 pairs of firm. We find that 4 pairs fail the test at 5% risk level and 8 at 10%. The failure proportion is 9% and 17%, respectively.

To sum up, the test for the exchangeability of bids performs better, because it produces fewer false negative results than the test for the conditional independence. Yet, false negative results remain important because more than half of the pairs pass the test, although they should fail. Furthermore, we also observe that the number of failure decreases for the post cartel period. This result is logical because, if the test of exchangeability is correct, we expect that the number of failure decreases in a more competitive market.

If we consider the simultaneous application of both tests at 5% risk level, we find that only 5 pairs fail both tests and 53 pairs fail solely one of them. The failure proportion is 4% and 40%, respectively. At 10% risk level, we find that solely 9 pairs fail both tests and 73 pairs fail one of them. The failure proportion is 7% and 55%, respectively. This result suggests that the failure of one test should be sufficient to raise concerns about the existence of bid-rigging cartel. We discuss it deeper in section 7.

Table 6: Summary of Econometric Tests

Summary of the Tests on 133 Pairs for the Cartel Period

Test	<i>Risk Level</i>	Failure	% of Failure
Conditional Independence	$\alpha = 0.05$	15	11 %
	$\alpha = 0.1$	24	18%
Exchangeability	$\alpha = 0.05$	42	32%
	$\alpha = 0.1$	58	44%
Fail one test	$\alpha = 0.05$	53	40%
	$\alpha = 0.1$	73	55%
Fail both tests	$\alpha = 0.05$	5	4%
	$\alpha = 0.1$	9	7%

Summary of the Tests on 47 pairs for the Post Cartel Period

Test	<i>Risk Level</i>	Failure	% of Failure
Conditional Independence	$\alpha = 0.05$	7	15%
	$\alpha = 0.1$	24	21%
Exchangeability	$\alpha = 0.05$	4	9%
	$\alpha = 0.1$	8	17%
Fail one test	$\alpha = 0.05$	11	23%
	$\alpha = 0.1$	18	38%
Fail both tests	$\alpha = 0.05$	0	0%
	$\alpha = 0.1$	0	0%

6 Robustness Analysis

In the previous section, we test for collusion, and we find a high number of false negative results. These results are erroneous, and they contradict the existence of the Ticino bid-rigging cartel. Thus, we examine in this section, if these results are robust only for the cartel period with two different sub-samples, composed by cover bids. We use cover bids, because they are less informative than the cartel winning bids; Cover bids are, by definition, fake. Then, we could assume that cover bids are less connected with costs than the cartel winning bids. If this is true, we should therefore find more rejection for these two sub-samples, respectively fewer false negative results.

For the first sub-sample, we consider only the pairwise observation, when firm i and firm j submit both cover bids. We call this first sub-sample, the *indirect cover bids* sample, because neither firm i nor firm j wins the contract, but they both submit a cover bid in favour of a third cartel member. Hence, the indirect cover bids contain solely cover bids, excluding all winning bids. Note also that, for the cartel period, all winning bids are the lowest submitted bids for each contract.

For the second sub-sample, we consider solely the pairwise observation, where firm i wins the contract and firm j submit a cover bid. We call this sub-sample the *direct cover bids* sample, because firm i wins the contract whereas firm j submit a cover bid; respectively firm j direct cover firm i . Note also that the second sub-sample contains all pairwise observation excluded in the first sample, so that the addition of the two sub-samples produces the whole sample.

In the following, we implement the test for the conditional independence and for the exchangeability of the bids on the indirect cover bids sample. Then, we apply solely the conditional independence test on the direct cover bids sample.

6.1 Testing Collusion for the Indirect Cover Bids Sample

6.1.1 The Conditional Independence Test

By analyzing the residuals of the regression from equation 11 for the cartel period, we find immediately that the residuals of the winning bids are significantly lower than the residuals of the cover bids.

Table 7 shows that the simple mean is -0.0277 for the winning bids and 0.0055 for the cover bids, with a standard deviation of 0.0187 and 0.0164, respectively. To sum up, the residuals of the winning bids are in average 5 times lower than those of the cover bids with an approximative equal spread. In other words, the residuals of the cover bids first order stochastically dominates the residuals of the winning bids. This important difference between the empirical distribution of both residuals may influence notably the estimated Pearson correlation coefficient. Then, it might be interesting to verify whether the results for the conditional independence test change, if we consider solely the residuals for the cover bids.

Table 7: Descriptive Statistics according to the Type of Residuals

	Mean	St. Dev.	Min	Max	N	L. Quartile	Median	U. Quartile
Resid. Cover Bids	0.0055	0.0164	-0.0473	0.0763	649	-0.0045	0.0042	0.0151
Resid. Winning Bids	-0.0277	0.0187	-0.0711	0.0262	129	-0.042	-0.0281	-0.0158

To implement the test, we use the same residuals of equation 11 from section 4, but we suppress the residuals of the winning bids for each contract. We calculate the Pearson correlation coefficient and use, as in section 4, the Fisher transformation. Table 12 in appendix recapitulates the results. The tests reject the null hypothesis for 14 pairs at 5% risk level and for 25 pairs at 10%; the failure proportion is 15% and 26%, respectively. If we consider the pairs composed solely by individual firms, we reduce the sample on 83 pairs, and we obtain 10 rejections at 5% risk level, 21 rejections at 10%; In sum, we notice approximatively the same proportion of failure (12% and 25%) for individual firms. Moreover, the proportion of failures for the conditional independence test does not change with this sub-sample. As for the whole sample of the cartel period, we find again too many false negative results.

6.1.2 The Test for the Exchangeability of the Bids

To implement the tests for exchangeability of the bids, we suppress all winning bids for the cartel period sample, and we estimate equation 11 again. We apply this test, only if we have at least five

pairwise observations for the two firms; this means if both firms participate at least for five common contracts, each firm submitting five cover bids in favour of a third cartel member.

The motivation to reduce the sample solely on the indirect cover bids is different from the reason mentioned for the conditional independence test. Looking at figure 2 drawn from *Imhof et al. (2015)*, we observe an important gap between the winning bids and the cover bids. In fact, the average gap is roughly 5%. However, we remark immediately from figure 2, that the gaps are smaller between the cover bids. This pattern is observable for the majority of the contracts during the cartel period (see *Imhof, 2017*). Therefore, if cover bids are very close, and if costs are different among firms, then the estimated coefficients of equation 11 could be different across firms. In other words, we expect a greater number of failure for this test.

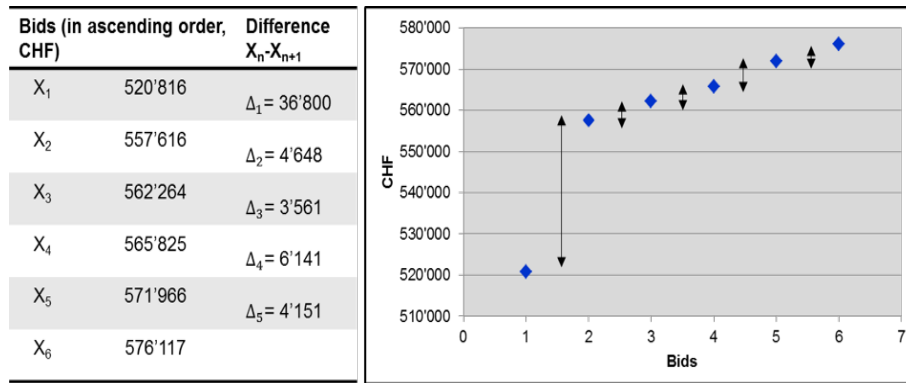


Figure 2: Typical Cover Bidding Mechanism in Ticino

Table 8 presents the results for the estimation of equation 11 for the indirect covers bids sample. We note that all variables are positive and significant. The distance has virtually the same effect on the bids as shown for the whole cartel period sample: if, all things being equal, the distance of firm i increases to 1%, it raises firm i 's bid by 0.75%. The own used capacity and the minimal used capacity among rivals have a weaker effect on the bids compared to the whole cartel period sample. They are significant only at 10% risk level. We observe interestingly that the minimal distance among rivals is positive and significant at 10% risk level, whereas it is not significant for the whole cartel period sample. The R-squared is also higher. This is certainly explained by the fact that we have fewer observations and almost the same number of regressors. The results of this regression may surprise:

we would have expected to find less consistency with a rational economic behaviour for the indirect cover bids sample. On the contrary, these results suggest that costs explain somehow the cover bids.

Table 8: OLS Estimation of the Reduced-Form Bid Function for the Cover Bids

Variable	Cover Bids
C (constant)	13.4877*** (0.0129)
LDIST (own distance)	0.0075*** (0.002)
CAP (own used capacity)	0.0092* (0.0047)
LMDIST (minimal distance among rivals)	0.0066* (0.0034)
MCAP (minimal used capacity among rivals)	0.0337* (0.0181)
Dummies for contracts	130
Dummies for firms	22
Sample Size	645
R^2	0.9998

Where ***, **, * denote significance level at 1, 5, 10 percent level.

Table 16 in appendix presents the results of the tests for 96 pairs. We find that 19 pairs fail at 5% risk level and 28 at 10%. The failure proportion is 20% and 29%, respectively. Then, the portion of pairs, failing the test of exchangeability for the indirect cover bids sample, decreases by 12% and 15%, respectively.

This result surprises again because we would have expected to find more failures for this sub-sample. We explain this result by two causes, which are mutually non-exclusive. First, the costs for the cover bids do not differ as much as we could have expected. However, if they differ, they enter in a symmetric way in the firm bid function. Second, firms gathered together each week, and they discussed extensively the bids for public contracts, as it is stated in the cartel convention. Regular discussions could explain why costs, if they differ, enter in a symmetric way in the firm bid function. Still, indirect cover bids fail less tests for the exchangeability than the whole cartel period sample.

We would have expected the contrary. In any case, this result confirms again the high number of false negative results, observed for the whole cartel period sample.

6.2 Testing Collusion for the Direct Cover Bids Sample

We turn now to test the conditional independence test on the direct cover bids sample. We are interested to analyse the residuals between the winning bids and the losing bids, where firm i wins the contract and firm j submit a cover bid. In fact, we postulate that a significant difference between the two types of residuals, as observed with simple descriptive statistics in 7, may produce a strong correlation pattern.

Again, we calculate the Pearson correlation coefficient and use, as in section 4, the Fisher transformation. Table 13 in appendix presents the results. We consider again all pairs with at least 5 simultaneous bids, and we retain 35 pairs for the direct cover bids sub-sample. As expected, 24 pairs reject the null hypothesis at 5% risk level, 28 at 10%. The proportion of failing pairs is 69% and 80%, respectively; we find also strong negative correlation for the failing pairs. The test produces substantially fewer false negative results for the direct cover bids sample, and is consistent with the Ticino bid-rigging cartel.

Intuitively, we can explain this phenomenon on the basis of figure 3 depicting the pairwise residuals of firms 9 and 15 for the whole cartel period sample, where both firms bid for the same contracts. We differentiate the type of cover bids between indirect and direct cover bids, represented on the figure by circles and crosses, respectively.

In the previous section, we found that pair (9,15) had 62 simultaneous bids with a non significant correlation of -0.0595 ; the pair does not fail the conditional independence test. Considering only the indirect cover bids (circles on the figure), we find 50 simultaneous (indirect) cover bids with a significant positive correlation of 0.3498 . However, if we restrict the sample solely on the direct cover bids (crosses on the figure), we observe 12 simultaneous bids and a significant negative correlation of -0.8866 .

In fact, the positive correlation from the indirect cover bid sample cancels the negative corre-

lation from the direct cover bid sample. Because of this antagonistic effect, the correlation for the whole cartel period sample is not significant. The pair passes the test, whereas we expect it to fail. This phenomenon is common for many pairs, which pass successfully the test of the conditional independence for the whole cartel period sample. This result indicates that the test of the conditional independence is better designated to detect bilateral agreement and not an all-inclusive bid-rigging cartel, as the Ticino case. We discuss this result in the next section.

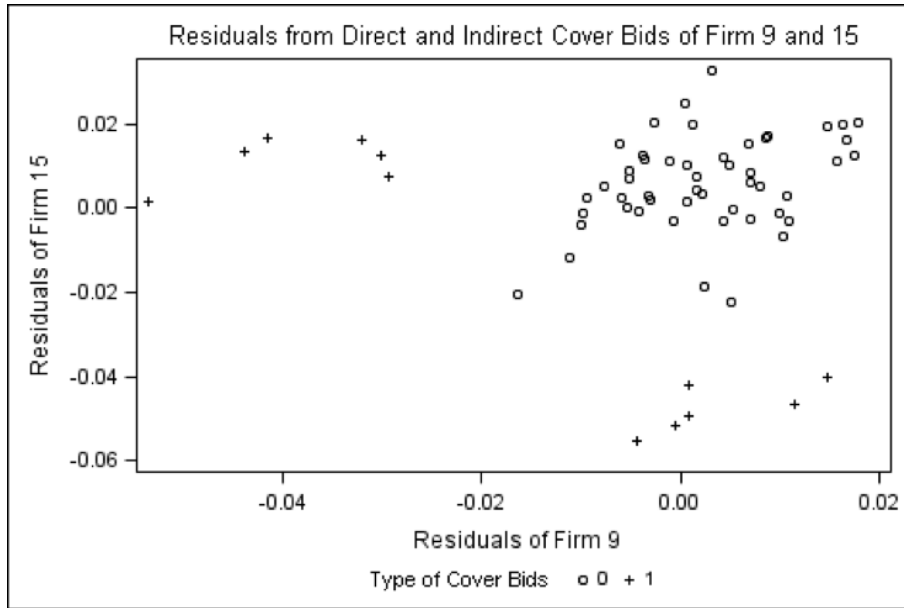


Figure 3: Pairwise Residuals of firm 9 and 15

7 Policy Implication for Competition Agencies

In this section, we discuss the high number of false negative results. Then, we address the question of classifying a pair of firms as potential cartel, if the pair fails solely one test or if it fails both tests. In other words, is the failure of one test a sufficient condition to alarm competition agencies? Second, we compare the method proposed by *Bajari and Ye* (2003) with a different method developed by *Imhof et al.* (2015) to screen for bid-rigging cartels. From this comparison, we deduce some recommendations for competition agencies.

Based on the results of the previous sections, we show that the method of *Bajari and Ye* (2003) produces too many false negative results for the Ticino case. In statistics, a false negative result is

an error of type II: the test should reject the null hypothesis but it does not reject it whereas the null hypothesis is definitively false. In our case, the null hypothesis is competition for both econometric tests, and we do not reject it for a large percentage of pairs for both tests, although we implement the tests for the cartel period. Again, we remind the reader that the bid-rigging cartel in Ticino rigged all contracts for the cartel period, and all firms participated to the bid-rigging cartel, without exception. Certainly, we study with the Ticino case a bid-rigging cartel of the worst kind. Therefore, considering the severity of the bid-rigging cartel, how can we explain the high number of false negative results observed?

Considering the high number of false negative results, we suggest first a data-related explanation. The data may be imprecise, or the construction of the variables incorrect. However, incorrect data or miss-constructed variables should rather contribute to reject the null hypothesis of competition. It would be very unlikely to have incorrect data or miss-constructed variables fitting the strong hypotheses of Nash equilibrium in a first-sealed bid asymmetric procurement model. Moreover, the results of the panel estimations contradict also this conjecture of data imprecision: if data or variables were incorrect, it would be again very unlikely to find that firms bid following a rational economical behaviour. Finally, one can attempt to put in question the assumed reduced-form of the bid function. Yet, the literature has well established the empirical identification for the reduced-form of the bid function used in this paper (see *Porter and Zona*, 1993, 1999; *Pesendorfer*, 2000; *Bajari and Ye*, 2003; *Jakobsson*, 2007; *Chotibhongs and Ardit*, 2012a,b; *Aryal and Gabrielli*, 2013). In any case, if the data used in this paper is insufficiently accurate, it means that the official records of the tender opening are not sufficient to construct the variables for the bid function. Then, the data requirement to meet is too high, if a competition agency wants to implement *ex ante* the econometric tests proposed by *Bajari and Ye* (2003), based only on the official records of the tender opening.

After excluding the data-related explanations, we turn now to discuss model-related causes for those false negative results. First, if firms pass the two econometric tests, although they collude on all contracts, it might imply that they manage to pass through the tests proposed by *Bajari and Ye* (2003). Under some circumstances, *Bajari and Ye* (2003) admit the possibility that the competitive

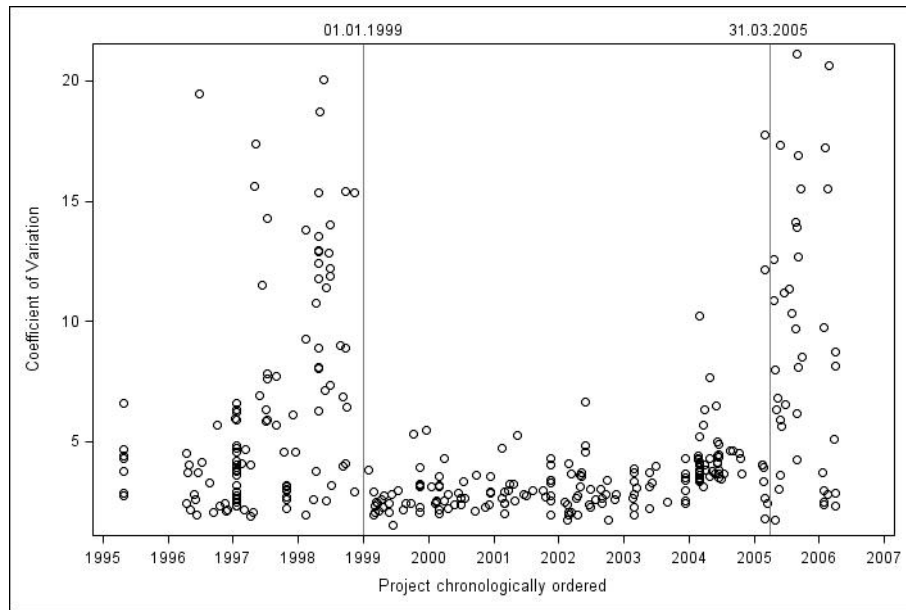


Figure 4: The Evolution of the Coefficient of Variation

model might also encompass collusion. Indeed, if cartel members scale their bids with a common factor, the assumptions underlying the competitive model proposed by *Bajari and Ye* (2003) remains non-violated: the cartel can pass through the tests.

However, we can exclude in our case this bid scaling phenomenon. *Imhof* (2017) presents the application of simple statistical screens to detect collusion for the Ticino case and finds that simple statistical screens capture well the impact of the bid-rigging cartel. Figure 4 drawn from *Imhof* (2017) depicts the evolution of the coefficient of variation, where the two vertical lines delimit the cartel period. The difference between the cartel and the post cartel period is eye-catching: the coefficient of variation is significantly lower during the cartel period indicating the existence of a bid-rigging cartel, as predicted by the variance screen (see *Imhof et al.*, 2015; *Imhof*, 2017).

Yet, simple screens function only if cartel members do not scale their bids. If they scale their bids, it is impossible to detect collusion with simple screens as shown by *Imhof* (2017). In sum, we can exclude the bid scaling phenomenon for the Ticino case. Therefore, it seems realistic to consider that a cartel can manage to pass through the tests proposed by *Bajari and Ye* (2003) without scaling their bids. This result is somehow pessimistic towards the method proposed by *Bajari and Ye* (2003). Because, if one bid-rigging cartel of the worst kind may pass through the tests, how many other ones

could there be?

Two arguments can moderate this pessimistic conclusion. First, we find comparatively better results for the tests of the conditional independence applied to the direct cover bids sample: 69% of the pairs fail the test. This may be a clue that the econometric tests, at least the test for the conditional independence, perform better to find rather bilateral agreement between firms than an all-inclusive cartel as the Ticino case. It is also worthy to notice that the test for the exchangeability performs better than the test of the conditional independence for the cartel period. In any case, our results strongly suggest that the requirement of the simultaneous failing of both tests is inappropriate to classify a pair as potential cartel: only 6% of the pairs fail both tests whereas 40% of the pairs fail one test. Even if we consider a higher risk level of 10%, only 7% of the pairs fail both tests, and 55% of the pairs fail one test. Therefore, if in an other case half of the pairs fail one of the two tests at a 5% standard risk level, it should be considered as sufficient to alarm competition agencies concerning potential bid-rigging cartels.

Second, the internal organization of the bid-rigging cartel can explain, why the cartel manages to pass through the tests. Indeed, cartel members meet every week, and they discuss extensively the bids to submit for each contract, considering criteria like firm capacity, the distance to contract location or firm specialization. These criteria to allocate contracts among them are the cost variables, the most used in the empirical identification of the model. Therefore, the submitted bids during the cartel period are certainly connected with the cost variables, in some ways that allow the bid-rigging cartel to pass through the tests proposed by Bajari with success.

However, if bids are cleverly fake, why can an alternative method, such as the screening method proposed by *Imhof et al.* (2015), perform better to detect the Ticino case than the method of Bajari? For comparison purpose, we apply the *ex ante* screening method based on simple screens proposed by *Imhof et al.* (2015) on the Ticino case. The screening method combines two simple screens, the coefficient of variation and the relative distance, to classify contracts as conspicuous or non-conspicuous. We find that the screening method classifies 82% of the contracts during the cartel period as conspicuous. Therefore, the comparison is striking with the method of *Bajari and Ye* (2003): Simple screens

produces significantly fewer negative results for the cartel period, even if the cartel members discuss extensively the fake bids to submit.

Finally, if one competition agency wishes to enforce law and destabilize bid-rigging cartels, which detection method should it choose in the first place? We believe that both methods may be complementary and not substitutable. The method based on simple screens provides quickly information on potential serious bid-rigging issues. It works well to detect bid-rigging cartels, and it seems to produce significantly fewer false negative results for the Ticino's case compared to the method of *Bajari and Ye* (2003). Moreover, its low data requirement is particularly advantageous to screen for a high number of contracts, since it uses solely information about bids and not about costs. Bids are easier to observe than costs, especially if we run the method *ex ante*, in secrecy, in order to impede the bid-rigging cartel to react and destroy hard evidence.

However, the screening method is not based on a theoretical model as the method proposed by *Bajari and Ye* (2003). Yet, the theoretical model proposed by *Bajari and Ye* (2003) focuses on bilateral firm interaction. In our case, the econometric tests, derived from this theoretical model, function – at least – to detect bilateral agreements. Because there is still some competition on the market, bilateral agreements among competitors are not the worst kind of collusion. Nevertheless, they affect the outcome of tenders and are therefore harmful. Then, if there is reason to suspect that collusion takes rather the form of bilateral agreements and not of an all-inclusive bid-rigging cartel, as the Ticino's case, it should be advantageous to implement the tests proposed by *Bajari and Ye* (2003).

A problem arises now from the fact that bilateral colluding firms may not collude on all contracts: they may partially collude on some contracts. This may be a serious problem, especially considering the high number of possible false negative results produced by the method of *Bajari and Ye* (2003). Yet, the screening method proposed by *Imhof et al.* (2015) can remedy to this problem of partial collusion among contracts. Indeed, the authors propose to construct a filter based on different screens to focus solely on conspicuous contracts. If there is some reason to suspect that firms do not collude on all contracts, then the screening method proposed by *Imhof et al.* (2015) may help to screen contracts the most likely to be bid-rigged. After this first selection, the investigator can

apply the method of *Bajari and Ye* (2003), and test for the exchangeability and for the conditional independence. However, requirement for the econometric tests, as for simple screens, should not be too high. Indeed, screening methods, implemented *ex ante* to detect bid-rigging cartels, should not bring the ultimate evidence to proof collusion, but they should provide solely a sufficient suspicion to open an investigation.

8 Conclusion

Our paper contributes to the literature of bid-rigging detection in multiple ways. We have shown that the detection method of *Bajari and Ye* (2003) produces a high number of false negative results for the Ticino bid-rigging cartel, and we cannot explain this result with the bid scaling phenomenon. Therefore, the Ticino bid-rigging cartel finds a way to pass through the tests, and to challenge the competitive model used by *Bajari and Ye* (2003).

We have also applied both tests on the first sub-sample composed by indirect cover bids, and we have found again that the tests produce too many negative results. Considering the severity of bid-rigging cartel, we would have expected to detect it with the method proposed by *Bajari and Ye* (2003). In contrast, we have shown that the test of the conditional independence produces results consistent with the existence of the bid-rigging cartel for the second sub-sample, composed by the direct cover bids. This result suggests that the method of *Bajari and Ye* (2003) would rather detect bilateral agreements than all-inclusive cartels.

Then, we conclude that the high number of negative results suggests that the failure of one test should be sufficient to classify a pair of firms as potential bid-rigging cartel. Moreover, if half of the pairs fail at least one test, it should also be sufficient to alarm competition agencies to delve into it.

Finally, we have compared the methods of *Bajari and Ye* (2003) with the results of the screening method developed by *Imhof et al.* (2015). We have found that it performs better to detect the Ticino bid-rigging cartel. We also believe that both methods may be complementary, and we propose a way to use the strength of both methods.

To sum up, bid-rigging cartels are a serious problem and competition agencies should be more

proactive in order to deter and destabilize them. Detection methods are not the unique instrument to achieve this goal, but only one instrument among a set of multiple possible actions. However, in order to use a detection method as a valid instrument, competition agencies must be able to gauge its performance, its strengths and its limits. Our paper contributes to treat this question concerning detection methods for bid-rigging cartels.

9 Appendix Table

Table 9: Firms Descriptive Statistics

Firm	Bids	Win. Bids	Success Rate	Workers	Vertical integr. Firm	SH Firm 1	SH Firm 2	Contracts won	Market Share
3	58	18	0.31	16	1	0	0	17'761'137.20	6%
4	143	17	0.12	45	1	0	1	17'742'856.60	6%
5	44	24	0.55	33	1	0	0	17'693'104.70	6%
6	77	11	0.14	39	1	0	0	13'498'334.30	4%
7	18	7	0.39	8	0	0	0	8'268'229.46	3%
8	125	24	0.19	35	0	1	0	21'954'142.30	7%
9	206	31	0.15	61	0	1	0	20'668'237.20	7%
10	132	21	0.16	70	0	1	0	19'278'461.80	6%
11	86	21	0.24	42	0	1	0	20'421'747.70	7%
12	58	34	0.59	41	0	1	0	26'726'938.70	9%
14	114	22	0.19	27	0	1	0	20'937'920.70	7%
15	192	34	0.18	48	0	1	0	25'287'349.40	8%
16	50	15	0.30	30	0	0	1	13'770'686.40	4%
17	143	20	0.14	36	0	1	0	16'384'310.40	5%
18	81	19	0.23	31	0	1	0	17'917'527.00	6%
19	143	21	0.15	60	0	1	0	19'971'476.70	6%
20	65	13	0.20	35	0	0	0	14'458'499.40	5%

9.1 Test for the conditional independence

Table 10: Test for the conditional independence for the cartel period

<i>Pair of firms</i>	<i>N</i>	<i>Pearson Coeff.</i>	<i>Z – statistic</i>
(6, 18)	19	−0.667	−3.2214
(3, 24)	5	−0.9718	−3.0039
(23, 24)	25	−0.5595	−2.9645
(12, 17)	9	−0.8198	−2.8318
(8, 17)	31	−0.4709	−2.705
(9, 12)	13	0.6652	2.5363
(23, 25)	13	−0.6459	−2.4294
(24, 26)	7	−0.8221	−2.3265
(14, 15)	34	−0.3894	−2.2891
(6, 20)	14	−0.5769	−2.1818
(4, 24)	21	−0.4655	−2.1394
(21, 22)	9	−0.7013	−2.1308
(9, 25)	5	−0.8968	−2.0584
(9, 17)	49	−0.2917	−2.0379
(6, 14)	24	−0.4041	−1.9635
(16, 18)	5	−0.8606	−1.8323
(4, 23)	17	−0.4527	−1.8262
(11, 24)	5	0.8564	1.8097
(11, 20)	9	−0.6246	−1.7944
(11, 15)	18	−0.427	−1.7671
(4, 17)	45	−0.2657	−1.7639
(17, 18)	17	−0.4365	−1.7509
(14, 19)	19	−0.4017	−1.7027
(4, 19)	31	0.3076	1.6823
(3, 11)	10	−0.5456	−1.6196
(22, 23)	16	−0.4178	−1.6044
(11, 14)	17	−0.4031	−1.5988
(4, 9)	58	−0.2113	−1.591
(5, 12)	8	−0.608	−1.5781

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<i>Pair of firms</i>	<i>N</i>	<i>Pearson Coeff.</i>	<i>Z – statistic</i>
(11,18)	15	−0.4134	−1.5233
(4,14)	36	−0.2571	−1.5108
(14,18)	25	0.3078	1.4922
(4,15)	51	−0.212	−1.4913
(6,19)	19	−0.3532	−1.4765
(8,18)	10	−0.4987	−1.4489
(3,17)	9	−0.5189	−1.408
(9,10)	33	−0.2451	−1.3704
(4,10)	31	−0.2499	−1.3511
(8,15)	30	−0.2537	−1.3475
(9,19)	34	−0.2269	−1.2857
(10,16)	7	0.566	1.2832
(3,9)	12	0.4033	1.2828
(16,17)	8	−0.5064	−1.2474
(4,18)	24	0.2541	1.1904
(15,24)	9	−0.437	−1.1476
(3,20)	6	0.5748	1.1339
(4,22)	7	0.5002	1.0992
(22,24)	13	−0.3289	−1.0801
(8,10)	16	−0.286	−1.0607
(21,24)	9	−0.4076	−1.06
(15,16)	9	−0.3961	−1.0264
(4,25)	8	−0.4196	−1.0001
(6,9)	29	−0.1926	−0.9946
(17,21)	5	0.6028	0.9866
(11,17)	14	0.2854	0.9737
(10,15)	32	−0.1774	−0.9653
(15,19)	31	−0.1803	−0.9646
(3,18)	14	−0.2781	−0.9474
(3,10)	6	−0.4898	−0.928
(5,19)	5	−0.5661	−0.9076
(6,17)	24	0.1945	0.9029

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<i>Pair of firms</i>	<i>N</i>	<i>Pearson Coeff.</i>	<i>Z – statistic</i>
(14,20)	15	0.2466	0.8723
(17,20)	29	−0.1671	−0.8602
(6,11)	15	0.2416	0.8538
(5,20)	6	−0.4531	−0.8464
(4,11)	21	−0.1878	−0.8061
(10,17)	24	−0.171	−0.7914
(3,15)	12	0.2575	0.7903
(6,15)	26	−0.161	−0.7791
(17,19)	26	−0.1583	−0.7658
(21,23)	11	−0.2601	−0.7529
(15,21)	5	−0.4868	−0.7522
(20,24)	6	−0.4058	−0.7457
(4,20)	31	−0.1378	−0.734
(18,24)	9	0.2848	0.7173
(10,20)	18	−0.1718	−0.672
(8,11)	10	0.2485	0.6715
(18,20)	12	0.2053	0.6248
(9,14)	38	0.102	0.6058
(9,24)	10	0.2204	0.5928
(12,19)	5	−0.3875	−0.5783
(17,24)	10	−0.2132	−0.5727
(8,24)	5	−0.3642	−0.5398
(16,20)	6	0.301	0.5379
(18,23)	5	−0.3626	−0.5372
(3,4)	13	0.1655	0.5283
(14,17)	25	−0.1121	−0.5282
(6,8)	15	0.1512	0.5279
(8,14)	19	−0.1291	−0.5193
(9,11)	19	−0.1256	−0.5049
(16,19)	5	−0.3342	−0.4915
(6,24)	6	0.2743	0.4875
(19,20)	18	−0.1243	−0.4838

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<i>Pair of firms</i>	<i>N</i>	<i>Pearson Coeff.</i>	<i>Z – statistic</i>
(15,17)	45	−0.0729	−0.4735
(12,20)	5	−0.3221	−0.4723
(9,15)	62	−0.0595	−0.4576
(4,21)	9	−0.1772	−0.4387
(19,23)	6	0.2354	0.4155
(8,19)	18	−0.1049	−0.4076
(14,16)	5	0.273	0.3961
(9,16)	10	0.1486	0.396
(12,15)	10	0.143	0.381
(15,20)	27	0.0753	0.3697
(6,16)	8	0.1638	0.3696
(9,18)	22	−0.0837	−0.3656
(4,8)	32	−0.0669	−0.3606
(8,16)	7	−0.1765	−0.3568
(15,18)	21	0.0817	0.3473
(10,18)	11	−0.1157	−0.3288
(3,14)	14	0.095	0.3159
(24,25)	5	−0.2158	−0.31
(6,23)	6	0.1747	0.3058
(10,11)	9	−0.1195	−0.2941
(14,24)	8	−0.1289	−0.2898
(10,19)	23	−0.0631	−0.2827
(5,17)	6	−0.1594	−0.2785
(23,26)	9	−0.1057	−0.2599
(6,10)	15	0.0735	0.2549
(10,14)	16	0.069	0.2493
(22,25)	5	−0.1697	−0.2423
(8,9)	33	−0.0441	−0.2417
(4,16)	10	−0.0881	−0.2336
(17,23)	6	0.1321	0.2302
(5,9)	8	−0.0929	−0.2083
(3,8)	7	−0.0865	−0.1734

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<i>Pair of firms</i>	<i>N</i>	<i>Pearson Coeff.</i>	<i>Z – statistic</i>
(18,19)	9	0.0695	0.1706
(9,21)	7	−0.0692	−0.1387
(3,6)	7	−0.0616	−0.1233
(8,20)	20	0.0176	0.0725
(4,6)	34	−0.0095	−0.0528
(9,20)	30	0.007	0.0365
(5,15)	6	0.0137	0.0238
(11,19)	8	−0.01	−0.0223

Table 11: Test for the conditional independence for the post cartel period

<i>Pair of firms</i>	<i>N</i>	<i>Pearson Coeff.</i>	<i>Z – statistic</i>
(4, 9)	13	−0.7623	−3.1676
(6, 8)	6	0.926	2.8227
(15, 19)	12	−0.673	−2.4487
(9, 15)	18	−0.5396	−2.3378
(4, 8)	9	−0.7177	−2.2117
(8, 9)	11	0.6227	2.0632
(4, 6)	9	−0.6683	−1.9784
(4, 16)	5	−0.8685	−1.8768
(9, 18)	5	0.8682	1.8746
(8, 19)	8	−0.666	−1.7968
(14, 19)	5	0.8029	1.5653
(10, 17)	10	−0.5271	−1.5508
(10, 15)	6	−0.6876	−1.4609
(6, 15)	7	−0.6204	−1.4514
(6, 14)	7	0.5959	1.3735
(6, 10)	9	−0.4926	−1.3215
(6, 19)	8	0.5055	1.2449
(16, 19)	6	−0.6038	−1.2108
(4, 15)	10	0.4023	1.1282
(9, 17)	18	−0.2665	−1.0577
(14, 16)	6	0.499	0.949
(16, 17)	8	−0.3692	−0.8665
(4, 18)	5	−0.5446	−0.8635
(10, 14)	5	−0.5317	−0.8379
(6, 16)	6	0.4229	0.7816
(9, 14)	9	−0.2988	−0.755
(8, 16)	5	0.472	0.725
(4, 14)	6	−0.3882	−0.7096
(14, 15)	5	−0.4514	−0.6879
(4, 19)	8	−0.298	−0.6873
(8, 10)	7	−0.2996	−0.6181

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<i>Pair of firms</i>	<i>N</i>	<i>Pearson Coeff.</i>	<i>Z – statistic</i>
(8,17)	11	−0.2106	−0.6048
(14,17)	9	−0.2293	−0.5719
(9,16)	6	−0.3066	−0.5486
(4,24)	5	−0.3674	−0.545
(4,17)	13	−0.1288	−0.4098
(15,17)	15	−0.1169	−0.4069
(15,16)	5	0.2616	0.3787
(17,18)	5	−0.2315	−0.3334
(6,9)	12	−0.1081	−0.3257
(10,19)	8	−0.1388	−0.3123
(9,10)	12	−0.0576	−0.1731
(6,17)	11	0.0559	0.1584
(9,19)	12	0.0527	0.1582
(17,19)	13	0.0442	0.1398
(4,10)	8	0.0264	0.059
(8,15)	9	−0.0221	−0.0541

Table 12: Test for the conditional independence only for the cover bids

<i>Pair of firms</i>	<i>N</i>	<i>Pearson Coeff.</i>	<i>Z – statistic</i>
(6,14)	20	−0.7212	−3.7526
(6,18)	12	−0.7717	−3.0736
(4,22)	5	0.9659	2.8673
(4,23)	8	−0.8519	−2.824
(4,17)	37	−0.437	−2.7318
(11,20)	7	−0.8682	−2.6516
(9,15)	50	0.3498	2.5038
(10,17)	17	−0.5791	−2.4737
(14,19)	17	−0.541	−2.2656
(9,12)	5	0.9175	2.2246
(6,20)	14	−0.5769	−2.1818
(23,26)	5	−0.9024	−2.0997
(22,23)	7	−0.7717	−2.049
(11,18)	12	−0.5861	−2.015
(14,18)	18	0.4578	1.9151
(11,14)	15	−0.4947	−1.8785
(4,19)	24	0.382	1.8438
(9,14)	35	0.3124	1.8283
(15,18)	14	0.4966	1.8067
(11,15)	14	−0.4943	−1.7968
(9,19)	30	−0.3318	−1.7917
(16,17)	5	−0.8457	−1.7546
(17,19)	24	−0.3639	−1.7477
(8,10)	12	−0.5127	−1.6991
(3,17)	5	−0.8246	−1.6561
(4,14)	31	−0.2983	−1.6279
(6,11)	12	0.4811	1.5731
(4,16)	7	−0.6508	−1.5534
(17,20)	26	−0.2959	−1.4628
(8,15)	23	−0.312	−1.4433
(17,18)	14	−0.4093	−1.4418

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<i>Pair of firms</i>	<i>N</i>	<i>Pearson Coeff.</i>	<i>Z – statistic</i>
(11,17)	13	0.408	1.3698
(8,9)	28	−0.2557	−1.3076
(6,9)	24	−0.276	−1.2986
(10,16)	7	0.566	1.2832
(15,20)	24	0.269	1.2639
(4,9)	50	−0.1683	−1.1648
(8,17)	23	−0.247	−1.1279
(8,18)	7	−0.5039	−1.109
(9,11)	16	−0.2944	−1.094
(18,19)	6	0.5587	1.0927
(10,15)	25	0.217	1.034
(4,24)	17	−0.2599	−0.9952
(6,8)	12	−0.3148	−0.9775
(3,11)	6	−0.51	−0.9747
(10,18)	6	0.4878	0.9234
(4,10)	23	0.2033	0.9221
(4,8)	23	−0.2029	−0.92
(22,24)	10	−0.334	−0.9189
(9,18)	16	0.248	0.9133
(14,20)	15	0.2466	0.8723
(23,25)	5	−0.5408	−0.856
(4,6)	28	0.1644	0.8295
(23,24)	9	−0.3143	−0.7968
(6,15)	24	−0.1581	−0.7306
(8,11)	9	0.2866	0.7221
(10,14)	13	0.2142	0.6879
(6,10)	14	0.2015	0.6776
(6,19)	17	0.174	0.6576
(9,16)	8	−0.2847	−0.6546
(10,20)	15	0.1831	0.6414
(3,14)	10	−0.2366	−0.6382
(14,17)	24	−0.1383	−0.638

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<i>Pair of firms</i>	<i>N</i>	<i>Pearson Coeff.</i>	<i>Z – statistic</i>
(4,20)	27	0.1271	0.6262
(15,16)	7	−0.3014	−0.622
(15,17)	38	−0.1016	−0.6032
(4,18)	19	0.1445	0.582
(18,20)	10	0.2132	0.5728
(3,4)	9	0.2282	0.5689
(16,20)	6	0.301	0.5379
(6,24)	5	0.3451	0.509
(3,18)	8	−0.2146	−0.4873
(19,20)	18	−0.1243	−0.4838
(6,17)	23	0.0961	0.4311
(3,6)	6	0.2314	0.4081
(9,20)	27	0.0789	0.3872
(11,19)	6	−0.218	−0.3838
(10,19)	21	−0.0852	−0.3623
(17,24)	5	0.229	0.3296
(8,20)	17	−0.0656	−0.246
(19,23)	5	0.1716	0.2451
(6,16)	6	0.1391	0.2424
(9,17)	41	−0.0393	−0.2421
(14,24)	5	0.166	0.2369
(3,15)	8	0.0983	0.2205
(8,14)	16	−0.0568	−0.2049
(9,10)	25	−0.0356	−0.167
(15,19)	27	−0.0311	−0.1522
(8,19)	15	0.0418	0.145
(3,9)	7	0.0658	0.1317
(14,15)	29	−0.0106	−0.054
(18,24)	7	−0.0239	−0.0478
(4,15)	41	0.0039	0.0237
(10,11)	6	0.005	0.0087
(4,11)	16	−0.0006	−0.0022

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<i>Pair of firms</i>	<i>N</i>	<i>Pearson Coeff.</i>	<i>Z – statistic</i>
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Table 13: Test for the conditional independence only for the direct cover bids

<i>Pair of firms</i>	<i>N</i>	<i>Direct Cover Bids</i>	<i>Pearson Coeff.</i>	<i>Z – statistic</i>
(9,15)	62	12	−0.8866	−4.2174
(4,9)	58	8	−0.9434	−3.9536
(9,17)	49	8	−0.9385	−3.8579
(4,10)	31	8	−0.9317	−3.7368
(4,15)	51	10	−0.8783	−3.6201
(10,17)	24	7	−0.9403	−3.4813
(10,18)	11	5	−0.9834	−3.3822
(6,18)	19	7	−0.9321	−3.3483
(10,15)	32	7	−0.9294	−3.3079
(8,15)	30	7	−0.9243	−3.2355
(23,25)	13	8	−0.877	−3.0469
(23,24)	25	16	−0.6826	−3.0069
(9,10)	33	8	−0.8728	−3.0069
(8,17)	31	8	−0.8668	−2.9518
(4,23)	17	9	−0.8342	−2.9438
(6,9)	29	5	−0.9672	−2.8949
(14,15)	34	5	−0.9602	−2.7556
(4,6)	34	6	−0.9181	−2.7311
(9,18)	22	6	−0.9141	−2.688
(4,11)	21	5	−0.9554	−2.6733
(4,8)	32	9	−0.7831	−2.5801
(4,17)	45	8	−0.8148	−2.5517
(4,14)	36	5	−0.9424	−2.4877
(15,18)	21	7	−0.8098	−2.2529
(15,17)	45	7	−0.7483	−1.9382
(3,9)	12	5	0.8571	1.8135
(17,24)	10	5	−0.8332	−1.695
(22,23)	16	9	−0.5916	−1.666
(9,12)	13	8	0.5261	1.3075
(8,9)	33	5	−0.6101	−1.0028
(4,18)	24	5	−0.5846	−0.9467

See next page

<i>Pair of firms</i>	<i>N</i>	<i>Direct Cover Bids</i>	<i>Pearson Coeff.</i>	<i>Z – statistic</i>
(21,23)	11	8	0.2557	0.5847
(3,18)	14	6	−0.3209	−0.5762
(14,18)	25	7	0.2372	0.4836
(12,15)	10	6	0.1019	0.1771

9.2 Test for the exchangeability of the bids

Table 14: Test for the exchangeability of the bids for the cartel period

<i>Pair of Firms</i>	<i>N</i>	<i>F – Statistics</i>	<i>Df.</i>	<i>P – Value</i>
(9,12)	13	9.0016	(4, 534)	0.0000
(5,19)	5	6.927	(4, 534)	0.0000
(5,9)	8	6.852	(4, 534)	0.0000
(12,19)	5	6.2252	(4, 534)	0.0001
(12,15)	10	5.7752	(4, 534)	0.0002
(3,9)	12	4.9744	(4, 534)	0.0006
(3,10)	6	4.6618	(4, 534)	0.001
(5,15)	6	4.6344	(4, 534)	0.0011
(3,4)	13	4.4522	(4, 534)	0.0015
(5,20)	6	4.4016	(4, 534)	0.0017
(4,8)	32	4.045	(4, 534)	0.0031
(12,17)	9	3.7659	(4, 534)	0.005
(8,9)	33	3.7452	(4, 534)	0.0051
(8,17)	31	3.5372	(4, 534)	0.0074
(3,15)	12	3.4913	(4, 534)	0.0079
(9,18)	22	3.4605	(4, 534)	0.0084
(12,20)	5	3.3704	(4, 534)	0.0097
(8,24)	5	3.3377	(4, 534)	0.0103
(8,15)	30	3.2351	(4, 534)	0.0122
(10,11)	9	3.2208	(4, 534)	0.0125
(4,11)	21	3.1885	(4, 534)	0.0133
(9,11)	19	3.1263	(4, 534)	0.0147
(3,8)	7	3.1031	(4, 534)	0.0153
(4,18)	24	3.062	(4, 534)	0.0164
(3,17)	9	2.9938	(4, 534)	0.0184
(23,25)	13	2.9051	(4, 534)	0.0213
(10,17)	24	2.8342	(4, 534)	0.024
(10,18)	11	2.8341	(4, 534)	0.024
(4,23)	17	2.8207	(4, 534)	0.0246

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<i>Pair of Firms</i>	<i>N</i>	<i>F – Statistics</i>	<i>Df.</i>	<i>P – Value</i>
(23,26)	9	2.8158	(4, 534)	0.0248
(3,20)	6	2.7972	(4, 534)	0.0255
(8,20)	20	2.7305	(4, 534)	0.0285
(18,19)	9	2.712	(4, 534)	0.0294
(9,21)	7	2.7031	(4, 534)	0.0298
(8,18)	10	2.6991	(4, 534)	0.03
(9,24)	10	2.5771	(4, 534)	0.0367
(19,23)	6	2.5283	(4, 534)	0.0398
(5,17)	6	2.4986	(4, 534)	0.0418
(17,23)	6	2.4587	(4, 534)	0.0446
(6,23)	6	2.4348	(4, 534)	0.0464
(9,17)	49	2.4317	(4, 534)	0.0466
(14,18)	25	2.397	(4, 534)	0.04933
(4,17)	45	2.3517	(4, 534)	0.0531
(8,10)	16	2.3232	(4, 534)	0.0556
(6,24)	6	2.2839	(4, 534)	0.0593
(24,26)	7	2.2576	(4, 534)	0.0618
(18,20)	12	2.2523	(4, 534)	0.0624
(6,8)	15	2.2275	(4, 534)	0.0649
(11,19)	8	2.1581	(4, 534)	0.0725
(17,19)	26	2.1227	(4, 534)	0.0767
(15,21)	5	2.119	(4, 534)	0.0772
(11,15)	18	2.0871	(4, 534)	0.0812
(24,25)	5	2.082	(4, 534)	0.0819
(20,24)	6	2.0247	(4, 534)	0.0897
(4,19)	31	2.0179	(4, 534)	0.0906
(8,11)	10	2.0086	(4, 534)	0.092
(4,21)	9	2.0037	(4, 534)	0.0927
(17,24)	10	1.9348	(4, 534)	0.1033
(15,18)	21	1.9338	(4, 534)	0.1035
(6,18)	19	1.9319	(4, 534)	0.1038
(4,22)	7	1.8959	(4, 534)	0.1098

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<i>Pair of Firms</i>	<i>N</i>	<i>F – Statistics</i>	<i>Df.</i>	<i>P – Value</i>
(11,24)	5	1.8057	(4,534)	0.1263
(17,21)	5	1.7372	(4,534)	0.1404
(3,6)	7	1.7036	(4,534)	0.1478
(9,14)	38	1.6967	(4,534)	0.1493
(17,18)	17	1.6456	(4,534)	0.1614
(22,23)	16	1.6339	(4,534)	0.1643
(3,14)	14	1.6058	(4,534)	0.1714
(14,24)	8	1.5417	(4,534)	0.1887
(15,17)	45	1.5251	(4,534)	0.1935
(9,25)	5	1.5135	(4,534)	0.1968
(21,22)	9	1.5106	(4,534)	0.1977
(8,14)	19	1.5085	(4,534)	0.1983
(9,19)	34	1.492	(4,534)	0.2032
(15,24)	9	1.4854	(4,534)	0.2052
(4,6)	34	1.4818	(4,534)	0.2063
(4,25)	8	1.4536	(4,534)	0.2151
(8,19)	18	1.4308	(4,534)	0.22243
(4,14)	36	1.4074	(4,534)	0.2302
(8,16)	7	1.4047	(4,534)	0.2311
(11,20)	9	1.3945	(4,534)	0.2346
(3,11)	10	1.3899	(4,534)	0.23612
(10,14)	16	1.375	(4,534)	0.2413
(22,25)	5	1.365	(4,534)	0.2449
(11,17)	14	1.3607	(4,534)	0.2464
(11,14)	17	1.3123	(4,534)	0.2642
(4,24)	21	1.3105	(4,534)	0.2649
(16,18)	5	1.2626	(4,534)	0.2836
(4,9)	58	1.2286	(4,534)	0.2976
(14,17)	25	1.2174	(4,534)	0.3023
(5,12)	8	1.1416	(4,534)	0.336
(10,19)	23	1.1215	(4,534)	0.3455
(3,18)	14	1.1148	(4,534)	0.3487

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<i>Pair of Firms</i>	<i>N</i>	<i>F – Statistics</i>	<i>Df.</i>	<i>P – Value</i>
(6,17)	24	1.0585	(4, 534)	0.3764
(3,24)	5	1.0113	(4, 534)	0.401
(6,10)	15	0.9976	(4, 534)	0.4083
(9,15)	62	0.9811	(4, 534)	0.4173
(18,24)	9	0.9753	(4, 534)	0.4205
(22,24)	13	0.9731	(4, 534)	0.4217
(18,23)	5	0.9612	(4, 534)	0.4284
(6,9)	29	0.9598	(4, 534)	0.4291
(19,20)	18	0.8989	(4, 534)	0.4643
(14,15)	34	0.881	(4, 534)	0.475
(17,20)	29	0.8448	(4, 534)	0.4972
(21,23)	11	0.7895	(4, 534)	0.5323
(15,19)	31	0.7231	(4, 534)	0.5764
(10,15)	32	0.7183	(4, 534)	0.5797
(4,15)	51	0.7002	(4, 534)	0.5921
(4,20)	31	0.6913	(4, 534)	0.5982
(9,10)	33	0.6701	(4, 534)	0.6129
(16,17)	8	0.6629	(4, 534)	0.618
(9,16)	10	0.6416	(4, 534)	0.633
(14,19)	19	0.6354	(4, 534)	0.6375
(4,16)	10	0.6337	(4, 534)	0.6387
(6,19)	19	0.6212	(4, 534)	0.6476
(6,15)	26	0.5975	(4, 534)	0.6646
(6,11)	15	0.5814	(4, 534)	0.6762
(10,20)	18	0.5728	(4, 534)	0.6825
(23,24)	25	0.5511	(4, 534)	0.6983
(14,20)	15	0.5138	(4, 534)	0.7257
(15,20)	27	0.4836	(4, 534)	0.7478
(4,10)	31	0.4759	(4, 534)	0.7535
(21,24)	9	0.4731	(4, 534)	0.7555
(11,18)	15	0.463	(4, 534)	0.7629
(16,20)	6	0.4619	(4, 534)	0.7637

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<i>Pair of Firms</i>	<i>N</i>	<i>F – Statistics</i>	<i>Df.</i>	<i>P – Value</i>
(6,20)	14	0.4364	(4, 534)	0.7824
(14,16)	5	0.4261	(4, 534)	0.7899
(16,19)	5	0.4194	(4, 534)	0.7947
(10,16)	7	0.3396	(4, 534)	0.8513
(6,14)	24	0.3017	(4, 534)	0.8769
(6,16)	8	0.2129	(4, 534)	0.9313
(15,16)	9	0.1817	(4, 534)	0.9479
(9,20)	30	0.0617	(4, 534)	0.993

Table 15: Test for the exchangeability of the bids for the post cartel period

<i>Pair of Firms</i>	<i>N</i>	<i>F – Statistics</i>	<i>Df.</i>	<i>P – Value</i>
(8,16)	5	3.1582	(4,91)	0.0177
(10,19)	8	2.7524	(4,91)	0.0327
(16,19)	6	2.5916	(4,91)	0.0417
(9,14)	9	2.5847	(4,91)	0.0422
(10,14)	5	2.3966	(4,91)	0.056
(14,17)	9	2.1108	(4,91)	0.0858
(14,19)	5	2.1022	(4,91)	0.0869
(17,19)	13	2.0748	(4,91)	0.0905
(6,16)	6	1.9251	(4,91)	0.113
(6,9)	12	1.777	(4,91)	0.1403
(6,10)	9	1.7419	(4,91)	0.1476
(6,14)	7	1.7076	(4,91)	0.1551
(14,15)	5	1.4598	(4,91)	0.221
(6,19)	8	1.4532	(4,91)	0.223
(9,16)	6	1.4232	(4,91)	0.2326
(8,15)	9	1.4165	(4,91)	0.2348
(4,14)	6	1.3734	(4,91)	0.2494
(6,8)	6	1.3486	(4,91)	0.2581
(15,19)	12	1.331	(4,91)	0.2645
(9,10)	12	1.167	(4,91)	0.3307
(8,9)	11	1.1366	(4,91)	0.3444
(8,17)	11	1.1338	(4,91)	0.3456
(8,10)	7	1.0795	(4,91)	0.3714
(16,17)	8	1.0779	(4,91)	0.3722
(14,16)	6	1.0256	(4,91)	0.3985
(6,17)	11	1.0076	(4,91)	0.4078
(10,15)	6	0.9327	(4,91)	0.4487
(4,18)	5	0.9244	(4,91)	0.4534
(4,16)	5	0.9222	(4,91)	0.4547
(9,19)	12	0.8061	(4,91)	0.5245
(17,18)	5	0.8025	(4,91)	0.5267

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<i>Pair of Firms</i>	<i>N</i>	<i>F – Statistics</i>	<i>Df.</i>	<i>P – Value</i>
(4,19)	8	0.7878	(4,91)	0.5361
(9,15)	18	0.7516	(4,91)	0.5595
(9,18)	5	0.72568	(4,91)	0.5767
(6,15)	7	0.6854	(4,91)	0.6039
(4,6)	9	0.6748	(4,91)	0.6112
(8,19)	8	0.5898	(4,91)	0.6709
(4,24)	5	0.5735	(4,91)	0.6826
(15,16)	5	0.4881	(4,91)	0.7444
(10,17)	10	0.4051	(4,91)	0.8045
(15,17)	15	0.3887	(4,91)	0.8162
(4,10)	8	0.3569	(4,91)	0.8386
(9,17)	18	0.2711	(4,91)	0.8959
(4,15)	10	0.2581	(4,91)	0.904
(4,17)	13	0.2563	(4,91)	0.9052
(4,9)	13	0.2223	(4,91)	0.9254
(4,8)	9	0.193	(4,91)	0.9415

Table 16: Test for the exchangeability of the bids for the cover bids

<i>Pair of Firms</i>	<i>N</i>	<i>F – Statistics</i>	<i>Df.</i>	<i>P – Value</i>
(22, 23)	7	8.0317	(4, 406)	0.0000
(4, 23)	8	5.1874	(4, 406)	0.0004
(23, 24)	9	3.9651	(4, 406)	0.0036
(8, 15)	23	3.9448	(4, 406)	0.0037
(4, 22)	5	3.8624	(4, 406)	0.0043
(6, 9)	24	3.5694	(4, 406)	0.0071
(8, 17)	23	3.5612	(4, 406)	0.0072
(6, 15)	24	3.4618	(4, 406)	0.0085
(4, 6)	28	3.3789	(4, 406)	0.098
(8, 9)	28	3.3546	(4, 406)	0.0102
(6, 17)	23	3.3136	(4, 406)	0.0109
(6, 10)	14	3.2137	(4, 406)	0.0129
(6, 24)	5	3.192	(4, 406)	0.0134
(4, 8)	23	3.1462	(4, 406)	0.0145
(23, 25)	5	3.0913	(4, 406)	0.0159
(8, 14)	16	3.0425	(4, 406)	0.0172
(6, 8)	12	2.8831	(4, 406)	0.0224
(6, 19)	17	2.6106	(4, 406)	0.0351
(4, 24)	17	2.4795	(4, 406)	0.0435
(23, 26)	5	2.3597	(4, 406)	0.0528
(9, 24)	8	2.3432	(4, 406)	0.0543
(8, 10)	12	2.1611	(4, 406)	0.0727
(15, 19)	27	2.1508	(4, 406)	0.0739
(10, 11)	6	2.1066	(4, 406)	0.0792
(19, 23)	5	2.0967	(4, 406)	0.0805
(3, 6)	6	2.0394	(4, 406)	0.0881
(9, 11)	16	1.9982	(4, 406)	0.094
(17, 19)	24	1.9726	(4, 406)	0.0979
(17, 24)	5	1.9536	(4, 406)	0.1008
(10, 17)	17	1.9371	(4, 406)	0.1034
(9, 19)	30	1.9085	(4, 406)	0.1082

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<i>Pair of Firms</i>	<i>N</i>	<i>F – Statistics</i>	<i>Df.</i>	<i>P – Value</i>
(4,11)	16	1.9012	(4,406)	0.1094
(9,17)	41	1.8978	(4,406)	0.11
(4,19)	24	1.8688	(4,406)	0.115
(3,17)	5	1.813	(4,406)	0.1254
(11,15)	14	1.7788	(4,406)	0.1322
(8,20)	17	1.7431	(4,406)	0.1396
(10,19)	21	1.6728	(4,406)	0.1554
(11,17)	13	1.665	(4,406)	0.1573
(10,14)	13	1.5945	(4,406)	0.1749
(6,18)	12	1.5817	(4,406)	0.1783
(3,11)	6	1.5572	(4,406)	0.1849
(6,14)	20	1.4708	(4,406)	0.2102
(22,24)	10	1.4663	(4,406)	0.2116
(4,17)	37	1.3989	(4,406)	0.2335
(6,11)	12	1.2937	(4,406)	0.2718
(8,19)	15	1.2209	(4,406)	0.3013
(15,17)	38	1.2067	(4,406)	0.3074
(9,14)	35	1.1768	(4,406)	0.3204
(17,20)	26	1.1504	(4,406)	0.3324
(11,19)	6	1.1079	(4,406)	0.3523
(14,19)	17	1.0885	(4,406)	0.3617
(11,14)	15	1.085	(4,406)	0.3635
(14,24)	5	1.0368	(4,406)	0.3879
(3,4)	9	1.0099	(4,406)	0.402
(14,17)	24	0.9961	(4,406)	0.4094
(14,20)	15	0.9925	(4,406)	0.4114
(3,14)	10	0.9771	(4,406)	0.4198
(9,15)	50	0.9647	(4,406)	0.4267
(3,15)	8	0.9431	(4,406)	0.4389
(10,15)	25	0.9156	(4,406)	0.4547
(3,18)	8	0.9111	(4,406)	0.4573
(4,14)	31	0.9025	(4,406)	0.4624

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<i>Pair of Firms</i>	<i>N</i>	<i>F – Statistics</i>	<i>Df.</i>	<i>P – Value</i>
(19,20)	18	0.8946	(4,406)	0.4671
(10,18)	6	0.8654	(4,406)	0.4847
(3,9)	7	0.8555	(4,406)	0.4908
(6,20)	14	0.8272	(4,406)	0.5084
(11,20)	7	0.7853	(4,406)	0.5352
(16,17)	5	0.7776	(4,406)	0.5402
(9,12)	5	0.7451	(4,406)	0.5617
(8,11)	9	0.7371	(4,406)	0.5671
(8,18)	7	0.6726	(4,406)	0.6113
(15,20)	24	0.6085	(4,406)	0.6567
(4,18)	19	0.5857	(4,406)	0.6732
(9,18)	16	0.5842	(4,406)	0.6743
(6,16)	6	0.5608	(4,406)	0.6913
(14,15)	29	0.5279	(4,406)	0.7153
(18,20)	10	0.5222	(4,406)	0.7194
(10,16)	7	0.5192	(4,406)	0.7217
(18,19)	6	0.483	(4,406)	0.7483
(9,20)	27	0.4697	(4,406)	0.758
(11,18)	12	0.4538	(4,406)	0.7696
(10,20)	15	0.4306	(4,406)	0.7865
(18,24)	7	0.4223	(4,406)	0.7926
(17,18)	14	0.4214	(4,406)	0.7932
(4,20)	27	0.392	(4,406)	0.8144
(15,18)	14	0.376	(4,406)	0.8258
(9,10)	25	0.3681	(4,406)	0.8313
(4,10)	23	0.3285	(4,406)	0.8588
(4,16)	7	0.2957	(4,406)	0.8807
(9,16)	8	0.2726	(4,406)	0.8956
(14,18)	18	0.2513	(4,406)	0.9088
(15,16)	7	0.2087	(4,406)	0.9335
(16,20)	6	0.2026	(4,406)	0.9369
(4,15)	41	0.1809	(4,406)	0.9483

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<i>Pair of Firms</i>	<i>N</i>	<i>F – Statistics</i>	<i>Df.</i>	<i>P – Value</i>
(4, 9)	50	0.084	(4, 406)	0.9873

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Abstract

This paper tests how well the method proposed by Bajari and Ye (2003) performs to detect bidrigging cartels. In the case investigated in this paper, the bid-rigging cartel rigged all contracts during the collusive period, and all firms participated to the bid-rigging cartel. The two econometric tests constructed by Bajari and Ye (2003) produce a high number of false negative results: the tests do not reject the null hypothesis of competition, although they should have rejected it. A robustness analysis replicates the econometric tests on two different sub-samples, composed solely by cover bids. On the first sub-sample, both tests produce again a high number of false negative results. However, on the second sub-sample, one test performs better to detect the bid-rigging cartel. The paper interprets these results, discusses alternative methods, and concludes with recommendations for competition agencies.

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