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Network similarity and collusion

Carlo Morselli*, Marie Ouellet

Centre international de criminologie comparée/École de criminologie, Université de Montréal, Canada

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ABSTRACT

This study focuses on how collusive construction industry cartels structure their bidding patterns to increase their market shares, while preserving an illusion of competition. Using past research on the economics and social organization of bid-rigging and collusion, we examine a key issue related to similarities within bidding structures that are likely tainted by cartels. The study is empirically based on public procurement data to recreate the structure of interactions between construction industry firms in the province of Quebec (Canada) over a 12-year period (2002–2013). Cross-level multivariate analyses demonstrate that our indicator of similarities in bidding patterns, the Jaccard coefficient, is a positive factor of market shares, but particularly in cities that are targeted for collusive practices. We also emphasize the need to develop a monitoring system that allows researchers and analysts to track collusion patterns in various ways so as to prevent an increase of more sophisticated schemes and cartels.

The construction industry is a highly lucrative business that is vulnerable to many deviant practices extending from a combination of push and pull factors. In most countries, this industry accounts for five to seven percent of the gross domestic product and is estimated to be a $1.7 trillion industry worldwide (Kenny, 2007). Accounts of collusion and corruption emerge from many countries. In their global economic crime survey of 3000 senior representatives in 54 countries, Price Waterhouse Coopers (2010) found that corruption and bribery are increasing and are more prevalent in the construction industry than in the more general business world.

The construction industry is known for being extremely complex and diverse, involving non-standard activities that are difficult to assess and monitor. Moreover, numerous participants from various fields of expertise, ranging from engineers and architects to insurers and clients, must be involved to complete any given construction project. The high levels of uncertainty that typically characterize construction projects generate a wide range of vulnerabilities and criminal opportunities. Transparency International (2006) outlined the most prevalent crimes in this industry which include bribery, extortion, fraud, theft, and sabotage, but the emergence of cartels that set up collusive bidding systems is a more important challenge for authorities.

Collusive bidding refers to cases in which independent firms disclose their bidding prices with each other before the bidding process starts. This allows the bidding firms to predetermine who will win the contract. Collusive bidding over an extended period creates cartels of construction contractors and, if ignored or undetected over a lengthy period, it contributes to establishing increasingly organized deviant schemes between winning firms. This extremely lucrative practice is detrimental because construction project costs are likely to increase beyond the standards of a competitive market (Brockmann, 2009). Firms excluded from such cartels can become excluded from the general construction sector because they cannot compete with or within the bid-rigging system.

The objective of cartels is to benefit from anti-competitive behavior by giving themselves a market edge while preserving the illusion of competition. Anti-trust laws prohibit monopolization, trade restraints, and collusion among firms in order to protect clients (Brockmann, 2009), yet violations of these laws are some of the most pervasive and lucrative forms of corporate deviance (Van den Heuvel, 2005). Accounts of collusion in the construction industry have been reported in countrywide and citywide case studies in Japan (McCormack, 1995; Milhaupt and West, 2000; Hill, 2003), China (Ding, 2001; Zou, 2006), Italy (Savona, 2009; Lavezzi, 2008; Varese, 2011, 2006), Australia (Zarkada-Fraser and Skitmore, 2000; Vee and Skitmore, 2003), the United States (particularly in New York City: Goldstock et al., 1989; Ichniowski and Preston, 1989; Jacobs and Anechiarico, 1992; Thacher, 1995; Jacobs, 1999), and the Netherlands (Fijnaut et al., 1998; van de Bunt and van der Schoot, 2003; Graafland, 2004; Van den Heuvel, 2005; van de Bunt, 2010). Most of the factors and indicators identified to explain the rise of

* Corresponding author at: Centre international de criminologie comparée, Université de Montréal, C.P. 6128, Succursale Centre-ville, Montreal, Quebec, H3C-3J7, Canada.
E-mail address: carlo.morselli@umontreal.ca (C. Morselli).

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collusion in the construction industry are related to markets, logistics, surveillance, and culture, all components found at the root of many problems that typically emerge in this industry. Some of the most important factors and indicators are directly linked to structural components that generally characterize the construction industry. Experiences worldwide consistently demonstrate that the industry is generally large scale, time constrained, and composed of a few large firms and many small firms. Small firms are typically short-lived in this highly competitive landscape, whereas larger firms are more likely to have an exclusive status when they submit bids for larger, costlier, and more profitable projects. These large firms, whether they are successful and well-established or only just emerging, can also create the links of collusion or corruption required to guarantee their competitive edge across major projects.

Few studies have thoroughly examined the structural features of bidding in the construction industry, but some key cases do allow us to provide an initial assessment of this critical phase. In the ideal bidding process, each competing firm would submit an estimate for overall project costs without any knowledge of other competitors' bids. This ideal appears to be more of a rarity than a norm, particularly for firms that have considerable experience in bidding competitions. A more likely scenario involves a series of deviations from this ideal, which includes stifling the competition (also known as *predatory bidding*) whereby larger and more established firms bid lower than the market value and eliminate any realistic competitors. Another deviation emerges when cooperation is introduced into the bidding process. This behavior is generally labelled as anti-competitive and is most commonly identified in three scenarios: in *identical bidding*, where all competitors submit similar bids; in *territorial bidding*, where industry sectors (in the current study, the paving and sewer sectors) and regions are divided before the bidding process begins; and in *rotational bidding*, where a reciprocal pattern is established to ensure that losing firms in one bid become the winning firms in subsequent bids.

This kind of cooperative behavior among competitors suggests that the public authority no longer controls the public procurement process and it signals a heightened level of deviance inside the bidding system. The current study addresses this issue by using public bidding data to recreate the bidding structure for over 1000 active firms across competitive and collusive construction industry settings. Our main objective is to identify how firms involved in collusive bidding maintain an appearance of competition, while also hinting at their bid-rigging schemes. This inquiry focuses on how collusive firms become overly similar in their bidding patterns, while also gaining a great share in the construction market in which they participate. More specifically, we examine how similarities in the bidding structure influence a firms market shares, particularly in collusive contexts. To achieve this objective, we first examine past research on the economic and social organization factors that are often at the root of collusion. Past research is generally consistent with the practical aim of the current study: to devise a monitoring system that allows researchers and analysts to track collusion patterns and thereby prevent an increase in more sophisticated schemes and cartels.

Tracking collusion patterns

Tracking systemic deviant or illegal exchanges between private actors is a challenging task considering that these exchanges can occur for years and even decades before they are detected. However, detection is usually the result of extensive media scrutiny, whistleblowing, or lengthy enforcement efforts to prosecute participants. For instance, documenting all trade conspiracies filed by the US government over a 25-year period, Scott (1989) found that the average duration of antitrust violations was seven years, and most violations were only discovered after complaints were filed by competitors. Because most illicit exchanges are conducted behind closed doors, it has been practically impossible for researchers and authorities to monitor such behavior. Many researchers have gathered publicly available data because direct-observation options are largely inaccessible. As a result, several innovative collusion indicators have been created.

As prevention tools, tracking systems or screens are not designed to work in isolation, but in combination with other measures. Several studies have specified what these measures might include and what types of programs should be established to discourage deviant practices. These measures fall into two major categories: market indicators and structural indicators. Most models developed to detect collusive activities fall into the former, relying on economic features such as price and cost asymmetries among competitors, with attention given to variations in the price/cost ratio across time (Bajari and Ye, 2003; Porter and Zona, 1993). In contrast, structural indicators draw from organizational theories that explain the structure of behaviors and interactions of firms operating in cartel settings. Below, we review the main features of these two sets of indicators, and how they have been used to detect and understand cartel behavior.

Market indicators

There are many ways to track market trends within an industry. Abrantes-Metz and Bajari (2009) and Porter and Zona (1993) demonstrate that the construction industry is vulnerable to collusion because demand is inelastic and stable across most jurisdictions. This inelasticity and stability forces authorities to award contracts to firms even when the costs of these contracts are obviously rising and the lowest project bid consistently surpasses the cost estimated by authorities at the onset of the bidding process. The most straightforward way to detect potential collusion patterns in this context is by examining the dollar amounts of the submitted bids. Shifts in these values are a direct indication of the shape of competition (Bajari and Summers, 2002; Bajari and Ye, 2003). Competition weakens when independence between firms decreases and cooperation emerges as a key component. In the ideal competitive scenario, bids should be substantially different, but as firms begin to share information, they can adjust and agree on submitting higher bids. This is possible when there is a manageable number of competing firms. Therefore, the first two signals that the bidding process is becoming less competitive and more collusive are: 1) a decrease in the number of competing firms, and 2) an increase in 'competing' bids of a similar amount.

Using a spatial econometric approach to identify collusive behavior, Lundberg et al. (2015) explored a recent period in Swedish history during which an asphalt cartel's existence was detected. Seeking to determine whether bidding patterns for cartel-participating firms differed both before and after detection, Lundberg et al. (2015) tested for statistical dependence between cartel members. As evidence of an absence of collusion, their findings identified a positive correlation between losing cartel members' bids as evidence of complimentary bidding during the cartel period and an absence of correlation after detection (Lundberg et al., 2015). Studies have consistently found that price coordination is a crucial operational factor in a collusive cartel (Clark et al., 2017). In addition to dependency and similarity between cartel members' bids, price coordination has also been identified through long-standing stability and low variance around winning bids (Abrantes-Metz and Bajari, 2009; Bajari and Summers, 2002; Hüschelrath and Veith, 2014; Imhof et al., 2016). Past research has suggested that a warning signal exists when the coefficient of variation of submitted bid prices for a contract falls below the seven per cent range (Abrantes-Metz et al., 2005; Chassin and Joanis, 2010; Messick et al., 2011; Porter and Zona, 1993). Investigating whether market shares are equally or similarly split among dominant firms can also be used to screen for potential collusive agreements. When the market shares of winning firms remain too stable over an extended period, or when shares tend to be distributed rather evenly between competitors across time, collusion is likely taking place (Abrantes-Metz and Bajari, 2009). Recent research has established that core firms that submit very similar bids might be indicative of collusion (e.g. Reeves-Latour and Morselli, 2017).

Fluctuations in these measures often indicate the shape of competition within an industry. Irregular patterns are often detected by their stability and consistency. However, the need for multiple indicators is emphasized by discrepancies in the literature regarding whether price variations are effective mechanisms for detecting and identifying collusion.

Networks indicators

Focusing more closely on the internal functioning of cartels, Jaspers (2016) explored non-formal mechanisms that emerge for member retention and compliance across time. Jaspers conducted a qualitative analysis of 14 Dutch cartel cases that involved bid-rigging, price-fixing, and market allocation. He found that, internally, the primary threats to cartel survival were cheating and defection. Specifically, firms would remind cheating or defecting firms that the cartel was formed to increase profits, and abandoning the cartel would result in lower prices and profits. Jaspers also focused on coordination, compensation, and monitoring to identify mechanisms required for the organization of cartels. Coordination was complicated because although increased communication improved coordination, it also increased the likelihood of detection. As such, a pre-set rotational system in which firms would allocate certain contracts helped minimize the need for communication, thus suggesting that the structure of winning patterns provided a means to identify collusion around deviant firms.

One of the first studies to use social network analysis to study the social organization of collusion was Baker and Faulkner's (1993) study of price-fixing in Tennessee's heavy electrical industry. Relying on archival records derived from a public hearing detailing meetings between conspirators, the authors recreated the structure of interactions between cartel participants. One of the key findings of this study was that core or central participants exposed themselves to greater risk of being caught and receiving harsher penalties. Their finding emphasized the degree to which conspirators depend on secrecy and minimal contacts to avoid detection. Building from Baker and Faulkner's (1993) use of social-network analysis to study the structure of collusion, Ponce and Roldán (2016) examined the communication patterns of a price-fixing graphite electrode cartel in Europe. Similarly to Jaspers (2016), communication was identified as central to many of the cartel's mechanisms and Ponce and Roldán (2016) sought to determine how multiple tasks (including price-fixing, volume-allocation, market segmentation, entry deterrence, monitoring and enforcement) were handled within the cartel. By analyzing the logs of employee and management attendance at cartel meetings, the study found the network to be decentralized, with security prioritized over efficiency. Specific findings highlighted that cartel tasks were mostly apportioned by rank, with CEOs forming the governance structure of the cartel, middle managers negotiating agreements, and sales managers tasked with monitoring. Sales managers were the most exposed in this structure because they had the most frequent meetings. Middle-managers were more secure than CEOs in terms of exposure (Ponce and Roldán, 2016).

While Baker and Faulkner (1993) and Ponce and Roldán (2016) relied on meeting notes to record firm interactions, Reeves-Latour and Morselli's (2017) study is one of the first to rely on public bidding data to recreate firm interactions. Examining the interactions of firms across more than 7000 construction contracts administered by the public sector in the city of Laval (Canada) from 1966 to 2013, the authors created a two-mode network in which all firms that bid on contracts were included as nodes, with ties between firms represented by bids on the same contracts. Using core-periphery analysis, the authors identified a group of firms that remained within the core of the collusion network over time. These same firms were at the heart of the network, while also sustaining their dominance (they consistently received a high proportion of the total value of all contracts), remaining similar in their bidding patterns (low price variation across bids submitted) and the proportion of contracts that they received (suggesting the presence of rotational bidding).

Similarly, another study that identified deviant bidding patterns was conducted by Gupta (2001). Although the author did not adopt an explicit social network design, the study focused on the nature of contacts among competitors in the bidding process. Examining the bidding process of the highway construction auction market in Florida between September 1981 and September 1986, Gupta discussed the collusive schemes that can potentially arise from repeated contacts within construction firms on the procurement auction market. Repeated contacts between contractors in this market represented a key factor that gradually facilitated collusive schemes. Such signs of intense cooperation between competitors are potential indicators for identifying and successfully prosecuting collusion. Gupta devised an elaborate statistical framework that accounts for the level of multiple contacts between firms (and potential collusion) in the highway auctions market. Overall, he concludes that repeated and prevalent interaction patterns among firms is indicative of multimarket contact and is conducive to collusion.

Similarity in bidding patterns

Similarity between cartel participants is a common research component when identifying indicators of collusive practices. Market variables suggest that similar or correlated bid prices might indicate the emergence of a conspiracy. In the same vein, structural or network indicators also focus on similarities and dependencies between actors in the structure of firm bidding patterns. Fluctuations in these measures often indicate the shape of competition within an industry and irregular patterns are often detected because of their stability and sameness. Similarities in bids have consistently been observed in various collusive settings. Investigating whether market shares are equally or similarly split among dominant firms can also be useful for screening for potential collusive agreements. Collusive activities could be suspected when winning firms' market shares remain too stable over an extended period, or when shares tend to be distributed rather evenly between competitors across time (Abrantes-Metz and Bajari, 2009). In short, consistent similarity in these patterns among competitors suggests that vulnerabilities within a given industry are more likely to spread beyond the reaches of the authorities who regulate public procurement contexts.

Examining interactions between competitors is another way of determining whether various features of a construction industry are too similar. According to Gupta (2001), repeated contacts among competitors is an indicator of collusion, whereas Reeves-Latour and Morselli (2017) identified cartels among the clusters of firms positioned at the core of annual bidding networks. These studies indicate that even amidst complex schemes by collusive firms to coordinate activities and outcomes, and even while maintaining an appearance of bidding competitiveness, these firms operate in a closed system that sets them apart from non-cartel competitors. Collusive firms therefore become overly similar in their bidding patterns.

Anecdotal accounts have also highlighted how cartel members maintain structural similarity in their bidding patterns. In a study of a price fixing conspiracy in Tennessee, Geis (1967) found that cartel members consistently bid on the same contracts. Assessments of various meetings showed that "a low price would be established, and the remainder of the companies would bid at approximately equivalent, though higher, levels" (Geis, 2007 [1967]: 108). This case was not exclusive to the electrical industry, but has also been observed in Jasper's (2016) study of the Dutch cartel conspiracy and Gupta's (2001) Florida research. In each of these cases, cartel members other than the designated winner submitted artificially high bids. Guided by these accounts, we expect that such patterns between such firms also manifests in the bidding patterns surrounding emerging or established cartels. Specifically, we argue that cartels are more likely to adopt structurally equivalent bidding patterns, where they repeatedly rebid in similar ways with the same set of firms in collusive markets.

Our study proposes that the bidding structure of these firms is associated with a firm's success in collusive markets. More formally, our hypothesis is set in a cross-level interaction: the effect of co-bidding similarity on firms' winnings should increase in collusive environments. We address this hypothesis by using a combination of firm-level bidding data from public procurement records and city-level contextual data on whether a municipality is investigated for collusive behavior. We hypothesize that successful firms (those firms that win higher proportions of the overall market share) are more likely to exhibit co-bidding similarity in their bidding patterns in collusive contexts. This hypothesis is directed primarily at how dominant firms interact to create a collusive system. Our study is one of the few to consider the social organization of bidding patterns and the only study to undertake a temporal and multilevel model that examines the behavior of construction industry firms across cities.

Methodology

Quebec is a particularly interesting and significant region for examining collusion and corruption in the construction industry. Over a seven-year period, the construction industry in this Canadian province was at the center of a large-scale inquiry. Allegations of collusion and corruption emerged in 2009 when whistleblowers reported collusive practices to various media outlets. Following these reports, a series of law-enforcement agencies and task forces were formed to address this problematic context. Mounting allegations, coupled with rising public pressure, led to the creation of an ongoing provincial anticorruption unit, the *Unité permanente anticorruption* (UPAC), as well as a large-scale public inquiry in 2012: the Commission *of Inquiry on the Awarding and Management of Public Contracts in the* Construction *Industry*. One of the longest inquiries in Canadian history, the commission submitted its final report in 2015. This report substantiated many of the claims of corruption and collusion in various sectors of the construction industry across the province.

Over the past five years, Quebec administrators have become more conscientious and raised their monitoring standards for collusive and corrupt practices, but the focus remains largely centred on individual cases and anecdotal accounts obtained from informants. The current study analyzes public bidding data that is largely overlooked by administrative and regulatory actors within and beyond Quebec. Our aim is to balance the informant-based specific-to-general approach which traditionally underlies social reactions to such practices with a general-to-specific prevention and evidence based analytical framework.

Data

The empirical portion of the study begins with the gathering and coding of public procurement records linked to the construction industry across 111 municipalities in the province of Quebec from 2002 to 2013. Each public procurement record provides detailed information on the contract, including: 1) the work to be completed; 2) the names of the firms that bid on a given contract; 3) the amount of each firm's bid; 4) the name of the winning firm (typically the firm with the lowest bid); and 5) the date the contract was awarded. This data set is unique in two ways. First, because each procurement record contains information on the winning and losing firms we can create a two-mode network, where events are represented by contracts and nodes are represented by firms. This was then converted to a one-mode network where firms are linked if they compete on the same contract. This is unlike other public procurement datasets, which often only provide information on the winning firm (e.g., the European Union's Tenders Electronic Daily). Second, the dataset provides information on firms across space and time. Analyses of collusion are often static and restricted to a specific municipality or sector. This characteristic of our dataset enables us to compare patterns in collusive practices across cities and control for changes in firm bidding activity over time.

The final data set is limited to 39 municipalities with populations greater than 20,000 people, as per Statistics Canada figures. These cities combined to represent 69 percent of the total Quebec population in 2011. These municipalities also have more active firms and construction contracts, both in terms of the number and dollar value of contracts. Over time, this means firms benefit from greater stability in the awarding of public construction contracts, which allows us to examine variation in bidding behavior. One drawback of our data is that our sample excludes three major cities with populations over 20,000 (Baie-Comeau; Chateauguay; and Montreal). Procurement records for these cities had detailed information on the winners of the contract, but lacked data on the other bidding firms who were not awarded the contract (losing firms), which prevented us from replicating the networks of competing firms.

The data are also limited to contracts in which there were complete information. Because detailed and uniform records were not consistent within all cities, there were some discrepancies where information on the losing firms was not available for certain electoral periods. In addition, for some electoral periods, cities awarded few or no paving or sewer contracts, precluding us from including these observations in our final sample. Consequently, our dataset includes 211 of the potential 234 sector-city-electoral period combinations (two sectors nested within 39 cities, nested within three electoral periods), excluding electoral periods within the city where there was either insufficient contracts (e.g., less than three contracts awarded over a four-year period) or for which only information on the winning firm was provided.

The final sample includes 1187 firms that bid on paving and/or sewer contracts across 39 different cities and three electoral periods from 2002 to 2013.[1] Because some firms compete for contracts across multiple sectors (e.g., by bidding on both paving and sewer contracts) and multiple cities over time, this created an unbalanced data structure, where some firms contributed a high number of observations. Of the 1187 firms, 35 percent competed for bids in

[1] In Quebec, municipal elections are legally mandated to be held on the first Sunday of November every four years. For 2002 to 2013, this created three electoral periods (electoral period 1: 2002-2005; electoral period 2: 2006-2009; and electoral period 3: 2010-2013).

Table 1
Summary Statistics of Variables Used in Multilevel Logistic Regression for Whether a Firm Ever Won a Contract.

Variables	Mean	SD	Min.	Max.
Firm-period level[a]				
Firm won a contract = 1	0.37	0.48	0	1
Paving sector = 1	0.40	0.49	0	1
Ln number of bids	0.81	1.01	0	5.09
Ln number of cities	2.34	1.09	0	4.44
Co-bidding similarity	0.19	0.14	0	1
City-level				
Collusion target[b]	0.41	0.50	0	1

[a] Summary statistics represent 6189 pooled-observations.
[b] Summary statistics represent 39 municipalities.

Table 2
Summary Statistics of Variables Used in Multilevel OLS Regression for Amount of Market Share.

Variables	Mean	SD	Min.	Max.
Firm-period level[a]				
Ln market share	0.88	1.86	−5.73	4.61
Paving sector = 1	0.40	0.49	0	1
Ln number of bids	1.45	1.17	1	5.09
Ln number of cities	2.30	1.15	1	4.44
Co-bidding similarity	0.16	0.13	0	1
City-level				
Collusion target[b]	0.41	0.50	0	1

[a] Summary statistics represent 2295 pooled-observations.
[b] Summary statistics represent 39 municipalities.

both the paving and sewer sectors. On average, firms competed in 2.78 of the cities in the sample (SD 3.69) and across two electoral periods (mean 1.68; SD: 0.83). The pooled dataset contains 6189 firm-sector-city-electoral period observations.

Measures

Each firm-level covariate is calculated within the sector (paving or sewers), the municipality, and the electoral period in which the firm was active. Our decision to measure covariates as firm-period observations within the sector and municipality allowed us to isolate the factors that led to collusion. Whereas the context within one municipality might allow a firm to engage with a cartel, other contexts might require the firm to adopt more competitive behavior.

We are interested in market share, which is based on the total dollar value of all contracts awarded to a firm within a sector and municipality over an electoral period as a proportion of the total dollar value of the market. We aggregate market winnings over the electoral period (rather than annually) to account for variations in the number and value of contracts per year. Previous studies have demonstrated that electoral periods are a reliable indicator of changes in market shares for collusive firms (Reeves-Latour and Morselli, 2017). A high number of firms that did not win any market share required that we adapt our modeling strategy and provided us with the opportunity to look at two outcomes: 1) firms that won or did not win market shares; and 2) differences in market shares across firms that won. Descriptive statistics for our firm and city-level explanatory variables are provided in Tables 1 and 2 for these two samples.

To measure the predictors of a firm's market share, two levels of covariates were created: firm-period and city-level covariates. The firm-period covariates are time-varying, capturing a firm's bidding behavior (number of bids submitted; number of cities bid in; the paving or sewer sector bid in) and the interactions surrounding a firm's bidding behavior (co-bidding similarity) within the electoral period. The city-level covariate measures whether the municipality had been investigated for collusion over the previous five years.

Three covariates measured firms' bidding behavior. *Paving sector* is a binary variable that indicates whether the firm submitted a bid in the paving or sewer sector (sewer = 0; paving = 1). Although a fraction of firms actively bid across both sectors, the majority specialized in either paving or sewer work. In this sense, they represented two distinct sectors, requiring different firm-level capacities to complete the work required. By including a binary variable representing the sector the firm bid in, we are able to control for this in our models. The *number of bids a firm submitted* is a continuous variable that measures the number of bids a firm submitted within each municipality. Firms that submit more bids have greater odds of winning a higher number of contracts and are also more likely to exhibit specific network patterns by virtue of their presence in the market. The *number of cities in which a firm submitted a bid* represents a firm's competitive scope across a geographic range. It is assumed that firms equipped to bid across multiple municipalities have greater resources and operate on a scale where they may be able to offer more competitive bids. Due to the skewed distribution representing both variables, they were logged in all models.

The valued Jaccard coefficient is used to capture the co-bidding structure of firm bidding patterns. Before calculating this measure, two-mode matrices for each municipality were converted into one-mode networks, with connections between firms established if they competed on the same contract. The sociomatrices are valued in that they also record the number of times firms bid together and represent a firm's bidding interactions within a city, a specific sector of the construction industry, or a specific time period.

Formally, the valued Jaccard index can be expressed as $\sum \min(x_i, y_i) / \sum \max(x_i, y_i)$, where x and y represent a dyad and i represents the contract that they bid on. This equals 1 when x and y have identical bidding contracts when bidding on all the same contracts together and 0 when they do not bid on any contracts together (Borgatti, 2012). The valued Jaccard index provides an approximation of co-bidding similarity between two firms (Borgatti and Everett, 1992). We calculated the valued Jaccard index for each firm's set of alters and then took the average across all firm dyads.

Our final variable provides an indication of the collusive context. A binary measure was created to indicate whether a municipality was targeted by the provincial anticorruption task force (UPAC) or the Commission of Inquiry on the Awarding and Management of Public contracts in the Construction Industry (0 = no; 1 = yes). Cities with allegations of collusive behavior were identified through two sources: 1) the commission's final report that comprised of over 1700 pages detailing the outcomes of the two-year investigation and public hearings related to collusion in the province of Quebec; and 2) an information request that listed all cities investigated for collusion since the implementation of UPAC (Larouche, 2016). We acknowledge that this collusion indicator suffers from some bias. It only includes observed behavior that is detected and investigated by provincial law enforcement agencies and/or the public commission inquiry. As such, it can include false positives that reflect the typical dark figure that underlies much criminological research of official sources—cities that were investigated but where no charges were laid. Conversely, the lack of an investigation or allegation of collusion in a municipality does not necessarily imply there was no collusion. Collusive activities are often exposed by whistleblowers and might therefore only represent 'detected' conspiracies. Furthermore, investigations into collusion might be limited to specific periods. While the breadth and scope of the investigation into collusion mitigates some of these limitations (particularly following the creation of UPAC and a four-year long public inquiry into collusive practices), these official sources provide the strongest multi-city indicator of collusion currently available.

Analytic scheme

Our final analyses examine whether a firm's market share can be predicted by co-bidding similarity in their bidding patterns and, specifically, whether this measure predicts a firm's market share in cities with recognized collusion. In statistical terms, we want to estimate firm-level regression coefficients and how they vary with municipal-level indicators to predict our outcome. Conceptually, we want to examine whether firm bidding patterns in cities with collusive schemes can predict the market success of these firms. We thus apply multilevel techniques to test cross-level interactions and their impact on market success, measured as a firm's market share.

In addition to the cross-level interaction, our modeling strategy also required that we take into account the unique data structure of our sample. First, because firms could submit bids across more than one electoral period, many firms contributed more than one observation to this data. We account for this lack of independence by specifying a three-level multilevel model, including a random intercept at both the firm and city-level. Therefore, the modeling approach consists of a series of three-level multilevel models, with firm-period observations (level 1) clustered within firms (level 2) that are clustered in 39 cities (level 3). Multilevel models provide more accurate estimates of standard errors when observations are clustered into larger units, as it models the intra-cluster correlation (observations within the same cluster are correlated as they share the same cluster-level random effects), considering the likelihood that observations within cities are more likely to be similar than between-city observations (Snijders and Bosker, 1999). Applying individual-level techniques on data with multiple levels underestimates standard errors of the macro-level effects, thereby inflating significance (Raudenbush and Bryk, 2002; Snijders and Bosker, 1999).

Second, because firms' market shares could potentially vary according to whether they bid in the asphalt or sewer sector within any city, we specified a random slope for sector at the firm-level (level 2). The slope allows for variation across firms in modeling their relationship between sector (sewers = 0; paving = 1) and market share. Thus, the slope for sector is specified to vary across firms.

Third, because our dependent variable, the total value of the market share won by a firm, is highly skewed, given many firms competed but won no contracts (43%), this provided us with the opportunity to look at the two separate processes that explain: (1) how a firm won any market share (binary market share; 0 = no; 1 = yes) and, (2) for firms that won at least one contract, the total proportion of the market share they won. Thus, for each market share measure, multilevel models were estimated with the use of either the *xtmelogit* (binary market share) or *xtmixed* (total market share) in Stata version 14 (StataCorp, 2015). Our outcome measures and covariates are all specified for the firm-period (level 1) clustered within the firm (level 2) and the municipality (level 3), with the exception of *collusion target* which is only specified at the municipal-level (level 2) and remains constant across sectors and electoral periods.

With these modeling considerations in mind, our analysis proceeds in the following steps. We begin by estimating multilevel logistic regression models that examine the likelihood of firms winning at least one contract. We then hone in on firms that won at least one contract to estimate the total value of the market they won using multilevel OLS regression models. For all models, our examination of the Variance Inflation Factor (VIF) scores indicated no problems of multicollinearity. Correlations between all our variables are also provided in the Appendix A (see Tables A1 and A2).

Results

Results for the multilevel logistic models predicting firms' binary market shares (whether a firm ever won a contract) are presented in Table 3. Model 1 presents the baseline model that includes firm and municipality characteristics. Model 1 tests the extent to which a firm's ability to win a contract is driven by its market activity. Our measure of a firm's market activity (the number of bids a firm submits) is positive and statistically significant. These results confirm that firms that bid on a higher number of contracts are more likely to win at least one contract ($b = 1.73$, $SE = 0.07$, $p < .001$). However, firms that compete across a higher number of cities (a proxy of a firm's scale) is negatively associated with winning con-

Table 3
Multilevel Logistic Regression Models for Whether a Firm Ever Won a Contract.[a]

Fixed Effects	Model 1		Model 2	
	Coef.	SE	Coef.	SE
Firm-period effects (L1)				
Paving sector	−0.06	(0.09)	−0.04	(0.09)
Ln number of bids	1.73***	(0.07)	1.74***	(0.07)
Ln number of cities	−0.27***	(0.04)	−0.27***	(0.04)
Co-bidding similarity	−5.47***	(0.41)	−4.66***	(0.51)
City-effects (L3)				
Collusion target	−0.28	(0.21)	−0.28	(0.21)
Cross-level interaction (L1 × L3)				
Co-bidding similarity[b] × Collusion target	–	–	−1.85*	(0.73)
Constant	−1.19***	(0.17)	−1.22***	(0.17)
Random Effects	s^2	SD	s^2	SD
Firm-level (L2)				
Intercept variance	1.07	(0.26)	1.09	(0.26)
Slope variance (paving)	1.42	(0.54)	1.46	(0.54)
Intercept/slope covariance	−0.51	(0.29)	−0.54	(0.20)
City-level (L3)				
Intercept variance	0.34	(0.11)	0.33	(0.11)
AIC	6133.84		6129.45	
BIC	6201.15		6203.49	
Log likelihood	−3056.92***		−3053.73***	

*$p < .05$; **$p < .01$; ***$p < .001$.
[a] Level 1 (L1): N = 1992 firm-period observations; Level 2 (L2): N = 1187 firms; Level 3 (L3): N = 39 cities.
[b] Co-bidding similarity has been centered to facilitate interpretation.

Table 4
Multilevel OLS Regression Models for Firms Logged Market Share.[a]

Fixed Effects	Model 1		Model 2	
	Coef.	SE	Coef.	SE
Firm-period effects (L1)				
Paving sector	0.21^{**}	(0.07)	0.19^{**}	(0.07)
Ln number of bids	0.66^{***}	(0.03)	0.66^{***}	(0.03)
Ln number of cities	0.18^{***}	(0.03)	0.17^{***}	(0.03)
Co-bidding similarity	2.75^{***}	(0.27)	2.24^{***}	(0.34)
City-level effects (L3)				
Collusion target	−0.30	(0.26)	−0.30	(0.26)
Cross-level interaction (L1 × L3)				
Co-bidding similarity[b] × Collusion target	–	–	1.25^{*}	(0.52)
Intercept	0.05	(0.19)	0.08	(0.19)
Random Effects	s^2	SD	s^{2*}	SD
Firm-period (L1)				
Within-firm variance	1.17	(0.06)	1.16	(0.06)
Firm-level (L2)				
Intercept variance	0.83	(0.09)	0.82	(0.09)
Slope variance (paving)	0.80	(0.20)	0.81	(0.21)
Intercept/slope covariance	−0.42	(0.12)	−0.42	(0.12)
City-level (L3)				
Intercept variance	0.55	(0.14)	0.56	(0.15)
AIC	8021.80		8018.04	
BIC	8084.92		8086.90	
Log likelihood	-3999.90^{***}		-3997.02^{***}	

$^{*}p<.05$; $^{**}p<.01$; $^{***}p<.001$.
[a] Level 1 (L1): N = 1143 firm-period observations; Level 2 (L2): N = 675 firms; Level 3 (L3): N = 39 cities.
[b] Co-bidding similarity has been centered to facilitate interpretation.

tracts ($b=-0.27$, $SE=0.04$, $p<.001$). The fixed effect of whether a firm bid in the paving and or sewer sector had no significant effect on winning a contract. However, the negative correlation between the firm-level random intercept and random slope for the sector suggests that there was lower variance for firms that bid within the sewer market, as compared to firms that bid within the asphalt market.

Our measures of a firm's network position within the bidding structure show that market success is influenced by how firms bid with other competitors. When examining the Jaccard index effect, co-bidding similarity decreased the likelihood of winning contracts ($b=-5.47$, $SE=0.41$, $p<.001$). At this point, this network result runs counter to what we would expect, however, a very different picture emerges when assessing the level of market shares amongst firms that did win at least one contract during the study period (see results for Table 4 below). Results show that bidding on contracts within collusive municipalities has no statistically significant association with market shares.

The likelihood ratio test statistic ($\chi^2=176.54$, $p<.001$) suggest that the multilevel model is preferred to the single level model. The firm-period observations do not act as independent observations, but rather are clustered by higher order structures. Likelihood ratio tests were also conducted to compare the multilevel model to simpler two-level models, with firm-period observations clustered within firms ($\chi^2=73.28$, $p<.001$) and firm-period observations clustered within cities ($\chi^2=68.64$, $p<.001$), with results suggesting that both the firm-level variance and the city-level variance are significant. Lastly, likelihood ratio tests were also conducted to compare the multilevel model with and without a random slope for the sector at the firm-level ($\chi^2=10.35$, $p<.01$) demonstrating that the inclusion of a random slope improved model fit.

Model 2 adds the study's core construct: the interaction between co-bidding similarity and collusive settings. This allows us to assess whether firms' market shares in collusive settings can be predicted based on the similarity of their bidding patterns. Specifically, we integrate a cross-level interaction term between our city-level collusion indicator and our firm-level measure of co-bidding similarity. In contrast to our hypothesis, the cross-level interaction between co-bidding similarity and municipalities targeted for collusive behavior has a negative and statistically significant impact on a firm's market share ($b=-1.85$, $SE=0.73$, $p<.05$). This finding demonstrates that firms that consistently bid with the same sets of firms (an indicator of cartel formation) were less likely to win a contract in targeted municipalities. Test results confirmed the improvement in model fit by adding the cross-level interaction ($\chi^2=6.39$, $p<0.05$).

Shifting the focus from a dichotomous to continuous measure of market shares changes the narrative significantly. Table 4 presents the results for the models predicting market shares for all firms that won at least one contract. Model 1 estimates the direct effect of our firm and city-level variables on the proportion of market shares. Consistent with the logistic regression models in Table 3, the number of bids a firm submits is positively associated with their market share ($b=0.66$, $SE=0.03$, $p<.001$). In contrast to the logistic models, the number of cities a firm competes in is positively associated with market shares ($b=0.18$, $SE=0.03$, $p<.001$). This is consistent with what we would expect in a competitive market, where firms that operate on a larger scale with more ample resources are better equipped to submit competitive bids and win a greater proportion of the overall market share. Furthermore, bidding in the asphalt market, as compared to the sewer market was associated with higher market shares ($b=0.21$, $SE=0.07$, $p<.01$). Similar to the logistic models, the negative correlation between the firm-level random intercept and random slope for sector suggests lower variance in market share for firms that bid in the sewer market, as compared to firms that bid within the asphalt market.

In regard to our network measure, co-bidding similarity also re-emerges as a significant predictor of a firm's market share, but in this model, the effect is positive. Firms with bidding patterns that more closely resemble their competitors are more likely to win higher market shares ($b=2.75$, $SE=0.27$, $p<.001$). As in the previous models, results show that bidding on contracts within collusive municipalities has no statistically significant association with market shares.

The likelihood ratio test ($\chi^2 = 599.42$, $p < .001$) suggests the multilevel model is preferred to the single level model. Consistent with the logistic model, the results show that the firm-period observations are clustered into higher order structures. Likelihood ratio tests also showed that the three-level multilevel model was preferred to simpler two-level models that clustered firm-period observations within firms ($\chi^2 = 371.91$, $p < .001$) and firm-period observations within cities ($\chi^2 = 133.97$, $p < .001$). Lastly, likelihood ratio tests showed that models that included a random slope improved model fit, as compared to models that did not ($\chi^2 = 23.92$, $p < .001$).

In Model 2 of Table 4, we introduce the cross-level interaction between co-bidding similarity and our city-level indicator of collusion. This is the baseline for our collusion thesis. In a public-procurement driven industry, deviance emerges when competitors begin to cooperate (or collude) and their networks overlap and become structurally similar. In Model 2, results are largely consistent with Model 1, however, the inclusion of the significant cross-level interaction effect between the Jaccard index and targeted cities tells us that co-bidding similarity influences a firm's success in increasing market shares, especially in cities that are targeted for collusion by authorities ($b = 1.25$, $SE = 0.52$, $p < .05$). The likelihood-ratio test was also used to determine whether adding the cross-level interaction provided statistically significant improvement of the model fit to the data. Test results confirmed the improvement in model fit by adding the cross-level interaction ($\chi^2 = 5.76$, $p < 0.05$).

Conclusion

Previous research outlined two defining collusive cartel features. The first highlights social organization and defines a cartel as "any collection of competitive corporate actors that pursue repeated, enduring collusive relations with one another" (Faulkner et al., 2003:511). The second highlights cartel objectives as "a means for firms without significant individual market power to earn greater than competitive profits" (Hay and Kelley, 1974:13). In the current study, we merge the structural and market features of cartels to argue that firms maintain their dominant positions in conspiracies by creating stable sets of co-bidders to preserve an illusion of competition while ensuring their market success. We provide evidence that collusive behavior may be suggested by examining similarity in the patterning of interactions among participants.

The influence of co-bidder similarity (as measured by the Jaccard index) on a firm's success in Quebec's construction industry tells us two stories. We do find that firms with structurally similar bidding patterns had higher market shares (especially in cities that were targeted for collusion), but we also find that co-bidding similarity decreased the likelihood that firms would win contracts. This results in a negative Jaccard effect for contract success (in the binary sense) and a positive effect for market share success. Bidding similarity thus makes a firm less successful to win a contract, but more successful to win more of the market when compared to other firms that have won contracts. What this tells us is that being different may be a key factor for market entry, but once a firm is in that market, similarity takes hold and success is defined by the ability to keep the pace and gather as much of the market in the firm's favor. Whereas uniqueness may be effective at first, increased prominence and recognition are based primarily on how a competitor mixes with dominant others. In short, originality may get you in, but, once you are in, similarity gets you more. The problem in this study's construction industry context is that the incentive for similarity or conformity is particularly salient in cities that are deviant and collusive.

What are the implications of an association between structurally similar firm bidding patterns and market share success? Results can help identify the early formation of cartels. Best results for buyers (e.g. in the current study, government agencies that manage public tenders) are reached when competition exists between sellers (e.g. firms). This is the basic premise guiding public contracting procedures. At the opposite end of the bidding exchange, sellers reap greater benefits by cooperating. Bid auctions aim to create competition between potential bidders to obtain the best possible price. Sealed-bid auctions are thought to be less susceptible to collusion, yet cartels are formed nonetheless and participants are forced to predetermine the submitted prices and the winner of the auction. The objective of cartels is to benefit from anti-competitive behavior, allowing for market advantage and preserving the illusion of competition. We would also expect cartels to form in an unmonitored setting. This is the underlying thesis in Geis' seminal work: *"the elimination of competition meant the avoidance of uncertainty, the formalization and predictability of outcome, the minimization of risks. It is, of course, this incentive which accounts for much of human activity, be it deviant or 'normal'"* (Geis, 2007 [1967]: 116). As Geis illustrated, the recurring pattern of a price fixing conspiracy was directly related to the degree of law enforcement activity and market activity. In unmonitored settings, deviant behavior emerges and becomes increasingly organized and sophisticated.

Our study proposed a measure that can be used to monitor and identify deviant practices. Most regulatory frameworks rely on a specific-to-general approach that is dependent on whistleblowers and other market actors who emerge to denounce the development of collusive and corrupt schemes. Our results emphasize a general-to-specific approach that examines patterns in public tender data to detect anomalies in bidding and winning patterns. With a practical outlook in mind, we advance that systematic monitoring of firm bidding interactions can help detect changes in the competitive environment of contract allocations.

Capitalizing on a set of public data that is often overlooked in the study of economic or white-collar crime allows us to go beyond traditional data sources. Analogous research has demonstrated the usefulness of public data for understanding the social organization of collusion. One of the main findings of Baker and Faulkner's (1993) study of large-scale fraud is that communication between firms engaging in a collusive conspiracy is minimal. Fleshing out such collusive schemes is therefore not a simple task that relies merely on the identification of direct physical connectivity between participants, a scenario which is often sought when employing informant-based testimonies. In this sense, the identification of more discrete network patterns that are based on mass public procurement records are strong alternatives for detecting collusive behavior in that they tap into the "impersonal communication procedures and decision rules (. . .) used as a substitute for direct personal communication and negotiation" (Baker and Faulkner, 1993: pp. 843). This is also highlighted in the more recent Dutch experience, where firms relied on rotational winning schemes to limit firm communication (Jaspers, 2016), which was also consistent with testimony during the Quebec public inquiry (Commission of inquiry on the awarding and management of public contracts in the construction industry (CEIC, 2015). Thus, in collusive settings, public procurement records can be one of the most visible and underused resources to examine conspiracies insofar as these records provide detailed data on the setting in motion of bid rigging schemes.

Understanding the operations of bid rigging can assist in future research on collusion, corruption, and other forms of economic crime within and beyond the construction industry. Methods to detect collusive behavior can be used by scholars and policymakers to study the phenomenon and derive estimates, minimizing biases inherent in official and self-report data. Estimates of collusive bidding, including its scope and prevalence and the longevity of cartels, can be derived from public procurement data. As noted by Simpson (2013:319) in a review of the literature on white collar crime, "little is known about the criminal careers of companies (onset, frequency, specialization, and desistance)". Using diagnostic tools with a set of bidding data could allow for cross-country comparisons that would contribute to theories on the antecedents and connections of recurrent relationships that lead to collusive behavior. The market and network indicators that are applied in this study and the general research program within which it emerges are critical for developing a pro-active monitoring system of deviant patterns in any given public procurement setting.

Limitations

The public bidding data used for this study provide several advantages, particularly the ability to examine the structure of firm interactions across sectors and municipalities. The data also uniquely allow for examining the social interactions of firms over time, which sets this study apart from other investigations of collusion that rely on archival records of case studies or on official records of detected offenders. Other investigations have rarely examined how firms structure their behavior across time or contexts. Despite their positive features, the public bidding data and measures of the current study suffer from some limitations.

First, and consistent with Simpson's (2013) proposition, our data lack firm-level attributes. Differences in market shares may be predicted by a firm's resources: firms operating on a larger scale with greater resources might be better positioned to undercut the competition while still making profits. We attempt to measure this difference in firm size by using a proxy of the number of cities where they bid. However, this might overlook large companies that bid primarily within one location. Conversely, it might capture smaller firms that cannot succeed in a collusive market and that relocate to neighboring municipalities. Although it is an imperfect measure, we believe it provides a good proxy. Firms that submit bids across multiple municipalities are more likely operate on a larger scale and require greater financial and material resources.

Second, we lack data on alternative collusive arrangements that might not be observed in public procurement data. For example, some cartels might operate by sharing profits with other firms in the form of subcontracts. Although subcontractors (or *phantom bidders*) might contribute to the appearance of competition by submitting complementary bids, it is also possible that they simply withdraw from this process. Importantly, our results showed a positive relationship between co-bidding similarity and market share for firm's that won at least one contract in cities targeted for collusion; and a moderate negative relationship between co-bidding similarity and binary market share (firm won at least one contract = 1) across all firms in cities targeted for collusion. These results likely reflect two different processes, distinguishing between active market participants in the former scenario and more peripheral participants 'one-time bidders' in the latter scenario. However, the individuals who do not win any contracts may also be more important that they appear for understanding various collusive scenarios, particularly if such firms are amongst the phantom bidders that enable collusive schemes by providing an appearance of competitive behavior. Additional information on how subcontracting plays out in collusive markets might help isolate these firms and the processes that they contribute to.

Third, our measure of collusive municipalities, as discussed earlier, might contain false positives or negatives. Although our sampling strategy of municipalities with populations over 20,000 can help mitigate this—capturing larger markets and thus the dedication of more ample resources—it is possible that municipalities not targeted by UPAC were not devoid of collusion, and municipalities targeted were not necessarily collusive. The high-profile inquiry, which lasted over four years and contributed to increased law enforcement efforts (e.g. creation of provincial anticorruption task force), helps mitigate this risk, but we cannot confirm the exact nature of collusive bidding across these cities.

Future research would benefit from complementary data on cartel interactions during meetings designed to divide the market among participants, and how these data translate into firm bidding behavior. Similar to Baker and Faulkner (1993), these complementary sources could assist in augmenting the validity of research findings and could demonstrate how the observed bidding process influences the organization of cartels.

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Appendix A.

Table A1
Correlation Table of Variables Used in Multilevel Regression for Whether a Firm Ever Won a Contract.

	1	2	3	4	5
1. Firm won a contract	–				
2. Paving sector	−0.008	–			
3. Ln number of bids	0.487***	0.063***	–		
4. Ln number of cities	−0.027*	0.029*	0.147***	–	
5. Co-bidding similarity	−0.140***	0.224***	0.033**	0.120***	–
6. Collusion target	−0.048***	0.001	−0.070***	−0.003	−0.036

N = 6189 pooled observations.
*p < .05; **p < .01; ***p < .001.

Table A2
Correlation Table of Variables Used in Multilevel Regression for Logged Market Share.

	1	2	3	4	5
1. Market share	–				
2. Paving sector	0.132***	–			
3. Ln number of bids	0.373***	0.121***	–		
4. Ln number of cities	0.238***	0.025	0.196***	–	
5. Co-bidding similarity	0.407***	0.245***	0.173***	0.078***	–
6. Collusion target	−0.028	0.034	−0.091***	−0.023	−0.053*

N = 2295 pooled-observations.
*p < .05; **p < .01; ***p < .001.

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