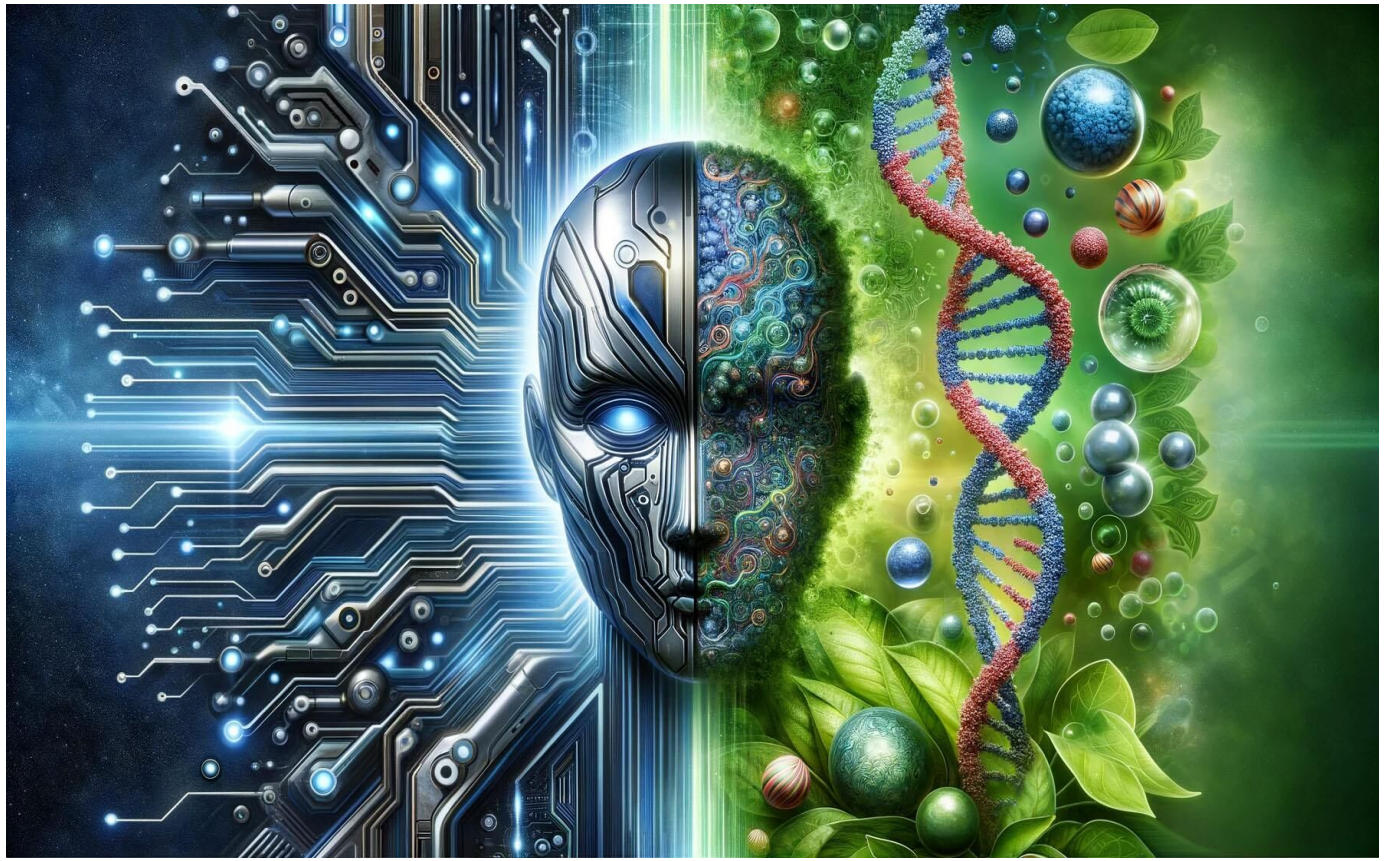


Fighting Cartels and Bid Rigging: Technological and Conceptual Challenges

Prof. Ioannis Lianos

i.lianos@ucl.ac.uk

Personal views – do not represent the Competition Appeal Tribunal

Bid rigging

- OECD countries spend approximately 13-15% of their GDP in public procurement
- EU: around €2 trillion per year
- Bid Rigging:
  - Illegal collusion in public tenders where competitors agree on bids (prices, winners, etc.) to distort competition
    - Includes cover bidding, bid rotation, market allocation, or bid suppression…
- Enforcement action: prevention, detection and sanctioning
- Digital transformation of procurement
- New issues: joint bidding, online bidding and algorithmic bidding
- Role of AI in public procurement

From Cartels 1.0: the "plain-vanilla" cartel

- Adam Smith, Wealth of Nations, 1776: 'People of the same trade seldom **meet together**, even for merriment and diversion, but the conversation ends in a conspiracy against the public, or some contrivance to raise prices'

- OECD Recommendation of the Council concerning Effective Action Against Hard Core Cartels (25 March 1998)

a) "hard core cartel" is an anticompetitive agreement, anticompetitive concerted practice, or anticompetitive arrangement by competitors to fix prices, **make rigged bids** (collusive tenders), establish output restrictions or quotas, or share or divide markets by allocating customers, suppliers, territories, or lines of commerce;

b) the hard core cartel category does not include agreements, concerted practices, or arrangements that

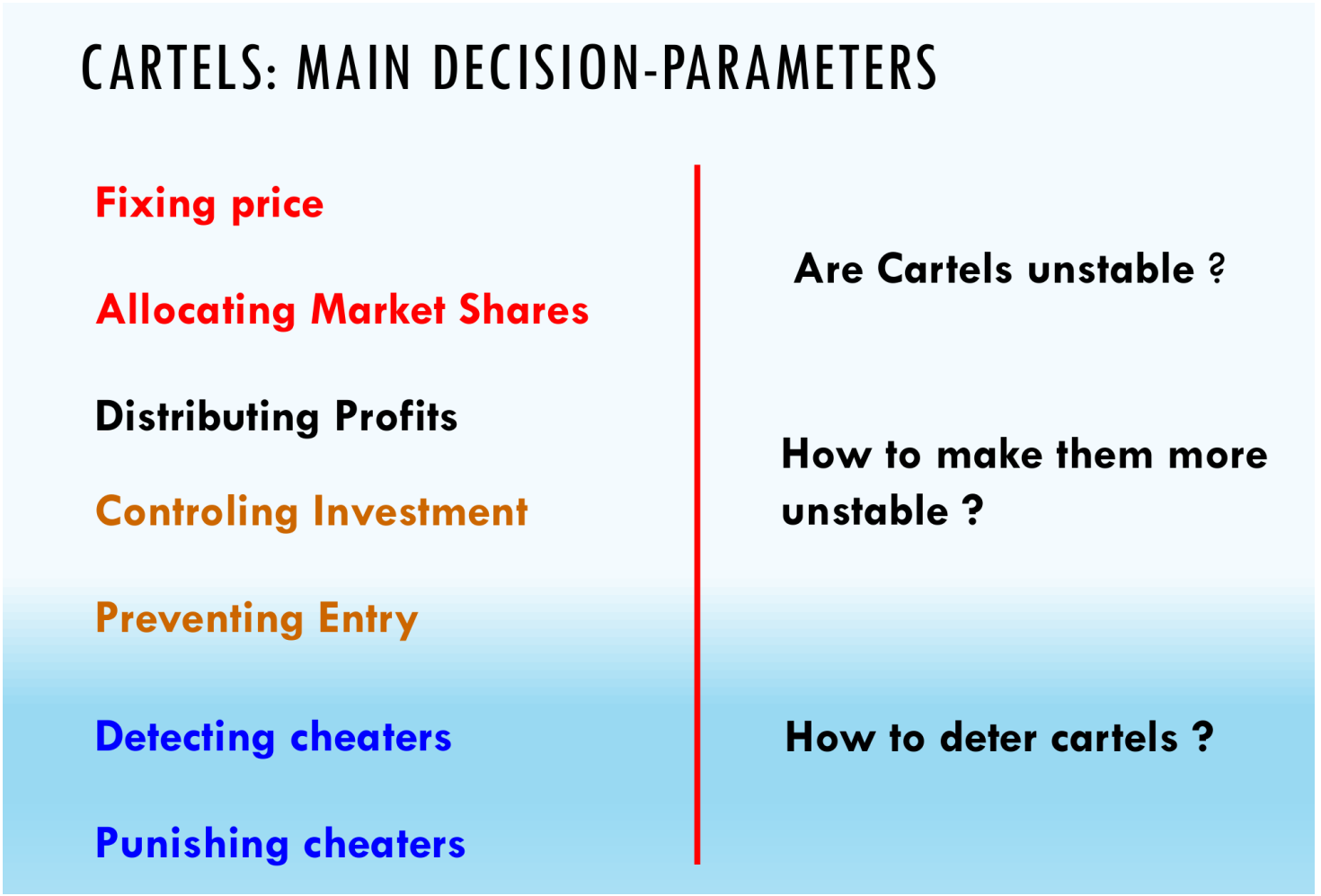
(i) are reasonably related to the lawful realisation of cost-reducing or output-enhancing efficiencies,

(ii) are excluded directly or indirectly from the coverage of a Member country's own laws, or

(iii) are authorised in accordance with those laws. However, all exclusions and authorisations of what would otherwise be hard core cartels should be transparent and should be reviewed periodically to assess whether they are both necessary and no broader than necessary to achieve their overriding policy objectives.

To Cartels 2.0.

- Uncover "reward-punishment schemes" among firms (Harrington, 2007)
  - Leniency programmes and the tip of the iceberg
  - Cartels and **facilitating practices**
  - **Information exchange** and cartels
    - mechanism for participants to signal price and output intentions to one another
    - EU takes a strict approach to information exchange
    - Invitation to collude & public announcements to investors (Section 5 FTC Act)



To Algorithmic coordination

- Firms' pricing decisions are increasingly delegated to software programs that incorporate the latest developments of artificial intelligence
- Not the first time: Pricing algorithms have been used by airline companies for decades, recent expansion in other sectors (financial markets and the hotels and insurance industries)
- Algorithmic Pricing has become affordable even for small businesses, as off-the-shelf machine learning solutions and computing capability are now being supplied by tech giants such as Amazon, Google and Microsoft
- Rely on buyer's entire past purchasing history
- AP may lead to consumer poaching, or to the use of exclusivity or market-share discounts, both of which may have anti-competitive effects. – price discrimination issue
- Digital cartels as a new issue:
  - U.S. v. Topkins, 2015
  - CMA, Online Sales of Posters and Frames (2016)

Algorithmic coordination/cartels

From simple adaptive algorithms…

- Bruno Salcedo, *Pricing Algorithms and Tacit Collusion* (2015) found that when four conditions were met simultaneously, namely that firms set prices through algorithms that can respond to market conditions (1), these algorithms are fixed in the short run (2), can be decoded by the rival (3), and can be revised over time (4), then every long run equilibrium of the game led to monopolistic, or collusive, profits
- Zhou et al (2018): even **without explicit communication or coordination**, algorithms in a Cournot duopoly learned strategies that resulted in output levels similar to those seen in collusive agreements.
- Byrne & de Roos (2017): **empirical** data from **gasoline** market show that stations were able to converge on collusive outcomes
- Emilio Calvano et al., *Algorithmic Pricing: What Implications for Competition Policy?*, 55 REV. INDUS. ORG. 155 (2019): **three possibilities of algorithmic collusion**: (a) conventional collusion enabled by pre-programmed pricing algorithms that use strategies to facilitate collusion, (b) collusion through third party pricing, e.g. software companies providing competing firms with similar algorithms, and (c) algorithmic collusion facilitated solely through coordination by sophisticated pricing algorithms, without explicit communication from humans.

Algorithmic coordination/cartels

- **To self-learning algorithms…**

❑ Computer simulated experiments where pricing algorithms in controlled (synthetic) environments, were analysed in their ability to sustain collusive strategies, and their speed of convergence to above-competitive prices

❑Q-learning algorithms, where agents learn from interacting autonomously through trial and error with their environment

❑Crandall et al. (2018); Leibo et al (2017): self-learning algorithms could solve the coordination problem through **trial- and-error** and with **no human intervention**

❑Klein (2018): learning algorithms **gravitate toward conscious parallelism** in simple oligopolistic setting

❑Calvano et al. (2019): the self-learning algorithms **identified** tacit collusion as an optimal strategy

❑Ezrachi and Stucke (2016): Digital Eye: self-learning algorithms **independently learn** to maximize profits by observing competitors' actions through continuous data analysis

- **Incentives to Coordinate even in Non-Oligopolistic Markets!**

Algorithmic coordination/cartels

- **And Collusion by Large Language Models (LLMs)**

❑ Emerging economic literature raises more important and distinct concerns regarding algorithmic collusion through Large Language Model (LLM) pricing agents, using simulations as an additional source of scientific evidence about algorithms

❑E.g. Sara Fish et al., Algorithmic Collusion by Large Language Models (2024)

❑ Algorithms pre-trained on very large datasets but without explicit instructions, learn to play optimally by experience and have more "discretion" as to the possible interpretation of their prompts

❑The LLM becomes "a randomized, ever-evolving 'black box' whose' intentions' are opaque and largely uninterpretable, even to its users"

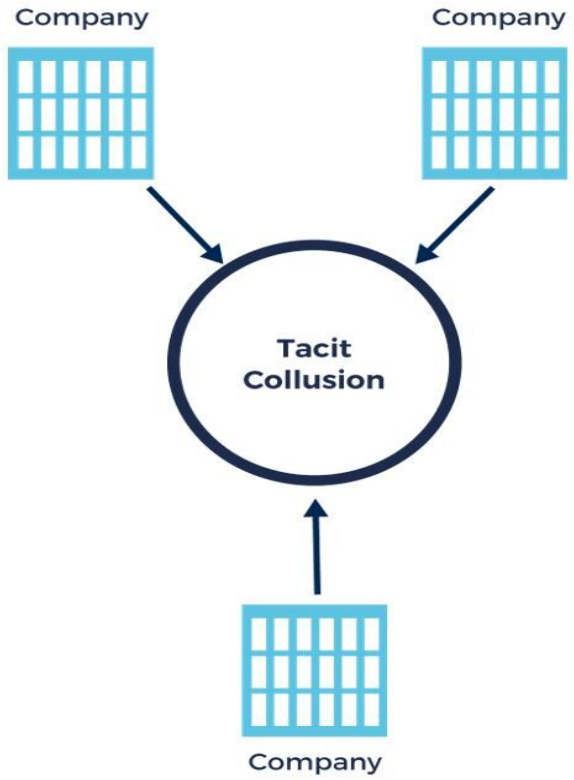
❑"(I)t is conceivable that LLM-based pricing algorithms might behave in a collusive manner despite a lack of any such intention by their users" even if the textual instructions they receive are "innocuous"

❑"*homo silicus*" collusion may look different!

Cartels 3.0.:Algorithmic (tacit) collusion

Possible scenarios

- ❑Monitoring algorithms
- ❑ Collusion by using the same algorithms
- ❑ Signalling algorithms
- ❑ Self-Learning algorithms



- ❑ **Preventing the Algorithmic Facilitation of Rental Housing Cartels Act. 2024 Bill**:
  - ❑ "[m]ake it unlawful for rental property owners to contract for the services of a company that coordinates rental housing prices and supply information, and designate such arrangements a per se violation of the Sherman Act."
- ❑ **Preventing Algorithmic Collusion Act of 2024 S. 3686, 118th Cong. (2024)**
  https://www.congress.gov/bill/118th-congress/senate-bill/3686

Cartels 3.0.: Competition law and algorithmic coordination

CL prohibits **explicit** collusion and **tacit** collusion only when no other plausible explanation available (see *Suiker Unie*, *Woodpulp II*)

It prohibits **collective dominance** (in theory!) (see *Airtours*) or mergers likely to have **coordinated effects**

It may prohibit **price signaling** behaviour that may facilitate algorithmic coordination

See, HCC Guidelines on the implementation of Article 1A (2023)

It may impose some **pre-commercialization auditing** of pricing algorithms (NCT) or **prohibit the use of some algorithms** (precautionary approach)

Computational antitrust and Surveillance/Screening technology

Bid rigging detection

- **Wide variety of cartel types:** Fazekas - Tóth (2016) 3 dimensions
  - a) elementary collusion techniques,
  - b) forms of rent-sharing, and
  - c) resulting market structure
- **Screening and Statistical detection**
  - Imhof, Karagok & Rutz (2018)
- **Machine-learning detection**
  - Huber & Imhof (2019)
  - Harrington & Imhof (2022)
  - Huber & Imhof (2023)
- **Graph (network) detection**
  - Carbone, C., Calderoni, F. & Jofre (2024)
- **Natural language processing (NLP)**
- **AI detection**
  - Wallimann, H., Imhof, D. & Huber, M. (2023)
  - Agentic AI procurement

Bibliography:

OECD (2024), "Detecting Cartels for Ex Officio Investigations," OECD Roundtables on Competition Policy Papers

Calini, Clara and Catenazzo, Alessandra and Iossa, Elisabetta, Using Multiple Tools to Enhance Competition in Public Procurement (November 18, 2024). CEIS Working Paper No. 594, Available at SSRN: https://ssrn.com/abstract=5153351 or http://dx.doi.org/10.2139/ssrn.5153351

Computational competition law and Bid rigging

Significant literature exists on computational methods for suspicious bid detection to combat collusion in public procurement. Various data sources are utilized, each with advantages and limitations:

Historical cartel datasets:

- Six datasets of known cartel cases (Rodriguez et al.)
- Publicly available, useful for model training
- Limited to historical data

Public tender and contract award databases (e.g., opentender.eu):

- Live, publicly available data with tender information
- Lacks information on individual bids, only shows winning supplier

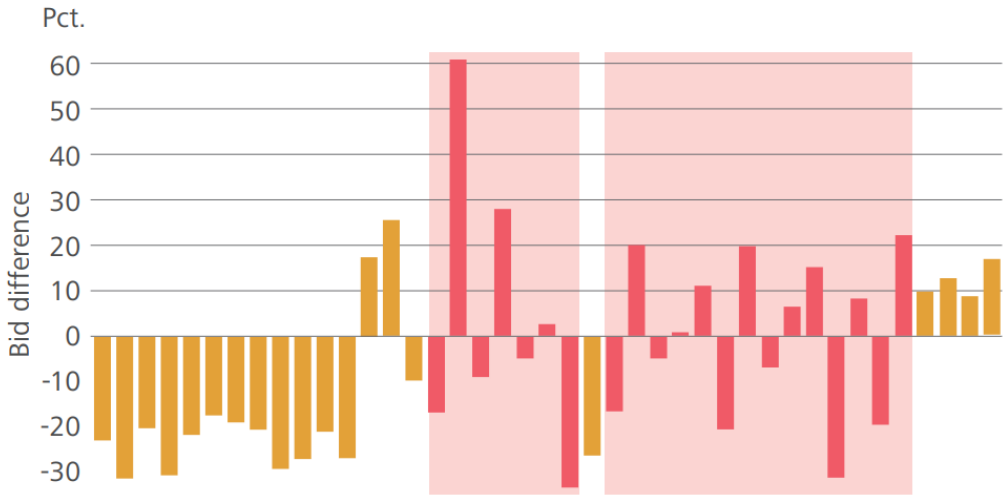
Electronic procurement platforms (e.g., eprocurement.gov.gr):

- Provides full information, including all submitted bids
- Data access must be granted by respective ministries
- New law enabling access

The HCC focused on 5 methods to determine the risk profile of a bid.

Method 1: pricing patterns

Image source: [Bid Viewer, Danish Competition And Consumer Authority]

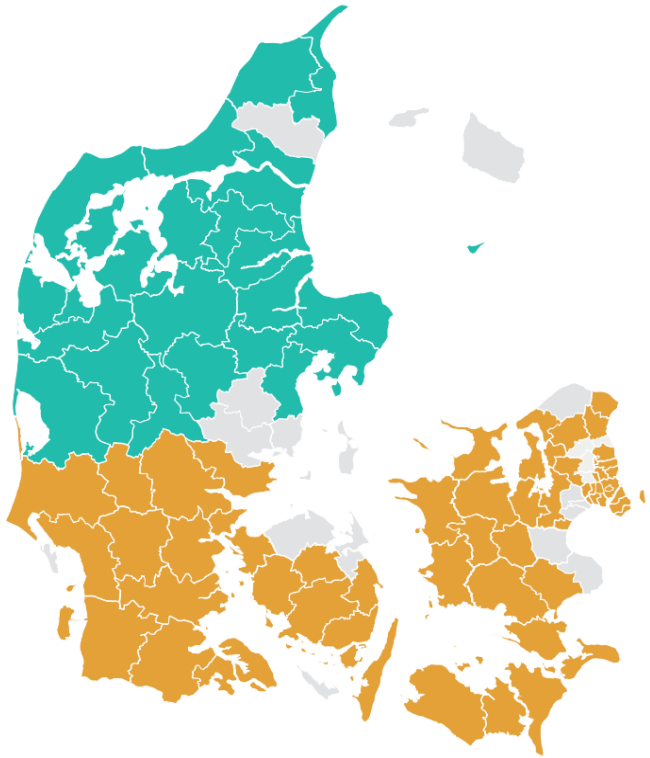


Concept: Companies A and B can take turns offering the lowest bids to secure a tender.

- Examination of the bid differences can reveal the presence of an ongoing price-fixing scheme.

Method 2: Geographical market sharing

Image source: [Bid Viewer, Danish Competition And Consumer Authority]



Concept: Companies A and B can collude by splitting regions between themselves to avoid bidding competitively in the same region. This can be carried out by more than two companies.

- By combining the geographical information each tender provides with GIS data provided by the Greek geodata service, we can detect if there are areas with systematically few or no competitive bids.

Method 3: Graph-based auction monitoring

Concept: Company A bids in many tenders, but never competes in the same tenders as Company B despite being active in the same market.

- Graph analysis of tender data can reveal companies that should be connected but are not. Such behavior may warrant additional analysis to identify whether the bidding pattern observed was the result of collusion or not.

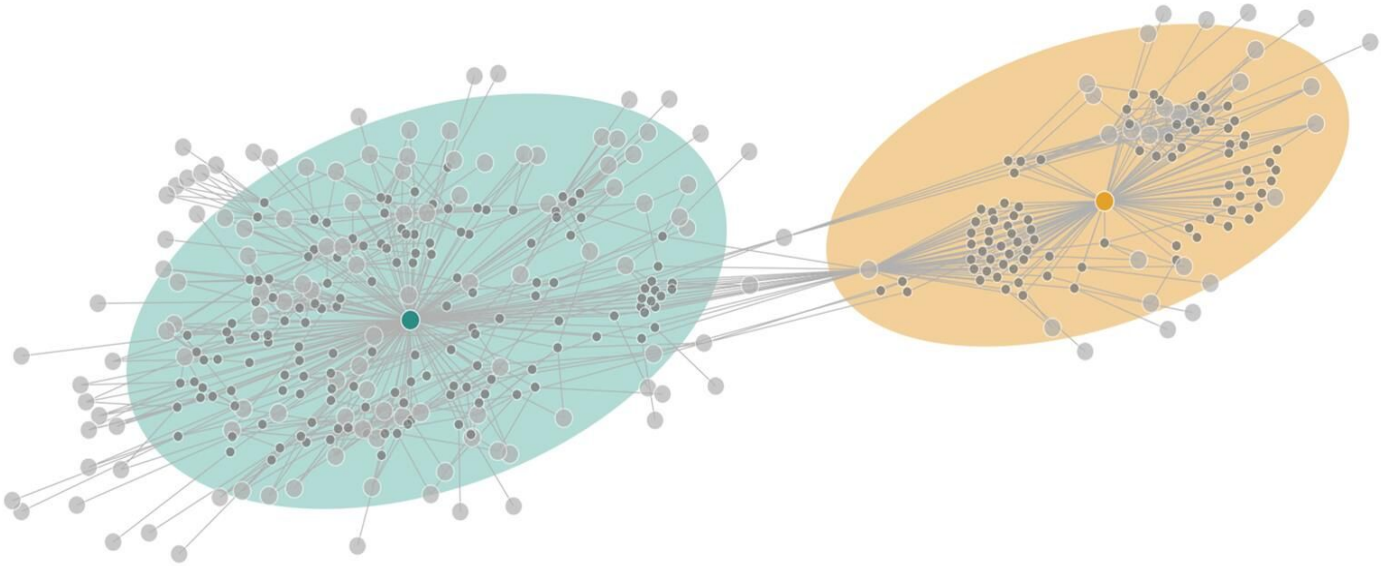
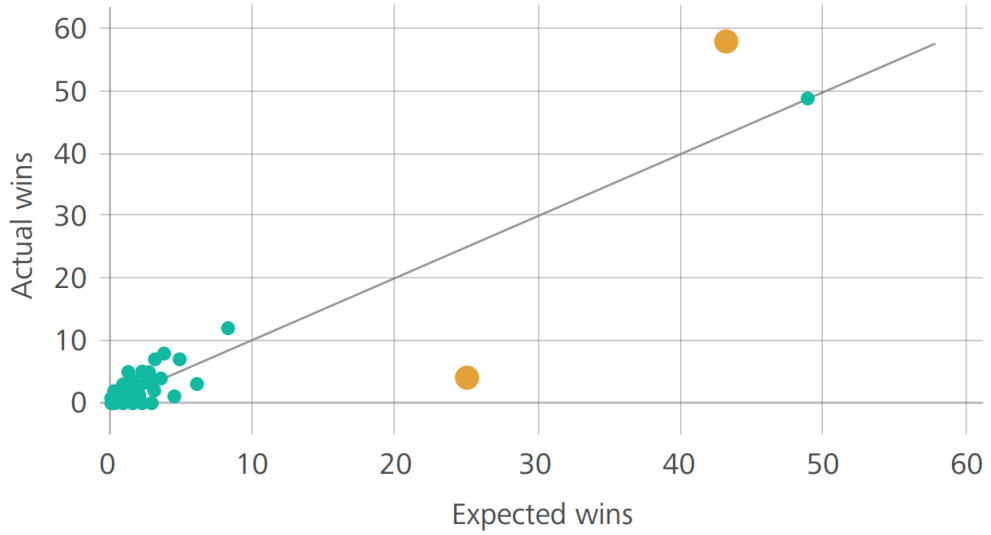


Image source: Bid Viewer, Danish Competition And Consumer Authority

Method 4: Auction win-rate monitoring

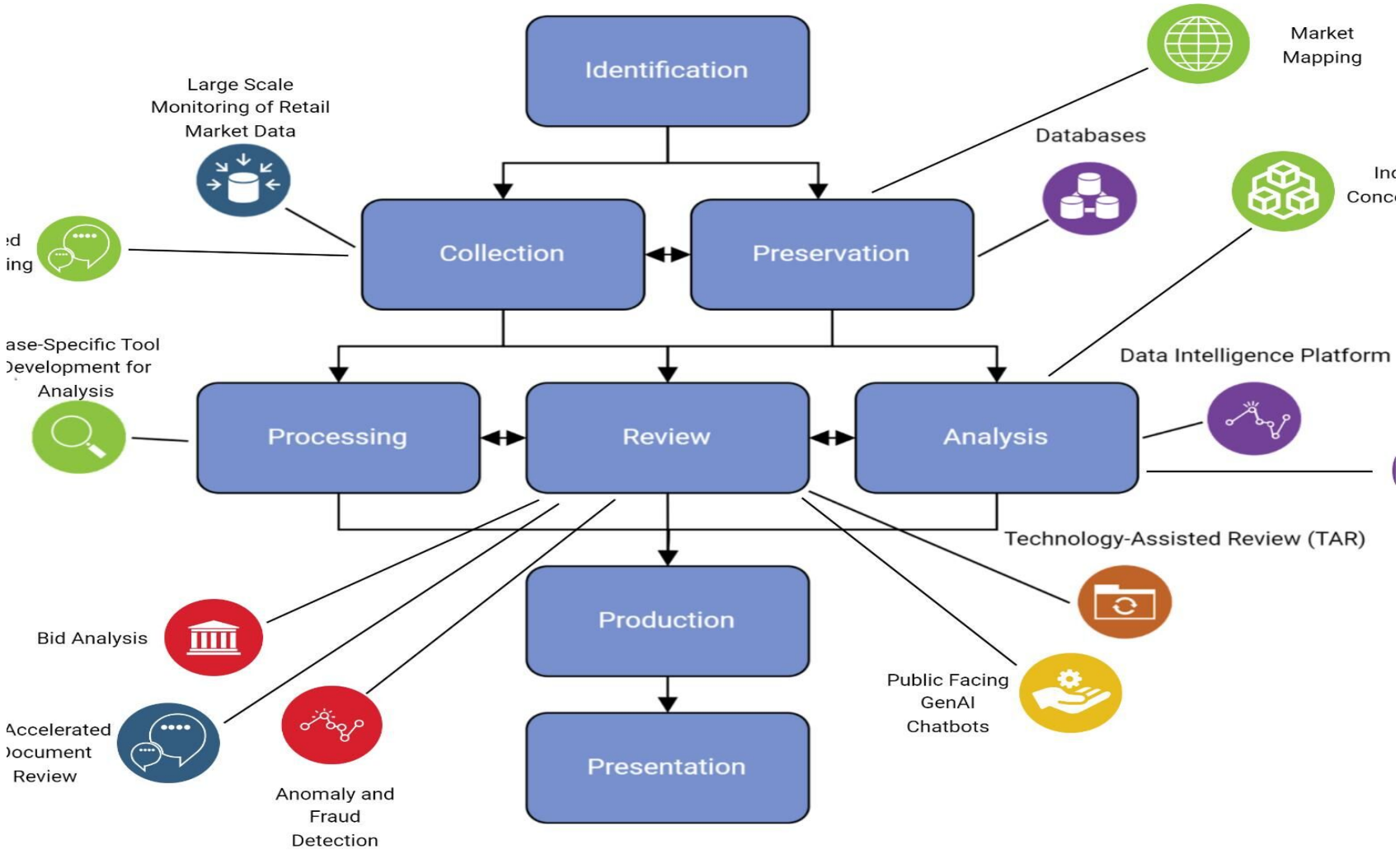
Image source: [Bid Viewer, Danish Competition And Consumer Authority]



Concept: Companies can coordinate and agree to participate in certain tenders without the intention of winning (sham bidding).

- It is possible to estimate the average number of times a company can be expected to win based on the number of tenders it participates in and the number of competitors in those tenders

Data Science solutions across the EDRM model



- *Source: EDRM 2023*

Illustration (not in bid rigging!): Alleged collusion among financial institutions case

- Email inboxes from several high-ranking employees from many Greek financial institutions
- Each harvested employee inbox contained .msg and .eml files of email threads, along with all attached files
- In total:
  - **~890.000** files to review
  - Roughly 88.000 manually inspected by HCC employees using ***keywords*** and a document indexer/search tool, prioritising certain people
    - **8.000** emails flagged as useful/crucial to the investigation
    - **80.000** flagged as non-applicable
  - Assuming 5 employees inspecting 100 emails per day 24/7 = **1780 days to complete!**
  - Impossible to manually inspect every email in a practical timeframe
- These already-inspected emails formed the basis on which we determine the suspiciousness of an email

Initial goal: Provide additional keywords to assist with the manual effort

Main goal: Use ML to filter out irrelevant emails (noise)
and return a smaller subset for final review by the HCC

Selection of suspicious emails

- By combining all the techniques mentioned, a reduction in the number of emails that would have to be examined by HCC employees was achieved by **~96%**!
- **1,031** emails were handed back to the Directorate for manual review, sorted by **relevance score**

Did this actually help? Case handlers say yes!

- An estimated ~90% of retrieved files were **relevant** to the case
- Approximately 170 files were used to **build** the case
- 35 files used for another, **similar** case

Additional Keyword Recommendations

- Initial selection of keywords was carried out by HCC experts
- Selection criteria? **Human intuition & experience**
- As a preliminary goal, the team attempted to propose additional keywords comparing:
  - Frequency of occurrence in the irrelevant files
  - Frequency of occurrence in the relevant files
- Logic: The relevant files that were retrieved based on the original set of keywords **probably** contain additional context and terms that were overlooked in the initial selection.

Graph Analysis

For each email:

- Extract To/From/CC/BCC fields
- Entity analysis to precisely identify the members of each email thread, detect aliases for each entity

Each entity is a node and each email is an edge connecting 2 or more nodes

Finally, nodes were selected that had:

- High influence on information flow (eigen centrality)
- Betweenness centrality
- Unread emails

And their emails were flagged for review