

Two Artificial Neural Networks Meet in an Online Hub and Change the Future (of Competition, Market Dynamics and Society)

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1. Introduction

In the future, one may imagine a new breed on antitrust humor. Jokes might start along the following lines: “Two Artificial Neural Network and one Nash equilibrium meet in an online (pub) hub. After a few milliseconds, a unique silent friendship is formed...”

Back to the present; we are not sure how this joke might end. Nor can we estimate how funny future consumers would find it. We can, however, explain, at present, how technological advancements have changed, and will continue to change, the dynamics of competition and subsequently the distribution of wealth in society. How algorithms may be used in stealth mode to stabilize and dampen market competition while retaining the façade of competitive environment. That tale is at the heart of this paper.

We first raised algorithmic tacit collusion in 2015.¹ In 2016 we provided further context and analysis in our book, *Virtual Competition: The Promise and Perils of the Algorithm-Driven Economy*.² We illustrate how online tacit collusion may emerge

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We are grateful for comments received from Ashwin Ittoo, University of Liege, on the technical aspects of Neural Networks.

¹ Ezrachi and Stucke ‘Artificial Intelligence & Collusion: When Computers Inhibit Competition’ Oxford Legal Studies Research Paper No. 18/2015, University of Tennessee Legal Studies Research Paper No. 267, available at SSRN: <https://ssrn.com/abstract=2591874> or <http://dx.doi.org/10.2139/ssrn.2591874>.

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HUP,

2016.

See:

when products are generally homogeneous and sellers do not benefit from brand recognition or loyalty, and when markets are transparent and concentrated. Since our book elaborates on the four collusion scenarios, we begin here by outlining one model of tacit collusion and its manifestation online. Taking note of advancement in technology and emerging policies, we move the debate forward and provide a review of the possible harm and means to address it. We begin our discussion with an illustration of how the move to an online pricing environment, under certain market conditions, may adversely affect the buyers' welfare. We note how new technologies may undermine enforcers' attempts to intervene - as stealth becomes a feature of future strategies. That tale, of course, is not immune from disruptive strategies. We consider these and reflect on the use of counter-measures to undermine tacit collusion. Further, we consider the effects and likelihood of secret dealings. We note how, somewhat counter intuitively, secret deals in an online environment could reduce, at times, consumer welfare.

2. Tacit Collusion on Steroids

While technology may be used to support traditional price alignment - help the colluders collude³ – our focus here is on instances where the same anticompetitive outcome may be achieved without agreeing to tamper with prices and without infringing current competition laws.⁴ Our focus is how the use of algorithms can change the market dynamics and foster interdependence among operators and tacit collusion. Such dynamic, also known as conscious parallelism, 'describes the process,

<http://www.hup.harvard.edu/catalog.php?isbn=9780674545472&content=reviews>

³ https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/565424/60ss-price-fixing-guidance-for-online-sellers.pdf;

https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/565424/60ss-price-fixing-guidance-for-online-sellers.pdf;

<http://www.reuters.com/article/us-usa-antitrust-e-commerce-plea-idUSKBN0MX1GZ20150406>

⁴ Marc Ivaldi, Bruno Jullien, Patrick Rey, Paul Seabright, and Jean Tirole, "The Economics of Tacit Collusion," Final Report for DG Competition (Toulouse: European Commission, March 2003),

http://ec.europa.eu/competition/mergers/studies_reports/the_economics_of_tacit_collusion_en.pdf

not in itself unlawful, by which firms in a concentrated market might in effect share monopoly power, setting their prices at a profit-maximizing, supracompetitive level by recognizing their shared economic interests and their interdependence with respect to price and output decisions and subsequently unilaterally set their prices above the competitive level.⁵

Algorithmic tacit collusion will not affect every (or even most) markets. As *Virtual Competition* explores, one would expect algorithmic tacit collusion in the near future in markets when several important conditions exist. First, algorithmic tacit collusion would likely arise in concentrated markets involving homogenous products where the algorithms can monitor to a sufficient degree the pricing and other key terms of sale.⁶ Conscious parallelism would be facilitated and stabilized by the shift of many industries to online pricing, as sellers can more easily monitor competitors' pricing and key terms of sale and any deviations from current equilibrium. In such an environment, algorithmic pricing provides a stable, predictable tool, which can execute credible and effective retaliation - in the form of price reductions. Special software may be used to report and take independent action when faced with price deviation, be it from the tacit agreement or the recommended retail price.

A second important market condition is that once deviation (e.g., discounting) is detected, a credible deterrent mechanism can be activated.⁷ Unique to an algorithmic environment is the speed of retaliation.⁸ Computers can rapidly police deviations, and calculate the profit implications of myriad moves and counter-moves to punish

⁵ Brooke Group Ltd. v. Brown & Williamson Tobacco Corp., 509 U.S. 209 (1993); R. S. Khemani and D. M. Shapiro, Glossary of Industrial Organisation Economics and Competition Law (Paris: Organisation for Economic Co-operation and Development, 1993), <http://www.oecd.org/dataoecd/8/61/2376087.pdf>

⁶ EC Merger Guidelines para 41.

⁷ EC Merger Guidelines para 41.

⁸ Contrast this with EC Merger Guidelines para 53 ("The speed with which deterrent mechanisms can be implemented is related to the issue of transparency. If firms are only able to observe their competitors' actions after a substantial delay, then retaliation will be similarly delayed and this may influence whether it is sufficient to deter deviation.").

deviations.⁹ The speed of calculated responses effectively deprives discounting rivals of any significant sales. The speed also means that collusion can be signalled in a matter of seconds. The greater the improbability that the first-mover will benefit from its discounting, the greater the likelihood of tacit collusion. As competitors' prices shift online, their algorithms can assess and adjust prices—even for particular individuals at particular times and for thousands of products—within milliseconds.¹⁰ Thus if each algorithm can swiftly match a rival's discount and eliminate its incentive to discount in the first place, the “threat of future retaliation keeps the coordination sustainable.”¹¹

A third condition, the Commission found, is “the reactions of outsiders, such as current and future competitors not participating in the coordination, as well as customers, should not be able to jeopardise the results expected from the coordination.”¹² Thus algorithmic tacit collusion would likely arise in concentrated markets where buyers cannot exert buyer power (or entice sellers to defect), sales transactions tend to be “frequent, regular, and relatively small,”¹³ and the market in general is characterized by high entry barriers.

The stability needed for algorithmic tacit collusion is further enhanced by the fact that computer algorithms are unlikely to exhibit human biases. As the European Commission observed, “Coordination is more likely to emerge if competitors can easily arrive at a common perception as to how the coordination should work. Coordinating firms should have similar views regarding which actions would be considered to be in accordance with the aligned behaviour and which actions would

⁹ <http://www.newyorker.com/business/currency/when-bots-collude>

¹⁰ Samuel B. Hwang and Sungho Kim, “Dynamic Pricing Algorithm for E-Commerce,” in *Advances in Systems, Computing Sciences and Software Engineering*, Proceedings of SCSS05, Tarek Sobh and Khaled Elleithy, eds. (Dordrecht: Springer, 2006), 149–155; N. Abe and T. Kamba, “A Web Marketing System with Automatic Pricing,” *Computer Networks* 33 (2000): 775–788; L. M. Minga, Y. Q. Fend, and Y. J. Li, “Dynamic Pricing: E-Commerce-Oriented Price Setting Algorithm,” *International Conference on Machine Learning and Cybernetics* 2 (2003).

¹¹ EC Merger Guidelines para 52.

¹² EC Merger Guidelines para 41.

¹³ <https://www.justice.gov/atr/file/801216/download>

not.”¹⁴ Human biases, of course, may be reflected in the programming code. But biases will not necessarily affect decisions on a case-by-case basis: a computer does not fear detection and possible financial penalties or incarceration; nor does it respond in anger.¹⁵ “We’re talking about a velocity of decision-making that isn’t really human,” says Terrell McSweeney, a commissioner with the US Federal Trade Commission. “All of the economic models are based on human incentives and what we think humans rationally will do. It’s entirely possible that not all of that learning is necessarily applicable in some of these markets.”¹⁶

The likely proliferation of interdependence online runs counter to one’s assumption as to the competitive nature of the online environment. And yet, when the above conditions are present, companies can embed the tacit collusion model in the algorithm, using it as a stabilizing mechanism. Interdependence and price increase may follow when each competitor in an industry adopts a pricing algorithm, which is set to follow a price increase, and punish any deviations. In such environment, maverick behavior may likely be unprofitable and irrational. Furthermore, as technology advances and artificial intelligence plays an increasing role in decision making, algorithms, through trial-and-error, can arrive at that outcome when they have a similar goal (profit maximization) and access to each other’s prices and other key market data. Algorithms will likely engage in “predictive analytics”—that is, the study of patterns in pricing and commercial decisions. Such an analysis will enable firms to combine “real-time, historical and third-party data to build forecasts of what will happen in their business months, weeks or even just hours in advance.”¹⁷ That technology would enable “moving away from ‘systems of record’ to ‘systems of

¹⁴ EC Merger Guidelines para 44.

¹⁵ <https://hbr.org/2016/10/how-pricing-bots-could-form-cartels-and-make-things-more-expensive>

¹⁶ <http://www.pros.com/about-pros/news/financial-times-policing-digital-cartels/>

¹⁷ Roland Moore-Colyer, “Predictive Analytics Are the Future of Big Data,” V3 (October 9, 2015), <http://www.v3.co.uk/v3-uk/analysis/2429494/predictive-analytics-are-the-future-of-big-data>

engagement' that use predictive analytics to cut through the noise in big data and uncover insights that can be acted on."¹⁸ One would expect a market norm to emerge.

3. Online Technology and Offline Effects

Importantly, an industry-wide use of pricing algorithms may increase the number of instances in which tacit collusion may be sustained. To be clear, no bright line exists when an industry becomes sufficiently concentrated for either express or tacit collusion. Two economists offer several explanations for the lack of a clear empirical relationship between industry concentration and cartels involving express collusion: "First, this ambiguity may reflect the bias introduced by focusing on cartels that were prosecuted by the U.S. Department of Justice; cartels with large numbers of firms or that had the active involvement of an industry association may have been more likely to get caught. Second, industries with a very small number of firms may be able to collude tacitly without resort to explicit collusion. Third, concentration is endogenous: collusion may have allowed more firms to survive and remain in the market."¹⁹

Generally, for illegal cartels involving *express* collusion which were detected and prosecuted, the empirical research has that cartels involving a trade association were on average over twice as large than cartels without a trade association involved.²⁰

¹⁸ Ibid., citing Larry Augustine, chief executive at SugarCRM.

¹⁹ Levenstein, Margaret C., and Valerie Y. Suslow. 2006. "What Determines Cartel Success?." *Journal of Economic Literature* 44, no. 1: 43-95. EconLit, EBSCOhost (accessed April 6, 2017).

²⁰ One empirical analysis of successfully prosecuted cartels between 1910 and 1972 showed that cartels on average had many participants: where a trade association facilitated collusion, 33.6 firms was the mean of firms involved, and fourteen firms was the median; in price-fixing cartels (without a trade association involved) 8.3 firms was the mean and six was the median. Arthur G. Frass & Douglas F. Greer, *Market Structure and Price Collusion: An Empirical Analysis*, 26 *J. Indus. Econ.* 21, 25, 36-41 (1977). One conservative assumption in that empirical study was that the number of cartel members prosecuted reflected the total number of firms in the relevant market. *Id.* at 24. But, aside from ineffectual fringe firms, the relevant market may contain more participants than reflected in the government's indictment or criminal information, which does not always identify all the co-conspirators. Consequently, the authors had to exclude from its sample of 606 cases, those cases where the number of firms allegedly involved were not specified

The belief is that express collusion generally represents the outer boundary. (Otherwise why would competitors expressly collude when they could tacitly collude legally?) One maxim is that tacit collusion is “frequently observed with two sellers, rarely in markets with three sellers, and almost never in markets with four or more sellers.”²¹ Whether this is empirically true is another matter.²²

Even if we accept the premise that tacit collusion is likelier in duopolies than triopolies and quadropolies, two factors should give us pause. One factor is that state of competition in major economies, like the United States, is worrisome, with evidence of increasing concentration and greater profits flowing into fewer hands.²³ Thus, if market concentration increase, more markets may be susceptible to tacit collusion. A

in the records. *Id.* at 25-26. Some co-conspirators conceivably could escape prosecution (through lack of evidence). Although the authors rely upon an earlier study, which showed a 0.959 correlation between the number of conspirators and total number of firms in the market, the sample size of that earlier study was 34 cases. *Id.* at 28 n.17, citing George Hay & Daniel Kelly, *An Empirical Survey of Price Fixing Conspiracies*, 17 *J.L. & Econ.* 13 (1974). For studies of cartels immunized from the antitrust laws, see, e.g., Andrew R. Dick, *Identifying Contracts, Combinations & Conspiracies in Restraint of Trade*, 17 *Managerial & Decision Econ.* 203, 213 (1996) (discussing that cartels formed more frequently in unconcentrated industries under Webb-Pomerene Export Trade Act); see also Paul S. Clyde & James D. Reitzes, *The Effectiveness of Collusion Under Antitrust Immunity: The Case of Liner Shipping Conferences*, Bureau of Economics Staff Report (Dec. 1995) (finding a positive, but economically small, relationship between overall market concentration and shipping rates), available at <http://www.ftc.gov/reports/shipping.pdf>; see also Maurice E. Stucke, *Behavioral Economists at the Gate: Antitrust in the Twenty-First Century*, 38 *Loy. U. Chi. L.J.* 513, 555-56 (2007) (collecting earlier empirical work on cartels in moderately concentrated and unconcentrated industries); Levenstein and Suslow, ‘Cartel Success’, above n**, 58 (finding no simple relationship between industry concentration and likelihood of collusion); Levenstein and Suslow, ‘Breaking up’, above n**, 12 (finding international cartels prosecuted between 1990–2007 had on average 7.4 members).

²¹ Potters, J. and S. Suetens (2013). Oligopoly experiments in the current millennium. *Journal of Economic Surveys* 27(3), 439–460.

²² Horstmann, Niklas and Kraemer, Jan and Schnurr, Daniel, *Number Effects and Tacit Collusion in Experimental Oligopolies* (October 24, 2016). Available at SSRN: <https://ssrn.com/abstract=2535862> or <http://dx.doi.org/10.2139/ssrn.2535862> (finding from the extant literature “no robust empirical evidence that would support this claim of a strictly monotonic relationship between the number of firms and the degree of tacit collusion in a given market,” but finding this monotonic trend from their own two experiments).

²³ See, e.g., Jonathan B. Baker, *Market power in the U.S. economy today* (March 2017); Grullon, Gustavo and Larkin, Yelena and Michaely, Roni, *Are US Industries Becoming More Concentrated?* (Feb 23, 2017). Available at SSRN: <https://ssrn.com/abstract=2612047> or <http://dx.doi.org/10.2139/ssrn.2612047>

second factor is that the industry-wide use of algorithms, given the speed and enhanced transparency, could expand the range of industries susceptible to collusion beyond duopolies to perhaps markets, as we'll see in petrol, dominated by 5 or 6 players. Markets in which conscious parallelism was unstable or not present, may see a new equilibrium emerge, due to increased concentration, transparency, greater stability and effective punishment. Ultimately we are likely to see more instances in which similar pricing is not the result of fierce competition, nor the result of cartel activity, but rather the result of tacit collusion. With the use of algorithms, operators in these markets will find it possible and rational to weave the tacit collusion model into the algorithm. While they may use different technologies or algorithms, they will share an incentive to embed a stabilizing strategy in their algorithmic long arm.

To illustrate, imagine an oligopolistic market for petrol with limited transparency. The market includes a relatively small number of sellers and prices are only available when reaching each petrol station. In such market customers may be subjected to search costs, but could mitigate them by asking their friends about any available deals, visit a few stations, and support the one with the lowest price. In such a market, a petrol station may increase its profits by offering a discount and may develop a reputation for having a low (if not the lowest) price. At times, competitors, aware of the price reductions and promotions, would follow with their own initiative. But the limited transparency and delayed action are likely to benefit the discounter. Under these market conditions, conscious parallelism is harder to sustain. The firms will likely compete as expected. We see here how markets “need to be sufficiently transparent to allow the coordinating firms to monitor to a sufficient degree whether other firms are deviating, and thus know when to retaliate.”²⁴

When transparency increases in concentrated markets with homogeneous goods, so too does the risk of tacit collusion. To illustrate the likelihood and emergence of such

²⁴ EC Merger Guidelines para 49.

strategies, let us explore three cases where posting petrol prices online promoted tacit collusion.

Our first example is the Chilean retail-gasoline industry. In February 2012, a Chilean regulation began requiring petrol stations to post their fuel prices on a government website and to keep prices updated as they changed at the pump. An economic study found that this had the overall effect of softening, rather than increasing, competition.²⁵ The petrol stations' margins increased by 10% on average following the prices being posted on the government website. The softening of competition was common across brands, and was not limited to a single city in Chile. Interestingly, although the stations' margins increased across Chile, the effect was not uniform: the petrol station margins "increased the most in areas with low or non-existent consumer search (low-income areas), while they increased the least, and even decreased, in areas with high search intensity (high-income areas)."²⁶

Our second example is Germany. The government suspected that the off-motorway petrol station business was subject to a dominant oligopoly composed of 5 firms: BP (Aral), ConocoPhillips (Jet), ExxonMobil (Esso), Shell, and Total.²⁷ To monitor pricing, the petrol station owners would drive past specified competitor petrol stations several times a day and note their prices. The monitored prices were then fed decentrally into the electronic system of the respective oil company. Generally,

²⁵ Fernando Luco, Who Benefits from Information Disclosure? The Case of Retail Gasoline, Working Paper, Department of Economics, Texas A&M University September 28, 2016, https://cf00f56d-a-62cb3a1a-s-sites.googlegroups.com/site/flucoe/home/Info_disclosure.pdf?attachauth=ANoY7colGaf66bKWn0h_BnbFaq4kHFB7rYJrb6vZVN6BhIZeTPbNs2LRUOiyuLeAP4jY8YXe3nuDW2dEE2wtLOd0YihxBS-4CB2hgafQqHf5a-uyPyq_DlPrThncKi7sNvnxgXomB_Hk3ROwYLV9tZWtIWn5YfDAzjA69ARs-8nxOrFEJzac5ULK2lBwGHkIO9QsN9sEdZfUnX1OjUL9J2qE_IWdgPuhA%3D%3D&attredirects=0

²⁶ Ibid.

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http://www.bundeskartellamt.de/SharedDocs/Publikation/EN/Sector%20Inquiries/Fuel%20Sector%20Inquiry%20-%20Final%20Report.pdf?__blob=publicationFile&v=14. Together, the five companies had a combined share of approx. 64.6 % of the annual fuel sales, with the remainder distributed among "a few other large oil companies and a large number of small and medium sized oil traders." Id.

when one competitor increased petrol price, rivals generally would respond between three to six hours later.²⁸ So to promote competition, the government required the petrol stations to report to its government's transparency unit any price changes for gasoline or diesel fuel in "real time."²⁹ The government's transparency unit then transmitted the price data to consumers, with the aim that they could easily find the cheapest petrol nearby. Rather than lowering prices, the enhanced market transparency, one economic study found, increased prices further. Compared to the control group, retail gasoline prices increased by about 1.2 to 3.3 euro cents, and diesel increased by about 2 euro cents.³⁰

Our third example is Perth, Australia.³¹ Its concentrated retail gasoline market was dominated by four major oil firms (BP, Caltex, Mobil and Shell) and two supermarket

²⁸ Id. ("If a round of price increases is begun by Aral, Shell reacts in 90 % of the cases exactly three hours later with a price increase in all of the regional markets, thereby adjusting its price level to that of Aral. Vice-versa, when Shell starts a round of price increases, in 90% of the cases Aral follows suit, again after exactly three hours. Total also generally reacts with price rises in all of the regional markets three or three-and-a-half hours after the start of the price round. Jet and Esso also react in the same way to rounds of price increases started by Aral or Shell, although the response patterns differ in some of the regional markets. Nevertheless it can be concluded that Jet often also raises its prices five hours after the start of a round of price increases, whereby it generally observes a price difference of one eurocent/litre to Aral and Shell's prices. Esso reacts between three and six hours after the start of a round of price increases. It is also apparent that on some regional markets Jet and Esso only react to rounds of price increases started in the evenings on the morning of the following day.").

²⁹ Ralf Dewenter, Ulrich Heimeshoff, Hendrik Lüth, The Impact of the Market Transparency Unit for Fuels on Gasoline Prices in Germany (May 2016), http://www.dice.hhu.de/fileadmin/redaktion/Fakultaeten/Wirtschaftswissenschaftliche_Fakultaet/DICE/Discussion_Paper/220_Dewenter_Heimeshoff_Lueth.pdf

³⁰ Ralf Dewenter, Ulrich Heimeshoff, Hendrik Lüth, The Impact of the Market Transparency Unit for Fuels on Gasoline Prices in Germany (May 2016), http://www.dice.hhu.de/fileadmin/redaktion/Fakultaeten/Wirtschaftswissenschaftliche_Fakultaet/DICE/Discussion_Paper/220_Dewenter_Heimeshoff_Lueth.pdf

³¹ Byrne, David P. and de Roos, Nicolas, Learning to Coordinate: A Study in Retail Gasoline (January 19, 2017). Available at SSRN: <https://ssrn.com/abstract=2570637> or <http://dx.doi.org/10.2139/ssrn.2570637>. According to the study, 'post 2010 we see a change. BP, the market leader, introduced Thursday price jumps. At first the price jumps were limited to the majority of its own stations, but soon we saw BP's competitors conform to the Thursday jumps at different rates. After only two years, Thursday jumps were solidified as a focal point for setting market prices.' See: <https://pursuit.unimelb.edu.au/articles/how-tacit-collusion-makes-consumers-pay>

chains (Coles and Woolworths). In 2001, the government introduced a gasoline price transparency program called Fuelwatch. Each firm had to submit before 2 pm their next day's station-level prices. When stations opened the next day, they by law had to post the submitted prices. Retail prices were fixed at these posted levels for 24 hours.

Fuelwatch proved useful in promoting tacit collusion. Rivals could see on-line the prices for every petrol station in the market, and after 2:30 pm each day, tomorrow's prices. What the economic study found was that the market leader, BP, through trial-and-error and experimentation, eventually facilitated tacit collusion, which "substantially improved retail margins, created price stability in the presence of aggregate shocks, and enabled firms to resolve conflict quickly."³²

Now imagine, as is the case in many states,³³ a smartphone app tells you the price of petrol at every local station. That may sound procompetitive. The increase in price transparency lowers your search costs for finding cheaper fuel. Indeed, in markets characterized by many sellers and many knowledgeable consumers, the gas app may promote competition. But also imagine if the petrol station owners shifted pricing decisions from humans to pricing algorithms. The combination of pricing algorithms and petrol apps can have the opposite effect.

In Perth, it took, the study's authors noted, 12 years from the start of the government's price transparency policy for the six competitors "to develop a stable collusive pricing structure."³⁴ With real-time pricing for each petrol station, competitors no longer have to drive past neighboring gas stations several times a day, report the pricing information to headquarters, and then react. Nor do they have to monitor the government website to identify when another station changes its prices. Rivals' pricing algorithms can observe all the competitively significant terms and promptly respond to any discount. By shifting pricing decisions to computer

³² Ibid.

³³ Fuel apps have become a common feature and can be downloaded for free.

³⁴ Byrne and de Roos, *supra*.

algorithms, competitors thereby increase transparency, reduce strategic uncertainty (when the pricing algorithm cannot grant secretive discounts), and thereby stabilize the market.³⁵ When one petrol station lowers the price by one cent at 11:33 A.M., within milliseconds other nearby stations can respond by lowering their price.

Thus, with each firm's algorithm tapping into its rivals' real-time pricing, no petrol station would likely profit by discounting. Given the velocity with which the pricing algorithms can adjust, no petrol station would likely develop among its customers a reputation as a price discounter. Accordingly, the competitors will have less incentive to discount. We can see that even in markets where tacit collusion should be unlikely given the number of significant competitors (such as five in Germany and six in Perth), an app that was meant to promote price competition could end up undermining it.

On the flip side, the algorithms' velocity of pricing decisions can shorten the time period for signaling price increases. Firms would no longer have to rely on lengthy (e.g., thirty-day) price announcements, where they wait and see what the competitive response is, to decide whether to raise prices (and to what extent). Computers can have multiple rounds whereby one firm increases prices and the rival computers respond immediately and without the risk that the firm that initiates the price increase will lose many customers to rivals. Essentially, companies may now need only seconds, rather than days, to signal price increases to foster collusion.

So the industry-wide use of pricing algorithms increases both market transparency and the risk of tacit collusion. Moreover, in programming its pricing algorithm, each firm will likely use historic pricing data and competitive responses to calibrate the dominant strategy. As such, when the algorithms operate within the greater transparency of their digitalized environment, the computers will already be programmed to anticipate and respond to rivals' moves. In this scenario, computers

³⁵ See Salil K. Mehra, "Antitrust and the Robo-Seller: Competition in the Time of Algorithms," *Minnesota Law Review* 100 (March 10, 2015), <http://ssrn.com/abstract=2576341>, on how pricing algorithms can promote tacit collusion under a Cournot model.

can rapidly calculate the profit implications of myriad moves and countermoves. With the computers' ability to police deviations and rely on prior strategies to punish deviations, prices, as a result of their conscious parallelism, will climb not only in duopolies but in other concentrated markets.

4. Enforcement challenges

The EU and US policymakers over the past 18 months have acknowledged algorithmic collusion as an antitrust concern.³⁶ The EU Commission, noted that, among other things, 'increased price transparency through price monitoring software may facilitate or strengthen (both tacit and explicit) collusion between retailers by making the detection of deviations from the collusive agreement easier and more immediate. This, in turn, could reduce the incentive of retailers to deviate from the collusive price by limiting the expected gains from such deviation.'³⁷ The French and German competition authorities similarly noted in a joint report that:

Even though market transparency as a facilitating factor for collusion has been debated for several decades now, it gains new relevance due to technical

³⁶ In its 2016 Preliminary Report on the E-commerce Sector Inquiry the European Commission noted the rise in use of monitoring algorithms: 'About half of the retailers track online prices of competitors. In addition to easily accessible online searches and price comparison tools, both retailers and manufacturers report about the use of specific price monitoring software, often referred to as "spiders", created either by third party software specialists or by the companies themselves. This software crawls the internet and gathers large amounts of price related information. 67 % of those retailers that track online prices use (also) automatic software programmes for that purpose. Larger companies have a tendency to track online prices of competing retailers more than smaller ones... some software allows companies to monitor several hundred online shops extremely rapidly, if not in real time... Alert functionalities in price monitoring software allow companies to get alerted as soon as a retailer's price is not in line with a predefined price.' Brussels, 15.9.2016 SWD(2016) 312, Paras 550-551
http://ec.europa.eu/competition/antitrust/sector_inquiry_preliminary_report_en.pdf

³⁷ Para 555. Also note the European Commission investigations into online sales practices launched on 2 February 2017. As part of the investigation into Consumer electronics manufacturers the commission will also consider the effects of pricing software that automatically adapts retail prices to those of leading competitors.

developments such as sophisticated computer algorithms. For example, by processing all available information and thus monitoring and analyzing or anticipating their competitors' responses to current and future prices, competitors may easier be able to find a sustainable supra-competitive price equilibrium which they can agree on.³⁸

Similarly, the U.K. House of Lords noted how the rapid developments in data collection and data analytics have created the potential for new welfare reducing and anti-competitive behaviour, including new forms of collusion.³⁹ And the OECD in 2016 commented that these strategies “may pose serious challenges to competition authorities in the future, as it may be very difficult, if not impossible, to prove an intention to coordinate prices, at least using current antitrust tools.”⁴⁰ Reflecting on these enforcement challenges, Lord David Currie of the U.K. Competition and Markets Authority observed that:

Algorithms can provide a very effective way of almost instantly coordinating behaviour, possibly in an anti-competitive way. Where algorithms are designed by humans to do so, this is merely a new form of the old practice of price-fixing. But machine learning means that the algorithms may themselves learn that co-ordination is the best way to maximise longer-term business objectives. In that case, no human agent has planned the co-ordination. Does that represent a breach of competition law? Does the law stretch to cover sins of omission as well as sins of commission: the failure to build in sufficient constraints on algorithmic behaviour to ensure that the algorithm does not learn to adopt

³⁸ 2016 joint report, *Competition Law and Data*, Page 14, with reference to our earlier work - Artificial intelligence and collusion: when computers inhibit competition. http://www.bundeskartellamt.de/SharedDocs/Publikation/DE/Berichte/Big%20Data%20Papier.pdf?__blob=publicationFile&v=

³⁹ Para 178 & 179, <https://www.publications.parliament.uk/pa/ld201516/ldselect/ldcom/129/12908.htm>

⁴⁰ para 81: BIG DATA: BRINGING COMPETITION POLICY TO THE DIGITAL ERA DAF/COMP(2016)14 27-Oct-2016 [https://one.oecd.org/document/DAF/COMP\(2016\)14/en/pdf](https://one.oecd.org/document/DAF/COMP(2016)14/en/pdf)

anti-competitive outcomes? And what if constraints are built in but they are inadequately designed, so that the very clever algorithm learns a way through the constraints? How far can the concept of human agency be stretched to cover these sorts of issues? I have suggested earlier that the competition tools at our disposal can tackle the competition issues that we face in the new digital world, but perhaps this last issue which I have touched on is one where this proposition is not true.⁴¹

Let us look in more detail at some of the key enforcement challenges posed by algorithmic tacit collusion. We divide the discussion under three main headings: Policy, Detection and Liability.

4.1. Policy and law

In most jurisdictions, the unilateral use of algorithms to monitor and set price will not amount to an illegal antitrust agreement or concerted practice. Rational unilateral reaction to market dynamics (free from agreements or communications) in itself, is legal under EU and US competition law, even if it leads to an equilibrium above competitive levels.⁴² After all, one cannot condemn a firm for behaving rationally and interdependently on the market.⁴³

When the algorithms increase market transparency, defendants will often have an independent legitimate business rationale for their conduct. Courts and the enforcement agencies may be reluctant to restrict this free flow of information in the

⁴¹<http://www.wired-gov.net/wg/news.nsf/articles/David+Currie+on+the+role+of+competition+in+stimulating+innovation+ 03022017141532?open>

⁴² As noted earlier, tacit collusion does not amount to concerted practice and therefore escapes Article 101 TFEU. Tacit collusion may serve to establish Collective Dominance under Article 102 TFEU, but absent a separate abuse, it will also escape scrutiny under this provision.

⁴³ See, for example, Case C-199/92, P Hüls AG v. Commission, [1999] ECR I-4287, [1999] 5 CMLR 1016; Joined Cases C-89, 104, 114, 116, 117, 125, 129/85, Ahlström Osakeyhtiö and others v. Commission (Wood Pulp II), [1993] ECR I-1307, [1993] 4 CMLR 407; Cases T-442/08, CISAC v Commission, [2013] 5 CMLR 15 (General Court).

marketplace. Its dissemination, observed the U.S. Supreme Court, “is normally an aid to commerce,”⁴⁴ and “can in certain circumstances increase economic efficiency and render markets more, rather than less, competitive.”⁴⁵ Indeed, concerted action to reduce price transparency may itself be an antitrust violation.⁴⁶

Accordingly, ‘pure’ forms of tacit collusion which result from a unilateral rational reaction to market characteristics would not normally trigger antitrust liability. On the other hand, intervention may be triggered when an illicit concerted practice ‘contaminated’ or ‘facilitated’ the conscious parallelism. In some instances, the unilateral nature of the action may be questioned. At times, either a horizontal or vertical agreement may be inferred. Condemned actions may include signaling, exchange of information, agreement to engage in common strategy, manipulation through the sharing of data pools and other collusive strategies.

Illustrative is the EU Commission’s recent investigation into suspected anticompetitive practices in e-commerce. In February 2017, the Commission announced an investigation into possible breach of EU competition law by Asus, Denon & Marantz, Philips and Pioneer. Among other things, the Commission is appraising whether the companies restricted the “ability of online retailers to set

⁴⁴ *Sugar Institute, Inc. v. United States*, 297 U.S. 553, 598 (1936).

⁴⁵ *United States v. United States Gypsum Co.*, 438 U.S. 422, 441 n.16 (1978); See also Richard A. Posner, *Antitrust Law*, 2nd ed. (Chicago: University of Chicago Press, 2001), 160. Generally, the more information sellers have about their competitors’ prices and output, the more efficiently the market will operate.

⁴⁶ See, for example, Federal Trade Commission, *Funeral Directors Board Settles with FTC* (August 16, 2004), <http://www.ftc.gov/opa/2004/08/vafuneral.htm> (a board’s prohibition on licensed funeral directors advertising discounts deprived consumers of truthful information); Federal Trade Commission, *Arizona Automobile Dealers Association*, FTC C-3497 (February 25, 1994) (a trade association illegally agreed with members to restrict nondeceptive comparative and discount advertising and advertisements concerning the terms and availability of consumer credit); Organisation for Economic Co-operation and Development, *Price Transparency*, DAF/CLP(2001)22 (September 11, 2001), 183, 185–186 (citing examples of U.S. enforcement agencies seeking to increase price transparency); compare *InterVest, Inc. v. Bloomberg, L.P.*, 340 F.3d 144 (3d Cir. 2003) (lack of price transparency in bond market not illegal if consistent with unilateral conduct).

their own prices for widely used consumer electronics products such as household appliances, notebooks and hi-fi products.” According to the Commission, “The effect of these suspected price restrictions may be aggravated due to the use by many online retailers of pricing software that automatically adapts retail prices to those of leading competitors. As a result, the alleged behaviour may have had a broader impact on overall online prices for the respective consumer electronics products.”⁴⁷

Evidently, antitrust intervention is easier when algorithms are part of a wider collusive agreement to tamper with market prices.⁴⁸ Similarly, weaker forms of signaling, aimed at coordinating practice of the market could be condemned. But, the challenging question remains: should ‘pure’ forms of conscious parallelism be condemned? Ought we condemn the facilitation of tacit collusion through artificial means? Should one condemn a firm for behaving rationally and developing, unilaterally, an algorithm that accounts publically available information while operating interdependently on the market?⁴⁹

One way to square this circle may be framing the issue as **market manipulation or an unfair practice**. The focus shifts from the presence of agreement among companies to the use of advanced algorithms to transform pre-existing market conditions in such a way to facilitate tacit collusion. While the mutual price monitoring at the heart of tacit collusion is legal under competition law, one may ask whether the creation of such a market dynamic, through “artificial” means, gives rise to antitrust intervention.

⁴⁷ http://europa.eu/rapid/press-release_IP-17-201_en.htm

⁴⁸ See for example: Topkins, <https://www.justice.gov/opa/pr/former-e-commerce-executive-charged-price-fixing-antitrust-divisions-first-online-marketplace>

⁴⁹ See, for example, Case C-199/92, P Hüls AG v. Commission, [1999] ECR I-4287, [1999] 5 CMLR 1016; Joined Cases C-89, 104, 114, 116, 117, 125, 129/85, Ahlström Osakeyhtiö and others v. Commission (Wood Pulp II), [1993] ECR I-1307, [1993] 4 CMLR 407; Cases T-442/08, CISAC v Commission, [2013] 5 CMLR 15 (General Court).

Using such an approach, one could consider application of legislation such as Section 5 of the FTC Act, which targets unfair facilitating practices.⁵⁰ Noteworthy is the fact that the US courts set a rather high level of intervention. Under the legal standard applied in *Ethyl*⁵¹, the FTC must show either (1) evidence that defendants tacitly or expressly agreed to use pricing algorithms to avoid competition, or (2) oppressiveness, such as (a) evidence of defendants’ anticompetitive intent or purpose or (b) the absence of an independent legitimate business reason for the defendants’ conduct.⁵² Accordingly, defendants may be liable if, when developing the algorithms or in seeing the effects, they were (1) motivated to achieve an anticompetitive outcome, or (2) aware of their actions’ natural and probable anticompetitive consequences.

An alternative route may target **“abuse” of excessive transparency, possibly where clear anticompetitive intent is present.** One could employ the rationale used in the U.S. Securities and Exchange Commission’s (SEC) case against Athena Capital Research.⁵³ In 2014, the SEC for the first time sanctioned the high-frequency trading firm for using complex computer programs to manipulate stock prices.⁵⁴ The sophisticated algorithm, code-named *Gravy*, engaged in a practice known as “marking the close” in which stocks were bought or sold near the close of trading to affect the closing price: “[t]he massive volumes of Athena’s last-second trades allowed Athena to overwhelm the market’s available liquidity and artificially push the market price—and therefore the closing price—in Athena’s favor.”⁵⁵ Athena’s employees, the SEC

⁵⁰ The FTC was unsuccessful in its attempt to prove such facilitating practices in *Boise Cascade Corp. v. F.T.C.*, 637 F.2d 573 (9th Cir. 1980) and *E. I. du Pont de Nemours & Co. v. F.T.C.*, 729 F.2d 128 (2d Cir. 1984).

⁵¹ *E. I. du Pont de Nemours & Co. v. F.T.C.*, 729 F.2d 128 (2d Cir. 1984).

⁵² *Ibid.*, 128, 139.

⁵³ U.S. Securities and Exchange Commission, Administrative Proceeding File No. 3-16199 (October 16, 2014), <http://www.sec.gov/litigation/admin/2014/34-73369.pdf>.

⁵⁴ The computer trading program was “placing a large number of aggressive, rapid-fire trades in the final two seconds of almost every trading day during a six-month period to manipulate the closing prices of thousands of NASDAQ-listed stocks.” U.S. Securities and Exchange Commission, SEC Charges New York-Based High Frequency Trading Firm with Fraudulent Trading to Manipulate Closing Prices, October 16, 2014, <http://www.sec.gov/News/PressRelease/Detail/PressRelease/1370543184457#.VEOZlfdV8E>.

Ibid.

⁵⁵ *Ibid.*

alleged, were “acutely aware of the price impact of its algorithmic trading, calling it ‘owning the game’ in internal e-mails.”⁵⁶ Athena employees “knew and expected that *Gravy* impacted the price of shares it traded, and at times Athena monitored the extent to which it did. For example, in August 2008, Athena employees compiled a spreadsheet containing information on the price movements caused by an early version of *Gravy*.”⁵⁷ Athena configured its algorithm *Gravy* “so that it would have a price impact.”⁵⁸ In calling its market-manipulation algorithm *Gravy*, and by exchanging a string of incriminating e-mails, the company did not help its case. Without admitting guilt, Athena paid a \$1 million penalty. This demonstrates that automated trading has the potential to increase market transparency and efficiency, but it can also lead to market manipulation.⁵⁹ Finding the predominant purpose for using an algorithm will not always be straightforward. Athena, for example, challenged the SEC’s allegations that it engaged in fraudulent activity: “While Athena does not deny the Commission’s charges, Athena believes that its trading activity helped satisfy market demand for liquidity during a period of unprecedented

⁵⁶ Ibid. As the SEC alleged Athena’s manipulative scheme focused on trading in order to create imbalances in securities at the close of the trading day: “Imbalances occur when there are more orders to buy shares than to sell shares (or vice versa) at the close for any given stock. Every day at the close of trading, NASDAQ runs a closing auction to fill all on-close orders at the best price, one that is not too distant from the price of the stock just before the close. Athena placed orders to fill imbalances in securities at the close of trading, and then traded or ‘accumulated’ shares on the continuous market on the opposite side of its order.” According to the SEC’s order, Athena’s algorithmic strategies became increasingly focused on ensuring that the firm was the dominant firm—and sometimes the only one—trading desirable stock imbalances at the end of each trading day. The firm implemented additional algorithms known as “Collars” to ensure that Athena’s orders received priority over other orders when trading imbalances. These eventually resulted in Athena’s imbalance-on-close orders being at least partially filled more than 98 percent of the time. Athena’s ability to predict that its orders would get filled on almost every imbalance order allowed the firm to unleash its manipulative *Gravy* algorithm to trade tens of thousands of shares right before the close of trading. As a result, these shares traded at artificial prices that NASDAQ then used to set the closing prices for on-close orders as part of its closing auction. Athena’s high-frequency trading scheme enabled its orders to be executed at more favorable prices.

⁵⁷ U.S. Securities and Exchange Commission, Administrative Proceeding File No. 3-16199, para. 34.

⁵⁸ Ibid., para. 36

⁵⁹ Peter J. Henning, “Why High-Frequency Trading Is so Hard to Regulate,” *New York Times*, October 20, 2014, <http://dealbook.nytimes.com/2014/10/20/why-high-frequency-trading-is-so-hard-to-regulate/>.

demand for such liquidity.”⁶⁰ A court might agree. Companies, learning from *Athena*, can be more circumspect in their e-mails.⁶¹

Another possible intervention path, of a more general nature, may involve the use of **market or sector investigations**. Such approach may prove useful in helping agencies understand the new dynamics in algorithm-driven markets and the magnitude of any competitive problems. In some jurisdictions, like the United Kingdom, market investigation laws also provide for a wide scope of behavioral and structural remedies.⁶² Following an investigation the agency may benefit from a flexible tool box that is unavailable through other means.

4.2. Detection

One interesting consequence of algorithm-driven tacit collusion is the difficulty in identifying the counterfactuals. In other words, the competitive position absent algorithmic activity. In practice, it may be difficult for an enforcer or regulator to conclude whether a market dynamic forms a ‘natural’ outcome or was ‘artificially’ enhanced or created.

One approach, which could help confront this challenge, may involve an **audit of the algorithm**. Under an auditing regime, the agency will assess whether an algorithm

⁶⁰ Steve Goldstein, “High-Frequency Trading Firm Fined for Wave of Last-Minute Trades,” Market Watch (October 16, 2014), <http://www.marketwatch.com/story/high-frequency-trading-firm-fined-for-wave-of-last-minute-trades-2014-10-16>.

⁶¹ Moreover, evidence of intent will likely be mixed when each firm has valid independent business reasons to develop and implement a pricing algorithm. After all, the first firm to use the pricing algorithm could not be accused of colluding, as the market was likelier less transparent, and rivals could not match the speed of the first mover’s price changes.

⁶² Take, for example, the powers of the U.K. Competition and Markets Authority to initiate market investigations, gather and appraise evidence, and, where necessary, impose structural or behavioral remedies; Competition Commission, *Guidelines for Market Investigations: Their Role, Procedures, Assessment and Remedies*, CC3 (Revised) (April 2013), https://www.gov.uk/government/uploads/system/uploads/attachmen_data/file/284390/cc3_revised.pdf (adopted by the CMA Board).

was designed to foster a change in the market dynamics. In essence, such approach resembles ex-ante merger appraisal - focusing on whether a proposed action would lead to a harmful change in market structure. Accordingly, algorithms could be activated in a 'sand box' where their effects will be observed and assessed.

The auditing function is feasible where the clear purpose and effect of the algorithms are to facilitate tacit collusion. But this cannot be the enforcer's only or primary tool. Several practical challenges exist, including, among other things, the sheer number of algorithms which would require scrutiny, the ease with which audited algorithm may be amended and set different optimization goals, the high level of expertise required to assess their effects, the ability to identify credible counterfactuals, and barriers associated with commercial secrecy.

Some challenges may be addressed by shifting the burden to the companies and imposing on them a duty to comply with a set of guidelines and principles of compliance by design. One could imagine the creation of an industry code of practice, which companies must follow when designing the algorithms. Random inspections perhaps could increase deterrence and compliance.

Yet, even if one shifts the burden of companies and assumes clear benchmarks for intervention - technology may undermine the effectiveness of intervention. Already we witness the use of advanced, more complex algorithms which, as a result are more difficult to audit. This trend will likely intensify as more data can be analyzed, and changing market dynamics can be addressed, through the use of Artificial Intelligence (AI).

Of relevance are recent developments in Artificial Neural Networks, also known as 'Deep Learning' which aim to mimic the brain's cognitive and computation mechanisms. These complex networks consist of a large number of computation units

(neurons), interconnected across several layers.⁶³ They have already contributed to significant advances in solving some of the harder, longstanding challenges for the AI community thus far. By 2017 they have matched or surpassed human performance in a variety of tasks, such as identifying malignant tumors in breast cancer images, image labeling, speech recognition and language translation.⁶⁴ Deep Learning techniques are now powering many of the applications that we use on a daily basis. These include voice recognition systems (on our mobile phones), and facial recognition systems (used by Facebook). Deep Learning has also shown much promise in directing self-driving cars.

The technology is often used in conjunction with another paradigm, known as Reinforcement Learning, which prescribes how agents should act in an environment in order to maximize future cumulative reward. The combination of Deep Learning and Reinforcement Learning is promising. It heralds the emergence of algorithms “ingrained” with advanced human cognitive abilities, such as playing Atari videogames and more importantly, beating the human champion at the GO game, considered as one of the AI holy grails.⁶⁵

An AI program, that its developers at Carnegie-Mellon University called “Libratus,” recently defeated several top poker players. This achievement becomes even more impressive when considering the following: First none of Libratus’s algorithms were

⁶³Ittoo, Nguyen and van den Bosch ‘Text analytics in industry: Challenges, desiderata and trends’, Computers in Industry, vol. 78, 2016, available at <http://www.sciencedirect.com/science/article/pii/S0166361515300646> or <http://dx.doi.org/10.1016/j.compind.2015.12.001>

⁶⁴ Yun Liu et al., Detecting Cancer Metastases on Gigapixel Pathology Images, <https://drive.google.com/file/d/0B1T58bZ5vYa-QlR0QlJTa2dPWVk/view>(in identifying for breast cancer patients whether the cancer has metastasized away from the breast, a trained algorithm could review large expanses of biological tissues, and automatically detect and localize tumors as small as 100 ×100 pixels in gigapixel microscopy images sized 100, 000×100, 000 pixels, with a rate of 8 false positives per image, and detecting 92.4% of the tumors, relative to 82.7% by the previous best automated approach, and a 73.2% sensitivity for human pathologists); Le Cun, Bengio and Hinton, ‘Deep Learning - Review’, Nature, vol. 521, 2015, available at <http://www.nature.com/nature/journal/v521/n7553/pdf/nature14539.pdf> or <http://dx.doi.org/10.1038/nature14539>

⁶⁵ <https://research.googleblog.com/2015/02/from-pixels-to-actions-human-level.html>

specific to poker. As one of developers told the press, “We did not program it to play poker. We programmed it to learn any imperfect-information game, and fed it the rules of No-Limit Texas Hold’em as a way to evaluate its performance.”⁶⁶ The AI program learned the optimal strategy. Second, Libratus playing style was unlike a human’s. The human players could not always identify the computer’s dominant strategy. What seemed like bad moves by the computer actually turned out to be good moves.⁶⁷ And the computer’s strategies seemingly varied hand-by-hand. Third, the computer’s strategies evolved day-by-day. When the humans found weaknesses in the computer’s play, the players could not quickly exploit these weaknesses. The computer already prioritized identifying and correcting these holes.⁶⁸ After twenty days of playing poker, Libratus won decisively.

Due to their complex nature and evolving abilities when trained with additional data, auditing these networks may prove futile. The knowledge acquired by a Deep Learning network is diffused across its large number of neurons and their interconnections, analogous to how memory is encoded in the human brain. These networks, based on non-linear transformations, are considered as opaque, black boxes.⁶⁹ Enforcers may lack the ability to trace back the steps taken by algorithms and unravel the self-learning processes. If deciphering the decision making of a deep learning network proves difficult, then identifying an anticompetitive purpose may be impossible.

In a market dominated by algorithms, absent a natural experiment or counterfactual (such as a similar market without algorithms), enforcers may not readily discern

⁶⁶ <http://www.csmonitor.com/Technology/2017/0204/Bot-makes-poker-pros-fold-What-s-next-for-artificial-intelligence>

⁶⁷ <https://www.youtube.com/watch?v=jLXPGwJNLHk>

⁶⁸ <https://www.youtube.com/watch?v=jLXPGwJNLHk>

⁶⁹ Castelvechi ‘Can we open the black box of AI?’, Nature, vol. 538, 2016, available at <http://www.nature.com/news/can-we-open-the-black-box-of-ai-1.20731> or <http://dx.doi.org/10.1038/538020a>

whether the market price is the result of artificial intervention or natural dynamics: the dynamic price may be the only market price.

4.3 Liability

The introduction of advanced algorithms will affect not only detection, but will also raise challenging questions with respect to liability. To what extent could human operators be liable for the actions of the algorithm?

In a simple scenario using today's technology, one could envisage the human operator embedding the tacit collusion model into the algorithm. If one opt to condemn that action, the human link may be relatively easy to detect. But, as noted above the future already heralds more advanced technologies.

Future enhanced networks will be able to act independently, with no human input and identify the dominant strategy. They will monitor, react and adjust to changing market reality, while taking note of the overall objective set. They will do so without requiring any prior programming of the dominant strategy they ought to pursue. Thought provoking is a recent experiment conducted in Google's advanced Deep Mind neural network.⁷⁰ The experiment set to identify the dominant strategy that Deep Mind will deploy. Interestingly, in an environment with limited resources Deep Mind deployed aggressive strategies, in an effort to win the competition. However, when collaboration was deemed more profitable (Wolfpace game) two neural agents learned from experimenting in the environment and collaborated to improve their joint position. One can draw parallel from the Wolfpace scenario to that of tacit collusion, where conscious parallelism would yield greater benefits to operators.

⁷⁰ Joel Z. Leibo and others, 'Multi-agent Reinforcement Learning in Sequential Social Dilemmas' <https://storage.googleapis.com/deepmind-media/papers/multi-agent-rl-in-ssd.pdf>; Also see short interview with Joel Z Leibo, the lead author on the paper on: <http://www.wired.co.uk/article/artificial-intelligence-social-impact-deepmind>.

AI calculating the benefit of collaboration provides an insight to future ability to identify the benefit of interdependence. When such is the dominant rational strategy, could the company using the algorithm be condemned, if it specifically did not program it to manipulate the market? To what extent can one be liable to the action of self-learning machine? And what checks and balances could one impose to prevent machines from changing market dynamics?

The European Commission, among others, is currently grappling these issues. It noted how more autonomous decision-making may “conflict with the current regulatory framework which was designed in the context of a more predictable, more manageable and controllable technology.”⁷¹ It recommended clarifying and, if necessary, adapting the legislative framework.⁷² Among the things under consideration are:

- a strict liability regime;
- a liability regime based on a risk-generating approach (whereby “liability would be assigned to the actors generating a major risk for others and benefitting from the relevant device, product or service”), and
- a risk-management approach (whereby “liability is assigned to the market actor which is best placed to minimize or avoid the realisation of the risk or to amortize the costs in relation to those risks”).⁷³

One significant obstacle with a risk-based approach for tacit algorithmic collusion is our ability to understand the magnitude and likelihood of risk and the actuality of harm. When a self-driving car hits a human, the harm is clear. But for decades,

⁷¹ European Commission, Commission Staff Working Document on the free flow of data and emerging issues of the European data economy Brussels, 10.1.2017 SWD(2017) 2 final, at 43.

⁷² European Commission, Commission Staff Working Document on the free flow of data and emerging issues of the European data economy Brussels, 10.1.2017 SWD(2017) 2 final, at 43.

⁷³ European Commission, Commission Staff Working Document on the free flow of data and emerging issues of the European data economy Brussels, 10.1.2017 SWD(2017) 2 final, at 45. As a complement to the above, the Commission also is entertaining voluntary or mandatory insurance schemes for compensating the parties who suffered the damage.

antitrust enforcers (even with an attractive leniency policy) have had a hard time detecting *express* collusion. Detecting tacit collusion is often more difficult (especially when interdependence can appear in competitive markets). Like the human poker players against Libratus, divining the strategy of a pricing algorithm may prove even more difficult. As EU Commissioner Vestager noted, “[t]he trouble is, it's not easy to know exactly how those algorithms work. How they've decided what to show us, and what to hide. And yet the decisions they make affect us all.”⁷⁴ Significant is the ability of Deep Learning to adjust to changing environment and engage in cognitively intensive tasks. As such they form a superior tool to determine market strategy in a changing environment.⁷⁵ Indeed, some studies have already highlighted the potential of simpler, basic ANN for dynamic pricing.⁷⁶ Another noteworthy characteristic is their ability to learn from experience.⁷⁷ This alleviates the need for prior “hand-crafted” knowledge fed in by human in order to learn a perceptual representation of the world. The self-learning nature enables them to untangle underlying factors in data and to adjust their learning process so that they progressively improve their performance until achieving the desired outcome.⁷⁸ For instance, AlphaGo, Google's Deep Learning-based GO champion, and Libratus learnt to discover new strategies.

Vestager commented on this challenge and opined that ‘Competition enforcers need to be suspicious of everyone who uses an automated system for pricing’ and that ‘businesses . . . need to know that when they decide to use an automated system, they will be held responsible for what it does, so they had better know how that system

⁷⁴ Algorithms and competition, Bundeskartellamt 18th Conference on Competition, Berlin, 16 March 2017. https://ec.europa.eu/commission/commissioners/2014-2019/vestager/announcements/bundeskartellamt-18th-conference-competition-berlin-16-march-2017_en

⁷⁵ <http://www.cs.stir.ac.uk/~lss/NNIntro/InvSlides.html>

⁷⁶ Ghose and Tran ‘A dynamic pricing approach in e-commerce based on multiple purchase attributes’, in Proceedings of the 23rd Canadian conference on Advances in Artificial Intelligence, Lecture Notes in Computer Science, vol. 6085, 2010, available at https://link.springer.com/chapter/10.1007/978-3-642-13059-5_13

⁷⁷ <http://www.cs.stir.ac.uk/~lss/NNIntro/InvSlides.html>

⁷⁸ Castelvechi ‘Can we open the black box of AI?’, Nature, vol. 538, 2016, available at <http://www.nature.com/news/can-we-open-the-black-box-of-ai-1.20731> or <http://dx.doi.org/10.1038/538020a>

works.⁷⁹ On a positive note, Vestager’s comments make clear that autonomous machines can play a greater role in our markets and lives and some accountability (or compensatory) measure must exist to promote an inclusive economy. The challenge is in adapting the legislative framework so that citizens can trust and benefit from this technology while enabling the industry to “lead and capture the opportunities arising in this field.”⁸⁰

5. Testing Potential Solutions in the Algorithmic Collusion Incubator

Rather than legally challenge algorithmic tacit collusion, policymakers or consumer organizations may attempt to actively destabilize it. While it may seem daunting, algorithmic pricing opens new opportunities for policymakers to explore.

At the basic level, the competition agencies can begin commissioning (or internally conducting) experiments with pricing algorithms. One way is if an agency examined the available pricing algorithms in the market, and then using the data and algorithms, ran simulations in a collusion incubator.⁸¹ The agency algorithms could shadow the industry’s algorithms, until it was mirroring the industry responses. The agency would then test what conditions added to (or removed from) the incubator would make tacit collusion likelier and more durable? What factors destabilize tacit collusion? How do the pricing algorithms respond when a company with a similar algorithm (but different discount factor) enters the market? When do firms become mavericks (or become co-opted)? What happens when price changes decelerate? Here

⁷⁹Lewis Crofts and Matthew Newman ‘Vestager warns of pricing algorithms’ antitrust impact’ MLex 16 March 2017 reporting on the Commissioner’s speech at the Bundeskartellamt IKK Conference.

⁸⁰ European Commission, Commission Staff Working Document on the free flow of data and emerging issues of the European data economy Brussels, 10.1.2017 SWD(2017) 2 final, at 43.

⁸¹ Jin Li & Charles Plott, Tacit Collusion in Auctions and Conditions for Its Facilitation and Prevention: Equilibrium Selection in Laboratory Experimental Markets, https://www.kellogg.northwestern.edu/faculty/li/htm/Published%20Papers/Li_Plott%20Tacit%20Collusion%20071121.pdf.

the agency can see how the algorithms respond, and what factors help promote, stabilize and destabilize algorithmic tacit collusion.

Granted such an incubator is imperfect. The incubator is relatively static and will not reflect changes in market dynamics over the long term and changes to the algorithms – a result of self-learning or human intervention. Nonetheless these algorithmic collusion incubators can help the agencies better understand what factors are worth exploring to destabilize tacit collusion. Below, are several factors worth testing in the incubator.

5.1 Deceleration

If the speed and frequency of algorithms' price adjustments facilitate collusion, then one disruptive approach may include **reducing the speed and frequency** with which sellers can adjust prices.

Such an approach has been implemented in the fuel sector in Austria and Western Australia, where sellers are limited in their ability to match each other's price more than once a day. The mechanism aims to reduce the number of price changes, open the way for competitors to undercut the collusive price, and promote a seller's reputation as a discounter. The pricing algorithms, while continually monitoring the rivals' pricing and business maneuvers, would now face a time delay in changing price. Under this scenario, the maverick—if the delay were long enough—could profit from being the first to lower prices.

Not surprisingly, state intervention on the market, through disruptive algorithm or other means, can lead to sub-optimal results. For instance, restrictions on the speed of price changes may result in the state preventing sellers from discounting.

An alternative would be if the government **allowed price decreases to be implemented immediately, but imposed a time lag for price increases.**

It would be interesting to test whether pricing algorithms, like humans, could game the system. For example, a dominant incumbent could punish the maverick by

undercutting its price. The maverick could not immediately raise its price, and might be forced to discount even further. Taking this into account, the maverick's algorithm, before discounting, would likely calculate the probability of incumbents retaliating, its costs (including lost profits) in discounting, and the benefits (which would be slight if rivals could instantly match the maverick's lower price). The governmental pricing delay—rather than helping the maverick and consumers—would instead serve as a punishment mechanism for defecting from the supra-competitive price. In reducing the maverick's incentives to lower prices in cases where retaliation is likely, the governmental pricing delay instead could foster unintentionally tacit collusion.

5.3 Reducing Transparency

A second counter-measure involves limiting transparency, to the buyers' advantage. The government, for example, can target public policies that help facilitate collusion without necessarily improving the buyers' welfare. As former FTC Chair Bill Kovacic observed:

A major example is the process for opening bids in a sealed bid procurement. Bids ordinarily are unsealed in a public setting and are displayed for all offerors to observe. This procedure enables cartel participants to determine whether their co-conspirators abided by the terms of their agreement to rotate bids or otherwise suppress rivalry. An obvious reform would be to permit inspection of bids by a guardian internal to the purchasing organization, such as an inspector general. This simple measure would complicate the detection of cheating by cartel members and still ensure that the winning offeror has been identified correctly.⁸²

One easy case is cheap talk, where sellers benefit from the information exchange, while customers do not.⁸³ Beyond the easy cases, one obvious challenge is fine-tuning the enforcement policy to interdict the factors responsible for the collusive

⁸² William E. Kovacic, *Antitrust Policy and Horizontal Collusion in the 21st Century*, 9 *Loy. Consumer L. Rep.* 97, 107 (1997).

⁸³ See, e.g., Maurice E. Stucke, *Evaluating the Risks of Increased Price Transparency*, 19 *ANTITRUST* 81 (Spring 2005).

equilibrium without undermining the competitive process itself. Such intervention may also lead to an arms race between sellers and buyers. The former may likely benefit from resources and technological advantage. With the ability to rely on advanced algorithms to change the market dynamics and the possibility to use artificial intelligence to perfect the strategy, could competition law enforcers effectively identify and target such strategies?

But transparency is not a light switch where consumers and sellers are either in the dark or sunlight. As the economic literature shows, “what matters is not what is directly observed by the firms, but what information firms can infer from available market data. When the market is stable, inferring deviations from collusive conduct is easier and requires less market data than when the market is unstable.”⁸⁴ Here testing in the algorithmic collusion incubator might enable the government to identify and fine-tune what information should be kept private to make it harder for the algorithm to infer what competitors are doing. This may prove problematic in online industries, as it may increase consumers’ search costs as well. Thus one potential experiment for the incubator is where pricing is conveyed only through asymmetrical price comparison websites (where customers can quickly see the competitors’ prices, but the pricing information is not captured by the algorithm).⁸⁵

5.4 Merger Review

Another approach may focus on the deterring structural changes that foster tacit collusion. As one U.S. court observed, “Tacit coordination is feared by antitrust policy even more than express collusion, for tacit coordination, even when observed, cannot easily be controlled directly by the antitrust laws. It is a central object of merger policy to obstruct the creation or reinforcement by merger of such oligopolistic market

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http://ec.europa.eu/competition/mergers/studies_reports/the_economics_of_tacit_collusion_en.pdf

⁸⁵ One risk of this approach is if the price comparison website’s market power increases, to the detriment of sellers and buyers. We explore this risk in *Virtual Competition*.

structures in which tacit coordination can occur.”⁸⁶ Thus stronger merger control, in particular, may be an option.

As a 2017 conference organized by the University of Chicago reflected, increasing market concentration raises a host of economic, political and social concerns.⁸⁷ Thus multiple policy reasons exist to arrest the trend toward highly concentrated industries. One factor is if tacit collusion, because of algorithms, spreads beyond duopolies to markets with as many as five to six significant players. The agencies can be more sensitive to whether the elimination of a particular player would increase significantly the risk of algorithmic tacit collusion. It may be preserving a market of diverse sellers with different horizons for profits and different capacity constraints.

One avenue is the target firm’s discount rate. Firms can sustain collusion when the weight they put on future profits, measured by their discount factor, is above a certain threshold. For example, if the firm’s discount factor is zero, then the firm needs and wants the money now (via discounts) rather than the profits from tacit collusion. As two economists noted, “One of the few broad generalizations that can be made from the repeated-game model of collusion is that collusive stability is inversely related to the discount rate. A collusive equilibrium that can be supported at one discount rate, above some critical level, will be unsustainable at a rate below that critical level... Firm-level changes in the discount rate may also affect cartel stability. For example, a firm’s rate of time preference may change if its financing shifts to depend more heavily on debt relative to equity. The increased reliance on debt requires fixed payments to lenders, reducing the firm’s discretion and increasing its need for cash flow in the short run.”⁸⁸ Collusion, tacit or express, is sustainable “if and only if firms

⁸⁶ *F.T.C. v. H.J. Heinz Co.*, 246 F.3d 708, 725 (D.C. Cir. 2001) (quoting 4 Phillip E. Areeda, Herbert Hovenkamp & John L. Solow, *Antitrust Law* ¶ 901b2, at 9 (rev. ed.1998)).

⁸⁷ Videos of the panels are available at <https://research.chicagobooth.edu/stigler/events/single-events/march-27-2017>. See also Ezrachi, *Sponge*.

⁸⁸ Margaret C. Levenstein & Valerie Y. Suslow, *Breaking Up Is Hard to Do: Determinants of Cartel Duration*, 54 *J.L. & Econ.* 455, 458 (2011).

put sufficient weight on future profits, i.e., if their discount factor is not too small.”⁸⁹ Thus, if the acquired firm’s discount factor deviates below the critical threshold, it may be effectively thwarting tacit collusion (or at least would be willing to do so if other countermeasures were in place).

So, if firm-specific discount rates are relevant for cartel stability,⁹⁰ the agency could ascertain in the incubator what happens when these firms are acquired. Moreover, firm-level changes in the discount rate may also affect cartel stability: “For example, a firm’s rate of time preference may change if its financing shifts to depend more heavily on debt relative to equity. The increased reliance on debt requires fixed payments to lenders, reducing the firm’s discretion and increasing its need for cash flow in the short run.”⁹¹ It is beyond the capacity or expertise for the competition authority to dictate which route (debt or equity) that the firm should undertake. But if the target’s choice is between a potentially anticompetitive merger or debt, the agency can consider the potential pro-competitive benefits of debt.

It should also scrutinize conglomerate mergers when the increase in multi-market contact softens competition.⁹² This may arise where the same type of product or service (e.g., airlines and retail stores) is offered in different geographic markets. Also one aspect of machine learning is to discover correlations in large data sets.⁹³

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http://ec.europa.eu/competition/mergers/studies_reports/the_economics_of_tacit_collusion_en.pdf (“What is robust is that “no collusion” is sustainable if firms are highly impatient (very small discount factor, δ close to zero) and that “full collusion” (i.e., monopoly outcome) is sustainable when firms are very patient (large discount factor, δ close to 1). There would thus exist two thresholds, one below which no collusion is sustainable, and one above which full collusion is sustainable. Between these two thresholds, “more collusion” is achievable as the discount factor increases, that is, firms can sustain higher prices when they have a higher discount factor.”).

⁹⁰ Margaret C. Levenstein & Valerie Y. Suslow, *Breaking Up Is Hard to Do: Determinants of Cartel Duration*, 54 *J.L. & Econ.* 455, 458 (2011).

⁹¹ Margaret C. Levenstein & Valerie Y. Suslow, *Breaking Up Is Hard to Do: Determinants of Cartel Duration*, 54 *J.L. & Econ.* 455, 458 (2011).

⁹² Federico Ciliberto and Jonathan W. William, *Does multimarket contact facilitate tacit collusion? Inference on conduct parameters in the airline industry* *RAND Journal of Economics*, Vol. 45, No. 4, Winter 2014, pp. 764–791.

⁹³ <https://blogs.biomedcentral.com/bmcseriesblog/2017/03/15/machine-learning-reveals-correlations-of-gene-expression-and-outcomes-in-ovarian-cancer/> (noting that their machine

Thus, the algorithms can ascertain and respond to punishment mechanisms in distinct product markets, which to the human may appear unrelated.

Merger control, however, won't work when other factors (such as the shift to algorithmic pricing itself, or firms exiting unilaterally) foster the tacit collusion.

5.5 Promoting Entry and Mavericks

Another set of counter-measures involves market structure. Entry, according to the empirical economic literature, helps destabilize express collusion.⁹⁴

Thus, one avenue to explore is whether promoting entry by mavericks and reducing regulatory entry barriers would destabilize algorithmic tacit collusion. Here the algorithmic incubator can examine for particular industries whether the entry by a firm is sufficient to destabilize collusion, and if so for how long.

5.6 Secret Discounts and Increasing Other Incentives to Deviate

Other counter-measures to test in the algorithmic collusion incubator entail increasing the incentives to deviate. One option may be facilitating secret deals – away from the market place – such as allowing companies to undercut the market price using direct communications with buyers. Secrete discounts and private sales could help destabilize algorithmic tacit collusion. As the European Commission noted, markets “need to be sufficiently transparent to allow the coordinating firms to

learning method called Correlation Explanation was “especially good at detecting weak correlations in large sets of variables, and this is likely why it was able to detect this particular pattern for the first time in ovarian cancer expression data”).

⁹⁴ Margaret C. Levenstein & Valerie Y. Suslow, *Breaking Up Is Hard to Do: Determinants of Cartel Duration*, 54 *J.L. & Econ.* 455, 485 (2011) (noting how entry destabilizes illegal cartels: “Cartels respond creatively to the threat of entry and take a variety of actions to prevent it. While these actions to create barriers to entry may prolong cartel life, their use reflects an active threat and is associated with increased probability of breakup. The threat of entry is an important feature to include in models of cooperative behavior.”).

monitor to a sufficient degree whether other firms are deviating, and thus know when to retaliate.”⁹⁵ The degree of transparency, the Commission noted “often depends on how market transactions take place in a particular market.”⁹⁶ The key element when evaluating the level of market transparency “is to identify what firms can infer about the actions of other firms from the available information.”⁹⁷

The government may explore, for example, whether reverse bids or giving buyers call options on multiple sellers helps destabilize seller tacit collusion.⁹⁸ Here the buyer, but not the rivals, learns the price of each seller for a future order. For example, rather than creating an app that simply tells you (and each competitor) the price of gas at nearby stations, one could create an app where the consumers (or their self-driving cars) simply say, “Need gas.” Each station then can offer the consumer the best price. Your app signals your demand, the competing neighboring gas stations offer their best quote, and the competing bid information (and geolocation data of where you ended up buying gas) are not shared among the gas stations.

One potential risk in this approach, as we discuss below, is that it may under certain market conditions foster price discrimination or the behavioral discrimination assessed in *Virtual Competition*.

The algorithmic collusion incubator can test whether enabling smaller buyers to pool their orders into less frequent, less predictable larger orders yields a better price from the sellers’ algorithms, in effect rewarding a seller with greater profits to deviate from the collusive regime.⁹⁹

⁹⁵ EC Merger Guidelines para 49.

⁹⁶ EC Merger Guidelines para 50.

⁹⁷ EC Merger Guidelines para 50: “The speed with which deterrent mechanisms can be implemented is related to the issue of transparency. If firms are only able to observe their competitors’ actions after a substantial delay, then retaliation will be similarly delayed and this may influence whether it is sufficient to deter deviation.” Ibid para 53.

⁹⁸ Ian Ayres & Eric Talley, *Solomonic Bargaining: Dividing A Legal Entitlement to Facilitate Coasean Trade*, 104 *Yale L.J.* 1027, 1117 (1995)

⁹⁹ Paul W. Dobson & Roman Inderst, *The Waterbed Effect: Where Buying and Selling Power Come Together*, 2008 *Wis. L. Rev.* 331, 354 (2008) (“With a large order up for grabs, suppliers may be more tempted to undercut any collusive regime and offer the large buyer a discount.”);

5.7 Algorithmic Combat

When algorithms and smart bots drive markets, another counter-measure may be in the form of a **‘disruptive algorithm’** rather than traditional enforcement. Such algorithm may be deployed to destabilize the existing equilibrium – through mixed signaling and other means - targeting the core conditions necessary to sustain conscious parallelism. State sponsored algorithms or other mechanisms for joint consumer bargaining or protection may try to undermine the collusive equilibrium or affect levels of transparency.

While the idea of a maverick algorithm skewing the signaling on the market and destabilize the tacit agreement seem appealing, it may generate inefficiencies and distort competition. Furthermore, it would likely lead to a race between algorithms, one destabilizing while another predicting its action and engaging in counter-action. Thus, the incubator can test multiple types of disruption, and the attendant effect on prices and consumer search costs.

A second avenue is the maxim, “It takes a computer to beat a computer.” Just as humans will infrequently beat a computer chess or checkers program, so too they, despite their best efforts, will not consistently defeat the pricing algorithm. In effect, whether shopping for gas or playing blackjack, the “house” often wins. To better the odds, consumers can rely on algorithms programmed to maximize consumer surplus.¹⁰⁰ Thus consumer-friendly algorithms in effect will play in the incubator against seller algorithms seeking to maximize profits. Consumers may not always win, but like the AI program that beat human poker players, they might generally win over many matches. If the seller algorithms routinely beat the consumer algorithms, government enforcers can test in the incubator measures to tilt the odds

but see Margaret C. Levenstein & Valerie Y. Suslow, *Breaking Up Is Hard to Do: Determinants of Cartel Duration*, 54 *J.L. & Econ.* 455, 482 (2011) (“Although large customers may be able, in principle, to destabilize cartels, in many cases they seem instead to extract concessions that reduce their incentive to do so.”).

¹⁰⁰ On this point, note discussion by Gal, Michal S. and Elkin-Koren, Niva, *Algorithmic Consumers* (August 8, 2016). Available at SSRN: <https://ssrn.com/abstract=2876201>, *Harvard Journal of Law and Technology*, Vol. 30, 2017.

in the consumer’s favor. Here the consumer algorithms – either individually or tacitly colluding--might enhance the buyers’ power and reveal strategies to further disrupt tacit collusion. This counter-measure, of course, raises its own risks, including issues of oligopsony power and the risk of distorting competition. Still, a controlled effort to engage in algorithmic combat may serve to limit possible adverse welfare effects.

5.8 Smart Regulation

As we explore in *Virtual Competition*, beyond the “laissez-faire competition good, regulation bad” refrain, challenging questions await us. For instance—is the algorithm price the competitive price, or merely a fiction created by the digitalized hand? Turning to the economist Friedrich A. Hayek, we inquire whether the emergence of super-platforms—companies that dominate the digital landscape—could indicate a monumental shift toward the attainment of all knowledge. Platforms’ sophisticated computer algorithms could increasingly determine the competitive market price. Data collection by leading platforms like the car-sharing app Uber, and super-platforms like Google, Apple, and Amazon, could create an economy which, for all purposes, is planned not by bureaucrats or CEOs, but by the techno-structure. If so, a subsequent question arises: if private firms can harness Big Data and Big Analytics to effectively set prices, can governments use the same tools to monitor industry prices, or even determine a competitive price? If Uber, which doesn’t own any cars or employ any drivers, can determine prices, why can’t the government?

Economist and policymakers over the past few years have been interested in developing screens and tools to identify industries where cartels are likely operating.¹⁰¹ Thus, one avenue to explore is harnessing Big Data and Big Analytics

¹⁰¹ <https://www.oecd.org/daf/competition/exofficio-cartel-investigation-2013.pdf> (identifying two general screening approaches: i) a structural approach, which includes the analysis of structural and product characteristics of a specific market or industry that make successful collusive strategies more likely; and ii) a behavioural approach, which includes the identification through screening of firms’ behaviour or market outcomes that may be the outcome by a collusive strategy).

to identify algorithmic tacit collusion. This might be attractive where the price is significantly determined by a baseline price (such as crude oil price for gasoline) and the other explanatory variables for price are observable. The legal obstacles in legally challenging the tacit collusion under the current law remain. But the screening tools can help policymakers prioritize the industries to test in the incubator and the likely effects of various counter-measures.

A slightly more intrusive measure is to post a “competitive” bench price. For example, the government can provide the gas apps with a “competitive” baseline price for gas, from which customers can compare how much each gas station is charging above or below that price. One risk is getting the competitive benchmark price wrong and its susceptibility to being gamed (and inflated).

6. The Wider Picture

Our analysis to this point focused on algorithmic tacit collusion and possible means to address it. One solution, which often attracts attention in our discussions with competition enforcers, concerns the ability to target ‘excessive’ transparency. This, as noted above, could be done through counter signaling on the markets or, more commonly, by encouraging secrete deals on many markets.

The centrality of secrete deals as possible counter measure, merit a closer look. In what follows we note the potential distortion which may result from the facilitation of alternative, non-transparent, trade channels to algorithmic tacit collusion.

We are all familiar with advertised secret deals (such as the secrete hotel) and with targeted promotions. These may indeed provide a valuable path which could re-introduce competition to markets susceptible to tacit algorithmic collusion. When these deals are carried away from the marketplace, they do not trigger a price war. They can provide a discount on the tacit equilibrium and as such benefit consumers.

Indeed, the agency may welcome product differentiation (as it introduces asymmetry among firms both in terms of cost and quantity) and reduces transparency. Without underestimating these potential benefits, policymakers should however be mindful of another anticompetitive outcome—namely behavioral discrimination.

Advances in customer profiling and novel personalized pricing strategies will enable sellers to better approximate a consumer’s willingness to pay – the reservation price – and charge accordingly. Thus, behavioral discrimination may form an increasingly popular strategy under certain market conditions.¹⁰² In such cases, the attempt to increase welfare through secrete deals may backlash.

Our concern here is with first degree price discrimination which is supported by the use of personal data to track consumers’ behavior, and approximate the buyer’ price sensitivity, awareness to outside options and willingness to pay. Increasingly, in our online environment, price becomes an individualized exercise. The net price for the product or service is changed based on a range of parameters, such as one’s postcode, the computer one uses, one’s search history, loyalty preferences etc.

At the basic level, sellers already ‘personalize’ price with no ‘private’ information - just by relying on the time and path used before making a purchase. For example, a direct log in to a seller website will often result in higher price than a referral from a price comparison website. The logic behind this simple distinction lies in the

¹⁰² 2010 US Horizontal Merger Guidelines § 3 (“For price discrimination to be feasible, two conditions typically must be met: differential pricing and limited arbitrage.”). Under the first condition, suppliers “must be able to price differently to targeted customers than to other customers. This may involve identification of individual customers to which different prices are offered or offering different prices to different types of customers based on observable characteristics.” Id. “In other cases, suppliers may be unable to distinguish among different types of customers but can offer multiple products that sort customers based on their purchase decisions.” Id. Under the second condition, “the targeted customers must not be able to defeat the price increase of concern by arbitrage, e.g., by purchasing indirectly from or through other customers.” Id.

assumption as to the buyer's awareness of outside options. In essence, the net price for a product is adjusted to cater to competition conditions (dynamic pricing), the awareness of the buyer to those conditions and its reservation price (personalized discriminatory pricing). If the buyer indicates hesitation – by continuing his search or leaving goods in the checkout – this can be remedied immediately by offering surprise discounts and coupons. Framing of the price change as discounts ensures customer satisfaction.

More advanced discrimination may take into account personal information, enabling the seller to create a more complex profile for the user – taking account of past behavior, preferences, communications and other data points. These could then be used to determine the order of search results and the price charged. The ultimate goal would be to remove the buyer from the competitive environment (what is often referred to as acquisition of the buyer) – create loyalty and trust – which would enable subsequent transfer of wealth from the buyer to the seller.

In our earlier work, we referred to this as the Truman Show – creating a façade of competition and cashing on the asymmetry of information. The buyer – unaware of the information the seller holds about his path, search and purchase history – assumes that the price is the market price. The profitability of these strategies have led to distinct increase in the use of dynamic personalized pricing.

To illustrate the way in which the strategy could be used, let us consider one recent experiment which involved about 1.5 million consumers of a Las Vegas casino owner.¹⁰³ Some consumers were loyalists: they would have played at the particular MGM casino even without a promotion. Others were “low-value” customers (e.g.,

¹⁰³ Nair, Harikesh S., Sanjog Misra, William J. Hornbuckle IV, Ranjan Mishra, and Anand Acharya. 2016. "Big Data and Marketing Analytics in Gaming: Combining Empirical Models and Field Experimentation." Working Papers (Faculty) -- Stanford Graduate School Of Business 1-47. Business Source Complete, EBSCOhost (accessed April 7, 2017).

highly skilled “experts” who win back from the house more than they wager, consumers “who utilize comps but do not play at the resort,” and consumers “who wager nothing more than their Free-play dollars, thereby gaining the upside from the promotion, with little downside for themselves and no gain for the ‘house’”).

The casino did not care to compete with promotions for the low-value players. The trick was identifying the “high value” consumers, those with the highest marginal propensity to respond to a promotion, and who would spend the most for the least amount of inducement. The problem was that the casino’s earlier promotions did not accurately distinguish the “high value” players from the “loyalists” who needed no inducements and the “low value” customers, whom it did not want to attract with any promotions. Moreover, as the study found, there was “an overarching concern that targeting more promotions to those who have played a lot in the past may be ineffective, because those consumers may already be on the flat or declining part of their promotion response curve.”

The challenge for the casino’s marketing team was to price optimize (what we refer to as behaviorally discriminate), namely to offer “a mix of promotions to each consumer based on what produces maximal marginal benefit at minimal cost.” There were multiple dimensions to behaviorally discriminate, such as *room offers* (like the room type, room discount, number of comp nights, whether comp is midweek or weekend); *entertainment, sports and facility offers* (including the type of amenity and discount); *casino event information*,¹⁰⁴ other *special event metrics*,¹⁰⁵ *retail and spa*

¹⁰⁴ Id. (like “inclusion in the casino event prize pool, the prize pool format, indicator for grand prize inclusion, grand prize format, prize value offered, cost of event for which offer is made, buy-in amount, points to entry if offered, tier credits to entry if offered”).

¹⁰⁵ Id. (“like indicators for special event, tier upgrade offers, tier credits offered, offers of points that count toward higher tiers in the MGM loyalty program, comps linked to points, point multiplier offers, and multipliers on points that count toward higher tiers (offered on visits that overlap with birthdays”).

offers,¹⁰⁶ *air and limo offers*,¹⁰⁷ *free-play and promo-chip offers* (like the free-play offer amount and promo-chip offer amount), *resort credits* (like resort credit type and resort credit amount), and *food and beverage offers* (like the food and beverages offered and the offer's amount). Moreover, the challenge wasn't just snagging the "high value" customer once. Rather it was incorporating the dynamic effects of promotions on each customer "to get an accurate picture of the ROI profile from the promotions, and to allocate them appropriately based on their expected long-run benefits to the firm." Thus, the aim was to maximize profits from each marginal consumer for whom the promotion would have an incremental impact.

The means to this end were to mine the casino's voluminous personal data on the gamblers to identify whom to target, their value, and the best inducement to maximize the greatest profit. The casino, through its loyalty program, had a lot of data on many of its customers. So the computer model used data on each consumer's observed behavior "at all past visits (and not just the most recent visits) to measure customer value." For those consumers on which very little data exist, the computer model pooled information from the behavior of similar consumers. The model also used "information across the entire range of activities by the consumer to measure how promotions affect behavior." Moreover, the model metrics were "both history-dependent (retrospective) and forward-looking (prospective)." One example is the customer who visited the casino once, but spent little. In just looking at the past purchase, the computer might deem the customer "low value." To avoid this error, the computer analyzed not only the historical first-visit information on the consumer but also "the observed long-run spending of other similar consumers." Even if the customer spent little on the first visit, the model, using data from other similar gamblers, estimated if she, like these other consumers, would spend a lot in future

¹⁰⁶ Id. (like "indicator for a retail offer, retail offer amount, indicator for spa offer, and spa service amount").

¹⁰⁷ Id. (like "indicator for an airline offer, air package amount, indicator for limo offer, indicator for VIP check-in flag").

visits. In processing all this data, the computer then identified the focal consumers to target, how they would likely respond to a myriad combination of promotions, and the likely profits from each consumer over the long-run.

The effect of the data-driven personalized promotions, the study found, was between \$1 million to \$5 million dollars of incremental profits per campaign compared to the casino's status-quo marketing strategy. Profits also increased from the improved matching of promotion types to consumer types. In sum, a dollar spent in promotions generated "about 20¢ more incremental profit using the model compared to the [then] current practice at the firm."

The above example illustrate the power of data. That power may be legitimately used for 'smart' promotions. In an online world, it may also be used to engage in behavioral discrimination – charging different prices for similar products while creating the illusion of a single market price. Such first-degree price discrimination, being anchored in asymmetry of information and the illusion of competition, should be of concern. While third degree price discrimination can enhance efficiency, such may not be the case when considering almost perfect price discrimination. Even more so when the practice is based on misleading strategies.

Importantly, algorithmic tacit collusion or behavioral discrimination can also occur *simultaneously* in markets where conditions for both exist. The seller may use the latter in order to lure the buyer away of the market, acquire it, and subject it to even higher prices (once loyalty is established and control over outside options is achieved).

Let us use the gas stations, which are already susceptible to tacit collusion, as our analogy. On one level is algorithmic tacit collusion, which leads to the inflated posted price at the pump. Suppose gas stations have loyalists (those who would patronize that gas station without any inducement), low-value customers (e.g., those who buy the lowest grade gas, use the restroom, and never buy anything from the store) and

high-value customers (those who are likely to purchase higher margin goods and services inside the gas station). Because of the ROI from the low-value customers, the gas stations will have little incentive to deviate from the posted price to attract them. Moreover, the rivals recognize that the ROI to attract loyalists are low. Thus, algorithmic tacit collusion may inflate the posted gas pump price, which the “low value” customers and loyalists pay.

On the second level, the gas stations may mine the personal data to identify and attract the “high-value” customers. The aim is to steer the profitable “high value” buyers to its petrol stations through personalized advertising, discounting, bundling of services, loyalty programs and other inducements. The “high-value” buyer, through a loyalty program, for example, might get a slight discount at the pump. As with the casino, the scope of the discount and promotions is determined on the predicted lifecycle spending of that customer. Once some level of loyalty is established, the aim, through personalized pricing and discounts, is to maximize profitability over the lifespan of the customers’ purchase history (the lottery tickets, snacks, food, drink, and merchandise they buy).

So at the acquisition stage, the gas station’s discounts, loyalty programs, coupons and other tools may appear competitive (and contrary to any tacit collusion scenario). In many ways, at this stage, the offline and online environment exhibit similar marketing strategies. The differences between the offline and online world emerge in the second phase, when personalized pricing, based on mining personal data, enables the seller to customize inducements to attract that particular customer, build its loyalty, and then maximize profits from that customer (price selectively for that package of goods to match what the customers’ willingness to pay). The buyer is no longer anonymous and the seller, benefiting from brand recognition, loyalty and asymmetric information, can reap profits above market levels. Optimization may be per deal, basket or lifetime cycle.

In the end, the pricing algorithms can simultaneously tacitly collude over the posted gas pump price (which attracts the low-value customers) and, like the MGM-owned casinos, employ “a scalable, data-driven micro-targeting policy” to attract (and maximize profits from) the high-value customers. Sellers that combine the two strategies can reap benefits on both markets. The prime market forming an environment for non-loyal customers, and a marketing effort on the way to customer acquisition. The secondary personalized market, enabling data gathering, and, over time, greater profits than those on the open market. In such markets buyers may be subjected to a “lose – lose” scenario.

Concluding Remarks

Our markets are changing. Fast. The promise of online markets – that of ample choice and competition – is at risk. In many markets, the invisible competitive hand that we rely upon has been pushed aside by the “digitized hand.” The latter has the capacity to be selective and generate different levels of competitive pressures and change the competitive dynamics.

One concern is the nature of electronic markets, the availability of data, the development of similar algorithms, and the stability and transparency they foster, will likely push some markets that were just outside the realm of tacit collusion into interdependence.¹⁰⁸

In parallel, as dynamic pricing yields a competitive advantage, no firm can afford staying out of this game. Increasingly, sellers are using algorithmic dynamic pricing.

¹⁰⁸ One would expect tacit collusion to be feasible with a larger number of participants than commonly assumed. On the common market assumptions, see generally R. Selten, “A Simple Model of Imperfect Competition, Where Four Are Few and Six Are Many,” *International Journal of Game Theory* 2 (1973): 141; Steffen Hucka, Hans-Theo Normann, and Jörg Oechssler, “Two Are Few and Four Are Many: Number Effects in Experimental Oligopolies,” *Journal of Economic Behavior and Organization* 53, no. 4 (2004): 435–446.

Those who do not, are pushed out of the market. With so much profit at stake and the ability to affect the market dynamic, it is no surprise that this area is attracting heavy investments. Ironically, even if some companies yearn for the days of printed list prices and secretive discounts, they may switch to pricing algorithms to prevent being at a competitive disadvantage.

As enforcers and policymakers increasingly recognize, the current antitrust enforcement toolbox may be limited in effectively deterring algorithm-driven tacit collusion and behavioural discrimination.¹⁰⁹ They recognize the difficulties and risks in fine-tuning the enforcement policy aimed at condemning “excessive” market transparency. Similarly, active intervention through ‘good’ algorithms may distort competition. This may be particularly challenging when the information and data are otherwise available to consumers and traders and it is the intelligent use of that information that facilitates conscious parallelism.

On a positive note, many enforcers, judges, and policymakers, with whom we met, appeared engaged and willing to meet the challenge. The overwhelming response we encounter at conferences and private meetings is not skepticism. Instead we are often asked, *What are we going to do about it?* in this paper we consider several ex-ante and ex-post measures, including the tacit collusion incubator. Nothing we propose is the elixir, the silver bullet to deter the anticompetitive collusion and behavioral exploitation scenarios. Nonetheless, these measures—in widening the toolbox—can bring us closer in tackling these issues.

Of course, any enforcement action should be measured and take account of the costs of over-intervention. Yet, the cost of under-intervention must also be acknowledged. Disruptive innovation as well, may be less formidable than some interested parties may argue. The legitimate profit motive of firms, in the current market dynamics, cannot be assumed to protect consumer welfare.

¹⁰⁹ <https://www.theguardian.com/commentisfree/2016/dec/04/how-do-you-throw-book-at-an-algorithm-internet-big-data>

So the aim for policymakers in the EU, US and elsewhere, remains the same: to develop an inclusive data-driven economy that benefits more than 1% of the population. Importantly, one cannot assume that market forces alone will yield the benefits of the data-driven economy while mitigating the risks. Further, one cannot assume that one agency can do the job. To effectively tackle behavioral exploitation, for example, we need greater coordination among the privacy, consumer protection and competition authorities. The good news is that the EDPS is seeking to launch a digital clearing house for enforcement in the EU digital sector. That's a positive step.

In a nutshell, the goals for a data-driven economy should be an economy that is inclusive, protects the privacy interests of its citizens, promotes the citizens' overall wellbeing, and also promotes a healthy democracy. The interests here at stake go beyond tacit algorithmic collusion, beyond behavioral discrimination, and beyond our pocketbook.