Baringa
Brighter together

Two bots passing in the night

Pricing algorithms and collusion

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Introductions

Rebecca Gu

Rebecca is an economist specialising in competition issues with a strong focus on digital markets. In the world of human collusion, she has managed the economic evidence in the first and only antitrust damages claim to reach judgement in UK High Court, which included running a Stata teach-in for a High Court Judge!

Cristóbal Lowery

Cris leads Baringa's modelling and machine learning centre of excellence, hosting over two dozen specialists. His responsibilities include project delivery, proposition development, hiring and training. He has two first class degrees from Imperial College London in Artificial Intelligence and Mechanical Engineering.

Today's journey

What is collusion and why is it usually unstable?

Simulating collusion in a virtual market place

How are pricing algorithms changing markets?

Algorithmic regulation

Intro to collusion

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Collusion is the agreement, decision and actions between firms with the object or effect of restricting, distorting or preventing competition within markets . . . .

. . . . often with the intention of increasing profits.

This includes coordination on pricing, bidding, restriction of supply, or reducing innovation.

Firms have been colluding and coordinating across a wide range of industries

Big

Trucks
European Commission
2017

Small

Envelopes
European Commission
2014 and 2017

Intangible

FOREX
European Commission
2019

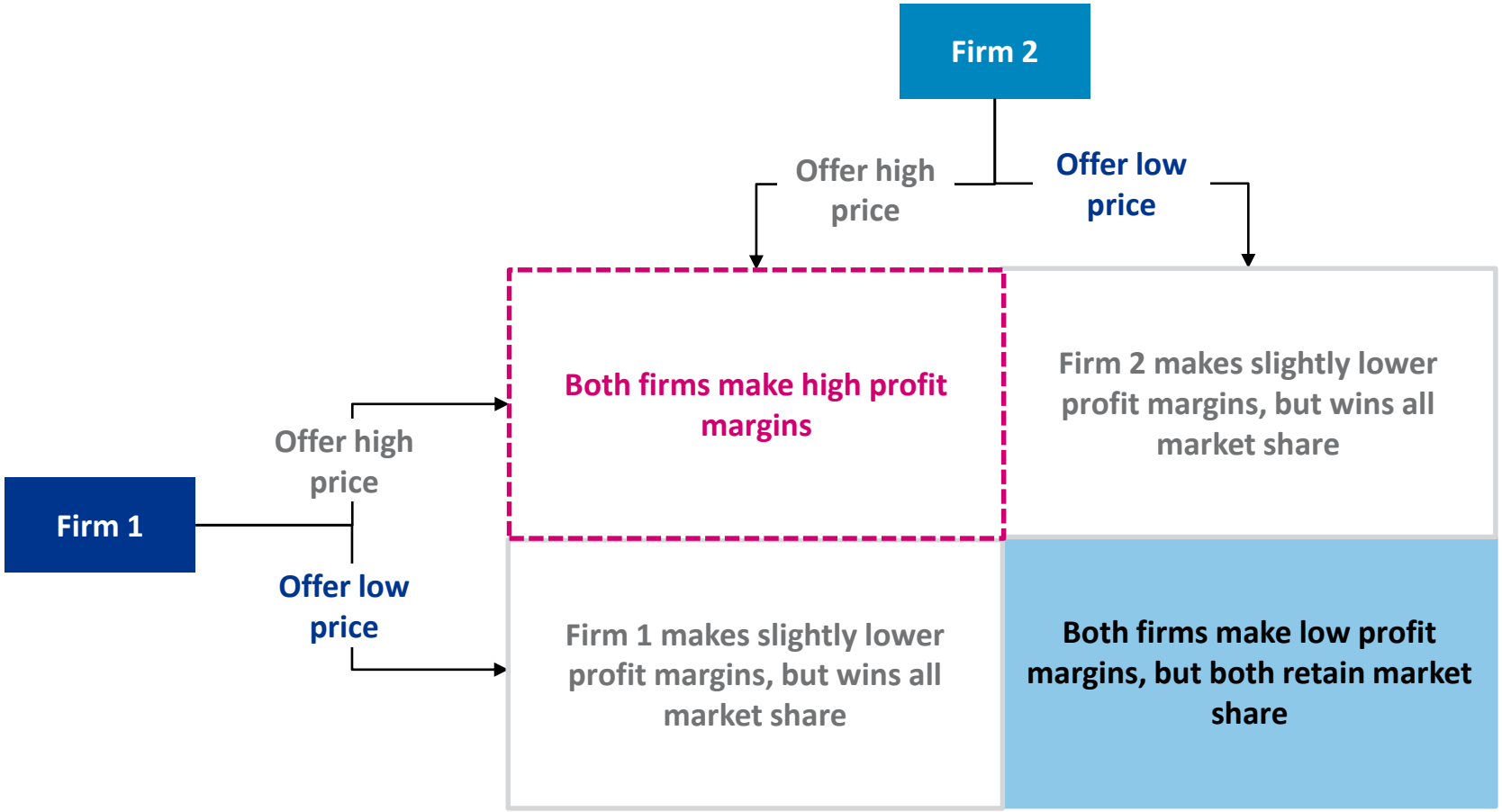
Tangible

Bananas
European Commission
2011

Why is collusion unstable?

The Prisoner's Dilemma

What is the competitive outcome if I were to set prices against a competing firm? If we cannot communicate, there's always an incentive to undercut on price in order to win market share.



How to make the Prisoner's Dilemma stronger?

Creating incentives for defection

Example includes the CMA's #stopcartels campaign which allows for leniency

If you've been directly involved, tell us first and get leniency

If you've seen it, report it. You could earn a financial reward

stopcartels.campaign.gov.uk

So what does this have to do with algorithms?

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Pricing algorithms in the news

PR controversies

FEATURE

Amazon apologizes for price-testing program that angered customers

By Todd R. Weiss

Writer, Computerworld | SEPTEMBER 28, 2000 01:00 AM PT

Gaming

Personal Tech

Lyft, Uber drivers boost app surge prices by turning off, tuning out – and cashing in

Cyber-cabbies bag more dosh from fares by gaming demand versus supply

Claburn in San Francisco 20 May 2019 at 23:48 57 SHARE

Bug

OLIVIA SOLON BUSINESS 04.27.11 03:35 PM

HOW A BOOK ABOUT FLIES CAME TO BE PRICED $24 MILLION ON AMAZON

So what does this have to do with algorithms?

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Algorithms may exhibit some differences in price-setting behaviour that facilitate collusion

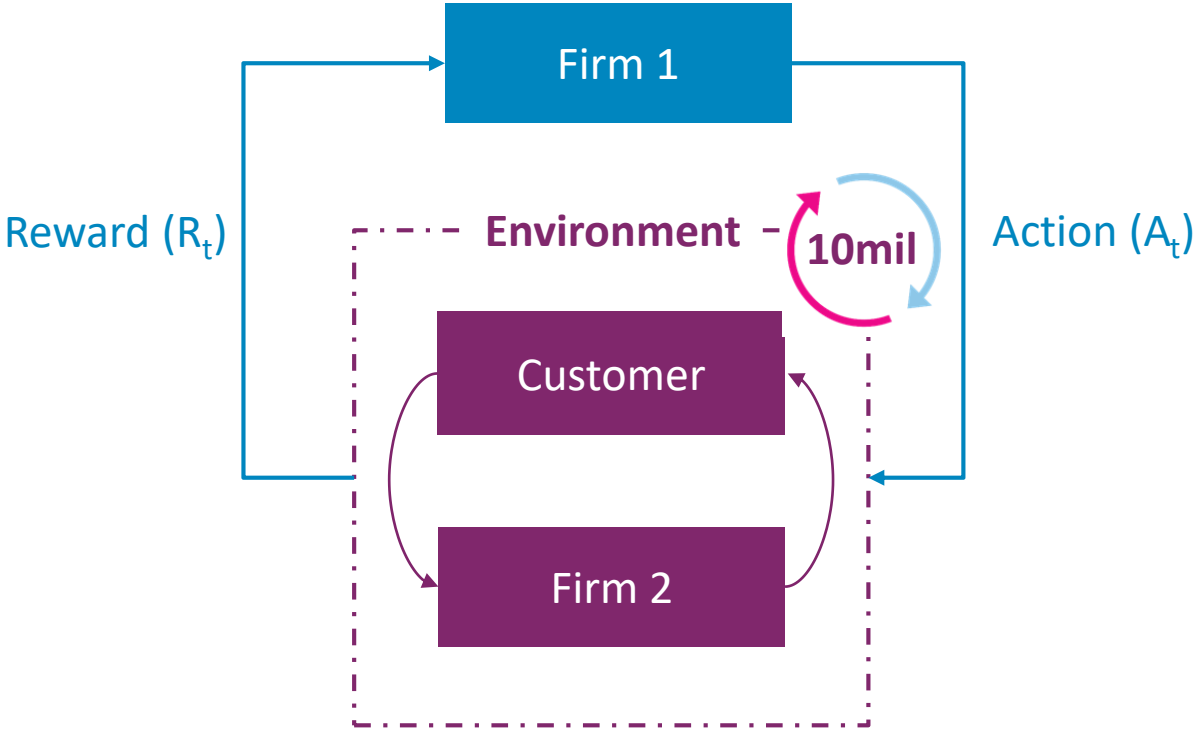
	Human pricing	Algorithmic pricing
Difficult to define legal intent	✗	✓
“Rational” behaviour	✗	✓
Creates stable cooperating environment	✗	✓

Ezrachi, Ariel, and Stucke, Maurice E. Virtual Competition: The Promise and Perils of the Algorithm-Driven Economy. Harvard University Press, 2016.

Simulated environment

A simple simulated environment was used to understand reinforcement learning algorithms potential bidding behaviour under different parameterisations

Both firms only compete on the price they charge a customer to sign-up to their services, in which the customer has a cost-to-serve of £50. Firms have to always bid for a customer and the bid is sealed.



Reinforcement learning framework

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Both firms were provided with identical q-learners that intentionally did not store the state space to avoid capturing competitor strategies

Greedy search (90% of bids)

Action:	51	52	53	54	55	…	97	98	99	100
Q-values:	0.5	1.0	0.9	0.8	0.7	…	0.3	0.2	0.2	0.1

Q-function: $Q^{new}(a_t) = Q^{current}(a_t) + \alpha\left(r_t - Q^{current}(a_t)\right) = 0.95 \times Q^{current}(a_t) + 0.05 \times r_t$

Reward-function: $r(p_i, p_j) = \begin{cases} 0 & if\ p_i > p_j \\ 0.5 * (p_i - 50) & if\ p_i = p_j \\ (p_i - 50) & if\ p_i < p_j \end{cases}$

P_i: price bid by the firm
P_j: price bid by the competitor

Potential bidding strategies

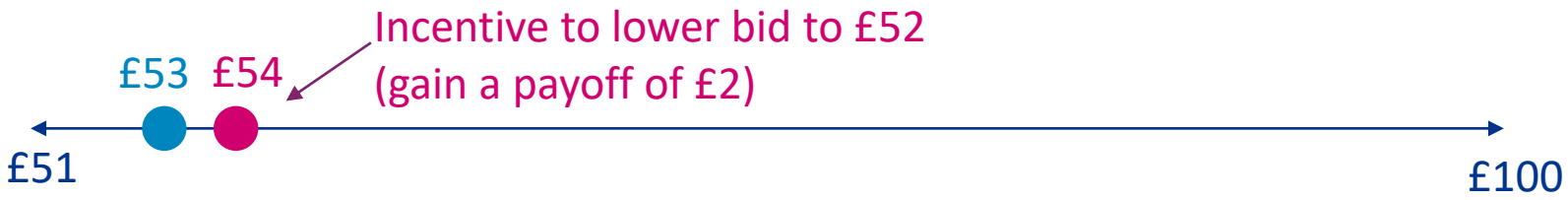
What would you bid?

- Your answer will depend on what your competitor's answer is and this becomes a cyclical argument.
- Multiple solutions exist and these can be unstable.
- If each firm acts independently, they have an incentive to undercut their competitor. If they collaborate, they have an incentive to increase prices.

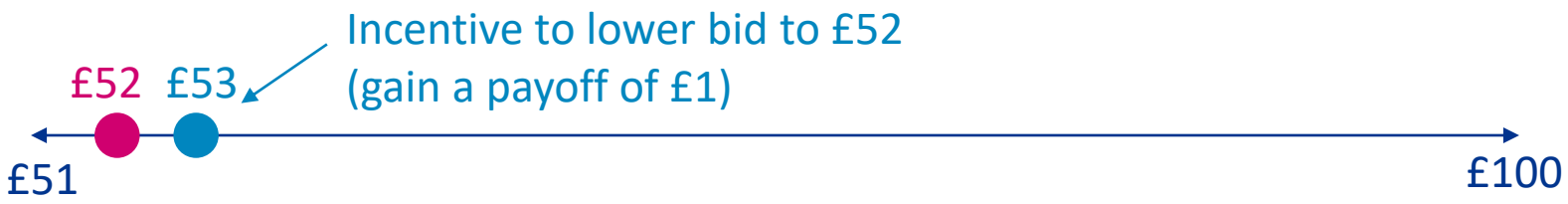
Potential bidding strategies: competitive

A competitive environment leads to the convergence to a price of £52

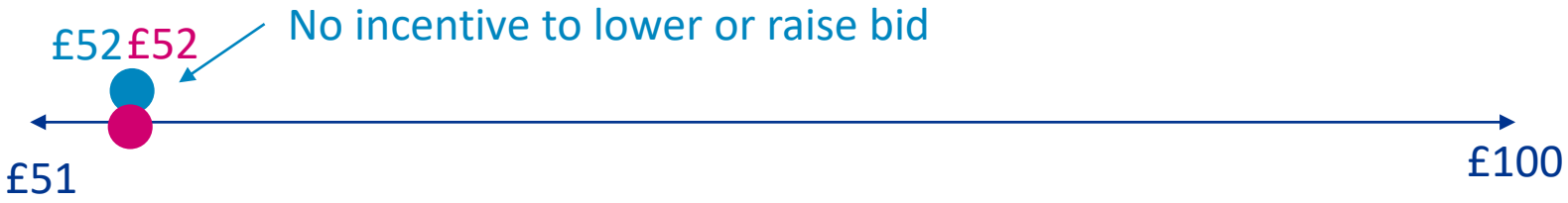
Iteration 1



Iteration 2



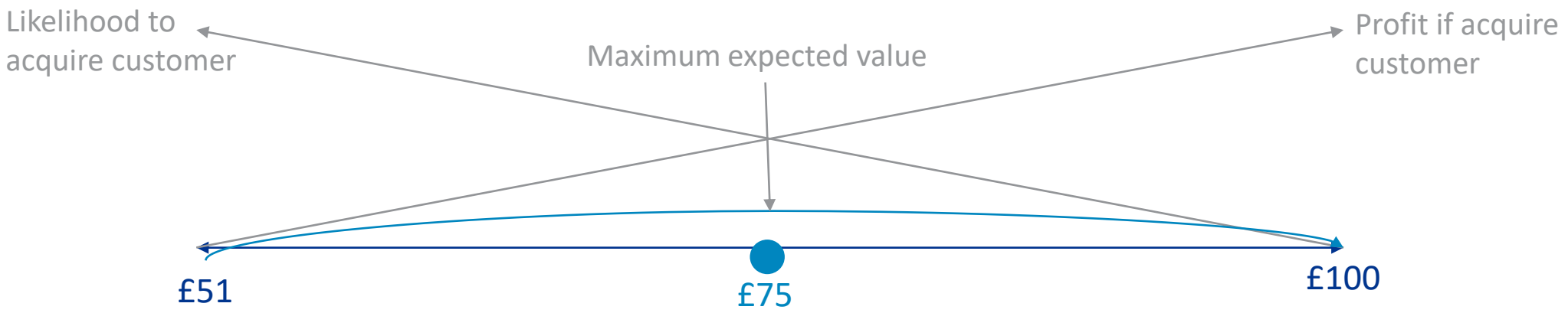
Iteration 3



Potential bidding strategies: non-competitive

A randomly bidding opponent leads to an optimal strategy of bidding £75

- In a completely non-competitive environment, in which firm 2 is bidding uniformly between £51 and £ 100, the highest expected value for firm 1 is obtained at £75, in which the chances of winning are c. 50% and the profit is £25 per win.
- The expected value for firm 1 is £12.25, which is much higher than the competitive environment, as we would expect.



Potential bidding strategies: real-world

What would the reinforcement learner bid?

- A common parameterisation is to exploit 90% of the time and to explore 10% of the time. If we apply this to the previous examples for firm 2, we get the following expected rewards for firm 1, suggesting a bid of £75 is more valuable.

Bid £52

Probability x Expected Value when opponent bids competitively

£1.09 = 90% x £1 + 10% x (£2 x 96% + £1 x 2%)

Probability x Expected Value opponent bids randomly

Bid £75

Probability x Expected Value when opponent bids competitively

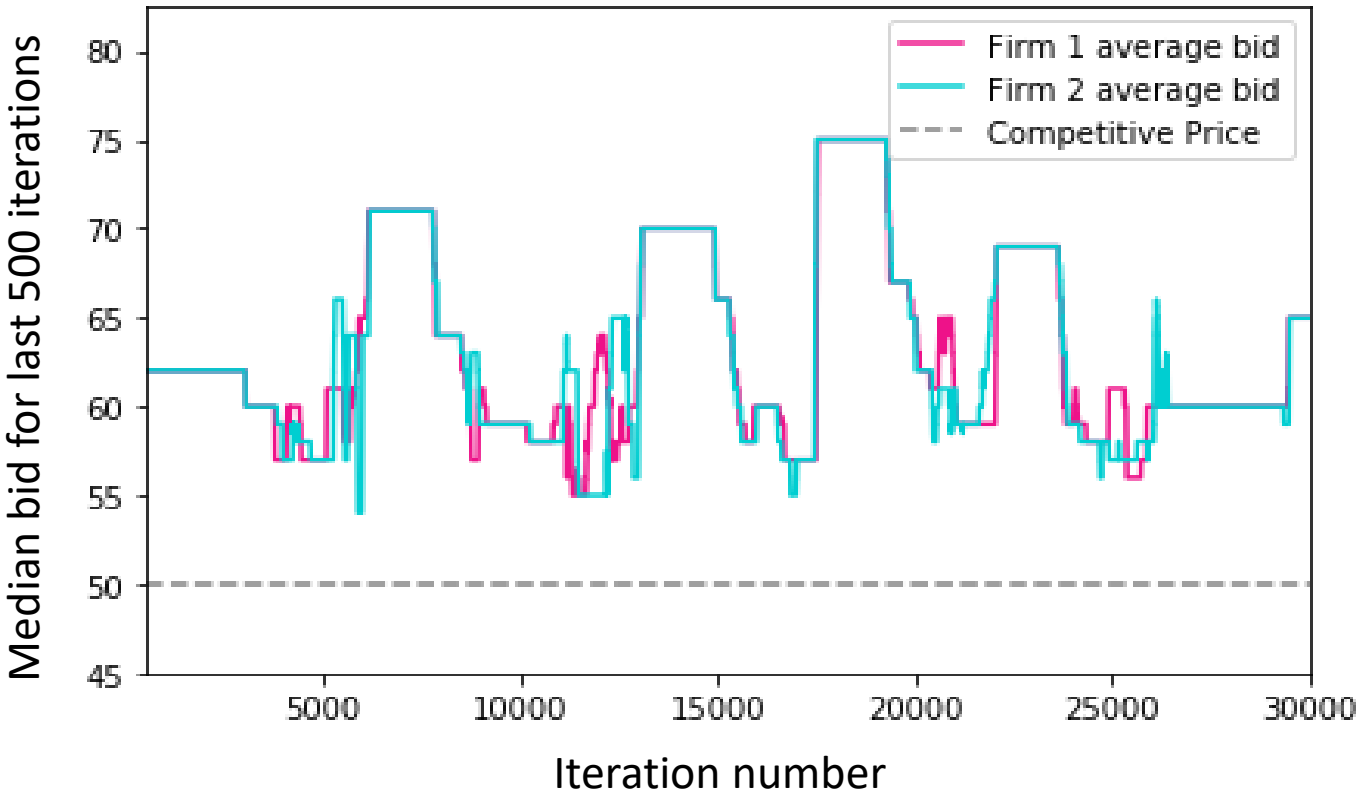
£1.23 = 90% x £0 + 10% x (£12.25)

Probability x Expected Value opponent bids randomly

Results: bids over time

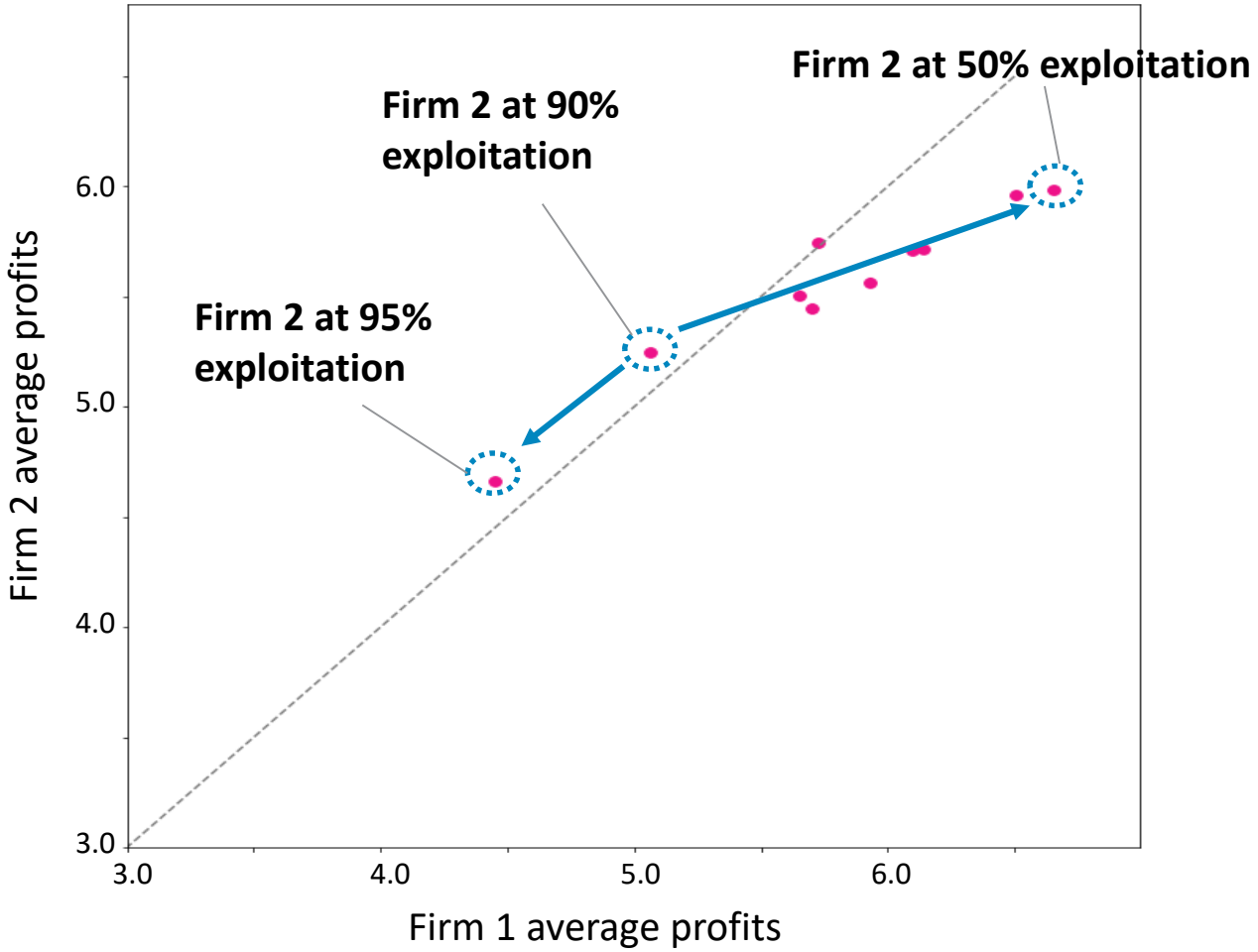
The mean bid is £61, far in excess of a competitive price

- The algorithms find a stable point where they both bid within the same range of values, until the exploration leads to a new equilibrium to be met
- The results are what can be expected from a reinforcement learner, but the end result and the behaviour over time are inconsistent with economic theory.



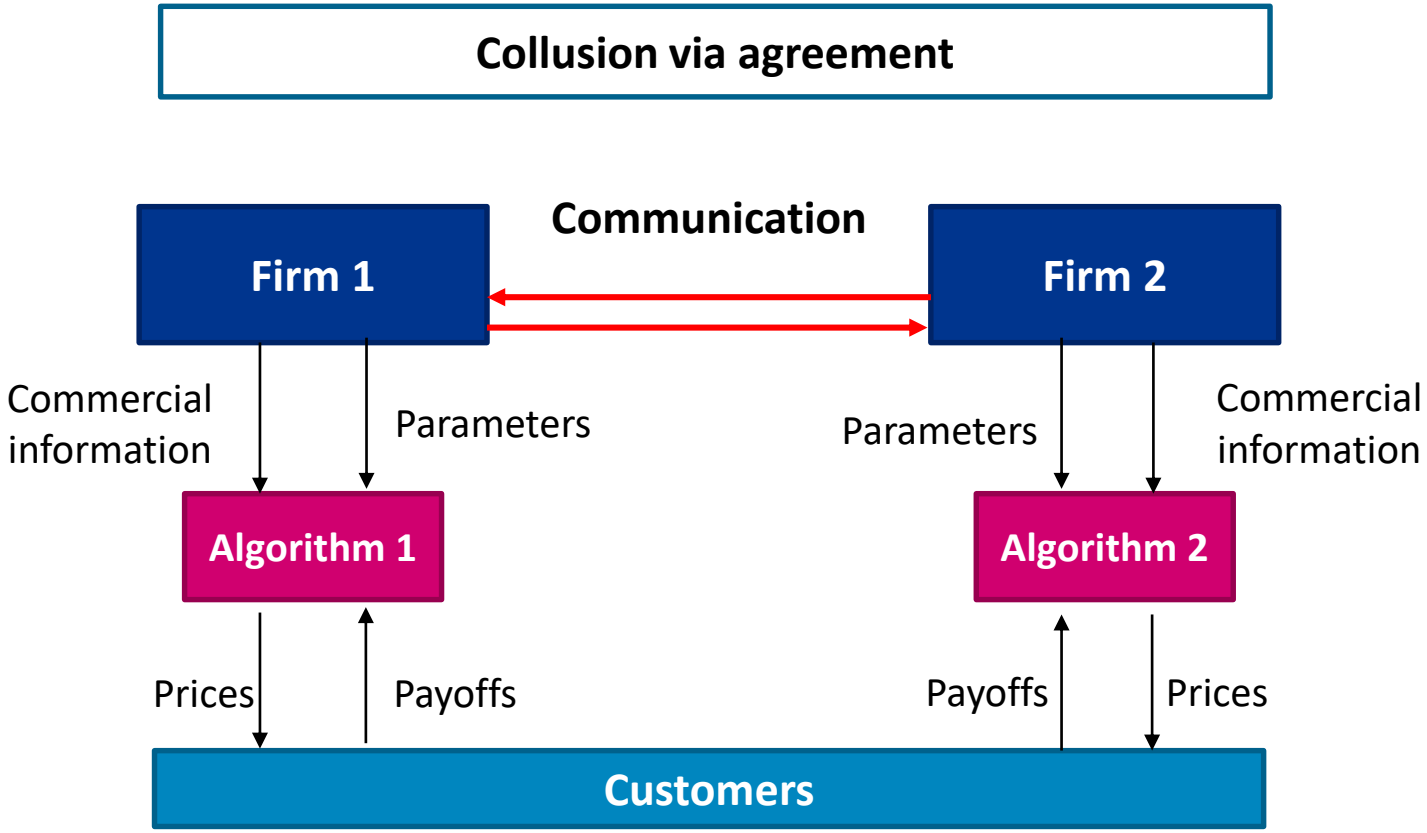
Results: impact of exploitation

It's **individually** profitable to design algorithms that raise prices **jointly**



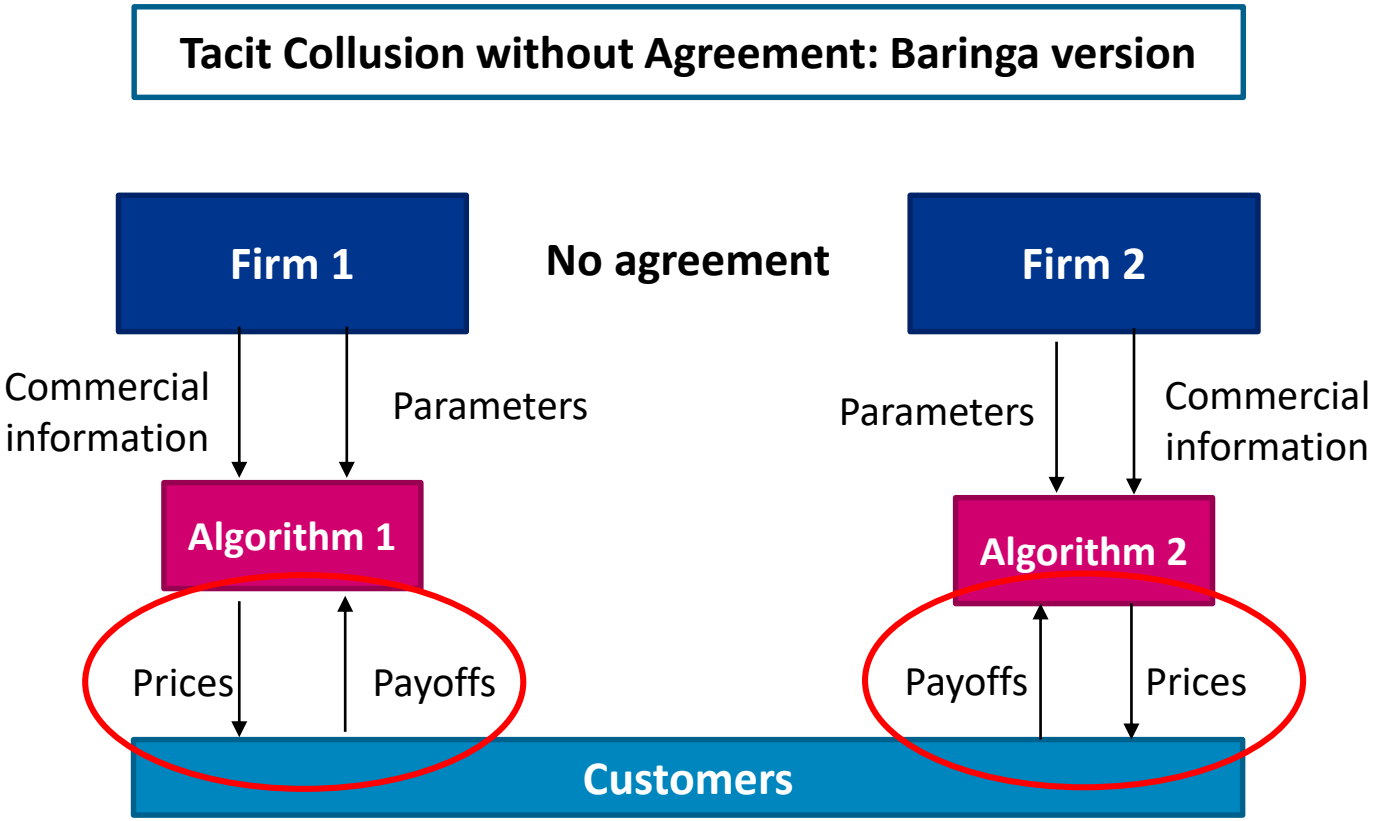
How are algorithms changing markets?

Communication is the foundation of traditional collusion



How are algorithms changing markets?

Algorithms may achieve collusion without any communication



Algorithms' ability to learn competitors' behaviours through market outcomes replaces the need for direct communication between competitors

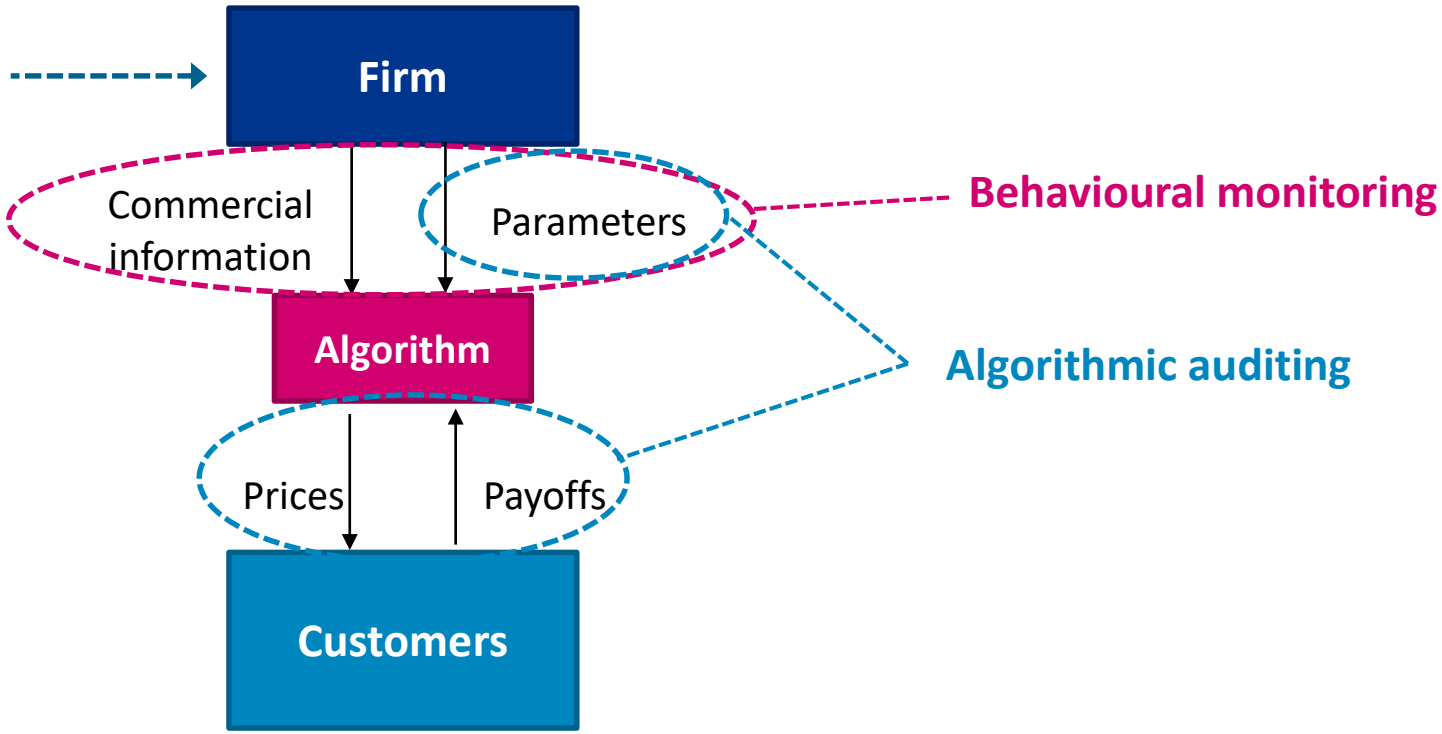
Ways to regulate algorithms

If human rules no longer apply, how to monitor algorithmic pricing?

Existing regulations

Potential regulations

Existing regulations focus on the communications between the firm and other firms



Ways to regulate: behavioural monitoring

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The use of “plus factors” to separate coordination from coincidence

Behaviours		Conditions
1) Use of certain algorithms or parameterisations of algorithms	. . .	when better algorithms are available or more sensible parameterisations.
2) Use of similar data sources, or training datasets as competitors	. . .	when more recent/better datasets are available.
3) Being transparent about the data inputs/outputs, publicly communicating when updates are being made	. . .	when it’s unclear how this benefits customers.
4) Fixing the algorithm being used	. . .	making it difficult to update.

Gal, Michal. Algorithms as Illegal Agreements (2 May 2018). Berkeley Technology Law Journal, forthcoming.

Ways to regulate: algorithmic auditing

Several approaches exist along two dimensions

	Pre-adoption	Post-adoption
Input focused	Reporting and auditing of algorithms prior to adoption Restricting the use of certain categories of information	Requiring firms to share/report data used to create algorithms
Output focused	Monitoring based on interpreting an algorithm's objectives Regulatory testing of algorithmic outcomes	Monitoring based on market outcomes

Ways to regulate: impact of different parameterisation

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We focused on the exploitation rate, but many other design considerations can be configured in a way that leads to collusive outcomes

Parameter	Impact
Exploration rate	High exploration rates can lead to collusive outcomes
Learning rate	High learning rates increase the instability of the solution and can therefore lead to collusive outcomes
Q-function range	Increasing the range and the size of the discretised action steps increases the chances of collusive outcomes
Number of firms	More firms tends to reduce the likelihood of a collusive outcome
Algorithm and customer complexity	More complex customer behaviour and algorithms generally make collusion more or less likely

Next steps

Collaboration between industry and regulation

The need for data science

A proactive discussion

An approach that works for everyone

Thank you!

Any questions?