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COLLUSION DETECTION IN PUBLIC PROCUREMENT USING COMPUTATIONAL METHODS

The Danish Competition and Consumer Authority (DCCA) has developed and implemented computational methods to identify suspicious bidding in public procurement.

This article describes a new screening tool for identifying collusion and cartels in public tenders. The tool is intended as a complement to traditional investigative methods and can be used to flag tenders and companies for additional scrutiny.

Read the article ↓

1. *Ex officio* screening: identifying collusion in public procurement

Effective competition between companies creates significant benefits for consumers and is a driver of innovation, productivity, and growth.

The goal of a cartel on the other hand, is to prevent competition and the benefits that competition creates. Cartels are estimated to increase prices by an average of 20% in Denmark and internationally, and at times by 50-100%.[1] Cartels are illegal in Denmark, with penalties that include fines and, in severe cases, imprisonment.

In the EU, studies show that cartels operate for a period of approximately 4-6 years, and the probability of a cartel being detected is estimated to be 13%.[2] The overall negative effects of cartels are difficult to measure but considered significant.[1]

Public procurement represents 14% of Denmark's GDP and 24% of the government's total expenditures.[3] Many of these purchases are made through public tenders. It is therefore important that public tenders benefit from competition, including that the bidders do not engage in anti-competitive behavior such as bid-rigging in connection with their submission of tenders.

The DCCA has investigated several complex cases in which companies rigged bids and fined approximately 40 companies during the past 10 years for participating in bid-rigging. These cases have involved the construction, demolition, and plumbing industries.

Identifying collusion and other illegal practices that affect public procurements is therefore important. The DCCA's enforcement efforts seek to ensure that competition for public contracts is fair and that public funds are used efficiently.

Competition authorities worldwide identify collusion by whistleblowers, anonymous tips, and *ex officio* case-by-case analysis. In addition to these methods, the DCCA has developed a screening-tool ("Bid Viewer") to identify potential collusion in public tenders. Bid Viewer utilizes computational screening methods, including machine learning and artificial neural networks, and is designed to uncover suspicious patterns in large public procurement datasets.

In the case of coordination between competitors, systematic patterns can be observed. It is possible to develop computational methods ("screens") that flag suspicious bids and potentially coordinating companies. Such flagged tenders and firms may then be investigated by agency staff using traditional tools and techniques.

The investigative steps are depicted in figure 1. Computational screens are only the first step that can inform an agency decision to open a traditional case process.

Figure 1. **The steps from a tender screen to a traditional case process.**

With historic and current public procurement data from multiple authorities in Denmark, the DCCA is well underway in its application of collusion screens and the screenings will become more accurate and efficient as more authorities share their data with the DCCA.

2. Methods to identify suspicious bids

Both theoretical[4] and empirical[5] models have been developed aimed at identifying cartels. The screens we present are based on empirical evidence of cartel behavior and the models are trained and validated on datasets with known collusive and non-collusive tenders.

Bid Viewer calculates several indicators that are used both directly to flag tenders and companies with potentially suspicious collusive bidding patterns and as input to more complex screens. Three complementary methods are used as screens:

1) Statistical indicators derived from the bids of a tender (described in Box 1). Having access to bid prices of all participants, such indicators are easy to calculate. The value of each indicator is either associated with competitive or non-competitive bidding behavior.

2) Statistical indicators are used as input into machine learning screens, which combine multiple indicators into a model.[5] The models are subsequently applied to relevant datasets, such as tenders from Danish authorities' public procurements. Machine learning models are often more powerful and accurate than individual statistical indicators.

1 Rapport fra udvalget om Konkurrencelovgivningen (2012). https://www.kfst.dk/analyser/kfst/publikationer/dansk/2012/20120331-rapport-fra-udvalget-om-konkurrencelovgivningen/

2 Combe, Emmanuel & Monnier, Constance & Legal, Renaud (2007). Cartels: The Probability of Getting Caught in the European Union. SSRN Electronic Journal.

3 Public procurement – Study on administrative capacity in the EU Denmark Country Profile (2016). https://ec.europa.eu/regional_policy/en/policy/how/improving-investment/public-procurement/study/

4 Harrington, Joseph & Chen, Joe (2006). Cartel Pricing Dynamics with Cost Variability and Endogenous Buyer Detection. International Journal of Industrial Organization; Athey, Susan & Bagwell, Kyle & Sanchirico, Chris (2004). Collusion and Price Rigidity. The Review of Economic Studies.

5 Huber, Martin & Imhof, David (2019). Machine Learning with Screens for Detecting Bid-Rigging Cartels. International Journal of Industrial Organization.

3) Company bidding pattern analysis, of both individual businesses and groups of companies. Typically, this analysis will be performed by comparing companies' bids and participation in tendering processes over time, geographic regions, and markets.

In addition to these three methods, it is also possible to, for example, utilize artificial neural network models that learn to differentiate collusive and non-collusive bidding directly from the bid values. Such models potentially can be more accurate than methods 1-3 above. Model interpretation might be more difficult, however, and training models requires large quantities of data.

Box 1. **Statistical and machine learning screens**

In Bid Viewer, statistical measures are calculated for each tender to differentiate potentially collusive and non-collusive bidding. In addition, other measures that may affect competition, including the **number of bidders** and the **value of the contract**, are utilized. For example, higher competition is expected with more bidders. The following statistical measures are calculated:

Normalized relative distance (NRD): The difference between the winning bid and the first loosing bid, compared to the mean difference between all losing bids. An NRD value greater than 1 may indicate collusion because of a larger difference between the first two bids compared to loosing bids.

Percent difference (PD): The difference between the two lowest bids divided by the value of the lowest bid. In cases of bid-rigging, the PD between the two lowest bids in a tender may increase.

Coefficient of variation (CoV): The standard deviation of the bids divided by the mean. In bid-rigging, the standard deviation may be smaller and the mean bid may be higher, than in fair competition. Thus, the CoV may decrease in the case of bid-rigging.

Skewness (S): A measure of the asymmetry of the bid distribution. In the case of collusion, compared to competition, the distribution may become more asymmetric, resulting in a decreased and negative S value.

Kurtosis (K): Describes the degree to which bids cluster in the tails or the peak of the overall bid distribution. In rigged, collusive tenders, the K may be positive and higher, indicating a narrower bid distribution compared to unrigged tenders.

These screens help differentiate between non-collusive bidding patterns and potentially unlawful, collusive bidding patterns. Suspicious tenders and companies are flagged and are further investigated prior to opening and proceeding with an investigation (see Figure 1). Subsequent investigatory steps include determining whether the observed bidding patterns can be explained by external factors not included in the computational analysis.

Next, in section 3 and 4, we present examples of how Bid Viewer can be applied to identify collusion. The examples focus on cases where companies appear to agree on specific bid prices (price fixing) and when companies agree to bid separately but appear to be sharing a geographical market.

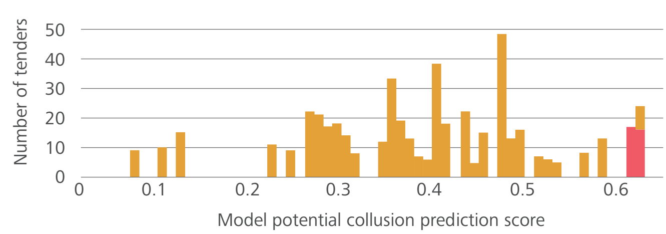
3. Screening methods to identify price fixing

Companies can collude by agreeing on prices. By doing so, the distribution of the bids changes, when compared to a competitive market. The bids are used to calculate statistical indicators and derive machine learning models that can help separate potentially collusive and non-collusive bidding.

When training and applying machine learning models, each tender receives a probability score between 0 and 1 that suggests how probable it is that the bids in the tender were subject to collusion based on the model.

Figure 2 illustrates a histogram of such scores. First, a machine learning model is trained on a set of tenders with known and proven cartels. Second, the model is evaluated on a different set of tenders with known collusion. The illustrated model generally assigns colluded tenders (red) a higher score (closer to 1), compared to non-colluded tenders (yellow).

Figure 2. **Histogram of scores from machine learning model trained on known cartel cases**



Tenders with known, proven collusion (red) generally score higher compared to non-collusive tenders (yellow), indicating the model predicts known collusive bidding patterns relatively well. *Data source: Multiple publicly available procurement datasets.*

We have developed several such models, which have been trained and evaluated on tender data from Brazil[6], United States[7] and Switzerland[8] with known cartels.

6 Signor, Regis & E. D. Love, Peter & T. N. Belarmino, Alexanders & A. Olatunji, Oluwole (2019). Detection of Collusive Tenders in Infrastructure Projects: Learning from Operation Car Wash. Journal of Construction Engineering and Management.

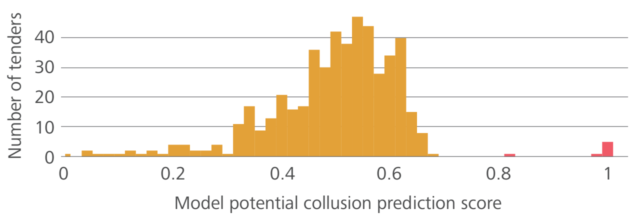
7 H. Porter, Robert & D. Zona, John (1999). Ohio School Milk Markets: An Analysis of Bidding. RAND Journal of Economics.

8 Huber, Martin & Imhof, David (2019). Machine Learning with Screens for Detecting Bid-Rigging Cartels. International Journal of Industrial Organization.

Because the model assigns a higher probability score to tenders with known collusion, it is possible, in a third step, to apply the model to procurement data from other sources and assume, that tenders with a higher score may have a higher risk of collusion.

In Figure 3, the model has been applied to a dataset that includes 7,800 bids over a 10-year period. Several tenders receive a high score, indicating that the bids of those tenders may be placed by colluding companies.

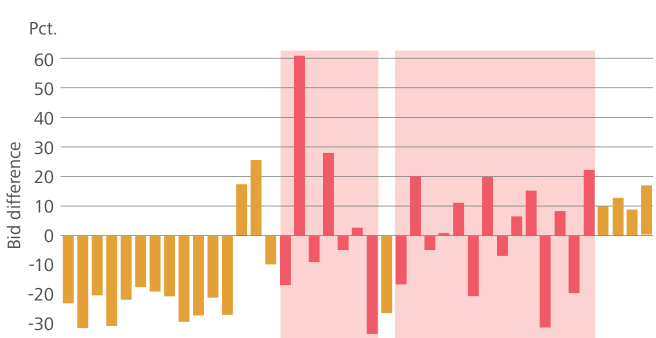
Figure 3. **Histogram of machine learning scores from public procurement dataset**



Tenders (and associated bidders) with a high score (red) are flagged for further analysis. *Data source: Public procurement data comprising 7,800 bids over a 10-year period.*

Another example of price fixing is when companies collude and coordinate their bids by taking turns having the lowest bid. In Figure 4, we show the bid values of Company B subtracted from those of Company A. A positive number thus indicates that Company B had the lowest bid. Alternating signs appear when the two companies take turns submitting the lowest bid (red regions).

Figure 4. **Company bid differences**



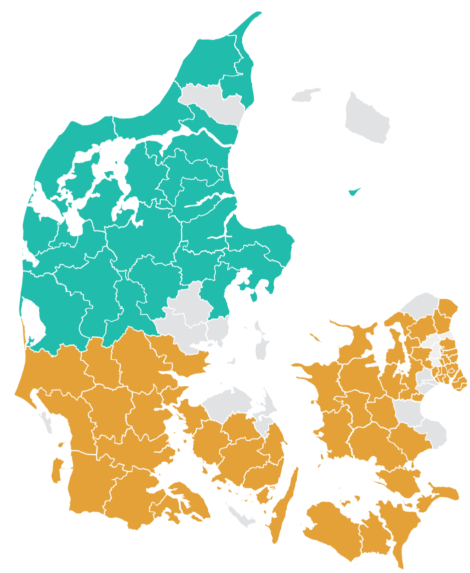
Values above 0 indicate a higher bid by Company A and values below 0 a higher bid by Company B. In the red regions the two companies take turn having the lowest bid. *Data source: Public procurement data comprising 7,800 bids over a 10-year period.*

4. Collusion by market sharing

A common form of bid-rigging is when companies split the market between one another and only bid on specific parts of the market.

Geographical market allocation is when companies divide one or multiple regions between each other and avoid bidding competitively on tenders in the same region. Bid Viewer is set up to detect such patterns. One example is illustrated in Figure 5, where each color represents the regions in which company A and B bid, respectively. The pattern indicates a potential geographic market sharing strategy of the two companies.

Figure 5. **Geographic market split**

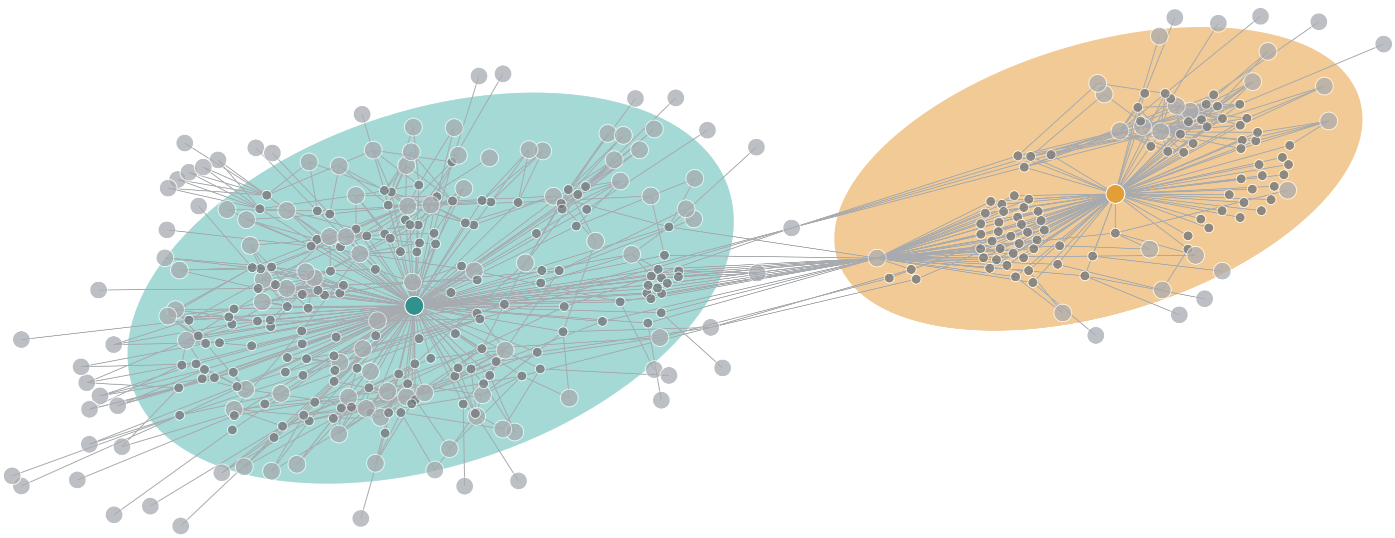


Each color illustrates the regions in which one of two companies placed bids. In this example, the companies never bid in the same region, and may also have divided the Danish market relatively evenly between one another. *Data source: Public procurement data comprising 7,800 bids over a 10-year period.*

It is also possible that companies pursue a market sharing strategy that does not have a geographical element. Such patterns were also detected in the dataset, cf. Figure 6. In this case, Company A (green dot) participated in many tenders (small dark grey dots) with other companies (grey dots), but never with Company B (yellow dot), as seen by the lack of direct connections between Companies A and B. The data show that Companies A and B never participate in the same tender, despite being major players in the market. Such behavior may warrant additional analysis to identify whether the bidding pattern observed was the result of collusion or not.

Another form of market sharing is when companies coordinate and agree to participate in tenders without the intention of winning ("sham" bidding). It is possible to estimate the average number of times a company can be expected to win based on the number of tenders it participates in and the number of competitors in those tenders. Deviations from this expected value may merit further analysis. In Figure 7, two highlighted companies (yellow dots) deviate from the expected win ratio, the x=y line.

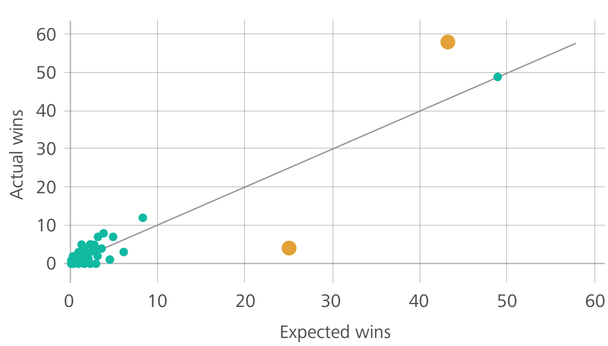
Figure 6. **Company market sharing**



The grey, green, and yellow circles represent companies. Smaller dark grey dots represent tenders. A line connecting a tender and a company indicates the company placed a bid in the tender. The two large colored eclipses illustrate that the green company and yellow company never bid in the same tender. *Data source: Public procurement data comprising 7,800 bids over a 10-year period.*

A deviation from the expected win ratio may have natural explanations, such as the capacity for some companies to place lower bids because they are larger or more cost-efficient than their competitors. It also may be that a company places a bid not to win but to be considered in the next round of tenders. Such behavior does not promote competition and may be illegal, for example if the bid is based on an agreement between competing bidders to submit a purposefully high, or sham, bid to ensure that the other firm wins the contract.

Figure 7**. Company win ratio**



Each dot represents a company. Two companies are highlighted (yellow) where the expected win ratio deviate from the x=y line, where actual wins equal expected wins based on participation. One company has won more than expected and the other won less than expected. *Data source: Public procurement data comprising 7,800 bids over a 10-year period.*

5. International collaborations

While challenges remain with *ex officio* bid-rigging screening, we believe that many of these can be overcome by sharing knowledge, data, and computational tools internationally and across agencies.

Because cartels rarely act in one specific way and it is unlikely that any two cartels collude in precisely the same manner, sharing international datasets and know-how will enable the construction of better and more accurate screens and models to detect collusion. By sharing computational methods and tools, competition authorities' implementation and application of screens can be standardized and accelerated.

The Danish Competition and Consumer Authority is developing and implementing these computational methods in collaboration with the Spanish and Swedish competition authorities, as well as other national competition authorities to identify collusion in public procurement. ■

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