Crime, Law and Social Change
https://doi.org/10.1007/s10611-024-10142-0

Bid-rigging in public procurement: cartel strategies and bidding patterns

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Accepted: 24 January 2024
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Abstract
Bid-rigging harms economies and societies. While existing research has primarily focused on quantifying the economic damages resulting from bid-rigging cartels, there is a relative dearth of studies exploring how firms interact and the specific techniques they use to rig tenders. Our paper examines the bidding behaviours associated with bid-rigging. Specifically, we investigate how cartel companies exploit legal opportunities, engage in joint and similar bidding and adapt tactics based on the number of colluding bidders. Our study relies on judicial evidence and a dataset of 1,242 companies (including 112 colluding entities) participating in 357 roadwork bid auctions in Italy. Through bootstrap logistic regressions, we analyse company-level indicators and their association with cartel involvement. The results reveal that cartels frequently exploit subcontracts and price similarity. Moreover, we find that bid-rigging tactics vary depending on the number of bidding cartel companies involved. When colluding companies are the majority of bidders, cartels rely on widespread member participation to cover a broad range of prices. Conversely, when cartel companies constitute less than half of the bidders, they tend to form temporary associations. These findings untangle the complexity inherent in cartel agreements and strategies, highlighting the importance of assessing firm interactions and relational patterns within co-bidding networks for a comprehensive understanding of collusive dynamics.

Keywords Bid-rigging · Collusion · Cartels · Public procurement · Network analysis

Introduction

In competitive environments with limited avenues for success, corporate organisations may deviate under pressure (Gross, 1978; Passas, 1990). Construction and other oligopolistic industries face specific challenges, including barriers to entry

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Published online: 20 February 2024

and intense competition (Marshall & Marx, 2012). To overcome these obstacles, companies exploit legal opportunities for profit enhancement, but also engage in collaboration and cartel formation to accelerate growth and alleviate competitive pressures (Clarke, 1983).

Cartels and anticompetitive agreements are common illicit conducts. Between 2015 and 2021, competition agencies in 33 European jurisdictions witnessed a 7% increase in decisions against cartels, reaching 184 cases (OECD, 2023). In 2021 alone, 39 of these decisions involved bid-rigging, a collusion tactic where companies cooperate in auctions to maximize profits instead of engaging in fair competition (OECD, 2009, 2023). Detecting and prosecuting colluding firms is challenging due to the diverse forms they assume and their clandestine nature (Abrantes-Metz et al., 2006; European Commission, 2021).

Bid-rigging is a criminal offense in 29 of the 37 OECD jurisdictions (Organisation for Economic Co-operation and Development), while it is illegal in all of them (OECD, 2021). However, bid-rigging is often addressed through civil or administrative systems, even in jurisdictions that criminalise it (OECD, 2020; Simpson, 2016). This aligns with Sutherland's seminal observations that most corporate violations in the US were not addressed through criminal law (Sutherland, 1949, Chap. 3). It is remarkable that bid-rigging, behaviour that causes significant social harm, is still seldom criminalised in advanced economies, even after almost 80 years of Sutherland's work. While the ambiguity surrounding its treatment contributed to a lack of interest from criminologists (Benson et al., 2009; Stephan, 2017), bid-rigging received more attention from economists (e.g., Bajari & Ye, 2003; Clark et al., 2018; Connor, 2005; Feinstein et al., 1985; Marshall & Marx, 2012; Weishaar, 2013). Despite prior research contributions, little is known about the specific circumstances in which cartels operate and the opportunities exploitable within the business environment. While previous literature has mostly attempted to estimate the economic damages caused by cartel agreements, these studies have often overlooked the crucial role of the relational dimension in shaping bid rigging.

We address these gaps by empirically examining the impact of legal opportunities such as subcontracts and temporary associations, price similarity and company co-bidding relations in determining the likelihood of being in a cartel. We exploit a unique dataset compiled from judicial evidence, which includes information on bidding companies, their bids and cartel affiliations, temporary associations and subcontractors. Findings indicate that cartel companies generally rely on subcontracting and similar pricing. They also adapt bid-rigging tactics depending on the number of bidding cartel companies involved: they rely on price similarity and frequent co-bidding to cover a broad spectrum of prices when they are the majority of bidders; when they are a minority of bidders, they tend to form temporary associations. Overall, our study unpacks collusive strategies by revealing the intricate nature of cartel agreements.

The rest of the paper is organised as follows: the next section reviews current literature in the field. "The current study" section outlines the objectives and hypotheses of the research. The "Methodology" section presents an overview of the data and empirical strategy. The "Results" section presents and analyses the findings, while the "Discussion and conclusions" section provides a discussion of the results. Descriptive statistics and additional results can be found in the Appendix.

Bidding strategies, opportunities and embeddedness in bid-rigging

Bid-rigging leaves traces in public procurement procedures. Several studies on bid-rigging attempted to predict the presence of collusion by detecting such traces. Traditionally, research focused on identifying anomalies in bids distribution: colluding companies often submit extreme offers to favour the predetermined winner, regardless of their cost structures, while honest companies tend to bid consistent with their costs (e.g., Bajari & Ye, 2003; Huber & Imhof, 2019; Porter & Zona, 1993, 1999). Collusion is often associated with low variability among bids (e.g., Abrantes-Metz et al., 2006; Feinstein et al., 1985; Imhof & Wallimann, 2021), negatively skewed bidding patterns (e.g., Padhi & Mohapatra, 2011; Silveira et al., 2023), extreme differences between the first and second bids (e.g., Imhof et al., 2018), bid roundness (e.g., Ishii, 2014) and high award prices (e.g., Busu & Busu, 2021; Froeb et al., 1993).

More recently, scholars have attempted to detect bid-rigging by focusing on patterns of similarity between colluding companies (Aoyagi, 2003; Conley & Decarolis, 2016a; Imhof et al., 2018; Ishii, 2009; Morselli & Ouellet, 2018; Reeves-Latour & Morselli, 2017; Wachs & Kertész, 2019). Studies demonstrated that cartel companies tend to co-participate frequently to increase their joint probability of winning. Revees-Latour and Morselli (2017) described the case of a Canadian cartel whose members repeatedly bid together for decades and took turns in winning. Over time, their contract shares became similar as a result of the rotational bidding scheme adopted. Other authors showed that colluding companies tend to bid similarly to cover higher price ranges (e.g., Fazekas & Tóth, 2016) or have their bids correlated (e.g., Bajari & Ye, 2003). Overall, these studies have demonstrated that, when bidding patterns become too similar between bidders, there is a risk of bid-rigging (Morselli & Ouellet, 2018; Reeves-Latour & Morselli, 2017).

The studies mentioned above point to the role of embeddedness in bidding exchanges in reinforcing collusive conspiracies against both internal and external threats. In this context, embeddedness refers to the interconnection between companies within a bid-rigging network based on their extensive and recurrent co-participation, which strongly suggests that they are participating as a group to rig tenders (Aoyagi, 2003; Reeves-Latour & Morselli, 2017). Repeated interactions between companies were found to reduce the likelihood of defections and cheating. Ishii (2009) described the system of favour exchange established within a Japanese cartel: companies submitted faulty bids to let others win until they reached a position where they could return their favours. Mutual dependencies based on debts increase the likelihood that companies will meet their respective obligations, while simultaneously discouraging cheating (Jaspers, 2016). Frequent co-bidding also allows cartels to supervise the behaviour of their members (Jaspers, 2016; Marshall & Marx, 2012), solve internal problems (Wachs & Kertész, 2019) and discourage honest companies from bidding (Moore, 2013).

Corruption reinforces collusive agreements. In a state-corporate context, actors who operate above the law provide cartels with security and stability (Reeves-Latour & Morselli, 2017; Van De Bunt, 2010; Van Den Heuvel, 2005). In this context, public officials are pivotal, due to the discretionary power they have over the administration of scarce resources. Indeed, the successful performance and the longevity of bid-rigging networks is often dependent on the corrupt exercising of such power, by providing information on the reserve price, directly nominating firms or tailoring evaluation criteria (Della Porta & Vannucci, 1997; Ishii, 2009; Marshall & Marx, 2012; Mungiu-Pippidi, 2016; Soreide, 2002). When collusion is endemic and proliferates across a state-corporate crime context, it comes to be regarded as a normal practice (Van Den Heuvel, 2005). The legitimisation of such non-transparent and corrupt behaviours, in turn, makes it easier for firms to collude, thus compelling other companies to adapt their behaviour, by either exiting the market or bearing the connected risks (Rose-Ackerman & Palifka, 2016).

Another strand of literature focused on the role of the business environment in facilitating collusion. Many studies demonstrated that specific market features, procurement regulation and the type of auction can profoundly influence the way in which collusion occurs (Benson & Simpson, 2009; Della Porta & Vannucci, 2012; Gupta, 2001; Harrington, 2008; Hendricks & Porter, 1989; Kovacic et al., 2006; Marshall & Marx, 2012; Porter & Zona, 1993; Weishaar, 2013). For example, Decarolis (2011) demonstrated that average bid auctions (ABAs) provide specific incentives to collude compared to first-price auctions (FPAs).

While in FPAs the tender is awarded to the lowest bidder, in ABAs the winner is identified through an algorithm that automatically excludes all bids that are unrealistically low.[1] In many cases, this entails the elimination of all the bids that are lower than an anomaly threshold set by the contracting authority (e.g., average price) (Conley & Decarolis, 2016a; Decarolis, 2018). The automatic exclusion of a set of bidders from an auction makes ABAs less competitive than FPAs. In ABAs, assuming that all bidders are truly competing against each other, the unique potential equilibrium would be when all of them submitted an offer equal to the reserve price, thus disregarding their costs in the process (Decarolis, 2011). In this case, the contracting authority must pay the maximum price, while the winning company, which is selected randomly, is rarely the most efficient. In such a scenario, bidders are incentivised to cooperate with each other and form cartels to increase the probability of winning the tender. In this 'lottery', cartel companies submit bids that are not correlated with costs, but, rather, designed purely to manipulate the anomaly threshold (Decarolis, 2011). To secure profits, cartel members must move the threshold to a figure that other bidders will not want to compete against. Consequently, awards in these auctions often yield larger payoffs than FPAs, as they are not bound to the lowest bidder and generally result in higher prices.

[1] ABAs are used in many regions of the world, among which Europe (e.g., Italy, Switzerland), Asia (e.g., China, Japan, Malaysia, and Taiwan), some states of the US (e.g., Florida, NY) and South America (e.g., Chile, Colombia, Peru) (Conley & Decarolis, 2016a).

ABAs also facilitate constant monitoring of cartel members to avoid defections. Monitoring is particularly useful as, in many cases, the defection of a single bidder may lead to a sharp decrease in profits (Wachs & Kertész, 2019). While this is generally true, its effects can be tougher in FPAs than ABAs. In ABAs, cartel companies actively engage in extensive co-bidding to span a wider price range, driven by their awareness of the potential drawbacks of the 'lottery' procurement system (Decarolis, 2011). For instance, if the lowest collusive bidder were to defect, the cartel can rely on the robust participation of other members. Therefore, in ABAs, the higher the number of cartel participants, the more mitigated the impact of a potential defection on the auction's outcome. In contrast, losing the lowest bidder in a FPA could jeopardise the cartel's chances of securing victory in the auction.

In accordance with crime opportunity theories (Cohen & Felson, 1979), companies may find favourable circumstances to rig tenders during their 'routine business activity'. As they operate in the legal market, companies become increasingly familiar with the environment in which they operate. Over time, they may exploit contextual opportunities to increase their profits, without arousing suspicion. Several studies stressed how cartels exploit temporary associations and subcontracts to share profits more easily, discourage smaller companies from bidding or split markets (Fazekas & Tóth, 2016; Italian Competition Authority, 2013; Marshall & Marx, 2012; OECD, 2009; Sabbatini, 2017; Tóth et al., 2015). For example, in some cases, colluding companies opt for joining a temporary association, even when they could bid individually, to facilitate the distribution of profits (Italian Competition Authority, 2013). In tenders awarded to the most economically advantageous offer, the formation of a temporary association by a cartel signals a deliberate strategy to hinder smaller enterprises from attaining the required qualitative score. Moreover, within many collusive schemes, only one cartel member secures the contract, while others receive compensation afterward, often through avenues such as subcontracts or side payments (Italian Competition Authority, 2013; OECD, 2009). Additionally, there are instances where cartel companies strategically refrain from participating in bidding processes, thus distorting competition, with the assurance of securing a subcontract once the contract is awarded.

A few studies have empirically tested the extent to which cartels misused subcontracts and temporary associations. Conley and Decarolis (2016a) showed that companies belonging to the same cartel were more likely to negotiate subcontracts or having bid jointly in a temporary association at least on one occasion (e.g., Conley & Decarolis, 2016a). However, it is still unclear the extent to which cartel companies are more inclined to exploit such legal tools compared to honest companies.

Despite the significant contributions reviewed above, it is still unclear what techniques are used by cartels, under what circumstances and what opportunities are available in the business environment for them to exploit. Moreover, extant literature did not fully acknowledge the relational dimension of bid-rigging. Many scholars have hitherto attempted to detect potential collusive schemes by looking at pairwise bidding interactions, for example, to assess the extent to which the bids depend on each other (e.g., Bajari & Ye, 2003; Porter & Zona, 1993, 1999). In contrast, a few studies went beyond the dyadic dimension to examine subgroup and broader network dynamics. Analysing how companies are connected and positioned within the co-bidding network, as well as their direct and indirect connections, may allow to identify potential collusive schemes.

The current study

This study assesses how colluding companies behave and interact in public procurement, which opportunities they exploit to collude and under which circumstances. It tests three hypotheses. The first hypothesis (H_1) is that *cartel companies are likely to exploit certain legal opportunities to collude, such as temporary associations and subcontracts*. Contracting authorities encourage these legal schemes to foster the participation of small and medium enterprises. Yet cartels often exploit these legal opportunities to their advantage (Albano et al., 2006a, b, 2009; Kovacic et al., 2006; OECD, 2021; Thomas, 2015). Colluding companies are likely to exhibit behaviours that closely resemble those of 'honest' counterparts: to cite Benson and Simpson (2009, 80), their behaviour has a "superficial appearance of legitimacy". Often in ABAs, what differentiates cartel from non-cartel bidders is the frequency with which they adopt certain bidding strategies. Once companies join cartels, they change their bidding behaviour to comply with the agreement established between the other members. We expect cartel firms to be more likely to jointly bid in temporary associations and to subcontract works compared to non-cartel companies. This mechanism may occur in two ways: first, cartel companies may use temporary associations and subcontracts to share profits and attract new partners in the cartel; second, companies may come into contact through temporary associations or subcontracts and subsequently decide to start a cartel together, with legal opportunities facilitating the rise of collusive agreements. These mechanisms consider that cartels do not emerge in a social vacuum, but are often embedded in pre-existing social and business connections (Benson & Simpson, 2009; Della Porta & Vannucci, 2012; Kleemans, 2014).

The second hypothesis (H_2) is that *cartel companies are likely to bid jointly and similarly to increase the probability that the cartel will win the contract*. As reviewed above, this is particularly true in ABAs (Conley & Decarolis, 2016a; Decarolis, 2009, 2011, 2018). In such auctions, cartel companies tend to frequently participate together and submit similar prices to cover the greatest price range possible and thus increase their chances to win (e.g., Choi & Gerlach, 2014; Conley & Decarolis, 2016a; Gupta, 2001; Italian Competition Authority, 2013; Imhof et al., 2018; Ishii, 2009; Jaspers, 2016; OECD, 2009). As companies active in the same market and bidding frequently are likely to know each other, the association of co-bidding and cartel membership may follow two mechanisms: first, cartel firms can coordinate bids to cover the widest possible price range and influence the award procedure to ensure that the cartel wins the contract; second, companies active in the same market can get in touch (e.g., while delivering the envelopes containing the offers) and subsequently decide to collude. Although co-bidding does not constitute a social tie in and of itself, frequent interactions can facilitate the emergence of cartels (Della Porta & Vannucci, 2012; Gupta, 2001).

The third hypothesis (H_3) is that *cartel companies switch between different colluding strategies*. As highlighted in the previous section, cartels adopt a wide array of techniques to collude. Often, they employ more than one strategy at the same time (OECD, 2009). This mechanism can depend, among the other factors, on the propensity of the cartel to shield itself against external threats. The diversification of collusion strategies may reflect an internal security mechanism used by cartels to avoid drawing the attention from law enforcement and competition authorities. Although it is not yet clear whether cartels prioritise security over efficiency (Jaspers, 2016), the literature stressed the pivotal role that security mechanisms play in guaranteeing the survival of cartels (e.g., Della Porta & Vannucci, 2012; Jaspers, 2016, 2019; Lambsdorff, 2002; Marshall & Marx, 2012). Cartels may adjust their colluding strategies by adjusting the balance between security and efficiency. When cartels adopt such security mechanisms to reduce the risk of detection, they sacrifice a part of their profits: "in choosing their bids, a smart cartel would tradeoff cartel profit with the probability of detection. A smart cartel may reduce the power of a test but may not eliminate it entirely" (Harrington, 2008, 40). Moreover, adopting certain strategies too frequently (e.g., repeatedly submitting similar offers) can expose cartels to a higher risk of detection. This awareness may lead cartels to switch between different strategies, thus reducing the power of screening tests used by antitrust authorities.

More specifically, we expect that where cartels cannot rely on the extensive participation from their associates in submitting 'supporting bids', they will make stronger use of temporary associations to increase their chances of winning. This is due to the fact that, by jointly bidding in temporary associations, they engage in a more aggressive bidding strategy (Bouckaert & Van Moer, 2021). Instead, when they can count on the availability of many cartel firms to participate, they will bid similarly and rely on embeddedness, while no longer need to bid in temporary associations to discourage honest firms from submitting offers.

Methodology

Data and samples

Our study is based on the *Appaltopoli* operation, a major investigation on bid-rigging conducted by the Italian Financial Police (*Guardia di Finanza*) between the late 1990s and early 2000s in public procurement in the construction sector. *Appaltopoli* exposed the presence of eight cartels that rigged many auctions awarded in the north western region of Piedmont (Custodero, 2002a, b, 2004). Prosecutors collected extensive evidence on cartel agreements, including confessions by some ring members and wiretaps.[2] The cartels involved in this investigation were established

[2] At the end of the investigation, in 2005, 112 companies were suspected of bid-rigging. By the start of the trial in the same year, the statute of limitations had run out on most of the offences (Tinti, 2014). This was one of the key reasons why, in 2008, only 29 companies were sentenced by the Court of Turin for this crime (Judgement No. 2549/06, 04/28/2008, Turin Court of Justice, 1st criminal Section). Subsequent trials ended up in acquittals due to the expiration of the statute of limitations.

along previous social and work ties. According to the public prosecutors, they were primarily set up by entrepreneurs that were either born in the same territory or lived close to each other. In other cases, cartels were established by entrepreneurs who previously worked together or who were friends or relatives.

Data were collected from 1,242 companies that submitted bids in 357 roadworks ABAs, of which 112 companies were colluding. The dataset expanded data previously gathered by Conley and Decarolis (2016b) with additional information manually drawn from the *Appaltopoli* trial files of the Court of Turin archives,[3] including (a) the names of bidding companies (both winners and losers), (b) the amount of the bid of each company, (c) participation in temporary associations, (d) names of subcontractors and (e) cartel affiliation, when applicable.

From the data, three cross-sectional datasets were generated that included different sets of auctions (Table 1): (1) *All auctions*: whole sample; (2) *Majority cartels*: auctions in which the majority of bidders were cartel companies (at least 50%+1); and (3) *Non Majority cartels*: auctions in which 50% or less of the bidders were cartel companies. In all samples, the unit of observation is the company. The decision to conduct the analysis on the second and third samples, in addition to *All auctions*, was made to better understand how colluding companies behave and what strategies they use depending on how many of them bid in the auction. As discussed in "Bidding strategies, opportunities and embeddedness in bid-rigging" section, in ABAs cartel companies are encouraged to bid jointly to support the bids of others (e.g., Choi & Gerlach, 2014; Conley & Decarolis 2016a; Gupta, 2001; ICA 2013; Imhof et al., 2018; Ishii, 2009; Jaspers, 2016; OECD, 2009). When analysing the whole sample, we noted that while in many cases cartel companies bid in large groups, in others they did not since relatively few of them participated together. This gave us the idea to explore whether cartel companies diversified collusion strategies across auctions depending on the extent of the support they can rely on from their affiliates.

The rationale behind the choice of the standard threshold of 50%+1 to split the whole sample of auctions into *Majority* and *Non-Majority cartels* lies in the assumption that cartel companies are better able to manipulate the winning threshold when bidding in large groups. This threshold was also chosen considering the distribution of the share of cartel bids per auction (see Fig. 3 in the Appendix). In preliminary analyses, an alternative 45% threshold was selected based on this same distribution: the results were consistent but affected by multicollinearity and thus are not shown in this paper.

Variables

The dependent variable, hereinafter *dummy cartel*, indicated whether a firm was a member of a cartel. In line with prior research on collusion (e.g., Clark et al., 2018; Conley & Decarolis, 2016a; Porter & Zona, 1993), all the companies identified as suspects in the *Appaltopoli* investigation were considered members of a

[3] Conley and Decarolis (2016a) gathered information on 812 companies (of which 95 colluding) bidding in 276 ABAs.

Table 1 Description of the three samples

Sample	Bidders (No. observations)	Cartel bidders (% of bidders)	Auctions	Auctions awarded to cartels (%)	Avg. no. bids per auction	Avg. coefficient of variation of discounts by auction
All auctions	1,242	112 (9%)	357	65%	73	29
Majority cartels	399	106 (27%)	108	79%	55	26
Non Majority cartels	1,212	111 (9%)	249	59%	81	30

cartel. Focusing only on convicted companies would have severely biased the results (Croall, 2001; Riccardi & Sarno, 2014; Tunley, 2014). Especially for corporate crimes, the dark number is usually very high and conviction data tend not to be representative of the entire pool of offending firms (Croall, 2001; Sutherland, 1949). This applies also to the *Appaltopoli* case, which resulted in acquittals due to expiration of the statute of limitations.

Our dependent variable disregarded the possible differences between the various cartels. Although the *Appaltopoli* cartels partly differed in terms of size and techniques used to rig tenders, the investigation showed signs of cooperation between companies from different cartels. Indeed, they frequently interacted by bidding in the same contracts. The prosecution showed that representatives of different cartels met regularly to discuss strategies to rig upcoming tenders and, on many occasions, cooperated by supporting each other's bids (Judgement No. 2549/06, 04/28/2008, Turin Court of Justice, 1st criminal Section).

We included different independent variables in the analysis of the three samples (descriptive statistics in Table 3 in the Appendix).[4] *No. bids (log)* (the natural logarithm of the number of bids submitted by a company) and *No. wins* (total number of auctions awarded to a company) were used as control variables.[5] We also included *No. temporary association*, the number of times that a company participated in temporary associations, and *No. similar price*, the number of times that a company submitted an offer similar to those of other companies. Bid similarity was computed on the rebate offered by a company as a percentage of the auction reserve price. Bids were considered similar if they differed by 0.009% points or less.[6]

For subcontracts, we employed alternative dummies. Of these, *Subcontracts* showed whether a company received at least one subcontract. *Subcontracts to cartel*, *Subcontracts by cartel* and *Subcontracts by/to cartel* measured whether a company gave, received, and received and/or gave at least one subcontract to/from a cartel company. Similarly, *Subcontracts to non-cartel*, *Subcontracts by non-cartel* and *Subcontracts by/to non-cartel* were constructed to consider non-cartel companies. *Subcontracts by cartel*, *Subcontracts by non-cartel*, *Subcontracts to cartel* and *Subcontracts to non-cartel* were exclusively used in additional models presented in Table 5 in the Appendix.

Embeddedness was measured by k-core, a variable used in social network analysis. For each sample, a two-mode affiliation matrix recorded bidders' participation in the respective set of auctions. These were transformed into one-mode binary matrices that reflected whether companies bid in the same auctions at least once (i.e.,

[4] We considered additional variables during preliminary exploratory analyses, but we restricted the final selection due to multicollinearity. These included the number of automatic exclusions from auctions and additional network measures such as degree centrality and coreness.

[5] The logarithmic transformation of the number of bids was preferred over the raw measure due to skewness and multicollinearity.

[6] During preliminary analyses, other price similarity thresholds were explored. We selected the threshold by analysing the ratios between the mean scores of cartel and non-cartel firms for each price similarity threshold.

co-bidding matrices), which allowed the computation of k-core.[7] A k-core is "a maximal group of actors, all of whom are connected to some number (k) of other members of the group" (Hanneman & Riddle, 2005, Chap. 11). K-core is often employed to uncover dense communities within larger networks (Batagelj & Zaveršnik, 2011; Seidman, 1983). The measures captures different patterns of connections that signal embeddedness into a larger set of relations, such as direct ties, indirect connections and links between node neighbours (Bastomski et al., 2017). In our analysis K-core defines the largest k-core to which a company belongs in the co-bidding network (Borgatti & Everett, 2002). For example, a k-core of 100 indicates that the company co-bids with a maximum of 100 other companies, all reporting a k-core score of at least 100. Colluding companies with a high *Embeddedness* (k-core) would be better able to protect the cartel against both external and internal threats by discouraging competition through mass participation and monitoring their members while bidding.

Empirical strategy

The selection of variables was based on theoretical assumptions, evidence from prior research and statistical tests. Statistical testing and correlation analysis guaranteed parsimonious models that do not present multicollinearity problems. We compared cartel and non-cartel companies with Mann-Whitney and T-tests (Table 3 in the Annex). With a few exceptions, the distribution of the selected variables was statistically different between cartel and non-cartel firms in all the samples. Moreover, the measures included in the same models were scarcely correlated. The correlation coefficient was lower than 0.7 (Fig. 4 in the Appendix) and the maximum Variance Inflation Factor (VIF) was lower than 3 in all the models (Table 2). Model selection relied on various measures of goodness of fit such as Pseudo R-squared, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Area Under the ROC Curve (AUC).

We used logistic regressions to estimate the probability that a company is a member of a cartel. To ensure that the non-independent nature of the data did not have an effect on the regression estimates (Tsionas, 2019), all models were run on 10,000 permutations using bootstrap, a resampling technique used for estimation on a population by iteratively sampling a dataset with replacement (Mooney & Duval, 1993). In doing so, 10,000 random samples of the same size from the original datasets were used to estimate the regression coefficients. The final values of the estimates are calculated as the average of the coefficients of all the bootstrap samples and are reported as unstandardised odds ratios to facilitate interpretation. A useful feature of this sampling method is that the estimates often follow a normal distribution thus confidence intervals can be calculated and used to present robust results (James et al., 2013, p.209–212).

[7] All the matrices were created and analysed using Ucinet software, version 6.716 (Borgatti & Everett, 2002).

Table 2 Results of logistic regressions on the probability of cartel participation

DV: Cartel (dummy)	All auctions				Majority cartels				Non Majority cartels			
	A	B	C	D	A	B	C	D	A	B	C	D
No. bids (log)	2.0903***	1.4837**	1.4066*	1.7068***	1.8712***	1.3312	1.3123	1.3820*	2.0160***	1.5289**	1.4557**	1.7053***
	(0.28)	(0.22)	(0.20)	(0.27)	(0.28)	(0.22)	(0.21)	(0.22)	(0.24)	(0.22)	(0.21)	(0.25)
No. wins	1.5645**	1.6429**	1.2516	1.7789**	1.8969*	1.9269*	1.5258	2.2465*	1.6334*	1.7168**	1.3136	1.8939**
	(0.27)	(0.30)	(0.20)	(0.36)	(0.51)	(0.57)	(0.45)	(0.80)	(0.31)	(0.35)	(0.25)	(0.43)
No. temporary association	1.0498*	1.0471	1.0384	1.0520*	1.1177	1.2013	1.1994*	1.1962	1.0663*	1.0645*	1.0615*	1.0706**
	(0.02)	(0.03)	(0.03)	(0.02)	(0.08)	(0.11)	(0.11)	(0.11)	(0.03)	(0.03)	(0.03)	(0.03)
No. similar price	1.0616**	1.1021***	1.1161***	1.0950**	1.1029*	1.1440**	1.1550**	1.1553**	1.0842**	1.1278**	1.1443***	1.1250**
	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)	(0.05)	(0.05)	(0.03)	(0.04)	(0.04)	(0.04)
Subcontracts	2.3050*	2.6671**			2.1806	2.3436*			2.4837*	2.6384**		
	(0.78)	(0.92)			(0.91)	(0.99)			(0.92)	(0.99)		
Subcontracts by/to cartel			4.2252***				2.5887*				3.9921***	
			(1.50)				(1.09)				(1.46)	
Subcontracts by/to non-cartel				0.8280				0.5906				0.8836
				(0.33)				(0.38)				(0.36)
Embeddedness		1.0123**	1.0117**	1.0107*		1.0402**	1.0394**	1.0392**		1.0094*	1.0087*	1.0088*
		(0.00)	(0.00)	(0.00)		(0.01)	(0.01)	(0.01)		(0.00)	(0.00)	(0.00)
Constant	0.0053***	0.0018***	0.0021***	0.0018***	0.0488***	0.0037***	0.0040***	0.0040***	0.0074***	0.0033***	0.0038***	0.0030***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
No. of auctions	357	357	357	357	108	108	108	108	249	249	249	249
Observations (No. of companies)	1,242	1,242	1,242	1,242	399	399	399	399	1,212	1,212	1,212	1,212
Pseudo R-Squared	0.43	0.44	0.46	0.43	0.29	0.32	0.32	0.31	0.38	0.39	0.40	0.38

Table 2 (continued)

DV: Cartel (dummy)	All auctions				Majority cartels				Non Majority cartels			
	A	B	C	D	A	B	C	D	A	B	C	D
% predicted cartel firms	41.96	42.86	50.89	41.07	48.11	49.06	50.00	48.11	37.84	39.64	44.14	36.04
% predicted non-cartel firms	98.58	98.85	98.41	98.76	94.88	94.20	94.20	94.20	98.27	98.37	98.55	98.91
% false positives	25.40	21.31	24.00	23.33	22.73	24.64	24.29	25.00	31.15	29.03	24.62	23.08
AUC	0.9167	0.9186	0.9224	0.9179	0.8257	0.8472	0.8486	0.8491	0.9047	0.9047	0.9112	0.9007
AIC*N	439.79	432.01	422.43	439.94	341.98	328.93	327.48	331.82	470.45	465.44	456.55	473.42
BIC	470.54	467.88	458.3	475.8	365.91	356.85	355.41	359.74	501.05	501.14	492.25	509.12
MAX VIF	2.26	2.82	2.88	2.85	1.80	2.23	2.26	2.23	2.06	2.79	2.83	2.81

Unstandardised odds ratios (standard errors)

Bootstrap logistic regressions (10,000 permutations). Standardised coefficients of these specifications are presented in Table 4 in the Appendix. Significance levels: * 0.05, ** 0.010, *** 0.001

Lastly, we conducted a sensitivity analysis to assess the robustness of our findings to the possible presence of undetected cartel companies. Specifically, for each sample, we replicated the regressions assuming that a percentage of non-cartel companies were, in fact, members of cartels. For each sample, we randomly assigned 1%, 2%, 5%, and 10% of non-cartel companies to the cartel. We also recomputed the subcontract-related independent variables. The resulting distributions of the new dependent variables under the specified scenarios are detailed in Table 6 in the Appendix. Our decision not to replicate the analysis for scenarios exceeding 10% of the original non-cartel companies being classified as cartel members is underpinned by two considerations. First, the *Appaltopoli* investigation provided substantial evidence, making it unlikely that a large number of cartel companies eluded detection. Second, in our main analyses we have already focused on suspect companies independently from their final conviction, thereby further mitigating the risk of overlooking cartel involvement within our samples.

The Results section features the outcomes of logistic regression presented in Table 2. This table presents four models (A, B, C and D) showing unstandardised coefficients. Table 4 in the Appendix showcases the same models but incorporating standardised coefficients. In the Appendix, Table 5 presents additional models (E, F, G, and H) that include alternative measures of subcontracting (*Subcontracts by cartel*, *Subcontracts to cartel*, *Subcontracts by non-cartel*, *Subcontracts by non-cartel*), predictors not considered in models A, B, C, and D. Lastly, Table 7 provides the results stemming from the sensitivity analysis.

Results

The models in the *All auctions* sample yielded an acceptable predictive power, with model C showing slightly better performance in terms of AIC/BIC, R-squared and predicted cartel firms (51%) (Table 2). The models reported mixed results for temporary association whereas subcontracts were always associated with a higher probability of being in a cartel. Having received at least one subcontract significantly increased the probability of being part of a cartel between +131% and +167% (models A and B), while giving and/or receiving at least one subcontract to/from a cartel company resulted in an even higher probability (+322%). Instead, giving and/or receiving at least one subcontract to/from a non-cartel company was not significantly associated with bid-rigging.[8] Price similarity and embeddedness were always associated with a higher probability of being in a cartel, with unit increases in these variables respectively leading to between +6–11% and around +1% greater probability of being in cartel in model C, all other variables equal.

Models in the *Majority cartels* sample reported worse predictive performance overall, but improved capacity to identify cartel firms. Temporary association was mostly non-significant, whereas the subcontract variables were significant but their

[8] These results are consistent with additional models presented in Table 3 in the Appendix that included alternative versions of subcontract variables.

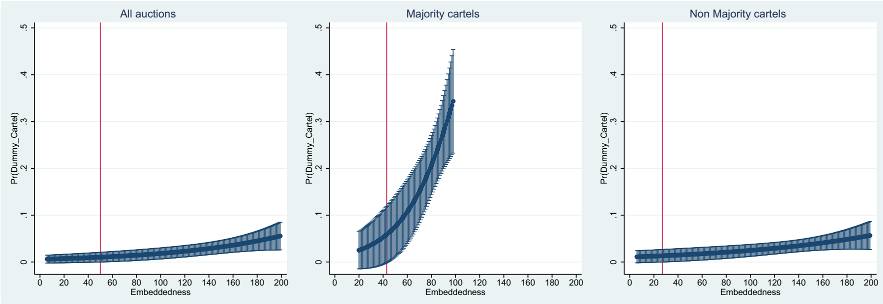

Fig. 1 Adjusted predictions of *Embeddedness* at the 95% confidence interval, by sample. Note: the figure shows adjusted probabilities of Embeddedness at the 95% confidence interval, computed after running the specification C on *All auctions*, *Majority cartels* and *Non Majority cartels* (see Table 2). Made by the authors in Stata v. 16.1

effect on the probability of being in a cartel was lower, particularly in the *Subcontracts by/to cartel* variable in model C.[9] Conversely, price similarity and embeddedness reported stronger effects, with the latter reporting four times the odds ratio of *All auctions* models.

Models in the *Non Majority cartels* sample showed that temporary association and subcontracting were always statistically significant and strongly associated with being in a cartel. Price similarity did not report higher coefficients than those of *All auctions*, slightly lower than those of *Majority cartels*. By contrast, embeddedness was less strongly associated with being in a cartel than in the *All auctions* and *Majority cartels* models.

The inspection of the standardised coefficients (Table 4 in the Appendix) enabled to compare the relative effects of each variable. In the *All auctions* and *Majority cartels* samples, *Embeddedness* and *No. similar price* had the greatest effect. In *Non Majority cartels*, on the other hand, *No. similar price* was the most important variable (besides the number of bids, which was used a control). These predictors have then been inspected to assess their predictive ability at different levels of the covariate, keeping all other predictors at their mean.

Across all samples, margins showed that predictions become significant only after a certain *Embeddedness* value (vertical red line), 50 for *All auctions*, 43 for *Majority cartels* and 27 for *Non Majority cartels*, respectively (see adjusted predictions of *Embeddedness* computed in model C in Fig. 1). In *All auctions*, a one-unit increase at different levels of embeddedness did not homogeneously increase the probability of collusion: the probability of being part of a cartel indeed increased at higher levels of *Embeddedness*, albeit slightly. In *Majority cartels*, the slope is steeper although the confidence interval increased. The margins computed in *Non Majority cartels* are similar to those of *All auctions*.

[9] Additional models using alternative versions of subcontract yielded similar results, except for *Subcontracts to cartel* which turned not significant (Table 3).

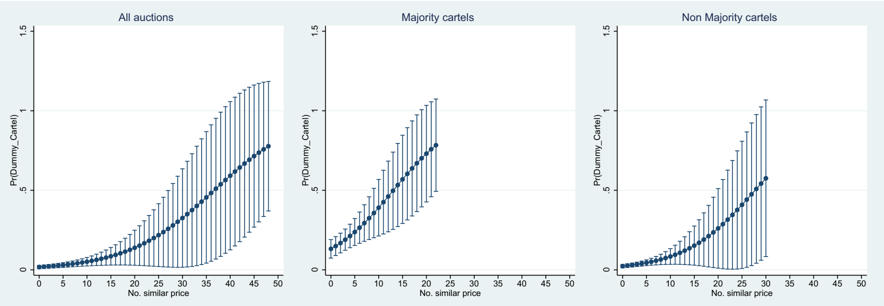

Fig. 2 Adjusted predictions of *No. similar price* at the 95% confidence interval by sample. Note: the figure shows adjusted probabilities of *No. similar price* at the 95% confidence interval, computed after running the specification C on *All auctions, Majority cartels* and *Non Majority cartels* (see Table 2). Made by the authors in Stata v. 16.1

The adjusted predictions of *No. similar price* computed in the model C in all samples showed that in *All auctions* and *Non Majority cartels* the slope became steeper at higher levels of the covariate (Fig. 2). Instead, in *Majority cartels*, a one-unit increase homogeneously increased the probability of collusion, regardless of the level of the predictor.

The sensitivity analysis revealed the robustness of the logistic regression results to variations in the set of cartel companies (see Table 7 in the Appendix). While the main results were consistent with the results reported in Table 2, the most sensitive variables were controls, namely *No. wins* and *No. bids (log)*. *No. temporary association* also demonstrated sensitivity to variations, but this was consistent with what we found in the main models. Surprisingly, in the *Non Majority cartels* sample, *Embeddedness* became non-significant in the 2%, 5% and 10% random experiments. This result is aligned with our hypotheses, as we anticipated *Embeddedness* to be less significant in auctions where the majority of bidders were non-cartel companies compared to those where most bids were submitted by ring members. Despite the overall robustness of the main findings to sensitivity analyses, the 10% experiments reported more discrepancies, as expected. However, as discussed earlier, we consider a 10% variation in the number of cartel companies highly unlikely, given the comprehensive evidence collected during the *Appaltopoli* investigation and our analyses covering all suspect companies.

Discussion and conclusions

Our results partially confirmed the first hypothesis regarding cartels exploiting legal opportunities to collude. In the *All auctions* sample, receiving and/or giving subcontracts from/to a cartel company substantially increased the probability of being in a cartel. However, the results regarding temporary associations were inconclusive.

The findings supported the second hypothesis, showing that price similarity and embeddedness increase the probability of cartel participation. In fact, cartel companies tend to bid jointly and similarly, increasing the chances of winning the contract through collusion.

We found partial support for the third hypothesis. In the *Majority cartels* sample, *Embeddedness* reported a stronger association with bid-rigging and temporary associations was not significant, while in the *Non Majority cartels* sample temporary associations reported a significant and positive correlation. These findings suggest that when enough colluding firms were available to participate and submit cover bids, cartels refrained from temporary associations, as this alone deterred non-cartel companies from bidding. Conversely, when cartels had only a limited number of colluding co-bidders, they were more inclined to form temporary associations. However, regardless of the number of supporting bids, cartels continued to rely on price similarity and subcontracts.

Overall, the findings revealed that cartels exhibited limited diversification in their colluding strategies. The use of co-bidding and temporary associations depended on the number of bidding cartel companies, while price similarity and subcontracting remained consistently influential factors.

Our results partially align with the literature. Studies have emphasised that participation in temporary associations and subcontracting works are legal opportunities that can facilitate profit sharing between colluding companies (Albano et al., 2006a, b, 2009; Kovacic et al., 2006; Thomas, 2015). In accordance with crime opportunity theories, the mere existence of such opportunities creates strong incentives for collusion (Benson & Simpson, 2009). However, our results indicate that the exploitation of these legal options by cartels is part of a broader collusive strategy agreed upon by ring members and adapted to specific circumstances.

The literature has underscored the crucial role of security mechanisms in ensuring the longevity of cartels (e.g., Della Porta & Vannucci, 2012; Jaspers, 2016, 2019; Lambsdorff, 2002; Marshall & Marx, 2012). Cartels are well aware of the risks associated with detection by law enforcement or antitrust agencies, which leads them to adopt strategies to protect themselves from such threats (Baker & Faulkner, 1993; Gupta, 2001; Jaspers, 2016, 2019; Marshall & Marx, 2012). However, our results reveal a more nuanced perspective. Cartels exhibited a degree of strategy diversification, particularly in the use of temporary associations and embeddedness, while consistently employing other strategies such as price similarity and subcontracting. This suggests that cartels struck a balance between security and efficiency when adopting specific strategies. The need to protect the cartel from both external and internal threats is also evident in the k-core structure of the network, where companies are densely interconnected through “loyal co-bidding” to support the predetermined winner, while preventing non-cartel companies from stealing cartels’ market shares or new bidders from entering the market. Our findings regarding embeddedness and price similarity align with existing literature, demonstrating that colluding companies are motivated to uphold the agreement and assist other cartel members to secure future contracts (Jaspers, 2016, 2019; Marshall & Marx, 2012).

The results of this study contribute to a deeper understanding of the nature of bid-rigging, the techniques used by cartels and the incentives provided by the procurement legislative framework. In bid-rigging, relations matter. The way in which cartel companies bid in procurement and therefore the connection with each other reveals the adoption of specific collusive strategies aimed at increasing the cartel's probability of winning and shielding it from potential threats. Such connections are often built on the basis of pre-existing ties (Della Porta & Vannucci, 2012): in the *Appaltopoli* case, indeed, local entrepreneurs formed cartels based on geographic proximity, family/friendship ties and previous collaborations (Judgement No. 2549/06, 04/28/2008, Turin Court of Justice, 1st criminal Section).[10] This highlights the importance of examining relational patterns within co-bidding networks to gain a better understanding of collusive dynamics. By considering these relational aspects, we can gain deeper insights into how cartels operate in procurement processes, uncovering their collusion strategies and the mechanisms they employ to rig tenders. Such an understanding is crucial to design effective measures to detect and deter bid-rigging activities, ultimately promoting fair and competitive procurement practices.

In addition to the issues discussed in the previous sections, this study has some limitations. First, the *Appaltopoli* dataset dates to the end of the 1990s and may be scarcely representative of current bid-rigging patterns. However, recent reports from the Italian Competition Authority indicate that certain bidding strategies analysed in this study, such as temporary associations and subcontracts, are still employed by cartels (Italian Competition Authority, 2020). More recent investigations on bid-rigging concerned small cartels rigging high-value contracts (Italian Competition Authority, 2019, 2020, 2021), which can pose challenges in terms of sample size and statistical analysis of cartel bidding behaviour. Despite these limitations, the *Appaltopoli* dataset offered a rare opportunity to study bid-rigging due to the extensive duration of the investigation, the involvement of many colluding companies and the detailed information provided by the prosecution. Second, the analysis did not include company data, such as location, financial status, ownership and management structure. The incorporation of such information could have contributed to a better understanding of bid-rigging dynamics (Fazekas & Tóth, 2016; Tóth et al., 2015). However, it was challenging to collect historical company data for all the companies, particularly considering that many of them ceased operations following the investigation.

To better understand collusive dynamics and patterns, future research should replicate the analysis in other samples. Further suspicious connections between bidders should be explored (e.g., co-bidders owned by the same shareholder), integrating comprehensive company and ownership data into the analysis. Studying cartel behaviours in different contexts, including ABAs vs. FPAs, various market sectors and procurement procedures, would further enhance our understanding of the phenomenon. Such research could unveil specific areas of risk within different contexts and shed light on the incentives provided by the legal framework for collusion. This will help maintain fair competition and integrity in procurement processes, while also addressing loopholes in the existing legal framework that can inadvertently encourage collusion.

[10] For example, *cartel 8* took its name from the surnames of the two entrepreneurs who were friends and founded it. One of the two men had a love affair with a businesswoman involved in *cartel 5*; some companies of *cartel 4* were managed by members of the same family. Furthermore, before starting to collude, one member of *cartel 2* worked as an employee in a company headed by a member of *cartel 1*.

Appendix

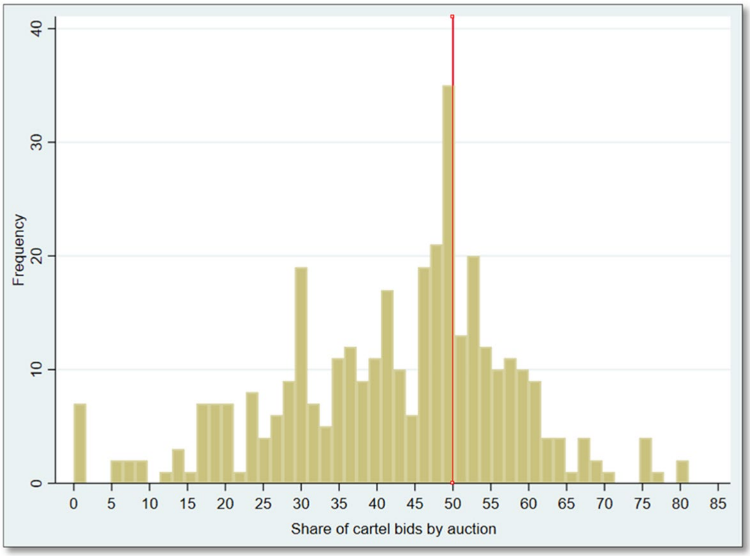

Fig. 3 Distribution of auctions by share of cartel bids. Note: the straight red line marks the threshold used to split the whole sample of auctions in *Majority cartels* and *Non Majority cartels* samples. Made by the authors in Stata v. 16.1

Table 3 Descriptive statistics for the three samples

	All companies						Cartels						Non cartels						
	mean	p50	sd	min	max	*N*	mean	p50	sd	min	max	*N*	mean	p50	sd	min	max	*N*	Diff.
All auctions																			
No. bids (log)	1.82	1.61	1.59	0	5.74	1,242	4.06	4.17	1.13	0.00	5.74	112	1.60	1.39	1.45	0.00	4.97	1,130	***
No wins	0.29	0	1.2	0	21	1,242	2.07	1.00	3.33	0.00	21.00	112	0.11	0.00	0.39	0.00	4.00	1,130	***
No. temporary consortia	1.44	0	4.82	0	64	1,242	7.02	2.00	10.69	0.00	64.00	112	0.89	0.00	3.30	0.00	46.00	1,130	***
No. similar price	2.65	0	6.17	0	48	1,242	13.45	9.50	12.07	0.00	48.00	112	1.58	0.00	3.84	0.00	43.00	1,130	***
Subcontracts	0.08	0	0.27	0	1	1,242	0.41	0.00	0.49	0.00	1.00	112	0.05	0.00	0.21	0.00	1.00	1,130	***
Subcontracts by cartel	0.06	0	0.24	0	1	1,242	0.38	0.00	0.49	0.00	1.00	112	0.03	0.00	0.17	0.00	1.00	1,130	***
Subcontracts by non-cartel	0.05	0	0.22	0	1	1,242	0.21	0.00	0.41	0.00	1.00	112	0.03	0.00	0.18	0.00	1.00	1,130	***
Subcontracts to cartel	0.06	0	0.24	0	1	1,242	0.44	0.00	0.50	0.00	1.00	112	0.03	0.00	0.16	0.00	1.00	1,130	***
Subcontracts to non-cartel	0.06	0	0.24	0	1	1,242	0.31	0.00	0.47	0.00	1.00	112	0.04	0.00	0.19	0.00	1.00	1,130	***
Subcontracts by/to cartel	0.1	0	0.3	0	1	1,242	0.58	1.00	0.50	0.00	1.00	112	0.05	0.00	0.22	0.00	1.00	1,130	***
Subcontracts by/to non-cartel	0.1	0	0.29	0	1	1,242	0.38	0.00	0.49	0.00	1.00	112	0.07	0.00	0.25	0.00	1.00	1,130	***
Embeddedness	121.94	118	58.26	6	199	1,242	169.38	199.00	42.64	54.00	199.00	112	117.24	102.50	57.51	6.00	199.00	1,130	***
Majority cartels																			
No. bids (log)	1.87	1.95	1.37	0	4.64	399	2.98	3.16	1.17	0.00	4.64	106	1.47	1.39	1.21	0.00	3.97	293	***
No wins	0.27	0	0.85	0	9	399	0.80	0.00	1.47	0.00	9.00	106	0.08	0.00	0.27	0.00	1.00	293	***
No. temporary consortia	0.63	0	2.05	0	17	399	1.38	0.00	3.16	0.00	17.00	106	0.37	0.00	1.35	0.00	9.00	293	***
No. similar price	2.48	1	4.44	0	22	399	5.92	4.00	6.32	0.00	22.00	106	1.24	0.00	2.57	0.00	15.00	293	***

Table 3 (continued)

	All companies						Cartels						Non cartels						
	mean	p50	sd	min	max	*N*	mean	p50	sd	min	max	*N*	mean	p50	sd	min	max	*N*	Diff.
Subcontracts	0.11	0	0.32	0	1	399	0.28	0.00	0.45	0.00	1.00	106	0.05	0.00	0.22	0.00	1.00	293	***
Subcontracts by cartel	0.1	0	0.3	0	1	399	0.27	0.00	0.45	0.00	1.00	106	0.04	0.00	0.19	0.00	1.00	293	***
Subcontracts by non-cartel	0.03	0	0.18	0	1	399	0.06	0.00	0.23	0.00	1.00	106	0.02	0.00	0.15	0.00	1.00	293	ns
Subcontracts to cartel	0.07	0	0.26	0	1	399	0.22	0.00	0.41	0.00	1.00	106	0.02	0.00	0.14	0.00	1.00	293	***
Subcontracts to non-cartel	0.06	0	0.23	0	1	399	0.15	0.00	0.36	0.00	1.00	106	0.02	0.00	0.14	0.00	1.00	293	***
Subcontracts by/to cartel	0.14	0	0.35	0	1	399	0.38	0.00	0.49	0.00	1.00	106	0.06	0.00	0.23	0.00	1.00	293	***
Subcontracts by/to non-cartel	0.08	0	0.28	0	1	399	0.19	0.00	0.39	0.00	1.00	106	0.04	0.00	0.21	0.00	1.00	293	***
Embeddedness	75.25	77	21.38	20	98	399	88.00	92.00	13.36	34.00	98.00	106	70.63	77.00	21.87	20.00	98.00	293	***
Non Majority Cartels																			
No. bids (log)	1.73	1.61	1.51	0	5.35	1,212	3.68	3.83	1.08	0.00	5.35	111	1.54	1.39	1.40	0.00	4.66	1,101	***
No wins	0.21	0	0.81	0	12	1,212	1.32	1.00	2.14	0.00	12.00	111	0.09	0.00	0.35	0.00	4.00	1,101	***
No. temporary consortia	1.25	0	4.17	0	58	1,212	5.75	2.00	8.72	0.00	58.00	111	0.80	0.00	3.05	0.00	41.00	1,101	***
No. similar price	1.91	0	3.95	0	30	1,212	8.12	6.00	7.00	0.00	30.00	111	1.28	0.00	2.82	0.00	29.00	1,101	***
Subcontracts	0.07	0	0.26	0	1	1,212	0.39	0.00	0.49	0.00	1.00	111	0.04	0.00	0.20	0.00	1.00	1,101	***
Subcontracts by cartel	0.05	0	0.22	0	1	1,212	0.33	0.00	0.47	0.00	1.00	111	0.02	0.00	0.15	0.00	1.00	1,101	***
Subcontracts by non-cartel	0.05	0	0.21	0	1	1,212	0.21	0.00	0.41	0.00	1.00	111	0.03	0.00	0.17	0.00	1.00	1,101	***
Subcontracts to cartel	0.06	0	0.23	0	1	1,212	0.38	0.00	0.49	0.00	1.00	111	0.02	0.00	0.15	0.00	1.00	1,101	***

Table 3 (continued)

	All companies						Cartels						Non cartels						
	mean	p50	sd	min	max	*N*	mean	p50	sd	min	max	*N*	mean	p50	sd	min	max	*N*	Diff.
Subcontracts to non-cartel	0.05	0	0.23	0	1	1,212	0.26	0.00	0.44	0.00	1.00	111	0.03	0.00	0.18	0.00	1.00	1,101	***
Subcontracts by/to cartel	0.09	0	0.29	0	1	1,212	0.52	1.00	0.50	0.00	1.00	111	0.05	0.00	0.21	0.00	1.00	1,101	***
Subcontracts by/to non-cartel	0.09	0	0.28	0	1	1,212	0.34	0.00	0.48	0.00	1.00	111	0.06	0.00	0.24	0.00	1.00	1,101	***
Embeddedness	122.18	122.5	57.79	6	199	1,212	166.98	199.00	44.83	62.00	199.00	111	117.67	111.00	57.03	6.00	199.00	1,101	***

Three tests assessed the differences between cartel and non-cartel companies, namely Mann-Whitney test, *T*-test and Chi-square test. The Mann-Whitney test was chosen given the skewness of the continuous variables; the *T*-test (two-tail), performed through Ucinet on 10,000 permutations, was computed to account for the non-independent nature of the Embeddedness variable. The Chi-square test was used for dummy variables. The results of the test are reported in the column "Diff." (* 0.05, ** 0.010, *** 0.001)

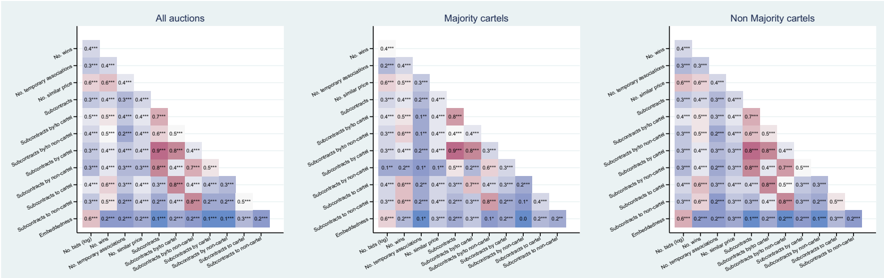

Fig. 4 Independent variables correlation matrices. Note: the figure shows pairwise correlations among the variables in the three samples. Associations between continuous variables were calculated using Pearson correlation, while those between the subcontract variables (dummies) and continuous ones (all the others) were computed through point bi-serial correlation. The matrix shows the correlation coefficients and the significance levels (* 0.05, ** 0.010, *** 0.001). Colours vary according to the strength of the association. Made by the authors in Stata v. 16.1

Author contributions All authors contributed to the study conception and design. CC conducted the data collection, data preparation and analysis, and drafted the first version. FC and MJ revised the first draft. All authors read and approved the final manuscript.

The authors are grateful to Francesco Decarolis for his contributions to the preliminary steps of the study.

Funding Open access funding provided by Università Cattolica del Sacro Cuore within the CRUI-CARE Agreement. No funding was received to assist with the preparation of this manuscript.

Data availability and/or code availability The dataset that supports the findings of this study is available from the corresponding author on reasonable request.

Declarations

Ethics approval This research did not contain any studies involving animal or human participants, nor did it take place on any private or protected areas. No specific permissions were required for corresponding locations.

Consent Not applicable.

Competing interests The authors have no relevant financial or non-financial interests to disclose.

Table 4 Standardised coefficients of regression models by sample

	All auctions				Majority cartels				Non majority cartels			
	A	B	C	D	A	B	C	D	A	B	C	D
No. bids (log)	3.23***	1.87**	1.72*	2.34***	2.36***	1.48	1.45	1.56*	2.87***	1.89**	1.76**	2.23***
No. wins	1.71**	1.82**	1.31	2.00**	1.73*	1.75*	1.43	1.99*	1.49*	1.55**	1.25	1.67**
No. temporary associations	1.26*	1.25	1.20	1.28*	1.26	1.46	1.45*	1.44	1.31*	1.30*	1.28*	1.33**
No. similar price	1.45**	1.82***	1.97***	1.75**	1.54*	1.82**	1.90**	1.90**	1.38**	1.61**	1.70***	1.59**
Subcontracts	1.25*	1.30**			1.28	1.31*			1.27*	1.29**		
Subcontracts by/to cartel			1.54***				1.40*				1.48***	
Subcontracts by/to non-cartel				0.95				0.86				0.97
Embeddedness		2.04**	1.97**	1.86*		2.32**	2.28**	2.27**		1.72*	1.65*	1.66*

The table shows standardised coefficients of models shown in Table 2. Significance levels * 0.05, ** 0.010, *** 0.001

Table 5 Further regressions models including subcontract alternative measures

DV: Cartel (dummy)	All auctions				Majority cartels				Non Majority cartels			
	E	F	G	H	E	F	G	H	E	F	G	H
No. bids (log)	1.4653*	1.7038***	1.6037**	1.6820***	1.3202	1.3755*	1.3655	1.3746*	1.4966**	1.6957***	1.6368***	1.6920***
	(0.22)	(0.26)	(0.24)	(0.26)	(0.21)	(0.22)	(0.22)	(0.22)	(0.21)	(0.25)	(0.24)	(0.25)
No. wins	1.6188**	1.7303**	1.2841	1.7085**	1.9106*	2.0360*	1.6673	2.1108*	1.7248**	1.8484**	1.3786	1.8527**
	(0.30)	(0.32)	(0.23)	(0.35)	(0.59)	(0.58)	(0.61)	(0.76)	(0.36)	(0.38)	(0.29)	(0.41)
No. temporary associations	1.0424	1.0525*	1.0485	1.0520*	1.1988	1.2018*	1.2017*	1.2017*	1.0595*	1.0707**	1.0713*	1.0705**
	(0.03)	(0.02)	(0.03)	(0.02)	(0.11)	(0.11)	(0.11)	(0.11)	(0.03)	(0.03)	(0.03)	(0.03)
No. similar price	1.1059***	1.0950**	1.1064***	1.0961**	1.1441**	1.1558**	1.1571***	1.1528**	1.1354***	1.1254**	1.1347**	1.1255**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Subcontracts												
Subcontracts by cartel	3.6010***				3.2088**				3.4686**			
	(1.37)				(1.42)				(1.46)			
Subcontracts by non-cartel		0.8223				0.5591				0.9507		
		(0.36)				(0.41)				(0.47)		
Subcontracts to cartel			2.9997*				1.6841				2.7986*	
			(1.29)				(1.32)				(1.28)	
Subcontracts to non-cartel				1.0047				0.7361				0.9743
				(0.47)				(0.63)				(0.47)
Embeddedness	1.0128**	1.0107*	1.0096*	1.0109**	1.0403**	1.0399**	1.0396**	1.0397**	1.0097*	1.0089*	1.0074	1.0089*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.0017***	0.0018***	0.0023***	0.0018***	0.0037***	0.0038***	0.0039***	0.0038***	0.0033***	0.0030***	0.0039***	0.0030***

Table 5 (continued)

DV: Cartel (dummy)	All auctions				Majority cartels				Non Majority cartels			
	E	F	G	H	E	F	G	H	E	F	G	H
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
No. of auctions	357	357	357	357	108	108	108	108	249	249	249	249
Observations (No. of companies)	1,242	1,242	1,242	1,242	399	399	399	399	1,212	1,212	1,212	1,212
Pseudo R-Squared	0.45	0.43	0.44	0.43	0.32	0.31	0.31	0.31	0.40	0.38	0.39	0.38
% predicted cartel firms	45.54	41.96	47.32	41.07	49.06	50.00	49.06	48.11	42.34	35.14	39.64	35.14
% predicted non-cartel firms	98.85	98.76	98.50	98.76	94.54	94.20	94.20	94.54	98.55	98.91	98.73	99.00
% false positives	20.31	22.95	24.29	23.33	23.53	24.29	24.64	23.88	25.40	23.53	24.14	22.00
AUC	0.9200	0.9181	0.9202	0.9176	0.8481	0.8483	0.8473	0.8476	0.9061	0.9006	0.9045	0.9008
AIC*N	428.54	440.03	433.32	440.21	326.53	332.06	331.95	332.34	462.69	473.52	467.72	473.53
BIC	464.41	475.90	469.19	476.08	354.45	359.98	359.87	360.26	498.39	509.22	503.42	509.23
MAX VIF	2.80	2.79	2.80	2.78	2.22	2.22	2.22	2.21	2.79	2.77	2.78	2.76

Unstandardised odds ratios (standard errors)

Bootstrap logistic regressions (10,000 permutations). Significance levels: * 0.05, ** 0.010, *** 0.001

Table 6 Distribution of the new dependent variables used for the sensitivity analysis

		All auctions	Majority cartels	Non Majority cartels
1% random experiment	1% of original non-cartel companies	11	3	11
	Num. of cartel companies (new)	123	109	122
2% random experiment	2% of original non-cartel companies	23	6	22
	Num. of cartel companies (new)	135	112	111
5% random experiment	5% of original non-cartel companies	56	15	55
	Num. of cartel companies (new)	168	121	166
10% random experiment	10% of original non-cartel companies	113	29	110
	Num. of cartel companies (new)	225	135	221

Table 7 Logistic regressions on the probability of cartel participation under the assumption that certain non-cartel members were instead cartel members (sensitivity analysis)

DV: New cartel (dummy)	1% random experiment			2% random experiment			5% random experiment			10% random experiment		
	All auctions	Majority cartels	Non Majority cartels	All auctions	Majority cartels	Non Majority cartels	All auctions	Majority cartels	Non Majority cartels	All auctions	Majority cartels	Non Majority cartels
No. bids (log)	1.2114	1.3255	1.3493*	1.2160	1.3373	1.2630	1.0650	1.2561	1.0919	1.0142	1.0053	1.1094
	(0.16)	(0.21)	(0.18)	(0.14)	(0.20)	(0.16)	(0.11)	(0.18)	(0.12)	(0.09)	(0.14)	(0.10)
No. wins	1.1783	1.4470	1.3115	1.2818	1.4909	1.2756	1.3656*	1.5091	1.3563	1.2077	1.7153	1.3382*
	(0.16)	(0.44)	(0.23)	(0.19)	(0.41)	(0.21)	(0.20)	(0.41)	(0.23)	(0.14)	(0.48)	(0.19)
No. temporary associations	1.0395	1.1769	1.0562*	1.0426	1.1620	1.0543*	1.0336	1.1817*	1.0586*	1.0180	1.2435*	1.0279
	(0.03)	(0.10)	(0.03)	(0.02)	(0.09)	(0.03)	(0.02)	(0.10)	(0.03)	(0.02)	(0.11)	(0.02)
No. similar price	1.1139***	1.1448**	1.1277***	1.0943***	1.1319**	1.1174***	1.0801***	1.1289**	1.1181***	1.0725***	1.1484***	1.0880**
	(0.03)	(0.05)	(0.04)	(0.02)	(0.05)	(0.04)	(0.02)	(0.05)	(0.04)	(0.02)	(0.05)	(0.03)
Subcontracts by/to cartel	5.1878***	3.8301**	3.9128***	3.3578***	2.6247*	4.0978***	2.9706***	2.6908*	3.8101***	3.4720***	1.6327	2.6051***
	(1.79)	(1.73)	(1.34)	(1.06)	(1.08)	(1.36)	(0.89)	(1.07)	(1.16)	(0.92)	(0.68)	(0.74)
Embeddedness	1.0092**	1.0327**	1.0071*	1.0064*	1.0233*	1.0051	1.0069*	1.0234*	1.0041	1.0050*	1.0358***	1.0012
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)
constant	0.0059***	0.0070***	0.0079***	0.0126***	0.0169***	0.0156***	0.0266***	0.0222***	0.0365***	0.0662***	0.0164***	0.0988***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
No. of auctions	357	108	249	357	108	249	357	108	249	357	108	249

Table 7 (continued)

DV: New cartel (dummy)	1% random experiment: All auctions	1%: Majority cartels	1%: Non Majority cartels	2% random experiment: All auctions	2%: Majority cartels	2%: Non Majority cartels	5% random experiment: All auctions	5%: Majority cartels	5%: Non Majority cartels	10% random experiment: All auctions	10%: Majority cartels	10%: Non Majority cartels
Observations (No. of companies)	1,242	399	1,212	1,242	399	1,212	1,242	399	1,212	1,242	399	1,212
Pseudo R-Squared	0.40	0.32	0.35	0.33	0.27	0.30	0.24	0.25	0.23	0.17	0.22	0.13
% predicted cartel firms	47.97	48.62	40.16	40.00	45.54	36.84	33.33	46.28	33.13	30.22	45.93	22.17
% predicted non-cartel firms	98.21	94.83	98.53	98.19	94.08	98.42	98.04	93.53	97.80	97.54	92.42	97.68
% false positives	25.32	22.06	24.62	27.03	25.00	25.76	27.27	24.32	29.49	26.88	24.39	31.94
AUC	0.8954	0.8453	0.8775	0.8540	0.8150	0.8434	0.7918	0.8049	0.7857	0.7233	0.7855	0.6985
AIC*N	493.75	333.93	529.65	584.02	359.93	601.30	757.57	380.88	754.88	992.65	410.91	1013.67
BIC	529.62	361.85	565.35	619.89	387.85	637.00	793.44	408.81	790.58	1028.52	438.83	1049.37
MAX VIF	2.89	2.26	2.83	2.88	2.26	2.83	2.88	2.26	2.84	2.88	2.27	2.84

Bootstrap logistic regressions (10,000 permutations). Significance levels: * 0.05, ** 0.010, *** 0.001. Unstandardised odds ratios (standard errors). For each sample, specification C of logistic regression analyses presented in Table 2 was replicated assuming that a certain percentage of alleged non-cartel entities (1%, 2%, 5% and 10%) were, in fact, members of cartels. The variable *Subcontracts by/to cartel* has been re-calculated considering the new distribution of cartel companies

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