Screening Market Data for Cartels

Autoridade da Concorrência

Joe Harrington

Penn - Wharton

1 March 2023

Introduction

- *Cartel screening* is the analyzing of market data (and text) for the purpose of discovering collusion.
- Deliverable: identifying markets worthy of investigation for unlawful collusion
- Analysis of market data has detected unlawful collusion
  - Generic drugs (Mexico)
  - Subway construction (Korea)
  - Cement (South Africa)
  - Glass vials (Chile)
  - Fire protection services (Brazil)
  - Road construction (Switzerland)

Introduction

- *Behavioral screening* identifies collusive patterns in firm conduct and outcomes (e.g., prices, sales)
- Behavioral screening can work because ...
  1. ... collusion means a change in the price-generating process which, in principle, can be identified.
  2. ... collusion is difficult and leaves an evidentiary trail.
     - Collusion imposes a unique set of challenges and constraints which manifests itself in terms of firm behavior.
     - Even if cartelists are strategic, they will be unable to beat some screens because it is costly for them to do so.

Introduction

Overview

1. Screening methods
2. Developing the best screen (machine learning)
3. Identifying markets to screen
4. Screening errors

Screening Methods

Requirements for behavioral screening

1. Data
    1. Prices, bids
    2. Quantities, market shares
2. Knowing what to look for in the data
    1. **Collusive markers**: patterns more consistent with collusion than competition
    2. **Structural breaks**: change in the data-generating process due to cartel birth, death, or disruption
    3. **Anomalies**: patterns inconsistent with competition (and possibly consistent with collusion)

Screening Methods

Collusive Markers

Collusive markers are regularities that distinguish collusion from competition.

- High prices (relative to competitive benchmark)
- Low price variability
- V-shaped pattern to prices (sharp drop then rise)
- Stable market shares
- Periodicity to price changes
- Periodicity to winning contracts
- ... and others

Screening Methods

Collusive Markers

Low price variability

- Under competition, a firm would change price in response to cost and demand shocks.
- Under collusion, a firm only changes price
  - in response to common cost and demand shocks
  - after communicating and coordinating
  - when cartel stability is not jeopardized
- Under collusion, prices are more stable.

Screening Methods

Collusive Markers

Low price variability

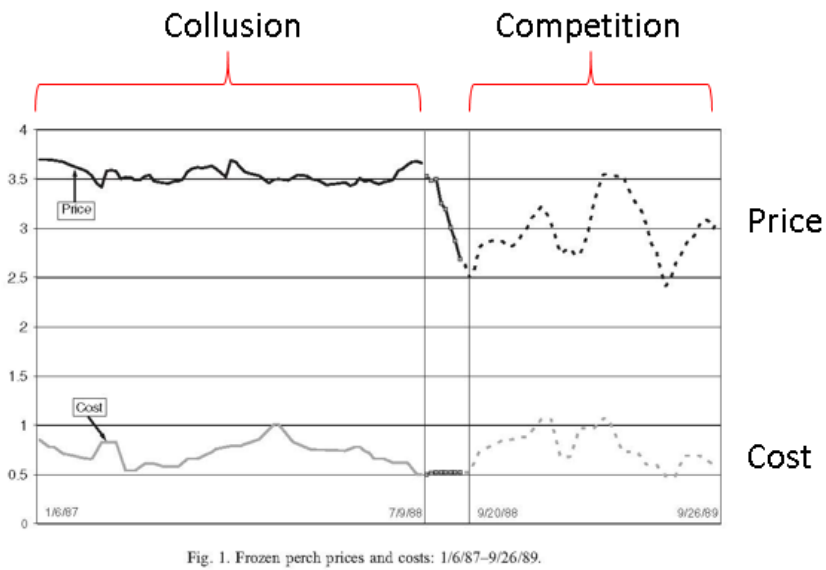
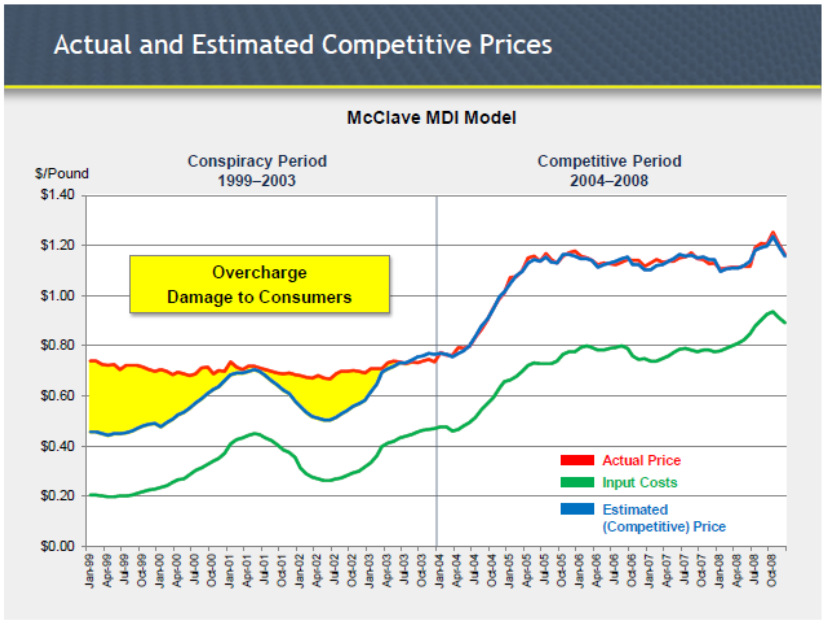


Fig. 1. Frozen perch prices and costs: 1/6/87–9/26/89.

Frozen Perch (U.S.)



Urethane (U.S.)

Screening Methods

Collusive Markers

Collusive Marker: low coefficient of variation of price

- Coefficient of variation of price = standard deviation of price / mean of price
- More stable prices lowers the standard deviation of price.
- Higher prices raise the mean of price.

Screening Methods

Collusive Markers

Abrantes-Metz et al (*International J. of Industrial Organization*, 2006)

- Procurement auctions to supply fish to the U.S. military.
- Price = winning bid
- Measure of cost = average monthly price of fresh perch in spot market

Screening Methods

Collusive Markers

Effect of collusion

- less correlation between price and cost: 0.049 under collusion, 0.578 under competition.
- higher mean and lower standard deviation of price $\Rightarrow$ lower coefficient of variation (= standard deviation/mean)

Table 1
Means and standard deviations for perch price and cost ($/pound)

Statistics	Collusion	Competition	Differences across regimes (%)
Price			
Mean	3.544	2.97	−16.2
Standard deviation	0.078	0.283	263
CV = standard deviation/mean	0.022	0.095	332
Cost			
Mean	0.722	0.771	6.8
Standard deviation	0.114	0.173	51.8
CV = standard deviation/mean	0.158	0.224	41.8

Screening Methods

Structural Break

Structural break is a change in the data-generating process due to cartel birth, death, or disruption

- Cartels can be detected at birth
  - Prices rise and become more stable (after a transition)
  - Cartel might "manage" the price process to make detection more difficult.
- Cartels can be detected at death
  - Prices fall and becomes more volatile.
  - Cartel will not be able to manage the price process.
- Cartels can be detected by temporary (internal or external) disruptions to collusion

Does conduct change in a manner consistent with a collusive marker?

Screening Methods

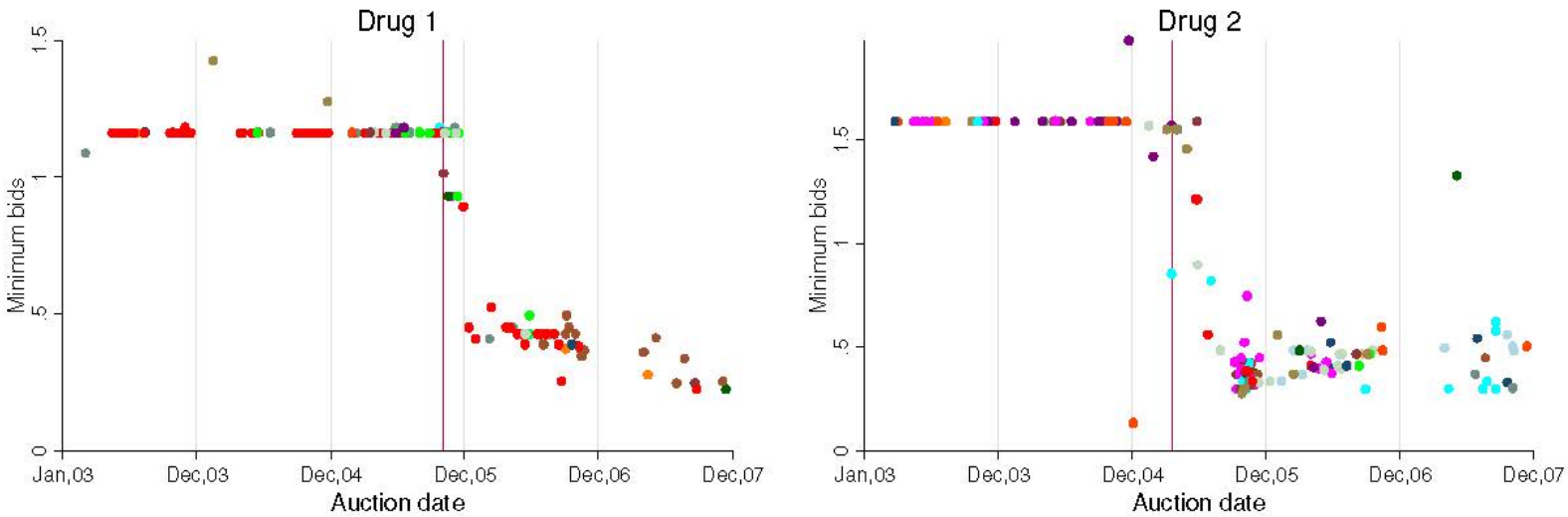
Structural Break: Detecting Cartel Collapse

Estrada and Vazquez (*Competition Policy International*, 2013)

- Generic drugs purchased by the largest public health provider in Mexico
- First-price sealed bid auctions
- Data: winning bids for the 20 top-selling drugs, 2003-2008
- Cartel death resulted in drastically lower and more variable prices for 10 of 20 drugs.

Screening Methods

Structural Break



Drug 1 - insulin, Drug 2 - calcium

Screening Methods

Structural Break

	1	*2*	3	4	*5*	6	*7*
Chg in mean price	*-46.8*	*-69.9*	4.0	0.1	*-32.3*	-20.6	*-6.0*
Change in mean CV	*51.5*	*52.3*	-2.3	-3.0	*20.2*	0.9	*12.8*

	8	9	10	11	*12*	13	14
Chg in mean price	*-15.3*	-7.1	-14.1	11.4	*-26.3*	3.1	-6.9
Change in mean CV	*13.9*	2.4	-5.9	18.6	*25.5*	-3.5	0.5

	15	16	*17*	*18*	*19*	*20*
Chg in mean price	5.3	0.5	*-19.8*	*-46.0*	*-22.3*	*-19.1*
Change in mean CV	-2.7	3.2	*16.2*	*56.5*	*20.2*	*14.3*

Screening Methods

Structural Break

- Standard structural break exercise: Fix the timing of a possible break and test for a change in the coefficients.
- Screening structural break exercise: Timing of a possible break is not fixed. Each period is being tested for a structural break.
- With a long enough time series, randomness will cause rejection of the null hypothesis of no structural break using a Chow test.
- Need to specify the proper test.

Screening Methods

Structural Break: Detecting Cartel Birth

Crede (*Review of Industrial Organization*, 2019)

- Reduced form equation for the change in price:

$$\Delta P_t = \alpha_1 \Delta C_t + \alpha_2 \Delta D_t + \alpha_3 \Delta S_t + \varepsilon_t$$

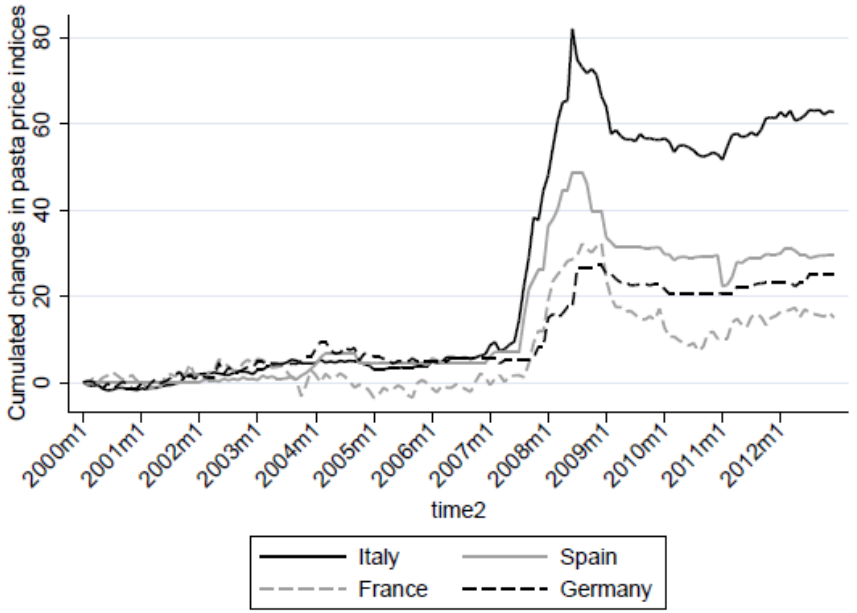
  - ΔC_t - supply (cost) shifters
  - ΔD_t - demand shifters
  - ΔS_t - market characteristics

- Hypothesis: Is there a change in the coefficients at some date?

Screening Methods

Structural Break

- Pasta markets in
  - France (no cartel)
  - Italy (cartel: Oct 2006 - Mar 2008)
  - Spain (cartel: July - Oct 2007)
- Data (monthly)
  - pasta prices
  - input prices (durum wheat, labor, energy)
- Big positive shock in the price of durum wheat

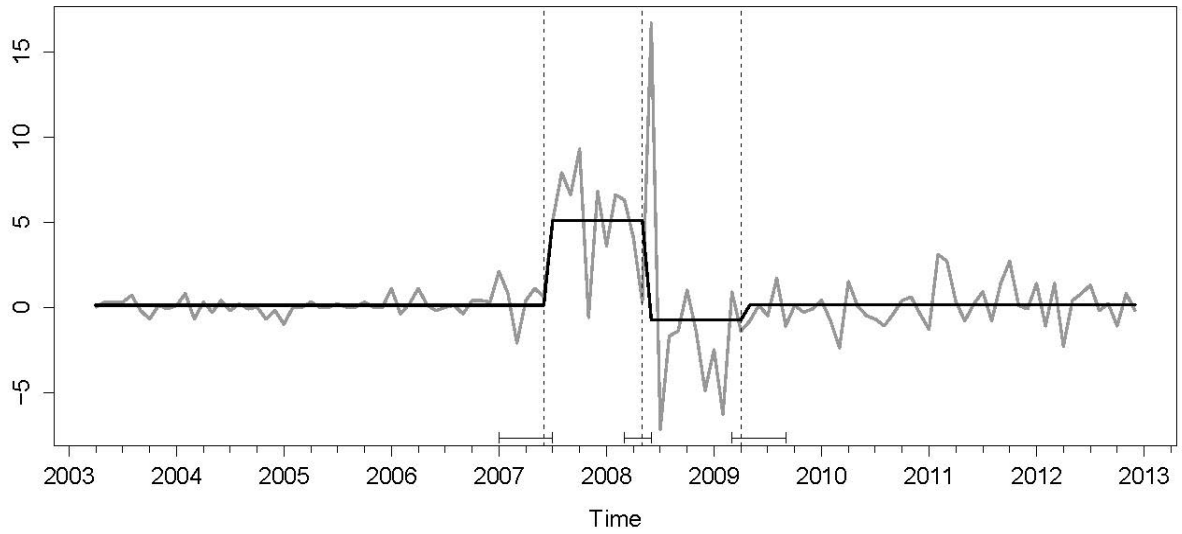


Screening Methods

Structural Break

- Structural break was found in Italy and Spain, not France. Input price rise triggered cartel formation.
- Break test p-values: Italy (0.000), Spain (0.015), France (0.755)
- Plot of price change residuals (Italy)

Figure 4: Identified structural breaks in the Italian pasta industry



Screening Methods

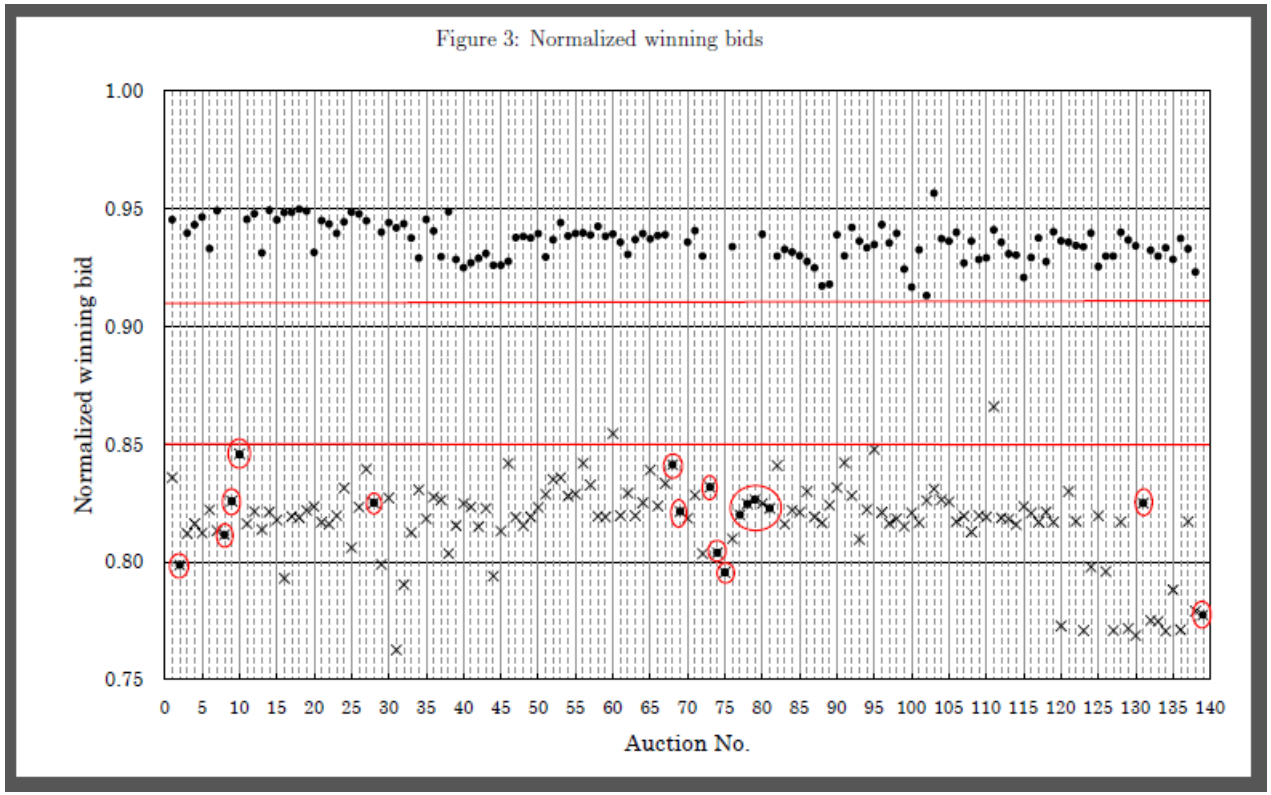
Structural Break: Detecting Periodic Cartel Breakdown

Ishii (working paper, 2008)

- Japan: 139 procurement auctions for road paving contracts
- Government sets a maximum bid (reserve price) and a minimum bid
- 123 (out of 139) auctions - winning bids are around 93% of the reserve price
- Other 16 auctions
  - Winning bid = minimum price (77-85% of the reserve price).
  - Bidding wars largely occurred when either of two particular firms submitted bids

Screening Methods

Structural Break



• denotes the winning bid (divided by the reserve price)

× denotes the minimum bid (divided by the reserve price) set by the government

red circle denotes × and • so winning bid = minimum bid

Screening Methods

Anomalies

- Examine data looking for strange patterns.
- Having identified a pattern, ask
  - Is this inconsistent with competition?
  - Is it consistent with some form of collusion?

Screening Methods

Anomalies

Chassang et al (*Econometrica*, 2022)

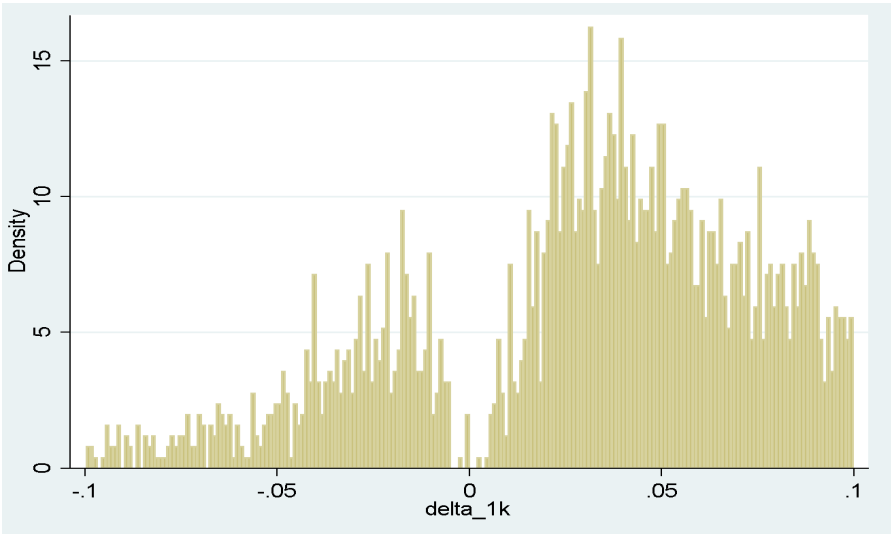
- Procurement auctions from Japan
  - 14,000 auctions/year
  - Mostly construction
  - Apr. 2001 to Dec. 2006
- Auction format
  - Lowest bidder wins the auction
  - Mostly price-only auctions
  - Secret reserve price

Screening Methods

Anomalies

Mitsubishi Electric

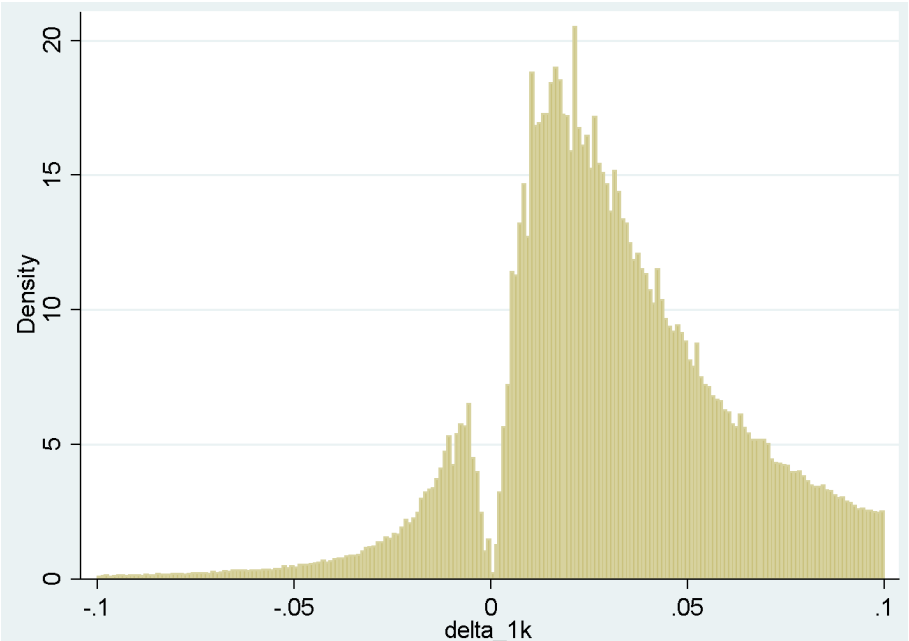
- Difference between own bid and most competitive rival bid: $\Delta_{ME} = b_{ME} - \min_{j \neq ME} b_j$
- If $\Delta_{ME} < (>) 0$ then Mitsubishi Electric was the lowest (not the lowest) bidder
- Why is there a gap around zero?



Screening Methods

Anomalies

All bidders - gap around zero



Screening Methods

Anomalies

- "Missing bids" is inconsistent with competition
  - If a firm anticipated a gap then it would want to slightly raise its bid because
    - when it is the lowest bidder, it will still win but now at a higher price and thus is better off
    - when it is not the lowest bidder, it will still lose and thus is no worse off
- "Missing bids" is consistent with collusion
  - Designated winner from the cartel informs other bidders of its bid.
  - Other bidders bid a bounded amount above it to ensure the designated winner wins.

Screening Methods

Anomaly produces Collusive Marker

- **Marker**: gap between second lowest bid and lowest bid
- **Marker**: lowest bid and non-lowest bids are generated by different processes
  - For competitive firms, those processes should be the same.
  - For members of a bidding ring, those processes could be different.
  - Lowest (non-lowest) bids may respond to cost and other factors in an economically sensible (non-sensible) way.
    - Porter and Zona (RJE, 1999) - lowest bid is increasing in cost, non-lowest bids are not (school milk procurement auctions)
  - Compare distributions of ratio of 2nd lowest to lowest bid and 3rd lowest to 2nd lowest bids

Screening and Machine Learning

Supervised learning to find the **best screen**

- Collect bid data on auctions with *collusion* (documented bidding ring) and *competition* (no documented bidding ring)
- Identify summary statistics of data at the auction level that are possible collusive markers
- Use machine learning to find the best algorithm ("screen") for classifying an auction outcome as "collusive" or "competitive"

Screening and Machine Learning

Huber and Imhof (*International J. of Industrial Organization*, 2019)

- Road construction and maintenance contracts (Switzerland)
- First-price sealed bid procurement auctions

Cartel	Collusive Auctions	Competitive Auctions	% Collusive
A	148	33	82%
B	19	19	50%
C	93	174	35%
D	39	59	40%
Total	299	285	51%

Screening and Machine Learning

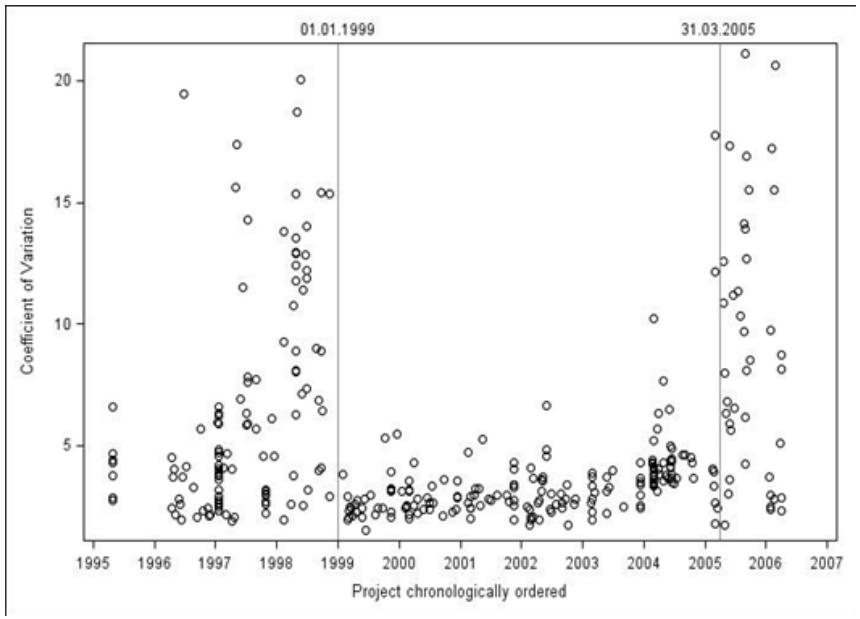
Summary statistics of bid distribution for a tender

- Coefficient of variation of bids
- Gap between second lowest bid and lowest bid
- Skewness of bids
- Kurtosis of bids

Screening and Machine Learning

Marker: coefficient of variation of bids within a tender is low

- Imhof (2017) - road construction cartel in the canton of Ticino (Switzerland)
- Data: 334 tenders, 1995-2006
- Coefficient of variation is much lower during the cartel phase



Screening and Machine Learning

Summary Statistic (Mean across tenders)	Collusive Periods	Competitive Periods
CV: $\frac{\text{standard deviation of all bids}}{\text{mean of all bids}}$	3.42	8.05
Rel Diff: $\frac{\text{2nd lowest bid - lowest bid}}{\text{standard deviation of all non-lowest bids}}$	2.69	0.83
NORM D: $\frac{\text{2nd lowest bid - lowest bid}}{\text{average gap between adjacent bids}}$	2.23	1.10
Skewness	-0.58	0.27
Kurtosis	1.50	0.07

Screening and Machine Learning

- Machine learning methods
  - Lasso regression
  - Ensemble method - bagged regression trees, random forests, neural networks
- Used 75% of sample for estimating the model's parameters
- Used 25% of sample for measuring performance
  - If the estimated probability of collusion $> \chi$ then it is classified as "collusion".
  - The higher is χ,
    - the lower is the likelihood of falsely concluding there is a bidding ring
    - the higher is the likelihood of falsely concluding there is not a bidding ring

Screening and Machine Learning

Results for $\chi = 0.5$

- Collusion is properly classified in 86% (83%) of auctions for lasso (ensemble)
- Competition is properly classified in 82% (85%) of auctions for lasso (ensemble)
- If threshold for classifying an auction as collusive is increased from 0.5 to 0.7 then
  - collusion is properly classified in around 70% of auctions
  - competition is properly classified in around 90% of auctions

Screening and Machine Learning

García Rodríguez et al (*Automation in Construction*, 2022)

- Six auction data sets: Brazil, Italy, Japan, Switzerland (2), U.S.
- 11 machine learning algorithms, 8 collusive markers
- 80% of data is used for training, 500 splits of the data
- Averaged over the 500 iterations, performance of screen:
  - (# of collusive bids correctly identified + # of competitive bids correctly identified/(total # of bids) $> 80\%$
  - False Positive and False Negative $< 10\%$

Screening and Machine Learning

Extensions and work in progress

- Cartel membership
  - Algorithm identifies whether there is a cartel and who is in it
- Transposition
  - Algorithm is trained on data in one market (country) and applied to screen for cartels in another market (country)
- Deep learning and visualization
  - Algorithm takes plots as inputs and learns to recognize visual patterns associated with collusion

Markets to Screen

Where to screen?

- Screen markets where
  - data is (relatively easily) available
  - cartels are (relatively) common
  - cartels can be (relatively easily) detected.

Markets to Screen

Data is available

- Retail prices
  - scrape online prices, credit card transaction data, purchase of third party data
- Intermediate goods
  - list prices may be public but transaction prices are often private
  - government indices
- Government procurement
  - requires government procurers to cooperate
  - procurers need to collect relevant data (e.g., non-winning bids)

Markets to Screen

Data is available

Case of German cement cartel

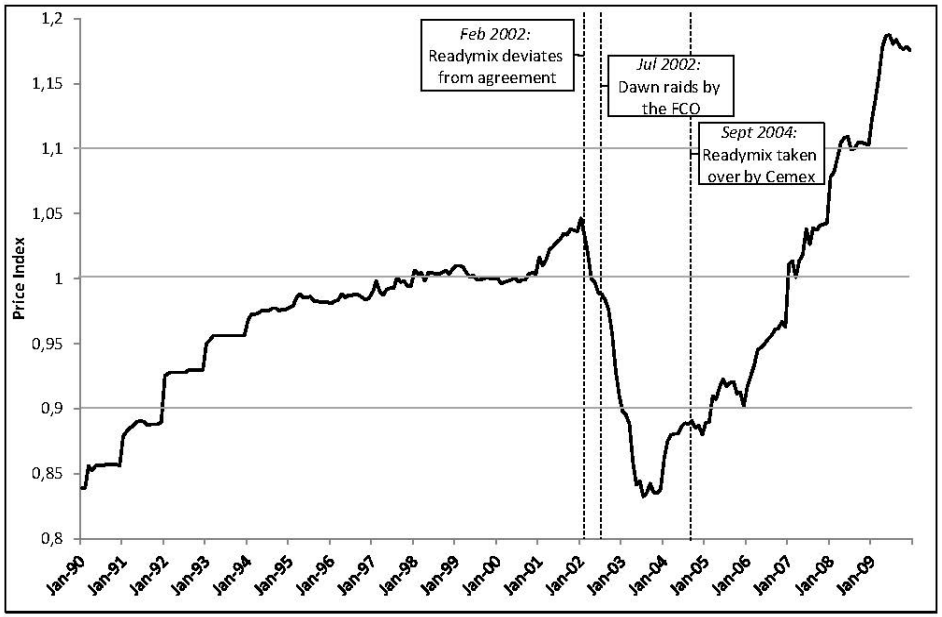


Figure 1: The public price index for cement from January 1990 to December 2009
Source: Own graph following Friederiszick and Röller (2010), p. 599

Markets to Screen

Cartels are common

Screen markets for which buyers' decisions are heavily based on price

- Strong incentive to collude because competition has a tendency to drive price down to cost unless capacity is limited
- Markets designed so that buyers' decisions are based only on price
  - Procurement auctions for a standardized product or service - contract goes to the bidder with the lowest price
- Intermediate goods markets with essentially identical products
  - Industrial buyers are not swayed by advertising, have low search costs, are willing and able to bargain, and have high-powered incentives to get as low a price as other buyers

Markets to Screen

Cartels are common

Screen markets for which illegal collusion has been commonly observed.

# of Countries	Markets
9	Petroleum products
8	Cement, Poultry
6	Medical & health services,
	Public transportation, Shipping
5	Industrial and medical gases
4	Bakeries, Beer, Concrete products, Insurance,
	Liquefied petroleum gas, Pharmaceuticals

Ivaldi, Jenny, and Khimich (World Bank & OECD, 2017)

Data: All prosecuted cartels in 22 developing countries (1995-2013)

Markets to Screen

Cartels are detectable

- Retail: parallel price movements unresponsive to cost
- Intermediate goods: collusive practices are well documented
- Government procurement: practices are well documented but smart, all-inclusive cartels can make detection difficult

Class of markets	Relative Data Availability	Relative Cartel Frequency	Relative Efficacy of Markers
Retail	Moderate	Low	Fair
Intermediate goods	Low	High	Good
Gov't procurement	High	High	Good

Screening Errors

- Errors in cartel screening
  - False positive: screen says there is a cartel when there is not
  - False negative: screen says there is not a cartel when there is
- What is the source of false positives and false negatives?
- What is the cost of false positives and false negatives?

Screening Errors

Source of False Positives

- Collusion that is lawful (or difficult to prosecute)
  - Generally, not a problem with collusion at procurement auctions
- Competition looks like collusion
  - Competitive dynamics can give the appearance of collusion
    - Example: retail gasoline
  - In procurement auctions, competing bidders with capacity constraints can look like bid rotation
    - Kawai et al (working paper, 2021) offers a test

Screening Errors

Source of False Positives

- Competition looks like collusion
  - Firms' prices are highly sensitive to some common input price
    - Prices may all rise what appears to be simultaneously.
    - Can be controlled for with input price data.
- To reduce false positives, use several screens.

Screening Errors

Source of False Negatives

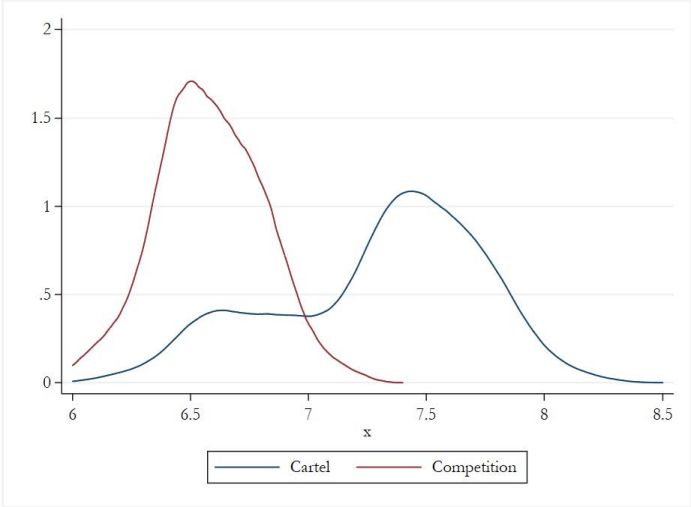
- Bad data - noisy, incomplete
  - Screen may be under-powered,
  - Prices or bids may be driven by other factors (such as input prices) which are not controlled for.
    - Collusion might mean firms keeping prices fixed in response to a reduction in cost or demand.
- Cartelists act strategically to avoid detection.
  - Procurement auctions - in principle, yes; in practice, no
  - Product markets - strategic behavior can reduce, but not eliminate, the power of a screen

Screening Errors

Source of False Negatives

Screen is based on the wrong collusive theory.

- There are many collusive schemes.
- Partial cartels
  - **Marker**: bi-modal distribution
  - Halliman, Imhof, and Huber (*Computational Economics*, 2022) develop a screen to identify a cartel and who is a member of it.



Garcia Pires and Skjeret (working paper, 2022)

Screening Errors

Error Costs

- Cost of a false negative is continued consumer harm.
- Cost of a false positive
  - Wasted resources
  - Reputational harm to the screening program and the competition authority
- Cost of false positive is observable, cost of false negative is (generally) not.

Concluding Remarks

Why screen?

- Leniency programs are delivering fewer cases.
- Screening can be a cost-effective method for detecting cartels.
- Screening could provide the evidence to justify a dawn raid.
- An effective screening program could deter cartel formation.