DATA SCREENING TOOLS FOR COMPETITION INVESTIGATIONS

OECD Competition Policy Roundtable Background Note

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Foreword

Data screening tools in competition investigations are empirical methods that use datasets to evaluate markets and firms' behaviour in them, identify patterns and draw conclusions based on specific tested parameters. This paper focuses on screens aimed at detecting cartels, as these are by far the most prevalent.

The true extent and success of screening cannot be estimated easily. Competition authorities often do not announce publicly their screening initiatives, for fear that this would lead companies engaged in anti-competitive conduct to become more creative and evade detection. Even when the use of screens is made public, competition authorities rarely detail their scope, frequency, methodology and rate of success. Still, there are some known successful cartel enforcement cases that relied on the screening of public procurement markets. Recent literature and authority announcements indicate an increasing interest in screens.

Screens are based on assumptions of the ways in which a market functions and the types of illegal conduct that may occur. Therefore, there is no single perfect screen able to identify all violations: different screens are tailored to different potential types of violations in different markets. As data are increasingly available in large volumes, machine-learning techniques allow combining various screens and enhancing the accuracy of screening outputs.

Data availability and quality determine the analysis that competition authorities are able to perform and are one of the main roadblocks preventing the systematic use of screens. Even well-designed screens fail if they are applied to defective or incomplete data.

Screens do not usually provide sufficient proof of a breach, unless in rare exceptional cases. Competition authorities more often rely on screens to check for suspicious behaviour in order to start an investigation or prioritise cases.

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1. Background

Data screening tools in competition investigations are empirical methods that use digital datasets to evaluate markets and firms' behaviour in them, identify patterns and draw conclusions based on specific tested parameters. In this note, the terms data and digital screens are used interchangeably. Screens aimed at detecting cartels are by far the most prevalent, and this paper focuses on them.

Competition authorities may use digital screens to look for suspicious behaviour that is flagged if certain criteria are met and support the opening of an investigation. Data screening may also follow a complaint or whistle-blower report, to check the potential validity of allegations and find indications that a specific conduct may indeed be problematic. Screens can also help prioritise enforcement, through the selection of cases with stronger indications and more potential evidence of illegal activity, and the closing of other cases, where indications of illegality are fewer or less conclusive.

The extent and success of screening cannot be estimated easily. Competition authorities often do not announce publicly their screening initiatives, for fear that this would lead companies engaged in anti-competitive conduct to make more sophisticated arrangements and, thus, render the screen ineffective. Still, there are some known successful cartel enforcement cases that relied on the screening of public procurement markets.

The OECD previously addressed cartel screens in the 2021 OECD Business and Finance Outlook (OECD, 2021, pp. 95-148[1]), a workshop on complex cartel case management (OECD, 2018[2]), a workshop on cartel screening in the digital era (OECD, 2018[3]), a roundtable on algorithms and collusion (OECD, 2017[4]), a roundtable on ex officio cartel investigations and the use of screens to detect cartels (OECD, 2013[5]), and in-country work on fighting bid rigging in public procurement.

When the OECD discussed ex officio cartel investigations in 2013, few jurisdictions used digital cartel screens. Since then, some competition authorities discontinued screens they were using, while others developed new screens. With the rise of digital technologies, there is a generalised increasing interest in the use of technology and artificial intelligence to support competition enforcement[1]. Several competition authorities are currently in the process of developing or have already developed and use new screens. There are developments in machine learning and significant recent academic research. This paper aims to explore these enforcement and research developments. It also provides a literature overview in Annex A and a brief explanation of machine learning techniques in Annex B.

Fundamental requirements for the success of screens and the biggest challenges for competition authorities seem to be, principally, access to reliable data, but also competition authority staff with the required skills and knowledge to organise the collection, cleaning, and manipulation of data so that these produce useful results. Many competition authorities have begun significant data collection and processing projects, and hired data and computer scientists, to complement the skills of lawyers and economists. As authorities work to develop digital screens, there can be substantial benefits from international co-operation, particularly in terms of sharing experience, resources, code and potentially even data.

This paper does not cover the use of digital forensics (used to analyse material found in digital devices) or eDiscovery (used to process electronic evidence in cases). These topics were discussed in a 2020 session of the Latin American and Caribbean Competition Forum on digital evidence gathering in cartel investigations (OECD, 2020[6]). This paper does not cover the use of digital screens in enforcement areas beyond cartels.[2]

The paper is organised as follows:

Section 2. sets out developments in digital screens.

Section 3. details the requirements for effective digital screens, and the benefits of international co-operation.

Section 4. discusses the value of screening results as evidence.

Section 5. concludes.

2. The development of digital screens

This paper focuses on screens aimed at identifying anti-competitive horizontal agreements, as these are by far the most common.

There are two main types of screens: structural and behavioural. Both approaches and their characteristics, use, pros and cons were analysed by the OECD in 2013 (OECD, 2013[5]). Neither this classification of screen types nor the economic theories on which screens are founded have changed over the years and they remain largely valid today. However, there are developments in academic literature and competition authority practice concerning digital behavioural screens, in their vast majority aimed at identifying cartels.

2.1. The classification of screens into structural and behavioural remains

Structural screens aim to identify markets with traits that are conducive to collusion based on structural market and product characteristics, such as market concentration and product homogeneity (Harrington, 2006[7]). These screens enable competition authorities to screen markets or industries and flag those where a cartel is more likely to occur, i.e. create an initial list of markets that are worthy of further scrutiny (OECD, 2013[5]).

Markers for structural screens, i.e. factors that can influence the potential gains and costs, and therefore the rationality and stability, of cartels and collusion in a market, can be grouped into structural, supply-related, and demand-related. They are founded on the conditions that determine cartel success.[3] Structural factors that ease collusion include a small number of competitors, high entry barriers (including indicators of entry such as churn rate), frequent interaction between firms such as repeated bidding opportunities, and market transparency. Demand-related factors include stable demand conditions and low demand elasticity. Finally, supply-related factors include the mature stage of an industry, product homogeneity and low pace of innovation, symmetry and commonality of costs, symmetric capacities, excess capacity, multi-market contacts, structural links (for example, structural connections between competitors, either shared ownership or members on boards), and a history of anti-competitive conduct in that market (OECD, 2013[5]), (Zlatcu and Suciu, 2017[8]).

Behavioural (conduct) screens look for firm activity that may indicate collusion in a given market, through patterns of unusual and unexplained behaviour that could show that a cartel agreement is in operation. Behavioural screens involve two main steps. First, the developer selects markers (flags), which allow distinguishing behaviour consistent with the competitive process from that consistent with collusion. The second step is the identification of structural breaks or exogenous shocks (like a change in input prices) that can explain a change in firms' behaviour (OECD, 2013[5]).

Behavioural screens have not materially changed over the years. The main markers (flags) that behavioural screens are designed to detect are based on what economic theory and analysis of discovered cartels tell us about factors that mark the creation, life, and break-up of a cartel. Markers typically include price (or bid values in case of bid rigging), and can consider costs, margins, quantities or market shares. Common markers for cartel screens are (Zlatcu and Suciu, 2017[8]):

- Markers based on prices, based on the premise that a successful cartel will normally result in increased prices. Most common markers are comparator methods and price correlation. Comparator methods such as "difference in differences" compares the evolution in prices between a treatment and control group. Price correlation methods look at co-ordinated increases and decreases in prices: if these are not explained by costs or demand, they could indicate collusion between firms.
- Markers based on variance. Lower variance in prices and lack of sensitivity to costs could indicate collusion. Time series models that analyse price volatility can be used to assess the impact of collusion on prices and variance of prices in the periods before, during and after cartel activity.
- Markers based on market share. Stable market shares over time could indicate collusion.
- Markers for bid-rigging conspiracies. There are several indications such as: (i) the same firm is often the lowest bidder; (ii) some suppliers unexpectedly withdraw from bidding; (iii) the winning bidder repeatedly subcontracts work to unsuccessful bidders; (iv) the winner does not accept the contract, but then turns out to be the subcontractor; (v) identical pricing; (vi) sudden elimination of anticipated discounts; (vii) increases in price that cannot be explained by cost; (viii) large differences between the winning bid and the losing bids; (xi) large differences between bids by the same supplier in two similar tenders (OECD, 2009[9]).

One way to describe the distinction between structural and behavioural cartel screens is that structural screens seek to identify markets for which it is more likely that a cartel *will form*, while behavioural screening seeks to identify markets for which a cartel *has formed* (Harrington and Imhof, 2022[10]). Structural and behavioural screens can be used together, with structural screens identifying at-risk markets worthy of investigation, and then behavioural screens implemented in those markets.

2.2. Interest in cartel screens is increasing

There is not ample public information on the use and success of screens. Many authorities do not wish to publicise their screening initiatives for fear that this would lead companies engaged in anti-competitive conduct to become more sophisticated and, ultimately, render the screen ineffective. Thus, the true extent of screening is not known nor can easily be estimated.

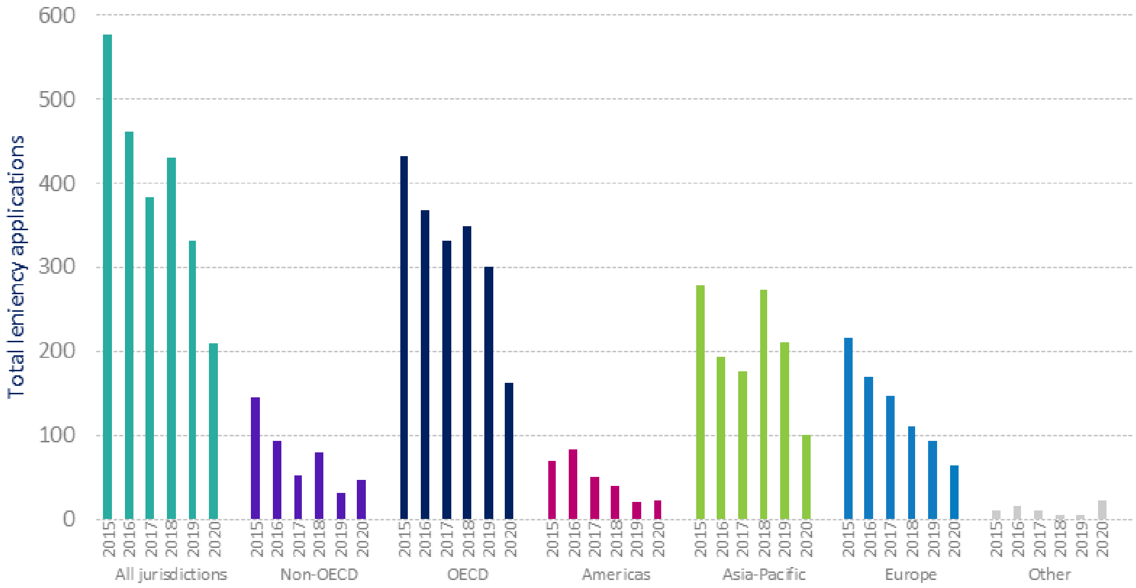
When the OECD discussed the use of screens to detect cartels in 2013, few jurisdictions used cartel screens systematically as ex ante detection tools (OECD, 2013, pp. 9,82-223[5]). While several jurisdictions engaged in some form of cartel screening, this was more on an ad hoc basis and often to corroborate already existing cartel suspicions (Beth and Gannon, 2022, p. 81[11]). There was also a greater focus on structural screens, through which authorities identified potentially at-risk markets that warranted further investigation, and more limited use of behavioural screens.

Since 2013, interest in screens has been increasing. Already in 2016, 15 out of 27 competition authorities surveyed by the International Competition Network reported they were doing some screening (Harrington and Imhof, 2022[10]). The Danish Competition and Consumer Authority reported at the 2022 CMA Data, Technology and Analytics Conference that they were co-developing the Bid Viewer cartel screening tool (Box 7) with several authorities and exchanging views on screens with over 15 authorities.[4] Beth and Gannon present a list of jurisdictions that have recently publicly announced that they either already have, or aim to, develop and use cartel screens (Beth and Gannon, 2022[11]).

The increasing availability of large amounts of digital data on prices and quantities, as well as the emergence of new technologies that allow extracting and analysing data in an increasingly automated manner, have enabled new screening methods (such as machine-learning, as detailed in Box 7) that can improve the accuracy of screening results. Several competition authorities are considering, recently started developing, or already use, new or enhanced digital screens to uncover anticompetitive conduct. Most of these screens focus on horizontal agreements.

The enabling digital environment may not be the only reason for the increasing interest in screens. In recent years, the number of leniency applications, the single most important cartel detection method, has declined.[5] Namely, from 2015 to 2020 leniency applications declined all over the world by 64% and, in Europe, there were 71% fewer applications in 2020 than in 2015 (OECD, 2022, p. 46[12]).

Figure 1. Total number of leniency applications, by region, 2015-2020



Note: This figure includes 48 jurisdictions that provided complete leniency applications data for all six years and have a leniency programme in force.
Source: Figure 5.4 (OECD, 2022, p. 46[12]). OECD CompStats database.

At the same time, cartel activity is not showing signs of abating. In the six-year period between 2010 and 2016 only, a record 75 new international cartels were uncovered each year (Connor, 2016[13])[6], and hard-core cartel prosecution remains an enforcement priority for OECD Members' competition authorities.

Cartel activity combined with the decline in the number of leniency applications means that more and better proactive enforcement through ex officio investigations is necessary, both to uncover new cases as well as to boost leniency programmes by creating a credible threat of discovery of cartels. Cartel screens are an important complement to leniency programmes (Abrantes-Metz and Metz, 2019[14]).

Competition authorities are improving their screens and developing new ones. Box 1 gives examples of screens that a have led to the successful uncovering cartels (in Brazil) and screens that are developed (in Colombia, Singapore and Catalonia).

Box 1. Examples of digital cartel screens: Brazil, Colombia, Singapore, Spain

Brazil

The Brazilian competition authority CADE has developed Cérebro (the “Brain”), a tool that relies on data-mining and statistical tests to detect suspicious bidding patterns in public procurement markets. Cérebro includes:

1. a data warehouse that combines public and private databases into a single searchable database;
2. data mining on i) patterns and similarities in competitors’ behaviour, ii) suspicious facts, iii) signs of simulation of competition;
3. statistical tests (models) based on i) academic literature on statistical cartel screens, ii) previous cartel cases, iii) microeconomic theory.

The data mining tools allow automating analyses that formerly required work by investigators and case handlers. Cérebro’s objectives are, on the one hand, to find indications of cartels in public bids, like implausible facts or behavioural patterns and provide evidence for dawn raids, and, on the other, support and enhance investigations.

Specifically, the tool looks for the following patterns in procurement data: bid suppression, cover bidding, bid rotation, superfluous losing bidders, stable market share, pricing patterns, text similarities, and submitted files’ metadata.

In 2018, CADE launched its first investigation based on the findings of the tool, which has become the day-to-day procedure for detecting bid rigging. The Cérebro data mining process and markers continue to improve through testing and use, and there is a small team dedicated to it.

Source: OECD (2021) Fighting bid rigging in Brazil: a review of federal public procurement https://www.oecd.org/daf/competition/fighting-bid-rigging-in-brazil-a-review-of-federal-public-procurement.htm; OECD (2018) “Workshop on cartel screening in the digital era”, https://www.oecd.org/competition/workshop-on-cartel-screening-in-the-digital-era.htm.

Colombia

The Superintendencia de Industria y Comercio (SIC) developed a tool, Sherlock, which analyses public procurement data to assist investigators in the identification of signs or patterns that suggest collusive behaviour.

In the first stage of the project, SIC created a tool to allow investigators to access public data retrieved from the web in a useable format. The purpose is to help case handlers to identify, for example, procurement processes with similar characteristics to the ones of interest; the bidders; the contracts awarded by the same entity to the same contractors; relationships between legal representatives and relevant participants, etc. The software provides access to a SIC database with clean and structured data and provides simple descriptive statistics. Furthermore, the tool allows for visualisation through a dashboard that can apply filters and generate graphs and comparisons.

In the second stage of the project, which is still ongoing, SIC is automating the implementation of screens for markers identified by international organisations such as the OECD. This automation will be achieved using machine-learning and deep machine-learning techniques.

Singapore

The Competition and Consumer Commission of Singapore (“CCCS”) has a Bid Rigging Detection Tool (“BRDT”) that it developed in-house. The BRDT analyses bid prices and patterns based on quantitative indicators that flag suspicious bidding behaviour.

The CCCS, in collaboration with the Government Technology Agency, is also designing a document similarity software that allows deep dives into bid documents submitted in "suspicious" tenders. The software uses text analytics techniques to generate similarity scores for sentence- and document-level comparisons. Investigators can thus focus on similar sentences and documents instead of having to comb through large volumes of documents, thereby significantly reducing the time and effort that goes into evidence review, as well as minimising the risk of overlooking relevant documents through human error.

Catalonia (ACCO)

In Spain, the Catalan competition authority (ACCO) has developed a cartel-screening tool called the Smart Administrative Procurement Collusion Research Tool (ERICCA). This computer tool aims to identify tenders with a higher probability of bid rigging practices. The tool provides full access to the underlying data, as well as basic descriptive statistics about the auction and bidders. Furthermore, it flags suspicious clusters of firms using an unsupervised machine-learning model.

The ACCO encountered issues related to the availability of baseline data, the identification of tenderers and access to the prices of all bids (and not just of the winning bid). It is now developing additional filters for the clusters of suspicious firms, such as identifying the winning bidders by contracting authority and the timeframe of winning bids. The ACCO will also add data and information from previous ACCO cases, as and when they become available.

Source (Colombia, Singapore and Spain): Schrepel, Thibault and Groza, Teodora, The Adoption of Computational Antitrust by Agencies: 2021 Report (June 21, 2022). 2 Stanford Computational Antitrust, 78 (2022), SSRN: https://ssrn.com/abstract=4142225.

The developments detailed in Box 1 are based on public information on screening initiatives by competition authorities. Other authorities may also develop and use screens, without announcing it however. A reason for secrecy is a concern that, if the existence and, in particular, the features of their screens become public, companies engaged in illegal activities would use this information to adjust their behaviour, "beat" the screen and thus avoid detection.

Other authorities see publicity around the use of cartel screens as a form of deterrence, causing companies to worry about detection and, hopefully, putting them off and causing them to desist from their activities or apply for leniency (OECD, 2013[5]). An effective cartel screen would induce firms to adapt their behaviour to avoid detection, likely reduce the cartel's efficiency and increase the costs of coordination, thus overall reducing incentives to collude (Kawai, 2022[15]). Complete shielding from detection would require not increasing prices at all.[7] As there is already a large amount of public information on cartel screens, and most cartel screening methods come from academic literature, cartels may already be adapting their conduct to evade potential screens. This in turn would require the sophistication of screening tools, in a cat and mouse game[8].

2.3. Digital screening methods in recent academic literature

There has been academic literature on cartel screens for decades now. Important early contributions focused on bidding functions[9] (these include (Porter and Zona, 1993[16]), (Porter and Zona, 1997[17]), (Porter and Zona, 1999[18]), (Bajari and Ye, 2003[19])), while others used statistical behavioural screens (these include (Harrington, 2006[7]), (Abrantes-Metz et al., 2006[20])).

In recent years, the academic literature has expanded considerably. Annex A provides an overview of some important papers since 2015, organised by screening approach. Approaches include bid/price distribution-based methods, bid roundness, cointegration-based methods, conditional independence using bidding functions, difference-in-differences, historic bid fractions, network methods, probabilistic methods, regression discontinuity methods, structural break methods, suspicious clusters in geographic spatial data, and the combination of several screens[10]. Most papers concern procurement data.

The academic literature in Annex A mostly examines behavioural screens, considered to be more effective. These screens require data and knowing what to look for in the data. Harrington and Imhof (2022[10]) identify three broad approaches to behavioural screens using bid and price data: collusive markers, structural breaks and anomalies[11]. A collusive marker is a pattern in the data that is more consistent with collusion than competition. A structural break is an abrupt change in the data generating process. An anomaly is a pattern in the data that is inexplicable or inconsistent with competition but may ultimately be found consistent with collusion.[12] A mix of collusive markers and structural breaks applied to procurement markets would be a good start for a competition authority looking to start a cartel screening programme with limited resources.[13]

Bid/price distribution-based methods (also sometimes referred to as “variance-based screens”) are behavioural statistical screens that mostly consider the moments of bids/prices, such as normalized relative distance, percent difference, standard deviation, coefficient of variance, spread, skewness and kurtosis. These cartel screens assume that cartel activity reduces bid or price variance. Several recent papers use machine-learning techniques to combine several bid distribution-based screens.

A bid roundness approach considers the number of consecutive zeros at the end of the bid price, for example, the “roundness level” for a bid price of 12 300 000 JPY would be five. This is based on the hypothesis that winners will choose round numbers for price to avoid miscommunication. The “roundness level” will be higher under collusion.

Cointegration-based cartel screens are a time series econometric methodology that test whether there is statistically significant co-movement of prices between firms, which would suggest potential collusion. Two-time series are said to be cointegrated if there is some long-run equilibrium relation tying the respective time series together that can be represented as a linear function of these two-time series.

Conditional independence using bidding functions is a popular method that assumes that a competitive bid by one firm should be uncorrelated with competitive bids by other firms, once controlling for information that may affect bid values. This approach estimates a bid function regression that tests for conditional independence between bids. Conditional dependence between bids is a sign of potential complementary bidding resulting from collusion.

Difference-in-differences is a standard econometric approach that uses panel data to determine an average treatment effect (e.g., the increase in bids/prices due to collusion) by calculating the difference between the average change over time for the treatment group (difference one) and the average change over time for the control group (difference two). In the context of cartel screening, the dependent variable could be the bid/price. The treatment group could be the bids/prices impacted by the alleged cartel, while the control group could be competitors operating in a separate geographic market, not impacted by the alleged cartel.

A historic bid fraction approach considers the distribution of bid fractions, which can be calculated as the bidder’s own bid minus the lowest of the other bids (i.e., the next closest bid). If cartelists avoid bidding close to the winning bidder, then few bids will be around zero, indicating suspicious behaviour.

Network methods examine whether there are hotspots where firms interact more frequently and thus collusion may be more likely and easier to sustain. Investigators can use unsupervised learning techniques (see section 2.5) to determine groups of firms that frequently interact in a given set of tenders.

Probabilistic methods use the distribution of non-collusive ‘honest’ bids to determine the probability that a given potentially collusive bid occurred by chance. Relatively high-priced bids (i.e., those in a high percentile) are considered more likely to be collusive. A separate distribution for non-collusive ‘honest’ bids can be constructed taking into account the number of bidders in the tender process (e.g., a separate distribution for one bidder, two bidders, three bidders etc.), to address the fact that a non-collusive bid may have a higher price when there is less competition for a given auction.

Regression discontinuity design (RDD) identifies an average treatment effect by considering differences in an outcome variable for observations that are marginally above or below a treatment cut-off threshold. This is useful to test for incumbency advantage or bid rotation. For example, RDD can determine whether bidders who marginally won tenders were more likely to be incumbents or not. It assumes that bidders that marginally won or lost tenders should be as if randomly allocated an outcome variable (such as whether or not they are an incumbent). If marginal bid winners are revealed to be more often incumbents, then this could be a sign of cartelists allocating tenders to incumbents (i.e., other cartelists promising not to compete for those tenders).

Structural break cartel screens estimate whether there are any structural breaks in the price function, that is, whether there are any unexplainable shifts in price over the period that would most likely be due to cartel activity. A structural break is a sudden change in the price data-generating process that could be due to the start, end, or disruption of a cartel. The price function can be estimated using a reduced-form regression that includes variables that determine market prices, such as supply and demand shifters, as well as controls for structural breaks that are induced by potential cartel activity.

Suspicious clusters in geographic spatial data consider whether there are geographic clusters of firms with suspicious pricing. For example, the coefficient of variation (see "bid/price distribution-based methods" above) could be used to identify suspicious prices, and then an algorithm can be applied to check whether these exist in geographic clusters. These could then be a sign of local agreement to raise prices. It has been applied in the context of petrol station gasoline prices.

There are also papers that **combine several screens**. (Fazekas et al., 2022[21]) combine screens such as bid/price distribution-based methods, bidding patterns and market concentration screens, using a supervised machine-learning random forests approach (see Annex B). The authors develop a theoretical classification of collusion types in public procurement markets that should capture "*most if not all collusive behaviours*" and identify which cartel screening indicators can detect these cartel types (Table 1). They expect that some screens will work better for certain types of cartels and that a combination of screens is required to identify collusion. Their empirical findings support this, indicating that single screens do not work in most cases and a multi-screen approach is the most effective.

Table 1. Cartel screen indicators matched to type of collusion in procurement markets

Collusion type				Indicator name									
Collusion type	Market structure	Collusion technique	Rent allocation	Prices		Bidding patterns						Market structure	
				Relative price	Benford's law	Single bidding	Missing bidders	Subcontracting	Consortia	Cut-point position	Winning probability	Concentrated market structure	Stable market structure
				1	2	3	4	5	6	7	8	9	10
A	Concentrated	Withheld bid	Sub-contractor	Y	Y	Y	Y	Y	N	N	Y	Y	N
B	Concentrated	Losing bid	Sub-contractor	Y	Y	N	N	Y	N	Y	N	Y	N
C	Concentrated	Joint bid	Consortia	Y	Y	Y	Y	N	Y	N	Y	Y	N
D	Stable	Withheld bid	Sub-contractor	Y	Y	Y	Y	Y	N	N	Y	N	Y
E	Stable	Losing bid	Sub-contractor	Y	Y	N	N	Y	N	Y	N	N	Y
F	Stable	Withheld bid	Coordinated bidding	Y	Y	Y	Y	N	N	N	Y	N	Y
G	Stable	Losing bid	Coordinated bidding	Y	Y	N	N	N	N	Y	N	N	Y

Note: "Y" indicates the indicator can detect the given collusion type, while "N" indicates that it cannot. Most, if not all, collusive behaviours in procurement markets can be categorised based on three dimensions: (1) collusion technique (withheld bids, losing bids/non-competitive bidding, joint bids); (2) form of rent sharing (sub-contractor, consortia/joint ownership, coordinated bidding, informal side-payments); (3) resulting market structure (concentrated market structure where firms allocate specific geographic or product markets to a given firm, or stable market structure where firms imitate a competitive market rotating the winner, resulting in stable market shares over time). A more detailed description of this cartel allocation can be found in (Fazekas et al., 2022, p. 14[21]).
Source: OECD Secretariat, based on Table 8 in (Fazekas and Tóth, 2016[22]) and Table 1.1 and Table 1.3 in (Fazekas et al., 2022[21]).

2.4. The risk of false negatives or false positives

Screens (digital or otherwise) carry an inherent risk of false positives or false negatives: they provide only economic evidence that is often ambiguous, as it may be consistent with either agreement or independent action. Competition authorities participating in the 2013 OECD roundtable on ex officio cartel investigations and the use of screens to detect cartels (OECD, 2013[5]) stressed particularly the risk of false positives that may induce them to take up a case where, in reality, no illegal activity has taken place, thus wasting time and resources.

False positives are often an issue with structural screens, as they are broader and less sophisticated. Concentrated industries with few players and high entry barriers would be flagged, even though they are not necessarily collusive[14]. At the heart of this problem are omitted variables (Harrington, 2006[7]).

Behavioural screens run the same risk when they do not capture circumstances that may explain the suspicious conduct. For example, price correlations may be the result of collusion (and therefore illegal), tacit collusion (and therefore, in most jurisdictions, not a violation) or coincidence. Screening results must therefore be carefully analysed to avoid jumping to conclusions, and distinguish cases of, for example, tacit collusion or exogenous shocks that may explain price changes.

The Korean Fair Trade Commission's Bid Rigging Indicator Analysis System (BRIAS) screening tool was found at some point to have produced too many positives. BRIAS has undergone improvements since 2018, and its use is picking up.

Box 2. The Korean Bid Rigging Indicator Analysis System (BRIAS)

In 2006, the Korean Fair Trade Commission (KFTC) launched an automated cartel detection system based on weighted indicators. The tool, known as Bid-Rigging Indicator Analysis System (BRIAS), aimed to detect bid rigging using screens applied to electronic procurement data of the Korean central e-procurement system KONEPS.

BRIAS collects data on procurement contracts of government agencies and state-owned enterprises above a certain amount. It selects contracts (with values at or greater than KRW 100 million for the purchase of goods and services, KRW 5 billion for general construction projects, and KRW 500 million for specialised constructions) and screens them based on criteria specific to bid and collusion types. BRIAS then produces a score on the likelihood of bid rigging, based on the assignation of weighted values to sector-specific factors.

The KFTC used past enforcement experiences and red flags for bid rigging to design the tool's indicators and their weights. Higher collusion likelihood scores are based on: (i) high successful winning rate of a company; (ii) small number of bidders in the tender process; (iii) large number of bids higher than the estimated price; (iv) use of non-competitive bidding processes; and (v) large gaps between winning and losing bids. The effectiveness of the tool relies on the balancing of the weights given to each of the indicators.

BRIAS was found to have provided a high amount of high-score results and selecting cases for investigation became challenging.

In 2015, the KFTC decided to improve some of BRIAS features and implemented the improvements by 2018. These include a new search function and a more efficient way of connecting bidding data to the BRIAS system, and the use of BRIAS is picking up. The KFTC used BRIAS to investigate and sanction 16 cases between 2007 and 2021, of which 13 on or after 2018.

Source: Kim, Daein. (2021). Korean Public Procurement Law, K-Law Academy, Korea Legislation Research Institute, https://www.researchgate.net/publication/348618992_Korean_Public_Procurement_Law ; OECD (2013) Ex officio cartel investigations and the use of screens to detect cartels, www.oecd.org/daf/competition/exofficio-cartel-investigations.htm; Information provided to the Secretariat by the Korean Fair Trade Commission.

Screens may also produce false negatives. Structural screens are less likely to come up with false negatives, given that collusion is difficult to sustain in markets that do not have “collusion-prone” characteristics. Behavioural screens are more likely to produce false negatives when applied in a context different from that for which they were designed, as the model may fail to recognise indications of illegal activity that have not been built into its design[15].

A way to minimise screening error risks may be to run a series of tests, rather than a single test, using a composite screen. The multi-screening approach enabled by machine learning and increased data availability should help in this regard.

2.5. Machine learning enhances digital screening

Screens are based on assumptions of the way a market functions and the types of illegal conduct that may occur. This means that different screens are tailored to different potential types of violations and different markets, and that there is no single perfect screen able to identify all violations in all markets. However, machine-learning techniques can optimise the prediction of whether a conduct is consistent with collusion. In the last 5 years, academic literature and competition authority practice in the context of cartel screens have largely focused on machine learning.

Machine learning is a subfield of artificial intelligence (“*the science and engineering of making intelligent machines*”) that gives “*computers the ability to learn without being explicitly programmed*” (OECD, 2017, p. 9[4]). It is “*an application of minimal-structure pattern-matching algorithms to (i) infer a classification rule from a training data set and (ii) make useful predictions on new data*” (Abrantes-Metz and Metz, 2018[23]). Simply put, machine learning has the same main goal as other, “classic”, empirical screens (classify and predict) but approaches this goal in a less structured and more data-driven way, which can be free(-er) from initial assumptions and gain in sophistication and accuracy through use.

In particular, authors argue that if there are sufficient data (including by merging data sources), machine learning allows to combine several screens (using methods such as ensemble learning - see Annex B) in a manner that may lead to a more accurate identification of collusion. Namely, screening results can be pooled into a composite index, with the allocation of weights to each (Fazekas et al., 2022[21]). In other words, given that there is not a single screen that correctly flags collusive activity in all cases, machine learning can combine several screens in a manner that can best identify potentially collusive cases and, lead to opening more indicator-based investigations. (Huber and & Imhof, 2021[24]; Imhof and Wallimann, 2021[25]; Huber and Imhof, 2019[26]; Imhof, Karagök and Rutz, 2018[27]).

There are three main types of machine-learning approaches: supervised learning, unsupervised learning, and reinforcement learning. Most academic papers on cartel screens use supervised learning approaches. The remainder predominantly use unsupervised learning approaches (usually to identify groups of firms that frequently interact). Very few, if any, use reinforcement learning approaches.

Supervised learning (Hastie et al., 2009, pp. 9-42[28]) uses inputs (also known as predictors or independent variables) to estimate an output (also known as the response or dependent variable). This typically relies on a training dataset of solved cases, known as “tagged” or “labelled” data, which provides a sample mapping of inputs to the output. Supervised learning can be thought of as learning through examples or learning with a teacher. The training dataset provides examples of the cartel screen values for collusive and competitive tenders. The model is trained on this dataset, estimating weights for each of the screens to optimise identification of illegal behaviour. The trained model is then applied on test data containing cartel screen values (preferably in the same or comparable market) to predict whether a conduct may indeed be collusive or competitive. The training dataset must be of sufficient size to minimise error and contain correct classifications of the outcomes as “collusive” or not (Abrantes-Metz and Metz, 2018[23]). Supervised learning is often the best suited to cartel screening as it can be used to predict whether a bid/price is collusive or not. However, it requires “labelled” data of existing examples of collusive and non-collusive bids/prices.

Unsupervised learning (Hastie et al., 2009, pp. 485-586[28]) has the same goal as supervised learning (i.e., to use inputs to estimate an output). The key distinction is that unsupervised learning uses “untagged” or “unlabelled” data, that is, data that only contain input values and not an associated output value. Thus, unsupervised learning can be thought of as learning without a teacher. Rather, there is a set of inputs with an underlying probability distribution, and the goal is to determine this probability distribution without the help of a supervisor or teacher indicating when an allocation is correct. In other words, the model tries to learn a structure from the “untagged” or “unlabelled” data. Unsupervised learning can be a useful alternative to supervised learning as it does not require labelled data, and rather identifies suspicious outliers that are most dissimilar to the ‘norm’ (Deng, 2017[29]).

Reinforcement learning (Barto and Dietterich, 2004[30]), similarly to unsupervised learning, uses “untagged” or “unlabelled” data, that is, data that only contain input values and not an associated output value. However, unlike unsupervised learning, reinforcement learning uses a performance criterion that rewards a positive outcome and punishes a negative outcome (i.e., learning through “trial and error”). The reinforcement learning algorithm selects inputs and observes the outcome from the performance criterion, ultimately choosing the input that provides the maximal value according to this performance criterion.

Specific supervised learning and unsupervised learning techniques used in academic papers on cartel screens are described in Annex B.

2.6. Digital screening by private companies

The uptake of cartel screens is not restricted to competition authorities. Some companies have also started using screens to investigate potential cartel activity in their supply chains[16] or as part of a compliance programme[17]. Box 3 shows Deutsche Bahn’s development of cartel screens.

Cartel screening has benefits for companies. It can deter cartels in the firm’s supply chain in anticipation of the risk of detection, provide evidence to support claims for damages compensation, and help companies identify markets prone to collusion and design their procurement strategies so as to counter these risks (Beth and Gannon, 2022, pp. 85-86[11]). Cartel screens can particularly benefit companies that purchase commodities or engage in price-only procurement auctions as cartels are most common in such markets (Harrington, 2021[31]; 2015[32]).

Private cartel screens have the potential of being even more effective than public screens, as companies have supplier data that competition authorities do not, thus enabling the screen to run on better datasets. For example, companies that use auctions to source products have access to real-time procurement data at the firm level, as well as business insights regarding competitive (or, alternatively, collusive) market conditions in the relevant supply market (Beth and Gannon, 2022, p. 85[11]).

Companies can also use cartel screens as part of their compliance programme (Abrantes-Metz, 2012[33]; 2020[34]), (Deng, 2017[29]), (Johnson and Sokol, 2020[35]), (OECD, 2021, p. 40[36]). A company can benefit from uncovering illegal conduct, be the first to file for leniency, and gain from the resulting advantages such as immunity or a reduction in fines (Abrantes-Metz and Metz, 2020[34]).

Box 3. Deutsche Bahn uses screening to identify cartels in its supply chain

Deutsche Bahn (the national rail company of Germany) uses structural screening to identify markets prone to cartels and obliges its suppliers operating in high-risk markets to introduce or maintain effective antitrust compliance programmes. Deutsche Bahn is also planning the introduction of behavioural screens to identify cartels in its supply chain.

The purpose of the screens is both the detection as well as the deterrence of collusion. Suppliers would be concerned that not only the relevant competition authority but also their customer monitors bidding patterns. If deterrence works, this may contribute to reduce the overall population of cartels. If detection works, the private screening results should be communicated to competition authorities. It is important that competition authorities have the tools to assess quantitative cartel screen evidence submitted by firms in formal complaints. On the part of harmed firm, screening results can be used in damage claims against cartelised suppliers.

Deutsche Bahn aims to implement a diverse range of algorithms to identify most forms of cartel agreements and take advantage of machine learning in order to automate screening as much as possible.

Source: Beth, H. and O. Gannon (2022), "Cartel screening–can competition authorities and corporations afford not to use big data to detect cartels?", Competition Law & Policy Debate 2022, Vol. 7, No. 2, pp. 1-12, https://doi.org/10.4337/clpd.2022.0001; Beth, H. and T. Reimers (2019), "Screening Methods for the Detection of Antitrust Infringements", https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3501700; Clemens, G. (2017), "Raising Rivals' Costs Through Cartel Detection-Why Downstream Buyers Rather Face an Upstream Cartel than Downstream Competition"

Co-operation between competition authorities and private companies is important in assisting companies to decide when suspicious procurement behaviour would need to be reported to competition authorities. Cartel screens can also help collect evidence when there are other indications of suspicious behaviour, such as complaints from consumers or competitors or whistleblowing. In case a suspicious indication is reported, the competition authority would need to understand the screening results and why a company found an activity suspicious. Thus, the company's screening results, underlying data, formulae used as part of the screening and the screening algorithms may need to be disclosed to competition authorities, in confidence. This would allow competition authorities to assess and even replicate the analysis, in order to determine whether to take further action (Beth and Gannon, 2022, pp. 87-88[11]).

3. Conditions for effective screens: data and staff requirements

Screening is not only about the choice of model. It also depends on the quality of the data on which it is applied, and the expertise of the team implementing it. Co-operation among competition authorities can help sharing knowledge, and even datasets and software and enable improving screening design and results.

3.1. Good screens require available data

Data availability and quality determine the type of empirical analysis that competition authorities are able to perform and are essential to implement even simple digital screens. Data needs to be accessible, robust and useable; even screens that are well designed in theory would fail in practice, if tested on defective or incomplete data.

In 2013 the OECD noted that "*sufficient, relevant and accurate information and data are necessary for all stages of screen implementation, from screen design, to the implementation of the screen, up to the interpretation of its results*" (OECD, 2013[5]). The challenges competition authorities face are the existence of data, to begin with, access to such data (and in particular disaggregated and raw data, and data that are not publicly available), format, integrity and quality of data, and data searchability, cleaning and use. Authority experience and literature both suggest that it is important to first tackle data issues, and then deploy screens (see Annex A).

The first step for a competition authority that would like to screen a market is look at available, or potentially available, data sources. These can be:

- Publicly available information including from companies' registries, chambers of commerce, e-procurement platforms (access to procurement information is detailed in section 3.2). Several cartel screens identify collusive behaviour by comparing collusive and competitive market outcomes (such as bids or prices). Therefore, authorities would need data on proven collusive and competitive tenders/prices available from previous cases, possibly combining several datasets. Cartel screening can be cost effective if it is possible to use readily available data (Harrington, 2021[31]).
- Information kept by public sector authorities including sector regulators, government bodies and procurement entities. If the information is not public, there may be issues of data privacy and confidentiality, and, in particular, whether sharing of information is allowed, even among public sector entities. For example, in Australia, the Crimes Legislation Amendment (Powers, Offences and Other Measures) Act 2018 ('CLAPOOM Act') enables data sharing across enforcement agencies in instances of fraudulent conduct[18], though cartel conduct is not explicitly covered under the definition of fraud.
- Web-scraping, a method for *"crawling websites and automatically extracting structured data on it. The use of algorithms may greatly facilitate the data collection process, as well as data analysis. Such tools have already been used in competition law investigations*" (Lianos,

2021[37]). Web-scraping is time consuming and may not be a viable long-term solution; it can however provide sufficient initial indications for concern to justify the purchase of commercial information from third-party data providers.

- Data bought from commercial data providers.

Several cartel screens identify collusive behaviour by comparing collusive and competitive market outcomes (such as bids or prices). Therefore, authorities will need data on proven collusive and competitive tenders/prices, which may be available from previous cases, and may have to combine several datasets.

Furthermore, if the data is used regularly, the authority can set up data pipelines ("*a set of data processing steps from a data source to a destination data set, with the output of one step being the input of the next*" (Hunt, 2022[38])). Data pipelines can be valuable when data sources are used repeatedly, to provide a dataset that can be used for screening.

Data availability does not mean that the data have the requisite level of granularity or quality, contain no omissions or errors, or have been properly handled in a way that maintains their integrity. Data detail and quality have been extensively analysed in the context of procurement data (examined in section 3.2). As digital procurement data exist and competition authorities often opt to start their cartel detection initiatives in procurement markets, the required data characteristics and eventual data shortcomings have received particular attention.

3.2. Focus on bid-rigging screens and procurement data

A lot of digital screening focuses on procurement markets where data are available in national and sub-national e-procurement systems. For example, BRIAS (Box 2), Cérebro (Box 1) and Bid Viewer (Box 7) all analysed digital procurement data for indications of bid rigging. Thus, the type of digital data needed to screen for bid rigging, and the possible defects or omissions of the available data have been both widely analysed as well as empirically tested.

A first obstacle in procurement data can be the absence of centralisation and data fragmentation. Lack of centralised data (which is, for example, often the case for federal countries, where tender data may be kept at national, regional/state and sometimes municipal level) means that, to begin with, there is no comprehensive dataset to screen. When the CMA withdrew its screening for cartels tool in 2020, one of the reasons was the lack of a centralised dataset.

Box 4. Decentralised data impaired the UK Screening for Cartels tool

In December 2017, the UK Competition and Markets Authority (CMA) launched its Screening for Cartels (SfC) tool to help procurers screen their tender data for signs of cartel behaviour, using various algorithms that spotted unusual bidder behaviour and pricing patters indicative of bid rigging.

SfC was an app that allowed public procurers to input data on tender procedures, perform an analysis and produce a report comprising a series of potential indicators of bid rigging. Namely, the tool was based on twelve tests targeting three key areas: (i) number and pattern of tenders; (ii) pricing patterns; and (iii) technical analysis of metadata to track document origin and low endeavour submissions. Separate algorithms were used for assessing each of the tests, leading to pass/fail checks that were then combined into a single weighted suspicion score. This score was presented in an easy-to-read format that allowed procurers to assess the collusive risk of tenders. The CMA emphasised that high scores should not be interpreted as proof of the existence of cartels, but rather "*cause to go back to the bid documents and look again and ask questions*".

Legal issues related to the ownership and availability of procurement data forced the CMA to opt for a "distributed model". Namely, public procurers could download the app from the CMA website and then use it within their own systems to analyse their respective tenders. The CMA emphasised the flexibility of the distributed model, claiming that it would enable SfC to function independently of the CMA and increase the scope for future tailoring and development of its parameters.

In practice however, the decentralised deployment of SfC meant that any new data fed to the algorithm by a procurer would remain unknown to the parallel versions of the algorithm used by different procurers. Therefore, the algorithms of the tool remained rigid: as contracting authorities would only feed data on their own tenders, there would not be sufficient information to improve the parameters and calibrate the algorithms. This was due to the absence of a reliable and centralised procurement database on which to train the algorithms. Thus, potential biases in the results of the suspicion score would start to arise.

Besides, the twelve parameters were criticised for the arbitrariness in their designation and weighting: instead of being developed through the training of algorithms, they were set based on theory. Furthermore, the three indicators targeted by the parameters did not seem to build on information about market structure or dynamics, thus biasing the results of the tool.

Combined, the design flaws and the lack of data to develop a more sophisticated version of SfC led to questioning of the tool's accuracy and capacity to detect bid rigging. The CMA withdrew the SfC from use on January 20th, 2020.

Source: Competition and Markets Authority https://www.gov.uk/government/publications/screening-for-cartels-tool-for-procurers/about-the-cartel-screening-tool#:~:text=cartel%2Dscreening%2Dtool-,About%20the%20tool,competing%20for%20customers%20or%20contracts
Sanchez-Graells, A. (2019). 'Screening for Cartels' in Public Procurement: Cheating at Solitaire to Sell Fool's Gold? *Journal of European Competition Law & Practice*, *10*(4), 199-211. https://academic.oup.com/jeclap/article/10/4/199/5537135?login=true;

Decentralised tools for procurement officers continue being developed. In June 2022, Canada's Competition Bureau launched a Collusion Risk Assessment Tool to fight bid rigging in procurement (Competition Bureau Canada, 2022[39]). This is an online resource available to both public and private sector procurement officers and purchasing agents. It is intended to be used as part of day-to-day due diligence to protect competitive bidding processes. It has a 10-minute questionnaire, which procurement agents can fill in with details on any tender that they are planning. The tool then produces a collusion risk score based on the specifics of the project and proposes mitigation strategies that can be taken to minimize those risks. This can help provide procurement agents with an early warning on potential risks of bid rigging, as well as suggestions for mitigation. The tool is, however, not a detection tool per se: it may be useful for better tender design and the prevention of cartels in procurement, but is unlikely to provide investigation leads to the Competition Bureau.

Another usual challenge is that bid data (such as tender offers) may not be machine-readable and thus unable to be fed directly into digital screening tools without further treatment[19]. Besides, bid data are sometimes not recorded in a consistent format or contain mistakes[20]. For example, data such as company names may not be standardised across datasets, making it difficult to match these datasets. Manually cleaning these variables (e.g., to identify when two slightly different company names refer to the same company) could be remedied by manual extraction, structuring and cleaning to form a consistent dataset, though this can be a resource-intensive process. For example, the Spanish competition authority CNMC built its own public procurement database based on data downloaded from the national public procurement platform, which it filters and cleans of errors (Campuzano, 2021[40])[21]. Matching algorithms may usefully automate much of this work, saving valuable time and resources (Fazekas et al., 2022[21]). For example, matching algorithms can create a similarity score based on the number of characters that two different company names have in common, limiting human supervision to only those that have a high similarity score (Bharadwaj et al., 2022[41]).

In addition, a sufficiently wide database is necessary for meaningful screening. Sometimes, national e-procurement systems have broad coverage but contain little information, i.e. few variables on which to test the screen. For example, some national digital platforms only record winning bids. Most European public procurement databases capture only the bidding and bid evaluation phases without any information on contract implementation or contract modifications (Fazekas et al., 2022[21]).

If, for any of those reasons, data crucial for a screen are missing in a specific procurement dataset, the screening results are unlikely to be accurate or useful, or, in any event, not as useful as they might be if the right variables were included. Fazekas and Tóth proposed an “ideal complete list” of variables (data fields) for cartel screening (Table 2)[22].

Table 2. An ideal complete list of variables for cartel screening in procurement markets

Variable Group	Variable	Included in the announcement		
		CFT	CA	CC
Buyer	Buyer’s name	●	●	●
	Buyer’s department/office	●	●	●
	Buyer’s unique ID	●	●	●
	Buyer’s address	●	●	●
	Buyer’s type	●	●	●
Bidder/Bids	Bidder’s name		●	●
	Bidder’s unique ID/tax ID		●	●
	Bidder’s address		●	●
	Number of bids submitted		●	
	Number of bids excluded		●	
	Bid price (details on total and unit prices)		●	●
	Exact time of bid submission		●	
	Bid type (winner/loser bid)		●	
	Beneficial owners		●	●
Tender/Contract	Procedure type	●	●	
	Framework agreement (1st/2nd stage)	●	●	
	Award criteria	●	●	
	Threshold (below/above EU thresholds?)	●	●	
	Estimated price (details on total or unit prices)	●	●	
	Procurement type (service, supply, work)	●	●	●
	CPV codes (% contract value per product)	●	●	●
	NUTS code(s) of contract implementation	●	●	●
	Status (cancelled, pending, etc.)	●	●	●
Dates	Call for tender publication date	●	●	●
	Bid submission deadline	●		
	Contract start and end dates	●	●	●
	Publication date of contract award		●	
	Contract signature date			
	Publication date of contract completion			●
Subcontracting	Subcontractor’s name and unique ID (tax ID)		●	●
	Subcontractor’s share		●	●
Consortium	Consortium members’ name and unique ID (tax ID)		●	●
	Consortium members’ share		●	●
Contract Performance	Contract performance end date			●
	Was performance according to the contract			●
	Explanation in case of deferring from contract			●
	Information on contract modification			●
	Information on performance quality			●

Note: CFT=call for tender, CA=contract award, CC=contract completion
Source: (Fazekas and Tóth, 2016[22])

Such lists of variables can be useful for competition outreach, to raise awareness of the variables and format of data that procurement authorities need to collect for competition law enforcement purposes. Still, in addition to outreach, it would be safer if governments, or delegated public procurement authorities or procurement oversight bodies, issued guidance on procurement data submission and storage, for example mandating the use of digital procurement platforms with defined standardised quality standards[23], and ensuring the collection of relevant data in a uniform manner through predetermined fields. Controlling the submission, content and quality of data at the point of data entry would help gathering reliable, timely and, importantly, comparable information (Fazekas and Tóth, 2016[22])[24].

It would likewise be useful for governments to take steps (including enabling legislation) to ensure that regulators, which have sector data, and public procurement bodies, which have tender data, share such data with competition authorities. Such data sharing can be allowed under appropriate confidentiality protections to ensure that data are safely stored, accessed and used, and that there is no further disclosure unless for defined lawful purposes.

In OECD in-country projects on fighting bid rigging in public procurement, the Secretariat has analysed domestic public procurement frameworks and provided recommendations on ways to make procurement databases comprehensive and relevant for procurement and competition authorities. The Secretariat has recommended good practices for data collection, quality, storage and access, and suggested variables that allow analysing bid-rigging patterns (Box 5).

Box 5. Requirements for procurement databases from a competition perspective

The OECD experience in projects on fighting bid rigging in public procurement

The following guidance aims to ensure that procurement databases are useful for the enforcement of the law against bid rigging:

Data targeting. The data should fit the purpose of any proposed analysis. Identifying this purpose in advance informs the type and format of the data collected. Procurement authorities should consult with competition authorities on building procurement databases that can be used to detect potential instances of collusion. Indicatively, all bids including firm level data and file metadata should be recorded.

Data quality. Good-quality data are paramount to producing useful results that can be interpreted correctly. Data input and validation methods should ensure that data are recorded in a standard, consistent and error-free manner. For example, pricing and units data fields should be uniform; text fields and naming conventions should be set; and checks for discrepancies in coding should be built into the data-input stage.

Data usability. Information should be stored in a searchable format that allows easy handling and use (for example, in spreadsheets or databases rather than scanned images of contracts), so that the necessary filters and analytical techniques can be easily applied. Databases kept across public authorities should be interoperable, in terms of formatting and cross referencing, to enable joining databases and screening across them for indicia of bid rigging.

Data access. Databases should have clear access rights, both in terms of inputs (centralised or decentralised databases) and outputs. Access should be granted to competition authorities for their law enforcement purposes.

Note: More information on OECD in-country work on fighting bid rigging in public procurement can be found at www.oecd.org/daf/competition/oecdrecommendationonfightingbidrigginginpublicprocurement.htm
Source: OECD (2018), Fighting Bid Rigging in IMSS Procurement: Impact of OECD Recommendations, pp. 167-170, www.oecd.org/daf/competition/fighting-bid-rigging-in-imss-procurement-impact-of-oecd-recommendations.htm

The forthcoming revision of the Recommendation on Fighting Bid Rigging in Public Procurement (OECD, 2012[42]) is planned to advise using electronic procurement systems for all stages of the procurement process, from the publication of the procurement opportunity to contract close-out. This would allow competition authorities to track and evaluate all procurement-related actions, as needed. The revised Recommendation is also likely to include guidance on the level of information that procurement databases should include to allow detecting bid-rigging patterns (such as data on winning and losing bids, contract amendments and subcontracts) and recommend giving competition authorities access to such databases.

3.3. Screening requires specialised knowledge and skills

Competition authorities have started investing in digital skills and knowledge, including for the development of digital screens on datasets. While the early development of screens relied on economists, most competition authorities now employ technology specialists, such as data and computer scientists, that work with economists to analyse data and develop screens. The increased hiring of data and computer scientists has been likened to the hiring of economists in the 1980s (Lianos, 2021, p. 17[37]).

Many competition authorities have set up dedicated data units tasked with data gathering and cleaning and support to teams working on cases concerning digital data and markets. In some cases, these units are also involved in the development of screening tools. Other authorities may not have formal units but hired chief technology officers, and/or embed staff dealing with big data, AI and machine learning in other units or teams (Hunt, 2022[38]).

In 2021, the Hellenic Competition Commission published a report on computational competition law and economics which lists developments in competition authorities across OECD Members and BRICS countries (Brazil, Russia, India, China and South Africa) and includes a detailed table with information on digital and forensics teams or units, and the hiring of chief technology officers and data scientists (Lianos, 2021, pp. 119-148[37]).

Box 6. Examples of data teams in competition authorities

UK: the Competition and Markets Authority's DaTA team

In 2019, the UK Competition & Markets Authority (CMA) set up a specialist DaTA (Data, Technology and Analytics) unit and hired a Chief Data & Technology Insight Officer to lead it. DaTA currently has almost 50 people across the disciplines of data science, engineering, technology insight, behavioural science, eDiscovery and digital forensics. It provides expert data and technology advice, and leads data acquisition, treatment and use. It also scrapes data and develops data pipelines.

DaTA is currently developing a data pipeline that takes records from all registered limited companies from Companies House, the UK's registrar. These data are frequently needed by the CMA for many reasons, including i) getting intelligence on companies with respect to suspected cartel activity, ii) understanding ownership structures in markets and iii) understanding the state of markets, especially concentration and profitability levels. Ordinarily CMA staff would navigate the publicly available search tool and download the data manually, which is time-consuming, and could lead to errors. The pipeline will regularly take in all the data, clean it, deduplicate it, and make it available in a tool designed for the CMA's needs.

Source: Hunt, S. (2022), The technology-led transformation of competition and consumer agencies: the Competition and Markets Authority's experience, https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1082753/Stefan_discussion_paper.pdf.

Greece: the Hellenic Competition Commission's forensic IT unit

The Hellenic Competition Commission (HCC) established a forensic IT unit in October 2020, which is headed by an economist and co-operates with several data scientists, who are acting as external experts for the authority.

The HCC is also in the process of setting up an expandable Big Data Management Infrastructure Platform/dashboard, tailor-made by an external contractor where real-time public data from different sources (price observatory of supermarkets, fuel prices, vegetables and fruits prices, public procurement data, etc.) will be automatically uploaded. The HCC appointed experts to design a programme drawing raw data from unstructured information available on the internet in pdf and other formats and extract them in csv (comma-separated values) editable files. The data are intended to be used mainly for cartel detection but also offer an integrated data analytics environment with various bespoke tools or off-the-shelf software that allow visualising and analysing data. The HCC also employed contractors to develop an integrated data template and dashboards as well as bespoke software programmes.

Source: Lianos, I (2021), Computational law and economics: an inception report, https://www.epant.gr/en/enimerosi/computational-competition-law-and-economics.html

It is important to note that while data science is needed for data screening, the decision about what variables to include, and what form they should take, should also involve economists and case handlers (Abrantes-Metz and Metz, 2018[23]). Knowledge of, and experience in, recognising and dealing with illegal conduct is required to help choose the right screening method, set the parameters for screening tools and assess the screening results[25].

3.4. International co-operation for data sharing and screen development

Digital screen development requires agencies to invest now and reap the benefits later. Thus, to be worthwhile, investment should be long-term, to develop, maintain and improve tools and methods.

This long-term investment would benefit from co-operation among competition authorities (Hunt, 2022[38]). Authorities are often acquiring skills, building datasets and developing data screens in parallel. Co-operation could save time and resources and is essential as cartels become more sophisticated. Authorities can share technical expertise and experience, as well as, if there are good working relationships and trust, code[26] and, under conditions, data to train screening models. Lianos (2021[37]) argues that competition authorities should share cartel data gained by the operation of existing screens, to create a training dataset containing collusive examples for screens that use machine-learning methods. Any new suspicious behaviour identified through this analysis of the dataset could be shared to help existing screening tools become more sophisticated and accurate. The usefulness of training cartel screening algorithms using cartel data from other jurisdictions is under on-going research (Huber, Imhof and Ishii, 2020[43]).

Since sharing data can raise data sensitivity and privacy issues and likely be subject to legal constraints, anonymising data or creating synthetic datasets ("*an approach to confidentiality where instead of disseminating real data, synthetic data that have been generated from one or more population models are released*") (OECD, n.d.[44]) may make it easier to share[27]. Synthetic data are gaining traction within the machine learning domain (European Data Protection Supervisor, n.d.[45]). Sharing trained algorithms should be easier, since in principle this would not reveal sensitive underlying data.[28]

International co-operation can support joint development of screening software. The DCCA developed a new screening tool, Bid Viewer, based on machine learning. In this process, the DCCA co-operated with the Spanish and Swedish competition authorities (amongst others).

Box 7. The Danish Competition and Consumer Authority Bid Viewer tool

The Danish Competition and Consumer Authority (DCCA) worked on computational methods and developed a software that screens for bid rigging called "Bid Viewer". The tool uses statistical indicators, machine learning, company bidding pattern analysis and artificial neural network models.

The statistical indicators include: (i) normalized relative distance; (ii) percent difference; (iii) coefficient of variation; (iv) skewness; and (v) kurtosis. The indicators are tested on submitted bid prices. Bid Viewer combines the statistical indicators using machine learning.

The machine-learning model is trained on a dataset with proven cartels. The model is then tested on a second dataset with proven cartels. If the second dataset analysis is accurate, the model is then applied to actual procurement data and flags tenders with a higher risk of collusion.

Bid Viewer tests for geographic market sharing and non-geographic market sharing (by identifying firms that do not overlap in the tenders that they bid for). Bid Viewer also tests for sham bids, i.e., bids that are intentionally too high and thus are intended to lose. It is possible to calculate the number of expected wins for a given company using the number of tenders in which it participates and the number of competitors in those tenders. Bid Viewer compares the number of tenders that the company actually won with the number it was expected to win. Companies are flagged if they are too far above or below these values.

In a recent presentation at an OECD meeting, the DCCA stressed the importance of bid-level data. Screening analyses would not be possible without information on winning and losing bids: winning bids only would not be able to show whether two companies never participate on the same tender. Ideally, the data would include withdrawn and invalid bids.

Bid Viewer has been made available to other national competition authorities, including the Spanish and Swedish ones. The UK Competition and Markets Authority is in the process of starting to use it.

Source: Summary Record of 134th meeting of the Working Party No 3 on Co-operation and Enforcement (30 November 2021), DAF/COMP/WP3/M(2021)2 (only accessible to OECD Members and Partners); Kultima, J. R. (2022) Collusion detection in public procurement using computational methods", https://www.en.kfst.dk/media/cnldn11q/bid-viewer_56_seneste.pdf; Hunt, S. (2022), The technology-led transformation of competition and consumer agencies: the Competition and Markets Authority's experience, https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1082753/Stefan_discussion_paper.pdf.

Competition authorities can exchange knowledge and expertise in international fora, like the OECD and the International Competition Network (ICN), as well as in conferences specifically covering the use of data science and artificial intelligence specifically in antitrust enforcement. The CMA Data, Technology and Analytics Conference (2022) was one of the first conferences to provide a forum for exchange among data scientists and technologists.

It is worth noting that many types of co-operation (like sharing experience, knowledge and expertise) would not be hampered by legal obstacles, as they would normally be viewed as sharing authority confidential information[29]. Several respondents to a survey of OECD and ICN members on international enforcement co-operation conducted in 2019 reported that they do not have legal restrictions on sharing authority confidential information and that such sharing could be valuable. Respondents noted that if the shared information was sensitive (and the sharing of data would be deemed sensitive), a high degree of trust between the authorities may be needed, along with knowledge of the respective procedures and processes in handling sensitive and confidential information, and a guarantee from the receiving authority that they would use the information only for the intended purposes (OECD/ICN, 2021[46]).

4. The value of screening

As a general rule, a screening result that identifies a suspicious conduct is not sufficient by itself to prove a breach of competition law[30]. Conversely, screening analysis that fails to spot an issue does not mean that no illegal conduct exists.

Screening results can support the opening of investigations and the prioritisation of cases more often and more easily than helping decide a case based only on the indirect economic evidence that they provide. The main reason is that the standard for opening investigations, or taking investigative steps like dawn raids (even when they involve convincing a judge to issue a search warrant -Box 8), is typically lower than the standard of proof for a final infringement decision, which must offer sufficient proof of the facts on which it is based and be able to convince a court of law that may hear the case.

4.1. Supporting the opening or closing of a case

Authorities can rely on screening results as grounds to start an investigation, and use their standard investigative tools like dawn raids and information requests (Heijnen, Haan and Soetevent, 2015[47]) to find better, and ideally direct, evidence of the suspected conduct (OECD, 2013[5]). Careful analysis of screening results before opening an investigation is still necessary, so that there is no enforcement bias to start cases with low likelihood to find illegal conduct.

Box 8 describes a successful case that the Swiss competition authority COMCO opened based on screening results, as well as a Brazilian case where the competent judge issued a warrant for a dawn raid on the strength of the screening conclusions (whereas judges in Brazil usually issue warrants only if there is a leniency application has been submitted).

Box 8. Cartel screens base the opening of investigations

The See Gaster road construction cartel in Switzerland

The Swiss competition authority (COMCO) developed a cartel-screening tool as part of a broader long-term project to fight against bid rigging. COMCO used the tool to uncover a bid-rigging cartel in the road construction sector in See Gaster (a region in Switzerland), in which participants agreed on bid prices and determined who should win the tenders between 2002 and 2009.

COMCO initially used two simple screens: coefficient of variation (standard deviation of the bids divided by the mean of the bids for a given tender) and relative distance (difference between the two lowest bids divided by the standard deviation of the losing bids for a given tender). However, these two simple screens did not provide conclusive evidence. COMCO realised that this may be due to partial collusion, i.e. collusion that did not involve all firms or tenders, and developed a screen for partial collusion.

COMCO used a four-step procedure to detect partial collusion. First, they identified suspicious tenders that exhibited a low coefficient of variance and high relative distance. Second, they identified whether there was a group of firms that frequently submitted bids for these suspicious contracts. Third, they considered the geographic coverage of these suspicious tenders to determine if there were other firms active in the region and whether the collusion was likely to be stable. Fourth, they applied a screen for bid rotation (i.e., where the winning bidder submits a low winning bid and the remaining bidders submit high bids intended to lose) looking at the distribution of normalised bids between pairs of suspicious firms.

COMCO opened an investigation based on the screening results. It was the first time that an ex ante statistical analysis of data led to starting a case. The investigation lasted between April 2013 and July 2016 and ended with fines against eight firms for a total of around 5 million CHF.

Source: Imhof, D., Y. Karagök and S. Rutz (2018), "Screening for Bid Rigging—Does It Work?", Journal of Competition Law & Economics 14(2), pp. 235-261, https://academic.oup.com/jcle/article-pdf/14/2/235/25640157/nhy006.pdf. Wallimann, H., D. Imhof and M. Huber (2020), "A machine learning approach for flagging incomplete bid-rigging cartels", arXiv preprint arXiv:2004.05629., https://arxiv.org/pdf/2004.05629.pdf. COMCO (2018), OECD-BWB Workshop on Complex Cartel Case Management, www.slideshare.net/OECD-DAF/swiss-competition-commission-on-cartel-detection-and-screening-in-public-procurement

The procurement of Fire Protection in Brazil

In September 2021, CADE's General Superintendence issued a technical note regarding a bid-rigging case in 'Fire Fighting and Prevention/Fire Brigade' (CADE's Administrative Proceeding nº 08700.004914/2021-05). The decision on the case, to be issued by CADE's Administrative Tribunal, is pending.

In the procurement for fire protection for 33 public sector entities, two tenderers provided the same contact email address (which was the address of one of them). The procurement authority noticed, and, upon further review, identified a person who worked for both firms and also had links to more firms in the same market. CADE then conducted an empirical analysis to check for suspicious bidding patterns and found indications of collusion. Specifically, CADE screened the tenders in which the suspected firms linked through the common person had bid, identified all competitors participating in these "suspicious" tenders, and screened all tenders where such "suspicious" competitors had bid. CADE essentially gradually expanded the coverage of its dataset, and the number of possible cartel participants.

The empirical analysis consisted of behavioural screens including average bid, average bid variance, bid coefficient of variation, average number of participants in each bid and number of times a firm was an outlier. The analysis also included the Benford and Entropy Tests, and cluster analysis to identify groups of firms that interacted more frequently and compare the results of behavioural screens for these groups.

The Benford Test identifies possible fictitious or cover bids. It relies on Benford's Law which "*is a mathematical formula that describes the regularly occurring distribution of digits*" (OECD, 2013, p. 55[5]). Bid values that depart significantly from the expected Benford distribution can be a sign of fictitious or cover bids. The Entropy Test is a ranking analysis to identify extreme cases of bidder rotation. These include "eternal winners", who always win in tenders, or "eternal loser", who always lose. Such tender outcomes can be signs of collusion since, in competitive contexts, the ranking of tenders normally varies.

The screens applied in this case are not systematically implemented by CADE. They were applied following an initial red flag (same email address, common person), and provided useful evidence for the detection of the case and the opening of the investigation. CADE sought and obtained a judicial warrant to conduct dawn raids on the strength of the screening results. This was exceptional in that, in Brazil, judges usually grant search warrants only following leniency applications, as inspections are deemed to be intrusive. In this case, the screening results and data mining were convincing. CADE conducted dawn raids in the premises of 14 companies that provided evidence that firms had indeed exchanged competitively sensitive information.

Source: Technical note Nº 7/2021/SG-TRIAGEM CONDUTAS/SGA2/SG/CAD; Schrepel, Thibault and Groza, Teodora, The Adoption of Computational Antitrust by Agencies: 2021 Report (June 21, 2022). 2 Stanford Computational Antitrust, 78 (2022), SSRN: https://ssrn.com/abstract=4142225

Screens can help prioritise cases to focus on those that appear better founded or have a higher chance of success, as well as close cases that are likely to fail. For example, the Brazilian Competition Authority (CADE), having received a large number of complaints of anti-competitive behaviour in the fuel retail market, developed a screen to separate cases that appeared to merit further investigation from those less worthwhile to pursue (Ragazzo, 2012[48]).

Box 9. Prioritising cases through screens

Fuel retail sector in Brazil

The Brazilian competition authority CADE developed a screen to identify which of several possible complaints in the fuel retail sector in Brazil would be the most useful to pursue.

The screen methodology included three statistical tests: (i) the evolution of the retail profit margins of the city where the cartel allegedly operated; (ii) the correlation between the retail margins and the coefficient of variation (level of dispersion in prices) for the city; and (iii) the correlation between the retail profit margin of the city compared to the retail profit margin of the respective state (region).

The methodology assumed that all three tests would be performed and that the analysis could give one of two results: (i) no likelihood of a cartel (i.e. reduction in the retail margins from time to time, a positive association between increases in the margins and price variability, and retail margins that evolve similarly to the state average); or (ii) likelihood of a cartel (i.e. increase of the retail margins over time; a negative association between the retail margins and price variability, and retail margins with a disparate evolution or an evolution that is not similar to the average of the respective state).

The screen was applied on existing ample data for the fuel retail market, collected by the Petroleum National Agency, and allowed rejecting groundless complaints. In few cases, the screening results flagged possible cartel behaviour.

Source: Ragazzo, C. (2012), Screens in the gas retail market: the Brazilian experience, https://www.competitionpolicyinternational.com/screens-in-the-gas-retail-market-the-brazilian-experience/.

4.2. Providing evidence for an infringement decision

Screening results and the indications of violations that these may flag are not direct evidence of illegal activity. They are indications, which must be interpreted to reach a conclusion, and can serve as indirect evidence. Section 2.4 mentions circumstances where screens fail to distinguish between false positives and illegal conduct, for example when a screen identifies price correlation but fails to distinguish between (illegal) explicit collusion and either (legal) tacit collusion or coincidence.

In most jurisdictions and in most cases, on cartels at least, direct evidence of explicit co-ordination is required to make a definitive adverse finding. It is hard to rely on economic evidence obtained through screening solely, particularly as the potential liability for having violated the anti-cartel provisions of the competition law is usually high. In countries where cartels are prosecuted as criminal offences, the standard of proof for a decision finding a breach of competition law is proof beyond reasonable doubt, or a similarly high standard. Therefore, it is more important that there is direct evidence of a cartel agreement for criminal enforcement cases, to meet the required standard and convince the court. However, even in criminal systems, indirect evidence is admissible and useful (OECD, 2006[49])[31].

Thus, economic analysis can play a supportive role and therefore is usually not the evidence on which a case is decided (Harrington, 2006[7]). Still, almost every country making a written or oral contribution to a

2006 OECD roundtable on prosecuting cartels without direct evidence described at least one case in which circumstantial evidence was used to significant effect; economic evidence is one of the two types of circumstantial evidence (the other is evidence of communications among suspected cartel members) (OECD, 2006[49]).

Few cases were almost entirely founded on economic evidence derived from screens. Box 10 presents a case where various factors (patterns) of economic evidence based on screening were considered together, helping to paint a picture of the conduct, which was convincingly consistent with collusion. The screening evidence was found to be sufficiently ample, clear and decisive for the judges who heard the case on appeal to find that the facts on which the decision was based were proven.

Box 10. The procurement of medicine in Mexico

Mexico's competition authority CFC (now COFECE) investigated collusion in the procurement undertaken by the Mexican Institute of Social Security (IMSS). The investigation started after a complaint from IMSS and concerned tenders between 2003 and 2006 for human insulin and electrolyte and intravenous solutions.

The CFC used price screens on data provided by the IMSS. It identified tenders with identical award prices and winner rotation, as well as market share screens and found that the bidders had similar market shares that converged over time. The tender prices did not appear to correspond to costs, and while the cartel members bid on average the same prices with minor variance, this changed upon the entrance of a new competitor in the market, after which prices decreased and their dispersion increased.

The CFC concluded that there was collusion, and imposed fines on the pharmaceutical companies Baxter, Fresenius, Eli Lilly and Pisa. The case was based on economic evidence from screening. The CFC also obtained communication evidence about the companies' opportunities to interact, that they knew each other, travelled together and communicated.

Mexico's Supreme Court upheld the CFC's decision in 2015, confirming the legitimacy of economic analysis as proof for the anticompetitive practice.

Source: Mena-Labarthe, C. (2012), "Mexican experience in screens for bid-rigging", Competition Policy International Antitrust Chronicle, March, https://www.competitionpolicyinternational.com/assets/Cartel-Column-June-New-Format-Full.pdf COFECE (2015), The Mexican Supreme Court of Justice upholds the decision of the Competition Authority concerning a bid-rigging in the pharmaceutical sector (Baxter, Fresenius, Eli Lilly and Pisa), www.competitionpolicyinternational.com/assets/COFECE-009-2015-English.pdf

The machine learning techniques that allow classification of conduct in a data-driven way that is free-er from assumptions and gains in accuracy through use (Section 2.5) might increase the reliability of screening outputs, and thus their value as evidence. This would in part depend on the extent that these outputs, and the way they were arrived at, can be presented in a clear and convincing manner before a court. It is probable that the greater use of digital screens and computational analysis techniques will lead to the development of specific case law regarding the relevant standards of proof and in particular the value of evidence obtained through data analysis (Lianos, 2021[37]).

To the extent that the screening results support an adverse final decision, affected parties arguably have a right to access a screen's methodology and data treatment methods (von Bonin Andreas, 2020[50]). This is a matter of the standards of review in each jurisdiction, but, broadly speaking, use of economic models, without explanation of their methodology or assumptions, may mean that the infringement decision can be annulled, if the company proves that, if it had access to such information, it would have been able to defend against it (OECD, 2019[51]).

Therefore, competition authorities may use screens, as long as the screening assumptions, methodology and results are sufficiently explained to the investigated parties, in particular if such screening results are used against them. Parties should also have appropriate opportunities to present their own arguments on the process and interpretation of screening before a final decision is taken against them. This would arguably require access to the screening code and underlying data, with appropriate confidentiality protections, such as disclosure to a restricted circle of persons with specific obligations concerning the handling of the disclosed information (OECD, 2019[52]).

Such disclosure would be consistent with the OECD Recommendation on Transparency & Procedural Fairness in Competition Law Enforcement (OECD, 2021[53]) which requires "*offering parties the opportunity to present an adequate defence before a final decision is made*" including "*granting them access to the relevant evidence collected by or submitted to the competition authority or court*" and "*providing parties a meaningful opportunity to present a full response to the allegations and submit evidence in support of their arguments before the key decision makers*".

In a merger case (Box 11), the Court of Justice of the European Union ruled that the European Commission's decision to block the transaction without disclosing the methodology and assumptions of the econometric model that it used for the analysis of the effects of a proposed merger infringed the merging parties' rights of the defence. Though this ruling concerned a merger decision, the Court's argument was based on observance of the rights of defence, and would apply in a similar manner in a cartel case.

Box 11. Econometric methodologies and assumptions should be disclosed to parties

Use of econometric models in merger review

In 2012, United Parcel Service, Inc. ('UPS') notified the Commission of its proposed acquisition of its competitor TNT Express NV ('TNT'). Both companies operated in the markets for the international express delivery of small parcels. The Commission blocked the merger in 2013.

On appeal before the General Court of the European Union, UPS alleged that the Commission infringed UPS' rights of defence by relying on a different price concentration econometric model from that which had been disclosed to the merging parties during the merger clearance procedure. The General Court agreed and annulled the Commission's decision. The Commission challenged the first-instance decision before the Court of Justice of the European Union.

The Court confirmed the General Court's decision and dismissed the Commission's appeal. The Court found that if "*it has been sufficiently demonstrated by the applicant [..] that there was even a slight chance that it would have been better able to defend itself*" had it known the details of the econometric model on which the Commission's decision was based, then the applicant's rights of defence have been infringed, and the Commission's decision should be annulled.

Source: Case C-265/17 P United Parcel Service, Inc. v Commission

5. Conclusions

There is increasing interest in cartel screens, largely due to the enabling digital environment. Large amounts of data can be accessed and processed. New technologies allow analysing such data in an increasingly automated manner, and have enabled new screening methods, using machine learning in particular. Recent academic publications, competition authority announcements and conferences indicate that digital screening is gaining in popularity.

There is not ample public information on the use and success of digital screens. We know of cases that started based on screening results, for example those based on Cérebro (Box 1), COMCO's tool (Box 8) and BRIAS (Box 2). However, since several authorities do not publicise their screening initiatives, the real success and impact of screening is not known and cannot be easily estimated.

What appears to be certain is that procurement data screening without ample good-quality data is unlikely to be effective, and that the success of screens, and the time and effort required for their deployment, often turns on data availability. The CMA's screening for cartels tool was withdrawn partly due to difficulties of importing and enriching data (Box 4), Cérebro is based on extensive data mining (Box 1), while several competition authorities are building their own datasets to be able to use them for cartel detection in the future.

The future of screening would benefit and will, to some extent, depend on co-operation among competition authorities. They are often acquiring skills, building datasets and developing data screens in parallel, and co-operation could save time and resources. Authorities can share technical expertise, successes and failures, as well as code and, under conditions, data. To the extent that cartels may be gaining in sophistication, international co-operation may provide an answer.

Annex A. Academic literature on cartel screens, 2015 to 2022

Academic literature on cartel screens has existed for several decades now. Important early contributions include (Porter and Zona, 1993[16]), (Porter and Zona, 1997[17]), (Porter and Zona, 1999[18]), (Bajari and Ye, 2003[19]), (Harrington, 2006[7]), (Abrantes-Metz et al., 2006[20]), (Bolotova, Connor and Miller, 2008[54]), (Abrantes-Metz and Metz, 2012[55]), and (Jiménez and Perdiguero, 2012[56]).

In recent years, this literature has expanded considerably. This annex presents some of the most important contributions since 2015, organised by approach. The approaches include are bid/price distribution based methods, bid roundness, cointegration-based methods, conditional independence using bidding functions, difference-in-differences, historic bid fractions, network methods, probabilistic methods, regression discontinuity methods, structural break methods, suspicious clusters in geographic spatial data, and papers that combine several screens. This classification is partly based on a recent presentation by Jens Roat Kultima, Danish Competition and Consumer Authority, at the CMA Data, Technology and Analytics Conference 2022 on "collusion detection in public procurement using computational methods"[32].

Bid/price distribution-based methods

Early notable contributions to bid/price distribution (also sometimes referred to as 'variance-based') screening methods are (Abrantes-Metz et al., 2006[20]) and (Bolotova, Connor and Miller, 2008[54]). A helpful review of empirical papers that use variance-based screening methods is provided in (Jiménez and Perdiguero, 2012[56]).

Imhof (2017[57]) applies simple statistical screens using road construction and pavement procurement data in the Ticino Canton in Switzerland ('Ticino cartel'). The cartel did not have side payments. The cartel allocated the winning bidder as the firm with the lowest cost, in order to maximise the ex-ante cartel profits. It then agreed on the winning bid price and the losing cover bid prices. All firms participated in the cartel and all rigged bids for five years. Therefore, the large scope and long duration of this cartel may not be representative of most bid-rigging cartels. The author uses screens that determine the distribution of bid prices. These include: (i) coefficient of variation (calculated as the standard deviation of bids submitted for a given contract divided by the arithmetic mean of bids submitted for a given contract); (ii) relative distance (calculated as the distance between the two lowest bids divided by the standard deviation of the losing bids) (iii) kurtosis; and (iv) skewness. The author calculates these statistics for the cartel period and compares them to the pre- and post-cartel period. Lower variation and a right-skewed distribution of bids during the cartel period indicate bid-rigging with artificial losing cover bids. The author applies this analysis ex post knowing the suspected dates of the cartel. If applying ex ante, the authors recommend looking for unexplainable structural changes in these test statistics.

Imhof et al. (2018[27]) apply simple statistical screens using Swiss road construction procurement data in the See-Gaster district of the St Gallen Canton ('See-Gaster cartel'). The Swiss Competition Authority (COMCO) used this analysis to perform dawn raids, in which the authority found evidence that resulted in an investigation and sanctions. The authors adopt a "toolbox approach" incorporating several bid/price distribution based methods including: (1) the coefficient of variation (calculated as the standard deviation of bids submitted for a given contract divided by the arithmetic mean of bids submitted for a given contract); (2) cover bidding screen using relative distance (calculated as the distance between the two lowest bids divided by the standard deviation of the losing bids); (3) screen for partial collusion; and (4) screen for bid rotation.

Huber et al. (2019[26]) combine statistical screens with machine-learning techniques using data for proven bid-rigging cartels in the Swiss road construction sector (which includes both the 'Ticino cartel' and 'See Gaster cartel' (see above) as well as two other cartels for which the authors keep the details confidential). The authors use seven behavioural statistical screens that consider the distribution of bid values in each tender (standard deviation, coefficient of variation, kurtosis, percentage difference, skewness, relative difference ratio, and normalized distance). The authors use two machine-learning techniques to combine these statistical screens: (1) Least Absolute Shrinkage and Selection Operator logit regression; (2) ensemble method, which consists of a weighted average of predictions based on bagged regression trees, random forests, and neural networks. These machine-learning approaches have two general steps: (1) split the data into training and test data, and train the model on the training data, which essentially gives weights to each of the screens; and (2) apply this trained model on the test data to predict whether tenders are collusive or competitive. The authors find both machine-learning techniques correctly identify over 80% of tenders as either cartelised or competitive. Two screens (normalized distance and coefficient of variation) have by far the most predictive power, i.e., the machine-learning models gave them the highest weights. In a robustness test, even when these two screens were excluded, both machine learning methods were still over 80% accurate, as the other screens "step in", meaning even with a more limited set of predictors, the approach can be quite accurate.

Wallimann et al. (2020[58]) develop a method to detect incomplete bid rigging for proven bid-rigging cartels in Swiss tenders for road construction and civil engineering projects ('Ticino cartel', 'See-Gaster cartel' (see above) and an asphalt cartel in Graubunden). Complete bid rigging occurs when all firms bidding in a tender are part of the cartel, while incomplete bid rigging is when only a subset of firms in a tender are part of the cartel. In incomplete bid rigging, competitive bids included in a tender can distort the traditional behavioural screens applied to tenders rendering them less accurate. To address this issue, the authors perform screens on all possible sub-groups of three or four bids in a tender. The authors use a random forest machine-learning approach. The authors find that the machine learning method outperforms individual traditional behavioural screens since it uses the wider set of behavioural screens as inputs and weights them in a data-driven way, choosing the best predictors in each case.

Huber et al. (2020[43]) combine statistical screens with machine learning techniques as suggested by (Imhof, Karagök and Rutz, 2018[27]), (Huber and Imhof, 2019[26]) and (Wallimann, Imhof and Huber, 2020[58]) that were developed in the context of Swiss road construction procurement data. The authors apply these bid-rigging screens to a proven and sanctioned cartel in Japanese procurement markets in the Okinawa prefecture for civil engineering and building construction tenders ('Japanese data'). They also use the Swiss procurement data from (Huber and Imhof, 2019[26]) ('Swiss data'). They use three different types of screens: (i) screens for the variance of bids (coefficient of variance, spread, kurtosis statistic); (ii) screens for the asymmetry of bids (percentage difference, distance, relative distance, normalized distance, alternative normalized difference, skewness statistic); and (iii) a screen for the uniformity of bids (Kolmogorov-Smirnov statistic). The authors use machine learning as follows: (i) random forests alone; and (ii) ensemble method, which is a weighted average of three algorithms: bagged regression trees, random forests and neural networks. The authors find that, using the Japanese data, the correct out-of-sample classification rate varied between 88% and 93%. However, when trained on a mix of the Swiss and Japanese data the highest was 85%. The accuracy further deteriorated when trained using one country and tested on the other country, partly due to the screen values for competitive tenders in one country being similar to anticompetitive tenders in the other country. For example, the coefficient of variance in collusive Swiss tenders was similar to competitive Japanese tenders, so when the model was trained on the Japanese data and then applied to the Swiss data, the coefficient of variance was not useful for detecting the collusive Swiss tenders.

Silveira et al. (2021[59]) use a time series econometric approach to assess variance in consumer prices for proven cartels in Brazilian local gasoline markets. The authors estimate a (i) Markov-Switching Generalized Auto Regressive Conditional Heteroskedasticity (MS-GARCH) model; and (ii) Local Gaussian Correlation (LGC) model. The MS-GARCH screen seeks to identify cartelized market behaviour by looking at price volatility and price dispersion (low price volatility during the cartel period). The LGC model uses the dynamic relationship between the average profit-margin and the variation of the average retail gasoline price (with increase in profit-margin and more stable price expected during the cartel period, meaning a negative intertemporal relationship between profit-margin and variation in price perhaps indicating a collusive agreement). The authors find the MS-GARCH model performed better than the LGC model.

Silveira et al. (2022[60]) combine statistical screens with machine-learning techniques to consumer prices for proven cartels in Brazilian local gasoline markets. The authors use five statistical screens (standard deviation, coefficient of variance, spread, skewness and kurtosis). They calculate these statistical screens at the city-level (there are four cities in the data) in a given week (between roughly 200 and 300 weeks in each of the cartel and non-cartel periods) using weekly gas station-level data. The authors combine these statistical screens using five supervised machine-learning methods (logit, least absolute shrinkage and selection operator logit, ridge logistic, random forest and neural network). They find the coefficient of variance and standard deviation to be the most powerful predictors, although this depends on the context. Thus, they conclude that all statistical screens are relevant. The underlying data and code (Python and Stata) for the analysis are described in Appendix A of the paper.

Rodriguez et al. (2022[61]) combine statistical screens with machine learning techniques using data for proven cartels in a range of industries in procurement data from Brazil, Italy, Japan, Switzerland and the United States. The authors use seven statistical screens including: (i) coefficient of variation; (ii) spread; (iii) difference between two lowest auction bids; (iv) relative difference; (v) skewness; (vi) kurtosis; (vii) Kolmogorov-Smirnov test. The authors use 11 (supervised learning) machine learning algorithms including: (i) Stochastic Gradient Descent (Linear Model); (ii) Extra Trees (Ensemble Method); (iii) Random Forest (Ensemble Method); (iv) Ada Boost (Ensemble Method); (v) Gradient Boosting (Ensemble Method); (vi) Support Vector Machines; (vii) K Neighbours; (viii) Multi-Layer Perceptron (Neural Network Model); (ix) Bernoulli Naïve Bayes (Naïve Bayes); (x) Gaussian Naïve Bayes (Naïve Bayes); and (xi) Gaussian Process. The authors perform 500 iterations (of training and test subsets of the data) for each algorithm. The three top performing algorithms were Extra Trees, Random Forest and Ada Boost (all Ensemble Methods). In the scenario where all auction information was available, these algorithms had accuracy (detection rates) between 81% and 95%. All underlying data and code (Python) are provided in a supplementary file.

Bid roundness

Ishii (2014[62])[33] adopts a measure of “bid roundness” using bid data from auctions for a proven bid-rigging cartel in construction and civil engineering works in Japan. The “roundness level” of a bid is the length of the consecutive array of zeros at the end of the bid price, for example, the “roundness level” for the bid 12,300,000 JPY is five. This is based on the hypothesis that winners will choose round numbers for bid prices to avoid miscommunication. The author uses several statistical and econometric methods to test multiple hypotheses. The author finds that “roundness level” is higher under collusion, amongst other things.

Cointegration-based methods

Kurdoglu and Yucel (2022[63]) adopt a cointegration-based cartel screen using data for a proven Turkish cement cartel. The cointegration-based approach is a time series econometric methodology that tests whether there is statistically significant co-movement of prices between firms, which would suggest potential collusion. Two time series (in this case, time series of prices at two cement manufacturers) are said to be cointegrated if there is some long run equilibrium relation tying the respective time series together that can be represented as a linear function of these two time series (Hamilton, 1994, pp. 571-572[64]). Kurdoglu and Yucel find, in several geographic regions in Turkey, that there was greater cointegration of cement manufacturer price time series during the cartel period than the non-cartel period.

Conditional independence using bidding functions

(Bajari and Ye, 2003[19]) was a landmark paper that set out the idea of conditional independence, that is that sealed bids are expected to be independent of each other (once controlling for observable factors). More recent papers analyse this approach using the spatial econometrics literature. Instead of the spatial element being geographic, it is based on the bidding environment. This literature does this using bidding functions.

Bergman et al. (2020[65]) adopt a spatial econometric approach using data for a proven bid-rigging cartel in the Swedish asphalt paving industry. The approach relies on the idea that a competitive bid by one firm should be uncorrelated with competitive bids by other firms, once controlling for information that may impact bid values (such as the degree of competition and project cost). The authors test for conditional independence between bids. Conditional dependence between bids is a sign of potential complementary bidding resulting from collusion. The authors test for conditional independence using a bidding function which regresses several independent variables, including a spatial weights matrix (the coefficient of interest) and variables that may impact bid values (controls), against bid values (the dependent variable). They find a positive correlation during the cartel period (i.e., a positive and significant coefficient on the spatial weights matrix), and a non-significant correlation during the post-cartel period, suggesting cartelists adopted complementary bidding during the cartel period. This paper verifies cartel existence rather than performing an ex ante screen, as the authors' methodology relies on knowledge of cartels. (Bergman et al., 2015[66]) appears to be an earlier working version of this paper.

Lundberg (2017[67]) uses a spatial econometric approach using data for a proven bid-rigging cartel in the Swedish asphalt paving industry (so related to the work in (Bergman et al., 2015[66])). The author uses Moran's I, a spatial correlation test, to detect potential complementary bidding. The Moran's I test statistic is calculated using bid values directly, as well as with the residuals from a bidding function.

De Andrade Lima and Resende (2021[68]) use a spatial econometric approach using data for an alleged bid-rigging cartel in the Brazilian implantable cardiac devices market. The author's use Moran's I, a spatial correlation test, to detect potential complementary bidding. The authors calculate the Moran's I test statistic using the residuals from a bidding function.

Difference-in-differences

Difference-in-differences is a standard econometric approach that uses panel data to determine the average treatment effect by calculating the difference between the average change over time for the treatment group (difference one) and the average change over time for the control group (difference two).

Clark et al. (2020[69]) use a difference-in-differences approach to compare winning-bid isolation and clustering of bids in a proven bid-rigging cartel in the Canadian asphalt industry. The dependent variable is a dummy variable based on the historic bid fraction (the bidder's own bid minus the minimum of the other bids, divided by the reserve price) or bid difference (when no reserve price is available). It is equal to one when the historic bid fraction or bid difference falls in a given interval. The treatment group is the Montreal asphalt industry. The control group is the Quebec City asphalt industry. The time period is the cartel (before the investigation) and post-cartel period (after the investigation). The regression controls for the auction characteristics (such as the lagged average price of crude oil, the quantity of asphalt in the call for tender, and the Herfindahl–Hirschman index (city-specific)). The authors find evidence of isolated winning bids (a result of the winner wanting a small margin to guard against any bidding errors) as well as clustering (a result of cover bidding at an agreed higher price) for the treatment group during the cartel period.

Perdiguero and Jiménez (2021[70]) use a difference-in-differences approach to test for the “Monday effect”. Spanish premium oil operators jointly cut gasoline prices on Mondays to lower the official prices of automotive fuels, which were collected on Mondays, so Spain would not be top of the European price ranking. When the government changed the regulation to use average weekly prices instead of Monday prices, the authors find this “Monday” effect suddenly stopped. The dependent variable is the retail price of petrol. The treatment group is branded mainland Spain petrol stations that were potentially impacted by the “Monday effect”. The control groups are petrol stations on the Canary Islands (a region of Spain) and those that are unbranded or operated by independent retailers. The time period is the cartel (before the change to regulation) and post-cartel period (after the change to regulation).

Historic bid fractions

Chassang et al. (2022[71]) consider historic competitive bid fractions using data from two public works procurement first-price sealed bid auctions in Japan with no proven cartel. The authors calculate the competitive bid fraction for every bid. They calculate the competitive bid fraction as the bidder’s own bid minus the minimum of the other bids, divided by the reserve price. A negative value means that the bidder won the bid, while a positive value means the bidder lost the bid. The authors then consider the distribution of these competitive bid fractions. A missing mass of bids around zero indicates suspicious behaviour, as it suggests that there were no bids that are close to the winning bid, and that there was a considerable gap between the winning bid and the remaining bids. This historic bid fraction approach is also used and described in (Ortner et al., 2022[72]) in the context of asymptotically safe cartel screens (i.e. screens that competitive firms pass with probability approaching one).

Network methods

Wachs et al. (2019[73]) use an unsupervised machine-learning network approach to reveal hotspots where firms interact more frequently and where collusion may be more likely and easier to sustain. This approach has been applied in other contexts, such as corruption. The authors apply this approach to two markets: (1) the proven Ohio school milk cartel; and (2) auctions awarded in the Republic of Georgia between 2011 and 2016 with no proven cartel. They find that in the Ohio milk cartel, collusive firms frequently interact in relative isolation from competitive firms, while in the Georgian procurement data groups with cohesive and exclusive interactions have higher prices and lower variance in bids and prices.

Probabilistic methods

Signor et al. (2021[74]) adopt a probabilistic method using auction data from Petrobras, the state-owned Brazilian oil company, in the “Operation Car Wash” case. These were construction projects that Petrobras tendered. The “Club of 16” was a group of construction companies that rigged dozens of public infrastructure projects. They were involved in some of the Petrobras tenders. The authors examine the likelihood of a particular set of bids occurring by chance. The authors calculate a bid ratio, which is the bid divided by the pre-tender estimate (which was provided by an expert at the time of the tender). The authors then consider the distribution of these bid ratios in benchmark ‘honest’ tenders (non-collusive tenders, i.e., none of the “Club of 16” participated in these tenders). The authors then calculate a probability that a given auction suffered from collusion based on the observed bid ratios. The authors found that their method seemed to outperform the results presented in (Imhof, 2018[75]) and (Bajari and Ye, 2003[19]) (although this conclusion was reached by comparing measures of performance from the respective papers, rather than implementing these approaches to their own data). Other probabilistic approaches are provided in (Signor et al., 2017[76]) and (Signor et al., 2020[77]) applied in the same “Operation Car Wash” case.

Regression discontinuity methods

Kawai et al. (2022[15]) adopt a regression discontinuity design to identify incumbency advantage and bid rotation using data from the proven Ohio school milk cartel analysed in (Porter and Zona, 1997[17]) and public works procurement first-price sealed bid auction data from Japan used in (Chassang, 2022[71]) in which no firms have yet been charged for collusion (but previous academic papers have suggested collusion occurred). A regression discontinuity design identifies an average treatment effect by considering differences in an outcome variable (in this case, either incumbency status or backlog) for observations that are marginally above or below a treatment cut-off threshold (in this case, winning or losing a bid). As bidding rings often adopt rotation schemes or give priority to incumbents in project allocation, bid rotation and incumbency advantage are often suggested as indicators of collusion. However, there are non-collusive cost-based explanations for them: bid rotation can arise under competition if marginal costs increase with backlog, and incumbency advantage can be explained by cost asymmetries among competitive firms or learning-by-doing.

Therefore, to disentangle these effects, the authors focus on auctions where the winning and losing bids are very close (i.e., they isolate the marginal winners and losers). Regardless of incumbency status or backlog, winning and losing should be as-if random for close bids. Thus, if marginal winners are more often challengers than incumbents, this may be a sign of anticompetitive bid rotation, while if marginal winners are more often incumbents than challengers, this may be a sign of incumbency advantage. Using the Ohio milk cartel data, the authors find that the marginal winner is more likely to be an incumbent suggesting an illegal incumbency advantage. Using the Japanese procurement data, the authors find potential evidence of a combination of both illegal incumbency advantage (observing that marginal winners are more commonly incumbents) and illegal bid rotation (observing that marginal winners have a lower backlog).

Structural break methods

Crede (2019[78]) adopts a structural break cartel screen using monthly domestic producer prices for pasta products with proven cartels in Italy and Spain and non-cartel data in France. Similar to the use of bidding functions, the author estimates the underlying data generating process (DGP), which can be considered as a price function. The author estimates the DGP using a reduced-form regression that includes variables that determine pasta prices, such as various types of production costs, proxies for demand and controls for structural breaks that are induced by potential cartel activity. The author tests whether there are any structural breaks in the data generating process, that is, whether there are any unexplainable shifts in price over the period, which would most likely be due to cartel activity. The author finds their structural break method correctly identifies cartels in Italy and Spain and no cartel in France.

While other approaches also use structural breaks comparing cartel period data with non-cartel period data using the exogenously given cartel dates, this is the only method that tests for structural breaks endogenously (i.e., without knowing when precisely the cartel was). This is why it can be used for ex ante screening.

The author compares this approach to variance screens, estimating a coefficient of variance screen (Abrantes-Metz et al., 2006[20]) and GARCH variance screen (Bolotova, Connor and Miller, 2008[54]). These variance screens do not perform as well (i.e., they do not identify cartels). However, the author considers that this may be due to the short duration of the cartel that had steep rises and falls in price, meaning that there was not an opportunity to observe reduced price variation resulting from stable collusion.

Crede (2016[79]) provides a short introduction to cartel screens, explaining the rationale behind price variance screens, as well as their potential limitations (e.g., that a cartel raising prices could increase the price variance measure, thus it would incorrectly identify this as non-collusive). The author then explains that testing for structural breaks can be a solution to this problem (because the increase in price above cost will cause an unexplained structural break in the relationship between cost and price). This article does not apply a structural break test to actual data, but rather explains the intuition.

Suspicious clusters in geographic spatial data

Heijnen et al. (2015[47]) identify suspicious clusters of petrol stations in a spatial approach using almost daily retail price data from the Dutch gasoline market, not based on a case or proven cartel. The authors use the variation coefficient, defined as the standard deviation of a firm's residual retail price (the retail price after controlling for the observed characteristics of the petrol station) divided by its mean. The authors consider the lowest 5% of outlets based on the variation coefficient as suspicious. The authors adopt a two-stage approach. First, they identify any clusters of these suspicious outlets. Second, they identify the most suspicious regions where an antitrust investigation may be warranted.

Combination of several screens

Fazekas et al. (2022[21]) combine several screens, such as bid distribution-based methods, bidding patterns and market concentration. The table below provides an overview of the screens used in the paper that the authors combine using a supervised machine-learning random forests approach. The authors match known cartel cases to procurement data from several industries and countries to create a final dataset and apply the random forests approach on the dataset. The authors find that no single screen works in the majority of cases and a multi-screen approach is the most effective. This paper builds on work by the same authors in (Czibik, Tóth and Fazekas, 2015[80]) and (Fazekas and Tóth, 2016[22]).

Table A A.1. Tested Indicators

Category	Nr	Indicator	Level of observation	Description
Prices	1	Difference between lowest and second lowest price	Contract	Relative difference between the lowest and second lowest bid price (1%, 5%, 10% etc differences)
	2	Relative price range	Contract	Relative price range based on the lowest and highest bid price is less than 10% or more than 90% of the distribution
	3	Relative standard deviation	Contract	Relative standard deviation of bid prices is less than 10% or more than 90% of the distribution
	4	Relative price	Contract	Ratio of the final price and the estimated price
	5	Benford's law	Market-period	Whether first digits of contract prices of a given market in a given period follow Benford's law
Bidding patterns	6	Single bidding	Contract	Contract receiving a single bid during the tendering process.
	7	Missing bidders	Company-period	The number of unique buyers/cities/regions/product codes companies submitting a bid.
	8	Subcontracting	Contract	Whether a contract has a subcontractor.
	9	Consortia	Contract	Whether the winning bid was a consortia.
	10	Cut-point position	Market-period	Whether there are companies in a cut-point position in a given market and time period.
	11	Winning probability	Market-period	The average winning probability of companies of a given market and time period
Market structure	12	Concentrated market structure	Market-period	HHI change from during to after the cartel period
	13	Stable market structure	Market-period	Average absolute market share changes during vs. after the cartel period

Source: (Fazekas et al., 2022[21])

Annex B. Machine-learning methods

There are three main types of machine learning approaches: supervised learning, unsupervised learning, and reinforcement learning. Most academic papers on cartel screens use supervised learning approaches, some use unsupervised learning approaches and very few, if any, use reinforcement learning approaches.

Cartel screening is usually considered as a *classification problem*, that is, the investigator would like to predict whether an auction is collusive or non-collusive, based on the characteristics of that auction. Economists would usually approach this problem with regression analysis, in this case, logit regression, given the binary outcome variable (collusive or non-collusive). However, machine learning offers additional approaches. Deng (2017[81]), Varian (2014[82]) and Athey & Imbens (2019[83]) provide a useful summary of these approaches, explaining the relevance of machine learning techniques for economics. There are also textbooks describing these approaches, such as (James et al., 2013[84]) (less advanced) and (Hastie et al., 2009[28]) (more advanced). Torres Berru et al. (2019[85]) also provide a literature review of artificial intelligence techniques (such as classification, regression, clustering, prediction, outlier detection, and visualization) used to detect other kinds of public procurement corruption (such as bribery, collusion embezzlement, misappropriation, fraud, abuse of discretion, favouritism, and nepotism).

This annex includes a description of several machine learning approaches used for cartel screening. This annex focuses on supervised and unsupervised learning, providing a description of techniques used in recent academic literature on cartel screens. For each method, there is a short explanation, followed by papers that have adopted each approach.

When authors compare machine supervised machine learning approaches, they usually use the same data for each model (e.g., the same underlying screening statistics, such as various types of bid/price distribution-based screens). When comparing machine learning algorithms, it is important to consider both accuracy (the ability to detect collusion) and complexity (the calculation time). For example, random forests is one of the simpler machine learning models and thus has a lower calculation time, while LASSO is more time-consuming as it requires calculating a penalty term. Ensemble method is one of the most time-consuming because it has to calculate optimal weights. However, the ensemble method can often have high accuracy.[34]

Linear regression

Linear regression (Hastie et al., 2009, pp. 44-66[28]) models the relationship between an output variable and at least one input variable. Often linear regression is modelled using a least squares approach, which minimises the sum of the residuals squared (where the residual is the difference between the predicted value and the actual output value). Linear regression is a method commonly used by economists. Therefore, many elements of supervised machine learning can be considered more of a evolution than a revolution (Abrantes-Metz and Metz, 2018[23]). It can be classified as machine learning because, as new training data is obtained, the linear function updates with this new information.

Logistic regression

Logistic regression (Hastie et al., 2009, pp. 119-128[28]) models the probability that an outcome belongs to a certain category (thus, the output variable takes values between 0 and 1), conditional on at least one input variable. For example, the output variable could indicate the probability that a tender is collusive.

(Silveira et al., 2022[60]) use logistic regression.

Ridge regression

Ridge regression (Hastie et al., 2009, pp. 61-67[28]) is similar to linear regression, although it shrinks regression coefficients by imposing a penalty on their size. For example, if there is no penalty term (i.e., it is set to zero), this approach is then just ordinary least squares (linear regression). In linear regression, when there are many variables, there may be correlated coefficients, which then cause high variance, with positive and negative coefficients cancelling each other out. Imposing size constraints on coefficients, as done in ridge regression, aims to resolve this problem.

(Silveira et al., 2022[60]) use ridge regression.

Least Absolute Shrinkage and Selection Operator (LASSO)

Least Absolute Shrinkage and Selection Operator (LASSO) (Hastie et al., 2009, pp. 68-69[28]) is a shrinkage method, just like ridge regression, with the penalty term being the main distinction between the two approaches. While ridge regression interacts the penalty term with the coefficient squared, the LASSO regression interacts the penalty term with the absolute value of the coefficient. The implication is that with a sufficiently small penalty term, under the LASSO approach some coefficients will have a value of zero (effectively a zero weight), while in a ridge regression coefficients will never have a value of zero.

(Imhof, 2018[75]), (Huber and Imhof, 2019[26]), (Wallimann, Imhof and Huber, 2020[58]), (Imhof and Wallimann, 2021[25]), and (Silveira et al., 2022[60]) use LASSO.

Neural networks

Neural networks (Hastie et al., 2009, pp. 389-416[28]) are essentially nonlinear statistical models. Neural networks form the basis of deep learning, which is a sub-field of machine learning. Neural networks can be thought of as a nonlinear generalisation of a linear function. The model takes in inputs, which it passes through one or more layers of neurons (which can be thought of as the processors of the model), and then predicts an output. If there is just one layer of neurons, then this is just a standard linear model.

(Imhof, 2018[75]), (Huber and Imhof, 2019[26]), (Huber, Imhof and Ishii, 2020[43]), (Wallimann, Imhof and Huber, 2020[58]), (Imhof and Wallimann, 2021[25]), (Rodríguez et al., 2022[61]) and (Silveira et al., 2022[60]) use neural networks (albeit as part of an ensemble approach). (Wachs and Kertész, 2019[73]) uses an unsupervised "network" approach. (Huber and & Imhof, 2021[24]) use a "convolutional neural network" approach.

Regression trees

Regression trees (Hastie et al., 2009, pp. 307-308[28]) are based on binary recursive partitioning which is an iterative process that divides the data into partitions and continues dividing each partition into smaller groups. Thus, regression trees are based on decision trees (which are effectively if-else statements). Regression trees, rather than a decision tree, are relevant when the output is continuous.

(Imhof, 2018[75]), (Huber and Imhof, 2019[26]), (Huber, Imhof and Ishii, 2020[43]), and (Wallimann, Imhof and Huber, 2020[58]) use bagged regression trees (although all as part of an ensemble approach).

Support vector machines

Support vector machines (Hastie et al., 2009, pp. 417-458[28]) can be used for classification problems, such as whether a tender is collusive or non-collusive. Optimal separating hyperplanes apply where two classes are linearly separable. Support vector machines apply when these classes overlap and are not linearly separable. The support vector machine approach creates a non-linear boundary to classify inputs. The support vector machine will select the boundary that maximises the margin (which is the difference between the boundary and the closest observation of a given class) from both classes.

(Imhof and Wallimann, 2021[25]) and (Rodríguez et al., 2022[61]) use a support vector machine approach.

Random forests

Random forests (Hastie et al., 2009, pp. 587-604[28]) is a machine learning approach that can be used to solve classification problems, so it can predict a binary outcome variable based on a number of ‘features’ (also known as explanatory variables). The approach builds on the concept of decisions trees (which are effectively if-else statements).

The random forests approach has the following steps. First, create a number of n datasets from the training dataset by randomly selecting observations (rows) from the data (this is called bootstrapping). The randomly selected datasets will have the same number of rows as the original one. Second, randomly select a number of features (or explanatory variables) for each of these datasets. Third, for each bootstrapped dataset and feature selection combination from the first two steps, create a decision tree. Fourth (and finally), for each new value in the test data, run it through all of these decision trees (i.e., through the ‘decision nodes’) and get an outcome (either 1 or 0) (from the ‘leaf nodes’). Then take the majority value, and allocate that as the result (this is called ‘aggregation’). The combination of the bootstrapping and aggregation is called ‘bagging’.

Random forest contains two random elements: (i) the random creation of new datasets from the training data in the bootstrapping step; and (ii) the random selection of features (or explanatory variables) in the feature selection step. It is called ‘forest’ because it uses several decision trees, to address the limitations of the decision tree approach and improve the accuracy of results.

(Imhof, 2018[75]), (Huber and Imhof, 2019[26]), (Huber, Imhof and Ishii, 2020[43]), (Wallimann, Imhof and Huber, 2020[58]), (Imhof and Wallimann, 2021[25]), (Rodríguez et al., 2022[61]), (Silveira et al., 2022[60]) and (Fazekas et al., 2022[21]) use a random forests approach (although some only as part of an ensemble approach).

Ensemble

The ensemble approach (Hastie et al., 2009, pp. 605-624[28]) aims to build a model that combines the strengths of several more ‘simple’ models. Effectively it takes several of the ‘simple’ models above (which could be logistic regression, LASSO, neural networks, random forests etc.) and runs the test data through each of these models, getting the prediction from each model, and then combining those (using weights) to get a final prediction.

(Imhof, 2018[75]), (Huber and Imhof, 2019[26]), (Huber, Imhof and Ishii, 2020[43]), (Wallimann, Imhof and Huber, 2020[58]), (Imhof and Wallimann, 2021[25]) and (Rodríguez et al., 2022[61]) use an ensemble approach.

Endnotes

[1] See the Stanford University's "Computational Antitrust" project, launched in January 2021, which combines competition authorities and academics from various disciplines, including law, economics and computer science, https://law.stanford.edu/codex-the-stanford-center-for-legal-informatics/computational-antitrust-project/

[2] The use of screening in merger control was partly considered in the recent Global Forum on Competition sessions on economic analysis in merger investigations (OECD, 2020[86]) and merger control in dynamic markets (OECD, 2020[99]).

[3] (Harrington, 2021[96]) sets out four conditions required for cartel success: (i) a common understanding between firms (coordination condition) on how not to compete; (ii) a collusive arrangement that incentivises its members to comply (internal stability condition); (iii) a way to limit supply of non-cartel members (external stability condition); and (iv) avoidance of detection and penalisation by the competition authority and customers (enforcement condition). Harrington concludes that that collusion is difficult but manageable.

[4] Please see: https://www.youtube.com/watch?v=Iovsp5aHcuU (2:40:12)

[5] The OECD is scheduled to have a roundtable on the "Future of leniency programmes" in June 2023. The OECD previously held a roundtable on "Challenges and Co-ordination of Leniency Programmes" in June 2018 (OECD, 2018[94]). Marvão and Spagnolo (Marvão and Spagnolo, 2018[95]) also provide a summary of some key theoretical and empirical studies on leniency.

[6] Between 1990 and 2016, nominal affected sales by international hard core cartels exceeded USD 50 trillion. Gross cartel overcharges exceeded USD 1.5 trillion. More than 100 000 companies were liable for international price fixing (Connor, 2016[13]). See also the OECD Recommendation concerning Effective Action against Hard Core Cartels https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0452#backgroundInformation

[7] A strategic cartel can reduce, but not eliminate, the power of most behavioural screens. Cartels typically form to extract profit by increasing price. A cartel may try to reduce the likelihood of detection by increasing price slowly, however this means giving up on some profit. A cartel would never go so far as to fully minimise the probability of detection, as that would mean not raising the price at all. (Harrington and Imhof, 2022[10]).

[8] "*The improvement and wider usage of the software screening tools will make colluders polish bid-rigging techniques to make them invisible to these tools. In its turn, the improvement of bid-rigging methods will require the development of better screening tools. Therefore, we are at the beginning of yet another sword and shield competition between competition authorities and colluders*", (Lianos, 2021[37])

[9] A bidding function details the variables that determine bid values. It is typically estimated using regression analysis, with bid value as the dependent variable and factors that determine bid value (such as the costs of a project) as the independent variables.

[10] This classification is partly based on a recent presentation by Jens Roat Kultima, Danish Competition and Consumer Authority, at the CMA Data, Technology and Analytics Conference 2022 on “collusion detection in public procurement using computational methods”, https://www.youtube.com/watch?v=Iovsp5aHcuU (2:38:33)

[11] Beth and Gannon summarise the breadth of cartel screening approaches into: (1) sales vs procurement screens; (2) structural screens vs behavioural screens; (3) screening with priors (i.e. prior beliefs or knowledge known in the statistics literature as prior) vs screening without priors; and (4) screens of tender bids vs screens of posted market prices (Beth and Gannon, 2022, pp. 78-80[11]).

[12] (Harrington and Imhof, 2022[10]) provide two older examples of anomalies. First, firms systematically not charging certain prices such as when Nasdaq market-makers avoided bid and ask quotes ending in an odd-eighth, which was a simple rule for supporting a higher price-cost mark-up (Christie and Schultz, 1994[92]). Second, firms charging lower prices when the cost is higher, such as when some milk suppliers submitted lower bids on school milk tenders for districts that were farther away from their plants (and thus had higher transportation costs) (Porter and Zona, 1999[18]).

[13] Episode 14: Cartel Screening and Machine Learning (Harrington & Imhof) https://www.youtube.com/watch?v=NVhoIi8mFys (18:13)

[14] “*To see why this could be the case, imagine the "ideal" market for collusion: two firms, homogeneous products, stable demand, no large buyers, excess capacity, and so forth. Even though such a market would surely be flagged by a structural investigative tool, my own prior belief is that a very high fraction of those markets are not cartelized. … There are multiple equilibria - some involving collusion, some not - and non-observed variables can influence whether firms settle upon a collusive equilibrium*” (Harrington, 2006[7]).

[15] “*Failure to find evidence of collusion may be due to misspecifying the collusive model; for example, we've focused on the wrong collusive equilibrium*” (Harrington, 2006[7]). A cartel screen is often only as good as the data it is trained on. Huber et al. found increased false negatives when using a model trained on Japanese auction data when applied to Swiss auction data. This was because the screening statistic of interest, the coefficient of variation, was quite similar for collusive Swiss tenders and competitive Japanese tenders, meaning the model was not able to effectively identify collusion in the Swiss data (Huber, Imhof and Ishii, 2020[43])

[16] There are tools based on algorithms that autonomously learn from procurement or market data whether and how suppliers collude, detecting differences in the dispersion of collusive and competitive prices (https://martinhuber.shinyapps.io/carteldetection/).

[17] There is an example of privately-developed software that uses neural-net AI to detect cartels and anti-competitive behaviour as part of a company compliance regime, www.dlapiper.com/fr/france/insights/publications/2022/02/lawand-aiscension-ai-tool-to-ensure-effective-risk-management-detect-anti-competitive-practices/.

[18] The Crimes Legislation Amendment Powers Offences and Other Measures Act 2018 (CLAPOOM) allows collecting, using and disclosing personal information that may be relevant for integrity purposes https://www.aph.gov.au/Parliamentary_Business/Bills_LEGislation/Bills_Search_Results/Result?bId=r5838

[19] “*Besides the existence of a central website, where all public procurement announcements are published, the format or 'machine-readability' of information is also essential for the quantitative analysis of public procurement data. While accessing the data through an application programming interface (API) or direct*

database download would be the best mode of access, countries mostly disclose structured xml or html/pdf files [..]. While xml files can be simply turned into an analysable database, information from html and pdf files is often hard to extract (Fazekas and Tóth, 2016[22])

[20] "*Publicly available databases on procurement generally do not contain accurate information on bid prices and other information relevant to cartel screens such as subcontractors identity. The high incidence of missing data and the common lack of persistent identifiers of market participants provide additional hurdles"* (Fazekas et al., 2022[21])

[21] "*The CNMC builds its own public procurement database based on the selected download of certain data from [the public procurement platform], carrying out an appropriate automated process of filtering and cleaning of manifest errors, as well as categorising data by quality levels*" (translated) (Campuzano, 2021[40])

[22] (Fazekas and Tóth, 2016[22]) set objectives for a quantitative collusion detection framework (applied to the Swedish procurement system, but valid in general), as follows: (1) set up a continuous automated data pipeline from public procurement data providers to ensure database quality and timely data availability; (2) collect missing information on selected high-risk markets to improve data quality and deploy indicators to their full potential; (3) collect and link additional data to public procurement records, in particular company registry, financial and ownership information; (4) conduct risk-based checks using the identified indicators for markets with sufficient data quality; (5) start collecting public procurement collusion information systematically as an input to continuously improve the indicator system.

[23] There are projects to gather public procurement data in standardised format such as EU DIGIWHIST (the Digital Whistle-blower). The project collects and analyses procurement data across 35 jurisdictions, including all European Union members, see https://digiwhist.eu/about-digiwhist/

[24] (Fazekas and Tóth, 2016[22]) made policy recommendations to improve procurement data quality for the Swedish public procurement system that can apply to more jurisdictions. These include (1) ensuring a uniform data capture process and safeguard data quality, ideally using the central public procurement platform and under the supervision of a dedicated public agency; (2) introducing standard forms defining the minimum required data content; (3) requiring the collection of information on contract implementation, such as contract modification, final total contract value and actual completion date, as well as information on factors supporting collusion risk analysis, such as consortia and subcontracting.

[25] *"An economist may be well positioned to identify which variables to include in X to get a useful prediction. Arguably the greater risk is that of over-fitting, that the computer may identify a spurious connection which happens to hold in the training dataset and assume that it will always hold. The best discipline against this over-fitting is the same sort of economic theory the econometrician uses*", (Abrantes-Metz and Metz, 2018[23])

[26] "*The marginal cost of copying code is close to zero. The problems that agencies around the world face are very similar, and with multinational firms we are often monitoring, regulating and tackling the same or similar behaviour. To the extent that agencies can share code with each other – for data pipelines, scraping, software/ tools, analysis – agencies can benefit from some of the same digital forces that are reshaping markets*", (Hunt, 2022[38]).

[27] "" *Synthetic data […] helps training machine learning algorithms that need an immense amount of labelled training data, which can be costly or come with data usage restrictions*". However, "*a privacy assurance assessment should be performed to ensure that the resulting synthetic data is not actual personal data. This privacy assurance evaluates the extent to which data subjects can be identified in the*

synthetic data and how much new data about those data subjects would be revealed upon successful identification", https://edps.europa.eu/press-publications/publications/techsonar/synthetic-data_en.

[28] Episode 14: Cartel Screening and Machine Learning (Harrington & Imhof) https://www.youtube.com/watch?v=NVhoIi8mFys (37:57)

[29] Authority sensitive information is "*information created or held by an authority that is not in the public domain, where the authority is not statutorily prohibited from disclosing but it is considered confidential or sensitive by the authority. […] analysis and compilation of public information by an authority can transform public information into 'agency confidential information', for example through the use of complex data analytics*" (OECD/ICN, 2021[46])

[30] "*An important disclaimer is that evidence supporting collusion need not imply evidence against competition*" (Harrington, 2006[7])

[31] It has been argued that indirect evidence should be used even less in administrative proceedings than in criminal enforcement, given the more lenient standard of proof in administrative matters (usually the existence of substantial evidence), and the fact that the first instance decision-maker is usually a competition authority and not a court that follows a more rigorous decision-making process, (OECD, 2006[49]), contribution by BIAC.

[32] Jens Roat Kultima, Danish Competition and Consumer Authority, at the CMA Data, Technology and Analytics Conference 2022 on "collusion detection in public procurement using computational methods", https://www.youtube.com/watch?v=Iovsp5aHcuU (2:38:33).

[33] (Ishii, 2014[62]) is included in Annex A despite being from 2014. Other than this, Annex A only includes academic papers from the period 2015 to 2022.

[34] Episode 14: Cartel Screening and Machine Learning (Harrington & Imhof) https://www.youtube.com/watch?v=NVhoIi8mFys (22:39).

References

Abrantes-Metz, R. (2012), "Why and How to Use Empirical Screens in Antitrust Compliance", *CPI Antitrust Chronicle* 1, http://cendoc.sc.gob.sv/textocompleto/927.pdf. [33]

Abrantes-Metz, R. et al. (2006), "A variance screen for collusion", *International Journal of Industrial Organization* 24(3), pp. 467-486, https://www.sciencedirect.com/science/article/pii/S016771870500158X. [20]

Abrantes-Metz, R. and A. Metz (2020), "Why Screening Is a'Must Have'Tool for Effective Antitrust Compliance Programs", https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3734004. [34]

Abrantes-Metz, R. and A. Metz (2019), "The Future of Cartel Deterrence and Detection", *CPI Antitrust Chronicle, January*, https://papers.ssrn.com/abstract=3360615. [14]

Abrantes-Metz, R. and A. Metz (2018), "Can Machine Learning Aide in Cartel Detection?", *Antitrust Chronicle, Competition Policy International*, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3291633. [23]

Abrantes-Metz, R. and A. Metz (2012), "How far can screens go in distinguishing explicit from tacit collusion? New evidence from the LIBOR setting", *CPI Antitrust Chronicle*, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2021515. [55]

Athey, S. and G. Imbens (2019), "Machine learning methods that economists should know about", *Annual Review of Economics*, Vol. 11, pp. 685-725, https://www.annualreviews.org/doi/full/10.1146/annurev-economics-080217-053433. [83]

Bajari, P. and L. Ye (2003), "Deciding between competition and collusion", *Review of Economics and statistics* 85(4), pp. 971-989, https://direct.mit.edu/rest/article/85/4/971/57436/Deciding-Between-Competition-and-Collusion. [19]

Barto, A. and T. Dietterich (2004), "Reinforcement learning and its relationship to supervised learning", *Handbook of learning and approximate dynamic programming*, https://web.engr.oregonstate.edu/~tgd/publications/Barto-Dietterich-03.pdf. [30]

Bergman, M. et al. (2020), "Interactions across firms and bid rigging", *Review of Industrial Organization* 56(1), pp. 107-130, https://link.springer.com/article/10.1007/s11151-018-09676-0. [65]

Bergman, M. et al. (2015), "Using spatial econometrics to test for collusive behavior in procurement auction data". [66]

Beth, H. and O. Gannon (2022), “Cartel screening–can competition authorities and corporations afford not to use big data to detect cartels?”, *Competition Law & Policy Debate* 7(2), pp. 77-88, https://www.elgaronline.com/view/journals/clpd/7/2/article-p77.xml. [11]

Bharadwaj, B. et al. (2022), “Game, Set and Fuzzy match”, https://www.compasslexecon.com/game-set-and-fuzzy-match/. [41]

Bolotova, Y., J. Connor and D. Miller (2008), “The impact of collusion on price behavior: Empirical results from two recent cases”, *International Journal of Industrial Organization*, Vol. 26(6), pp. 1290–1307, https://www.sciencedirect.com/science/article/pii/S0167718708000039. [54]

Buccirossi, P., G. Di Pierro and L. Giangregorio (n.d.), “Detecting Bid-Rigging in the “Big Data Era””, http://ippa.org/images/BOOKS/IPPC8/Chapter5_Buccirossi_Di-Pierro_Giangregorio.pdf. [100]

Campuzano, S. (2021), “Riesgos y oportunidades de la inteligencia artificial desde la perspectiva de la competencia. Un análisis desde la CNMC”, *Boletín Económico de la ICE*, https://doi.org/10.32796/bice.2021.3137.7259. [40]

Chassang, S. (2022), *Robust Screens for Noncompetitive Bidding in Procurement Auctions*, pp. 315-346, https://doi.org/10.3982/ECTA17155. [71]

Christie, W. and P. Schultz (1994), “Why do NASDAQ market makers avoid odd-eighth quotes?”, *The Journal of Finance* 49(5), pp. 1813-1840, https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1994.tb04782.x. [92]

Clark, R., D. Coviello and A. Leverano (2020), “Complementary bidding and the collusive arrangement: Evidence from an antitrust investigation”, *ZEW Discussion Papers* 20, https://madoc.bib.uni-mannheim.de/57783/1/dp20052.pdf. [69]

Clemens, G. (2017), “Raising Rivals’ Costs Through Cartel Detection - Why Downstream Buyers Rather Face an Upstream Cartel than Downstream Competition”, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2946114. [98]

Competition Bureau Canada (2022), *Collusion Risk Assessment Tool*, https://www.canada.ca/en/competition-bureau/news/2022/06/attention-procurement-agents-use-our-collusion-risk-assessment-tool-to-protect-your-contracts-from-bid-rigging.html. [39]

Connor, J. (2016), *The Private International Cartels (PIC) Data Set: Guide and Summary Statistics, 1990- July 2016*, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2821254. [13]

Crede, C. (2019), “A structural break cartel screen for dating and detecting collusion”, *Review of Industrial Organization*, Vol. 54(3), pp. 543-574, https://link.springer.com/content/pdf/10.1007/s11151-018-9649-5.pdf. [78]

Crede, C. (2016), “Getting a fix on price-fixing cartels”, *Significance* 13(1), pp. 38-41, https://rss.onlinelibrary.wiley.com/doi/pdfdirect/10.1111/j.1740-9713.2016.00882.x. [79]

Czibik, Á., B. Tóth and M. Fazekas (2015), “How to Construct a Public Procurement Database from Administrative Records. With examples from the Hungarian public procurement system of 2009–2012”, https://www.govtransparency.eu/wp-content/uploads/2017/11/GTI_publicprocurement_techreport_171109.pdf. [80]

de Andrade Lima, R. and G. Resende (2021), “Using the Moran’s I to detect bid rigging in Brazilian procurement auctions”, *The Annals of Regional Science* 66(2), pp. 237-254, https://link.springer.com/article/10.1007/s00168-020-01018-x. [68]

Deng, A. (2020), “Algorithmic Collusion and Algorithmic Compliance: Risks and Opportunities”, *The Global Antitrust Institute Report on the Digital Economy* 27, https://gaidigitalreport.com/wp-content/uploads/2020/11/Deng-Algorithmic-Collusion-and-Algorithmic-Compliance.pdf. [97]

Deng, A. (2017), “An Antitrust Lawyer’s Guide to Machine Learning”, *Antitrust* 32, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3082514. [81]

Deng, A. (2017), “Cartel detection and monitoring: a look forward”, *Journal of Antitrust Enforcement* 5(3), pp. 488-500, https://academic.oup.com/antitrust/article-pdf/5/3/488/21390250/jnw017.pdf. [29]

Doane, M. et al. (2015), “Screening for collusion as a problem of inference”, *Oxford handbook of international antitrust economics* 2, pp. 523-553, http://www.competitioneconomics.com/wp-content/uploads/2013/05/Screening-for-Collusion-as-a-Problem-of-Inference.pdf. [101]

European Data Protection Supervisor (n.d.), *Publications*. [45]

Fazekas, M. et al. (2022), “Public procurement cartels: A systematic testing of old and new screens”, *Government Transparency Institute*, http://www.govtransparency.eu/wp-content/uploads/2022/03/GTI-WP-Cartel_20220304-1.pdf. [21]

Fazekas, M. and B. Tóth (2016), “Assessing the potential for detecting collusion in Swedish public procurement”, *Konkurrensverket, Stockholm*. [22]

Hamilton, J. (1994), *Time Series Analysis*, Princeton University Press. [64]

Harrington, J. (2021), “Cartel screening is for companies, law firms, and economic consultancies, not just competition authorities”. [31]

Harrington, J. (2021), “The Practical Requirements of a Successful Cartel”, *Research Handbook on Cartels (Peter Whelan, ed.)*, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3798852. [96]

Harrington, J. (2015), “Thoughts on Why Certain Markets are More Susceptible to Collusion and Some Policy Suggestions for Dealing with Them”, *OECD Expert background paper (Global Forum on Competition)*, https://joeharrington5201922.github.io/pdf/OECD_Background%20Paper_Harrington.pdf. [32]

Harrington, J. (2008), “Detecting cartels”, *Handbook of antitrust economics* 213, pp. 215-258, http://mis.kp.ac.rw/admin/admin_panel/kp_lms/files/digital/SelectiveBooks/Economics/Handbook%20of%20Antitrust%20Economics.%20Edited%20[Buccirossi,%20Paolo.].pdf.pdf#page=236. [87]

Harrington, J. (2006), “Behavioral screening and the detection of cartels”, *European competition law annual*, pp. 51-68, https://joeharrington5201922.github.io/pdf/Florence.pdf. [7]

Harrington, J. and D. Imhof (2022), “Cartel Screening and Machine Learning”, *Stanford Computational Antitrust*, https://www-cdn.law.stanford.edu/wp-content/uploads/2022/08/harrington-imhof-2022.pdf. [10]

Hastie, T. et al. (2009), *The elements of statistical learning: data mining, inference, and prediction*, New York: springer, https://link.springer.com/content/pdf/10.1007/978-0-387-84858-7.pdf. [28]

Heijnen, P., M. Haan and A. Soetevent (2015), "Screening for collusion: a spatial statistics approach", *Journal of Economic Geography* 15(2), pp. 417-448, https://academic.oup.com/joeg/article/15/2/417/928498. [47]

Huber, M. and D. & Imhof (2021), "Deep learning for detecting bid rigging: Flagging cartel participants based on convolutional neural networks", *arXiv preprint arXiv:2104.11142*. [24]

Huber, M. and D. Imhof (2019), "Machine learning with screens for detecting bid-rigging cartels", *International Journal of Industrial Organization* 65, pp. 277-301. [26]

Huber, M., D. Imhof and R. Ishii (2020), "Transnational machine learning with screens for flagging bid-rigging cartels", *Université de Fribourg*, https://doc.rero.ch/record/329575/files/WP_SES_519.pdf. [43]

Hunt, S. (2022), "The technology-led transformation of competition and consumer agencies: the Competition and Markets Authority's experience", https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1082753/Stefan_discussion_paper.pdf. [38]

Imhof, D. (2018), *Empirical Methods for Detecting Bid-rigging Cartels*, Université Bourgogne Franche-Comté, https://tel.archives-ouvertes.fr/tel-01963076/document. [75]

Imhof, D. (2017), "Simple statistical screens to detect bid rigging", *Université de Fribourg*. [57]

Imhof, D., Y. Karagök and S. Rutz (2018), "Screening for Bid Rigging—Does It Work?", *Journal of Competition Law & Economics* 14(2), pp. 235-261. [27]

Imhof, D. and H. Wallimann (2021), "Detecting bid-rigging coalitions in different countries and auction formats", *International Review of Law and Economics*. [25]

Ishii, R. (2014), "Bid roundness under collusion in Japanese procurement auctions", *Review of Industrial Organization*, Vol. 44(3), pp. 241-254, https://link.springer.com/content/pdf/10.1007/s11151-013-9408-6.pdf. [62]

James, G. et al. (2013), *An introduction to statistical learning*, Springer, https://link.springer.com/book/10.1007/978-1-4614-7138-7. [84]

Jiménez, J. and J. Perdiguero (2012), "Does rigidity of prices hide collusion?", *Review of Industrial Organization* 41(3), pp. 223-248, https://link.springer.com/content/pdf/10.1007/s11151-012-9337-9.pdf. [56]

Johnson, J. and D. Sokol (2020), "Understanding AI Collusion and Compliance", *Cambridge Handbook of Compliance (Forthcoming)*, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3413882. [35]

Kawai, K. (2022), *Detecting Large-Scale Collusion in Procurement Auctions*, http://www.journals.uchicago.edu/doi/10.1086/718913. [90]

Kawai, K. (2022), *Using Bid Rotation and Incumbency to Detect Collusion: A Regression Discontinuity Approach*, https://doi.org/10.1093/restud/rdac013. [15]

Kultima, J. (2022), “Collusion detection in public procurement using computtional methods”, *Danish Competition and Consumer Authority: Competitive Markets and Consumer Welfare* 56 (April), https://www.en.kfst.dk/media/cnldn11q/bid-viewer_56_seneste.pdf. [105]

Kurdoglu, B. and E. Yucel (2022), *A Cointegration-based cartel screen for detecting collusion*, https://mpra.ub.uni-muenchen.de/113888/1/MPRA_paper_113888.pdf. [63]

Laitenberger, U. and K. Huschelrath (2011), “The adoption of screening tools by competition authorities”, *Antitrust Chronicle* 9, https://www.competitionpolicyinternational.com/assets/0d358061e11f2708ad9d62634c6c40ad/HuschelrathSEP-112.pdf. [91]

Lamontanaro, A. (2019), “Bounty Hunters For Algorithmic Cartels: An Old Solution for a New Problem”, *Fordham Intell. Prop. Media & Ent. LJ* 30, 1259, https://ir.lawnet.fordham.edu/cgi/viewcontent.cgi?article=1760&context=iplj. [102]

Lianos, I. (2021), “Computational competition law and economics - an inception report”, https://www.epant.gr/en/enimerosi/publications/research-publications/item/1414-computational-competition-law-and-economics-inception-report.html. [37]

Lundberg, J. (2017), “On cartel detection and Moran’s I”, *Letters in Spatial and Resource Sciences* 10(1), pp. 129-139, https://link.springer.com/article/10.1007/s12076-016-0176-4. [67]

Marvão, C. and G. Spagnolo (2018), “Cartels and leniency: Taking stock of what we learnt”, *Handbook of Game Theory and Industrial Organization*, Vol. II, https://www.econstor.eu/bitstream/10419/204750/1/site-wp0039.pdf. [95]

Nicholls, R. (2021), “Regtech as an antitrust enforcement tool”, *Journal of Antitrust Enforcement* 9(1), pp. 135-151, https://academic.oup.com/antitrust/article-pdf/9/1/135/37173888/jnaa011.pdf. [103]

OECD (2022), “OECD Competition Trends 2022”, https://www.oecd.org/daf/competition/oecd-competition-trends-2022.pdf. [12]

OECD (2021), “Competition Compliance Programmes”, *OECD Competition Committee*, http://oe.cd/ccp. [36]

OECD (2021), “OECD Business and Finance Outlook 2021”, https://www.oecd-ilibrary.org/sites/ba682899-en/1/3/5/index.html?itemId=/content/publication/ba682899-en&_csp_=02d27ef0d7308d76a010fd2a9882228f&itemIGO=oecd&itemContentType=book. [1]

OECD (2021), *Recommendation on Transparency & Procedural Fairness in Competition Law Enforcement*, https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0465. [53]

OECD (2020), “Digital Evidence Gathering in Cartel Investigations”, https://one.oecd.org/document/DAF/COMP/LACF(2020)2/en/pdf. [6]

OECD (2020), “Economic analysis in merger investigations”, https://www.oecd.org/daf/competition/economic-analysis-in-merger-investigations-2020.pdf. [86]

OECD (2020), “Merger Control in Dynamic Markets”, https://www.oecd.org/daf/competition/merger-control-in-dynamic-markets-2020.pdf. [99]

OECD (2019), *Access to the case file and protection of confidential information*, http://www.oecd.org/competition/access-to-case-file-and-protection-of-confidential-information.htm. [52]

OECD (2019), *Standard of review by courts in competition cases*, http://www.oecd.org/daf/competition/standard-of-review-by-courts-in-competition-cases.htm. [51]

OECD (2018), "Challenges and Co-ordination of Leniency Programmes", https://one.oecd.org/document/DAF/COMP/WP3(2018)1/en/pdf. [94]

OECD (2018), *OECD-BWB Workshop on Complex Cartel Case Management*, https://www.oecd.org/daf/competition/oecd-bwb-workshop-on-complex-cartel-case-management.htm. [2]

OECD (2018), "Workshop on cartel screening in the digital era", https://www.oecd.org/competition/workshop-on-cartel-screening-in-the-digital-era.htm. [3]

OECD (2017), "Algorithms and Collusion: Competition Policy in the Digital Age", http://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm. [4]

OECD (2015), *Recommendation on Public Procurement*, http://www.oecd.org/gov/public-procurement/recommendation/. [89]

OECD (2013), "Ex officio cartel investigations and the use of screens to detect cartels", http://www.oecd.org/daf/competition/exofficio-cartel-investigations.htm. [5]

OECD (2012), *Recommendation on Fighting Bid Rigging in Public Procurement*, https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0396. [42]

OECD (2009), *Guidelines for Fighting Bid Rigging in Public Procurement*, https://www.oecd.org/daf/competition/guidelinesforfightingbidrigginginpublicprocurement.htm. [9]

OECD (2006), *Prosecuting cartels without direct evidence*, http://www.oecd.org/daf/competition/prosecutionandlawenforcement/37391162.pdf. [49]

OECD (n.d.), *Glossary of Statistical Terms*. [44]

OECD/ICN (2021), *Report on International Co-operation in Competition Enforcement*, http://www.oecd.org/competition/oecd-icn-report-on-international-cooperation-in-competition-enforcement-2021.htm. [46]

Ortner, J. et al. (2022), "Screening adaptive cartels" No. 2020-59, https://people.bu.edu/jortner/index_files/screening_adaptive_cartels.pdf. [72]

Pavanelli de Lorenzi, C. (2022), *CADE eyes development of gun-jumping detection tool*. [88]

Perdiguero, J. and J. Jiménez (2021), "Price coordination in the spanish oil market: the monday effect", *Energy Policy* 149, 112016, https://www.sciencedirect.com/science/article/pii/S0301421520307278. [70]

Porter, R. and J. Zona (1999), "Ohio school milk markets: An analysis of bidding", *The RAND Journal of Economics*, Vol. 30/2, pp. 263-288, https://www.jstor.org/stable/2556080. [18]

Porter, R. and J. Zona (1997), "Ohio school milk markets: An analysis of bidding", https://www.nber.org/system/files/working_papers/w6037/w6037.pdf. [17]

Porter, R. and J. Zona (1993), "Detection of bid rigging in procurement auctions", *Journal of political economy* 101(3), pp. 518-538, https://www.journals.uchicago.edu/doi/abs/10.1086/261885. [16]

Ragazzo, C. (2012), *Screens in the gas retail market: the Brazilian experience*, https://www.competitionpolicyinternational.com/screens-in-the-gas-retail-market-the-brazilian-experience/. [48]

Rodríguez, M. et al. (2022), "Collusion detection in public procurement auctions with machine learning algorithms", *Automation in Construction* 133, 104047, https://www.sciencedirect.com/science/article/pii/S0926580521004982. [61]

Schrepel, T. and T. Groza (2022), "The Adoption of Computational Antitrust by Agencies: 2021 Report", *Stanford Computational Antitrust*, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4142225. [93]

Signor, R. (2021), "Collusion detection in infrastructure procurement: A modified order statistic method for uncapped auctions", *IEEE Transactions on Engineering Management*, https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9336335. [74]

Signor, R. et al. (2020), "Detection of collusive tenders in infrastructure projects: learning from operation car wash", *Journal of Construction Engineering and Management*, Vol. 146(1), https://ascelibrary.org/doi/abs/10.1061/%28ASCE%29CO.1943-7862.0001737. [77]

Signor, R. et al. (2017), "Collusive bidding in Brazilian infrastructure projects", *Proceedings of the Institution of Civil Engineers-Forensic Engineering* 170(3), pp. 113-123, https://espace.curtin.edu.au/bitstream/handle/20.500.11937/59452/257611.pdf?sequence=2. [76]

Silveira, D. et al. (2021), "Cartel screening in the Brazilian fuel retail market", *EconomiA* 22(1), pp. 53-70, https://www.sciencedirect.com/science/article/pii/S1517758021000011. [59]

Silveira, D. et al. (2022), "Won't get fooled again: A supervised machine learning approach for screening gasoline cartels", *Energy Economics* 105, 105711, https://www.sciencedirect.com/science/article/pii/S0140988321005594. [60]

Torres Berru, Y. et al. (2019), "Artificial Intelligence techniques to detect and prevent corruption in procurement: a systematic literature review", *International Conference on Applied Technologies*, pp. 254-268, https://link.springer.com/chapter/10.1007/978-3-030-42520-3_21. [85]

Vadász, P. et al. (2017), *Chapter 16 Identifying Illegal Cartel Activities from Open Sources*, Springer, http://197.156.112.159/bitstream/handle/123456789/862/Babak%20Akhgar.pdf?sequence=1&isAllowed=y. [104]

Varian, H. (2014), "Big data: New tricks for econometrics", *Journal of Economic Perspectives*, Vol. 28(2), pp. 3-28, https://pubs.aeaweb.org/doi/pdf/10.1257%2Fjep.28.2.3. [82]

von Bonin Andreas, S. (2020), *The Use of Artificial Intelligence in the Future of Competition Law Enforcement*, https://doi.org/10.1093/jeclap/lpaa077. [50]

Wachs, J. and J. Kertész (2019), "A network approach to cartel detection in public auction markets", *Scientific Reports* 9(1), pp. 1-10, https://www.nature.com/articles/s41598-019-47198-1. [73]

Wallimann, H., D. Imhof and M. Huber (2020), "A machine learning approach for flagging incomplete bid-rigging cartels", *arXiv preprint arXiv:2004.05629.*, https://arxiv.org/pdf/2004.05629.pdf. [58]

Zlatcu, I. and M. Suciu (2017), "The role of economics in cartel detection: A review of cartel screens", *Journal of Economic Development, Environment and People* 6(3), pp. 15-26, http://jedep.spiruharet.ro/RePEc/sph/rjedep/JEDEP22_2Zlatcu_p16-26.pdf. [8]

www.oecd.org/competition

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