### Competition Law and Pricing Algorithms

Bergen Competition Policy Conference
Bergen Center for Competition Law and Economics

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Penn - Wharton

25-26 April 2019

#### Introduction

## Competition Law and Pricing Algorithms









### Introduction

- A pricing algorithm is a software program for determining the price of a product or service.
- It takes data on the market environment cost, sales, inventories, rival firms' prices. etc. – and assigns a price.
- Traditional example: airline pricing
- The use of pricing algorithms has increased because of
  - Big Data
  - computing power

### Introduction

Have pricing algorithms created new opportunities for collusion?

- Conventional collusion coordination on pricing algorithms: Illegal
- Third party pricing: Legal or illegal?
  - Platforms
  - Outsourcing
  - Software developer as facilitator
- Algorithmic collusion coordination by pricing algorithms: Legal (but how do we make it illegal?)

- Travel agencies (Eturas, European Commission, 2016)
  - System administrator proposed programming the online travel booking system to prevent discounts of more than 3%.
  - A travel agency could issue larger discounts though it would take additional steps.
  - European Court of Justice found it to be a concerted practice under Article 101.
- Wall posters
  - Online retailers fixed the prices of posters sold online through Amazon Marketplace, 2013-14.
  - Coordination involved the adoption of pricing algorithms ensuring identical prices.
  - U.S.: U.S. v. Topkins, U.S. Dept of Justice (2015)
  - UK: Trod Limited and GB eye Limited, CMA (2016)



#### Wall Posters

Agreement - GB eye internal email:

Trod ... have agreed not to undercut us on Amazon and I have agreed to reciprocate. We will therefore be aiming to be the same price wherever possible, put prices up and share the sales.

- DOJ: "the defendant and his co-conspirators ... wrote computer code that instructed algorithm-based software to set prices in conformity with this agreement."
  - Algorithm searched for the lowest price offered by other suppliers
  - Algorithm set the price just below that level
  - DOJ: "That let the conspirators' products appear near the top of the search query without having to compete with each other."

Collusion may be more profitable and more effective when coordination is on pricing algorithms

- Coordination on collusive prices is more effective
  - No need for many meetings "once and done"
  - Collusive price can quickly adjust to market conditions.
    - Collusive pricing is often less responsive to market conditions.
  - Price leadership and matching can occur instantaneously.

- Monitoring is more effective
  - Price transparency with online prices.
  - Any deviations are clearly intentional and not due to error or overzealous employees.
- Punishment is more effective
  - Immediate response to price cuts
  - Programming "price matching" makes deviations unprofitable

### Big Data and pricing algorithms allow for

- personalized pricing
  - tailoring prices to consumers based on past purchases and demographic information
  - example: Home Depot, Orbitz, and Staples made price sensitive to a user's location and browser history
- dynamic pricing
  - rapidly adjusting prices to demand changes
  - example: Uber's surge pricing

How do these features affect the incentives for and efficacy of collusion?

- Prices depend on firm-specific information about customers
  - If coordinated pricing algorithms condition on firm-specific information then there is the challenge of private monitoring ⇒ collusion is less effective
  - If coordinated pricing algorithms do not condition on firm-specific information then there may be foregone profit from less sophisticated pricing \$\Rightarrow\$ collusion is less profitable
    - But if price discrimination under competition reduces firms' profits, they may coordinate not to engage in price discrimination.
- Prices respond to predictable demand fluctuations
  - Greater incentive to deviate when demand is high (Rotemberg and Saloner, 1986) ⇒ collusion is less effective



- Practices fall under existing jurisprudence
- Collusion may be more effective but may or may not be more profitable.

- Platform sets prices
- Outsourcing of pricing
- Software developer as facilitator

#### **Platforms**

- Platform matches buyers and sellers
  - Uber: drivers and passengers
  - Airbnb: property owners and renters
  - TaskRabbit: people who need a task performed and workers
- Platforms vary in their role in pricing
  - Uber sets price
  - Airbnb recommends price
  - TaskRabbit no role in price







#### **Platforms**

### Spencer Meyer v. Travis Kalanick (2016)

- Plaintiffs: "Mr. Kalanick had conspired with Uber drivers to use Uber's pricing algorithm to set the prices charged to Uber riders, thereby restricting price competition among drivers."
- Defendants: In the contract, a driver "shall always have the right to charge a fare that is less than the pre-arranged fare."
- Plaintiffs: "Though Uber claims to allow drivers to depart downward from the fare set by the algorithm, there is no practical mechanism by which drivers can do so."

#### **Platforms**

#### Questions

- Is it illegal for a platform to control the prices at which the two sides of the platform transact?
- Is it illegal for competing firms (drivers) to allocate pricing authority to a common third party (Uber)?
- How is welfare affected by the platform controlling price?

#### Some relevant factors

- Market power of platform
- Technological feasibility of decentralizing pricing authority

#### **Platforms**

- BMI v. CBS (U.S., 1979) "An agreement is per se illegal as price fixing only if it affects the price at which the parties will sell something, which they could have sold individually."
- Platform pricing should not be a per se violation because
  - it might not be technologically feasible to decentralize pricing authority and still provide the service.
  - the platform might not have entered the market if it could not control price.
- What is technologically feasible?
  - Example: A driver selects a multiplier to be used on the Uber-calculated fare. Drivers compete in the multipliers.

#### **Platforms**

- Liftago (Czech Republic)
- Driver programs in several tariffs
  - Tariff has a per kilometer fare, flagging fee, per minute waiting fee.
  - Typical driver has 5 fare combinations.
- When pinged, a driver sees the fare combinations for that ride and selects one of them.
- Customer observes price, waiting time, car type and driver rating for each driver.

Should Uber be required to give such pricing authority to its drivers?



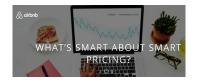
#### **Platforms**

- Suppose Airbnb was to decide that it would set the prices for rental properties.
- Should that be prohibited?
- Does it depend on the algorithm's objective?
  - Equate supply and demand?
  - Maximize local property owners' revenue?

#### **Platforms**

### Airbnb offers a recommended price

 "Smart Pricing lets you set your prices to automatically go up or down based on changes in demand for listings like yours."



- Could it allow property owners to coordinate their prices?
- Suppose the algorithm reported when your price was "below average" but not when it was "above average"?
- What is the algorithm's objective in recommending a price?



Outsourcing

- Efficiency rationale for outsourcing pricing is that they have more data and more sophisticated algorithms.
- Concern: Third party is contracted to set the prices of competitors, and maximizes a collective objective such as aggregate profit or revenue.
- Case: Digital marketing agencies

Outsourcing

### Digital marketing agencies

- Companies bid for keywords at Google sponsored search auctions.
  - Example: Dell and Samsung submit bids to appear alongside Google's search output to the word "tablet".
- Many companies have outsourced bidding to a digital marketing agency (DMA).
  - 77% fully outsource their search engine marketing activities (survey of 74 large U.S. advertisers)

Outsourcing

### Digital marketing agencies

- A DMA's clients may be competitors at sponsored search auctions.
  - Aegis-Dentsu's clients included Dell, Samsung, Apple, HP, IBM/Lenovo, Intel
  - Martin Agency's clients included Bank of America, Travelers, Geico, State Farm (all bid on "online banking")
- Number of keywords with at least two bidders sharing the same DMA:
   13,000 in 2011 ... 56,000 in 2016 (Google and Bing)

Outsourcing

Decarolis and Rovigatti (2017, working paper) - preliminary findings

- Estimated effect of 2016 merger of Aegis-Dentsu and Merkle on average cost-per-click
- Difference-in-difference:
  - How does the change in average cost-per-click between before and after the merger ...
  - ... compare for keywords shared by a Merkle client with at least one advertiser for Aegis-Dentsu to keywords not shared
- Preliminary result: Merger reduced average cost-per-click in most cases

#### Outsourcing

- Enhanced efficiency vs. risk of collusion
  - Should we prohibit a firm from using the best third party pricing consultant because a rival firm is a client?
- If a third party sets or recommends price, should there be constraints on the algorithm's objective?
  - Allowed? Equating supply and demand is allowed
  - Prohibited? Maximizing a collective objective such as joint revenue of drivers or property owners.

Software developers

#### Scenario

- Third party develops a pricing algorithm that conditions on rival firms' prices
- Third party claims it will generate higher profits by preventing low prices and unprofitable price wars
- Pricing algorithm is designed to detect when another firm is using the same algorithm
- When enough of these algorithms have "recognized" each other, they go into "collusive" mode (e.g., price leadership and price matching)
- Did algorithms engage in "unlawful communication"?

Analysis of three scenarios

### Are these arrangements hub-and-spoke cartels?

- Hub is the third party that facilitates collusion by the spokes
  - There is a hub platform, pricing consultant, software developer
- **Spokes** are the sellers whose prices are coordinated
  - There are spokes drivers, online retailers
- Rim is the horizontal agreement among the spokes
  - There is no rim spokes lack communication, mutual understanding

#### Analysis of three scenarios

- Rule of reason applies (U.S.)
  - Series of vertical agreements
  - No horizontal agreement
- Are sellers liable?
  - Outsourcing and Software Facilitator
    - They made the choice to use the third party but
    - ... no first-hand knowledge that prices were coordinated
    - ... but should they have known that prices were coordinated?
  - Platforms
    - Sellers knew that prices were set for all sellers but not how they were set.
    - They had no choice other than to join the platform



Analysis of three scenarios

- Is the third party liable?
  - Outsourcing and Software Facilitator
    - If they chose to coordinate prices to reduce competition then "yes".
  - Platforms?
- Is the third party liable for all customer damages?

- An autonomous artificial price-setting agent (AA) is a software program that adapts a pricing rule to achieve a human-imposed objective (e.g., profit)
- Competitors independently adopt AAs.
- Due to their complexity, the behavior of AAs is unpredictable from the perspective of managers.
- Each manager observes its AA results in higher profits.
- AAs have developed collusive pricing rules.

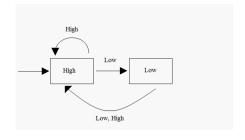
#### Questions

- How easily can this happen?
- Is it illegal?
- If it is legal, how can it be made illegal?



How easily can this happen?

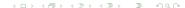
- Can software programs collude? Yes
  - Collusive strategy can be modelled as a finite automaton
  - Folk Theorems based on players' strategy sets being finite automata



• Can software programs *learn to collude*?

How easily can this happen?

- Autonomous artificial price-setting agent (AA) has two components:
  - pricing algorithm selects a price depending on the state (= environment as perceived by the AA)
  - learning algorithm modifies the pricing algorithm based on its performance
- Human agent selects the performance metric for the AA and the particular class of AAs (set of feasible pricing algorithms and how it learns)
- General classes of learning algorithms used for the purpose of price setting
  - Estimation-optimization learning algorithm
  - Reinforcement learning



How easily can this happen?

### Estimation-optimization learning algorithm

- Estimation module
  - Estimates the firm's environment (e.g., demand) and delivers predictions as to how the firm's price determines its performance (e.g., revenue or profit)
  - Estimation methods OLS, maximum likelihood, artificial neural network
- Optimization module
  - Chooses price to maximize performance based on the estimated model.
- Review article: A. den Boer, "Dynamic Pricing and Learning ..."
   (Surveys in Operations Research and Management Science, 2015)



How easily can this happen?

### Reinforcement learning

- Reinforcement learning is model-free in that it learns directly over actions (or policy functions)
- Identifies the best action for a state based on past performance
- Example: Q-learning

How easily can this happen?

### Q-learning

- In each period, an agent chooses an action  $a \in A$  given the state  $s \in S$ .
  - a is price.
  - s is the state of demand, cost, history (past prices, sales), etc.
- $Q^t(a, s)$  = value in period t associated with action a and state s (proxy for the present value of profits)
- ullet Status of the algorithm in period t is defined by  $\{Q^t(a,s)\}_{(a,s)\in A imes S}$ 
  - Could be a table of values when  $A \times S$  is finite
  - Could be a vector of estimated coefficients for a function that maps  $A \times S \to \Re$  (function approximation)



#### How easily can this happen?

- Selection of an action in period t
  - Optimization (exploitation): Choose  $a^* = \arg \max Q^t(a, s)$ .
  - Perturbation (exploration)
    - Choose  $a^* + noise$
    - With probability  $\varepsilon$ , choose a random action.
- Given current state s', selected action a', realized profit  $\pi'$ , and new state s'',  $Q^t(a', s')$  is updated:

$$Q^{t+1}(a', s') = (1 - \alpha)Q^{t}(a', s') + \alpha[\pi' + \delta \max_{a} Q^{t}(a, s'')]$$

- $\delta \in (0,1)$  is the discount factor
- $oldsymbol{lpha} lpha \in (0,1)$  controls the rate at which values are adjusted



How easily can this happen?

- Can autonomous artificial agents learn to collude in simulated markets?
  - Yes Calvano, Calzolari, Denicolo, and Pastorello (working paper, 2018)
- Can autonomous artificial agents learn to collude in real markets?

Is it illegal?

Is collusion by autonomous artificial agents illegal?

- An agreement is illegal where an agreement is
  - "meeting of minds in an unlawful arrangement" American Tobacco
     Co. v. United States (U.S., 1946)
  - "conscious commitment to a common scheme" Monsanto Co. v. Spray-Rite Serv. (U.S., 1984)
  - "joint intention" ACF Chemiefarma NV v Commission of the European Communities (EU, 1970)
  - "concurrence of wills" Bayer AG v Commission of the European Communities (EU, 2000)
- An agreement is mutual understanding to constrain competition.

Is it illegal?

Evidentiary methods for establishing firms have an agreement (U.S.)

- Sufficient: "explicit, verbally communicated assent to a common course of action"
- Insufficient: "It is not a violation of antitrust law for a firm to raise its price, counting on its competitors to do likewise ... and fearing the consequences if they do not."
- U.S. courts have been guided by the requirement that "there must be evidence that tends to exclude the possibility that the [firms] were acting independently." - Monsanto Co. v. Spray-Rite Serv. (1984)
- Necessary element: an overt act of communication instrumental in coordination or consistent with the execution of a collusive scheme.

Is it illegal?

### **Claim**: Collusion through the use of AAs is legal.

- As there is no overt act of communication, evidentiary threshold is not met.
- As managers acted independently and did not foresee collusion, there is no agreement.
- Just as a company is liable for its employees, could a company be liable for its software programs?
  - Could AAs possess a "meeting of minds" or a "concurrence of wills"?
  - John Searle (1980) famously argued that computers cannot understand (Chinese Room Argument).
  - Without understanding, there cannot be mutual understanding.



How can it be made illegal?

Why is communicating to collude illegal but colluding is legal?

- Collusion is the use of a reward-punishment scheme to sustain supracompetitive prices
  - If you price high, then I will reward you by pricing high.
  - If you price low, then I will punish you by pricing low.
- The strategy (reward-punishment scheme) is not observable.
- Prices are observable but we cannot confidently determine whether they are the product of a reward-punishment scheme.
- Evidentiary requirement: overt act of communication

Acts that facilitate collusion are illegal, rather than collusion itself.



How can it be made illegal?

When the price-setting agent is a piece of software, the strategy (reward-punishment scheme) is, in principle, observable.

- **Liability:** There is a *per se* prohibition on certain pricing algorithms that support supracompetitive prices.
- Evidentiary Methods: Liability would be determined by dynamic testing: entering data into the pricing algorithm and monitoring the output in terms of prices to determine whether the algorithm is prohibited.
- J. Harrington, "Developing Competition Law for Collusion by Autonomous Artificial Agents" (*J. of Competition Law & Economics*, 2019)

How can it be made illegal?

- What might be candidate properties?
  - Price matching
  - Pricing rules are asymmetric in their response more sensitive to price decreases than price increases
- The set of prohibited pricing algorithms should be
  - as inclusive as possible of those algorithms that promote collusion
  - as exclusive as possible of those algorithms that promote efficiency.

How can it be made illegal?

- pa = pricing algorithm
- PPA = set of prohibited pricing algorithms.
- Measure for assessing the efficacy of PPA is the likelihood ratio:

$$LR(PPA) = \frac{Pr(pa \in PPA | pa \text{ is collusive})}{Pr(pa \in PPA | pa \text{ is competitive})}.$$

 Challenge: Find a set PPA such that the likelihood ratio is reasonably high.

How can it be made illegal?

Research program to identify a class of prohibited pricing algorithms.

- Step 1: Create a simulated market setting with learning algorithms that produce collusion and competition as outcomes.
- Step 2: Inspect or test the resulting pricing algorithms for the purpose of identifying those properties that are present when supracompetitive prices emerge but are not present when competitive prices emerge.
- Step 3: Test the effect of prohibiting a set of pricing algorithms.

## Competition Policy Goals

- Evaluate how coordinating on pricing algorithms affects the efficacy and profitability of collusion.
- Develop rules for how a platform can intervene in the setting of prices.
- Develop rules for how a third party can price when it has competitors as clients.
- Develop competition law for collusion that occurs without human intervention.