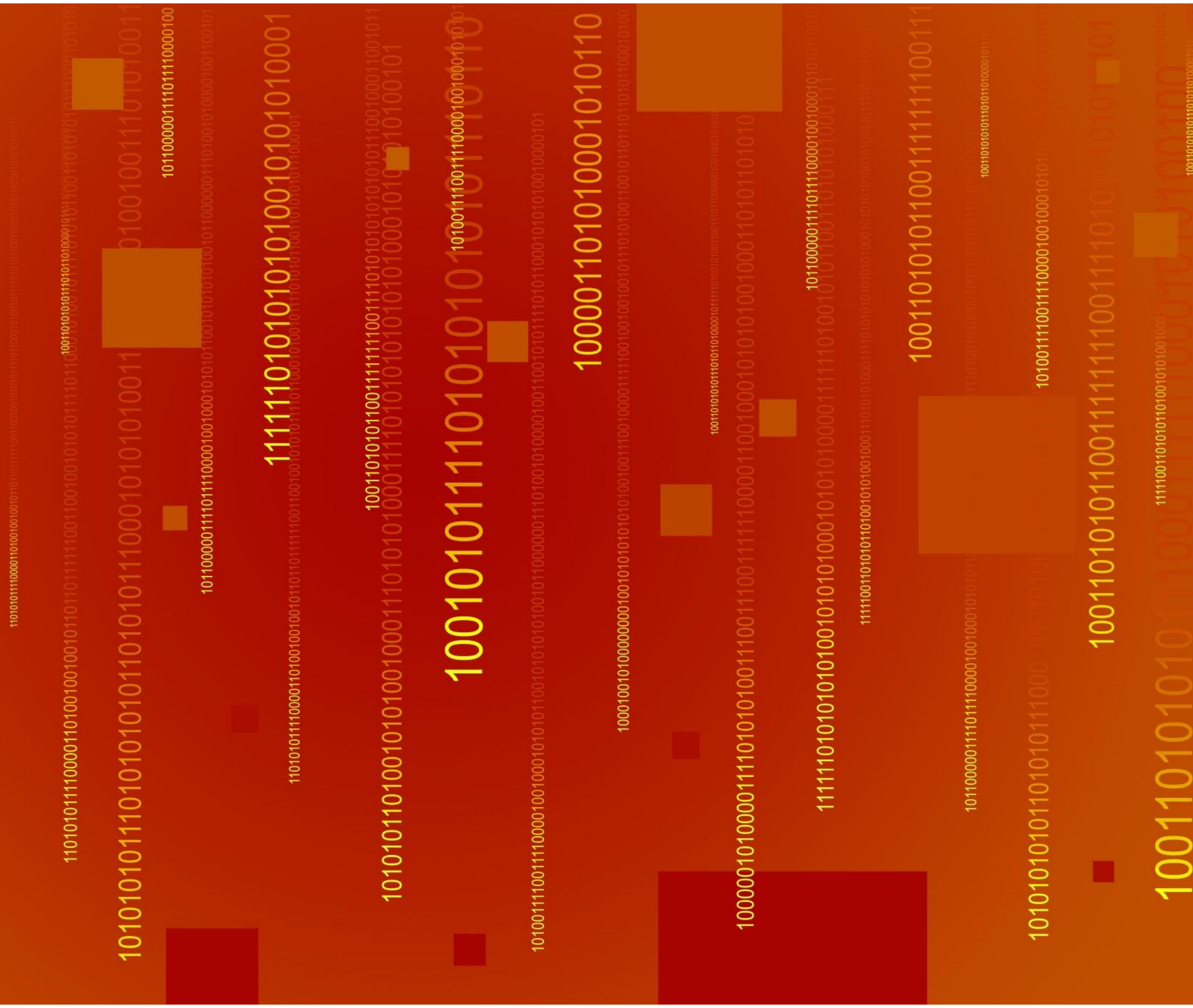
ALGORITHMS AND COLLUSION

Competition policy in the digital age



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Algorithms and Collusion: Competition Policy in the Digital Age

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Foreword

The combination of big data with technologically advanced tools, such as pricing algorithms, is increasingly diffused in everyone's life today, and this is changing the competitive landscape in which many companies operate and the way in which they make commercial and strategic decisions. While the size of this phenomenon is to a large extent unknown, a growing number of firms are using computer algorithms to improve their pricing models, customise services and predict market trends. This phenomenon is undoubtedly associated to significant efficiencies, which benefit firms as well as consumers in terms of new, better and more tailored products and services.

However, a widespread use of algorithms has also raised concerns of possible anti-competitive behaviour as they can make it easier for firms to achieve and sustain collusion without any formal agreement or human interaction. This paper focuses on the question of whether algorithms can make tacit collusion easier not only in oligopolistic markets, but also in markets which do not manifest the structural features that are usually associated with the risk of collusion.

This paper discusses some of the challenges algorithms present for both competition law enforcement and market regulation. In particular, the paper addresses the question of whether antitrust agencies should revise the traditional concepts of agreement and tacit collusion for antitrust purposes, and discusses how traditional antitrust tools might be used to tackle some forms of algorithmic collusion. Recognising the multiple risks of algorithms and machine learning for society, the paper also raises the question of whether there is need to regulate algorithms and the possible consequences that such a policy choice may have on competition and innovation.

This paper was prepared by Antonio Capobianco, Pedro Gonzaga and Anita Nyeső of the OECD Competition Division as a background note at the OECD Competition Committee Roundtable on "Algorithms and Collusion" that took place in June 2017 www.oecd.org/daf/competition/algorithms-and-collusion.htm. This report contributes to the OECD Going Digital project which provides policy makers with tools to help economies and societies prosper in an increasingly digital and data-driven world. For more information, visit www.oecd.org/going-digital.

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1. Introduction

The importance of algorithms in today's life cannot be understated. According to some scientists, algorithms are so pervasive in modern society that they track, predict and influence how individuals behave in nearly all aspects of life (Hickman, 2013 and O'Neal, 2016). Although few would dispute the great benefits offered by algorithms, especially in terms of improved automation, efficiency and quality, for both firms and their customers, there are questions about the extent to which human decision-making will be supported (or even replaced in certain cases) by machines and the implications of the automation of decision-making processes for competition.

Scientists have identified this dilemma clearly. In 2015, over 70 scientists and artificial intelligence (AI) experts signed an open letter calling for more research on the societal impacts of these new technologies.[1] These scientists believe that AI has great potential benefits for society, including eradicating diseases and poverty, but they have identified a need for more concrete research on how to prevent potential "pitfalls": in other words, researchers must not create something which cannot be controlled. They have called for an interdisciplinary research effort bringing together disciplines ranging from economics, law and philosophy to computer security and, of course, various branches of AI itself.

The impact of data-driven innovation on competition and social well-being has been well-documented by the OECD.[2] Examples of recent policy discussions include the benefits of data-related disruptive innovations in financial markets (OECD, 2016g), land transport (OECD, 2016e) and the legal sector (OECD, 2016f), recognising the risks of consumer harm in the absence of an adequate competition framework that disciplines these new market realities. In 2016, the OECD Competition Committee Hearing on Big Data attempted to identify the more broad implications of data-driven business models for competition law enforcement and market regulation (OECD, 2016a). One of the concerns highlighted was that the use of data and computer algorithms may enable new forms of collusion, a topic that is analysed in more detail here.[3]

This paper describes how algorithms are changing the competitive landscape by offering opportunities to firms to achieve collusive outcomes in novel ways that do not necessarily require the reaching of an agreement in the traditional antitrust sense, or may not even require any human interaction. Economic theory suggests that there is a considerable risk that algorithms, by improving market transparency and enabling high-frequency trading, increase the likelihood of collusion in market structures that would traditionally be characterised by fierce competition. The analysis in this paper shows that algorithms might facilitate tacit co-ordination, a market outcome that is not covered by competition law, by providing companies with automated mechanisms to signal, implement common policies, as well as monitor and punish deviations. The paper also emphasises how algorithms can make tacit collusion more likely, both in oligopolistic markets with high barriers to entry and a high degree of transparency, and in markets where traditionally tacit collusive outcomes would be difficult to achieve and sustain over time, widening the scope of the so-called "oligopoly problem".

In light of these findings, this paper reviews some of the possible responses that competition law enforcers could give to this new phenomenon, including: (1) conducting market studies and sector inquiries to evaluate whether algorithms actually pose a significant competition problem; (2) reviewing merger control to account for the impact of algorithms on the likelihood of coordinated effects; and (3) designing remedies to prevent companies from programming specific codes that could be recognised as facilitating practices for tacit collusion. Acknowledging the limitations of current antitrust tools, the paper discusses whether it is necessary to revisit some traditional antitrust concepts, by developing a more clear notion of agreement for antitrust purposes and even by reconsidering the position of competition policy towards tacit collusion (with its pros and cons). Lastly, while the increased risk of tacit collusion and other market failures might support some regulatory interventions, this paper warns about the risks that regulating algorithms could pose on competition and innovation.

The paper is structured as follows. **Section 2** provides a brief overview on the main concepts behind algorithms and their programming principles, such as artificial intelligence, machine learning and deep learning. It also provides an overview of how algorithms are used by businesses and governments. **Section 3** is dedicated to the benefits and possible efficiency gains from algorithms. **Section 4** sets out some of the anti-competitive risks of algorithms for collusion, by changing market conditions and providing companies with new tools to coordinate strategies. **Section 5** addresses the possible competition law enforcement challenges in the current legal and economic framework, and discusses possible solutions emphasising the difficulties in identifying the adequate level of intervention. **Section 6** identifies the potential benefits and risks of alternative regulatory interventions. Finally, **Section 7** offers some concluding remarks.

2. Algorithms: How they work and what they are used for

This section provides a brief insight into the basic concepts and programming principles behind algorithms, discussing as well some of their applications by businesses and governments. Applications by consumers and the benefits they create on the demand side will be explored in section 3.

2.1 Concepts and definitions

Although the concept of "algorithm" has existed for a long time, far before the creation of the first computers, a universal definition that is consensually accepted is still missing (Moschovakis, 2001). Intuitively, an algorithm is a sequence of rules that should be performed in an exact order to carry out a certain task. Thus, an algorithm is an instance of logic that generates an output from a given input, whether it is a method to solve a mathematical problem, a food recipe or a music sheet. Given the lack of precision of these intuitive notions, this paper uses a more formal definition proposed in the literature:

> An algorithm is an unambiguous, precise, list of simple operations applied mechanically and systematically to a set of tokens or objects (e.g., configurations of chess pieces, numbers, cake ingredients, etc.). The initial state of the tokens is the input; the final state is the output. Wilson and Keil (1999)

Algorithms can be represented in multiple ways, such as plain language, diagrams, codes or even programmes that can be read and executed by a machine. With the evolution of computer science, algorithms have been developed to automatically perform repetitive tasks involving complex calculations and data processing that could be costly to execute for human beings. Recent developments in artificial intelligence and machine learning have brought algorithms to a new level, allowing computers to solve complex problems, make predictions and take decisions more efficiently than humans, frequently achieving desirable policy goals for society.

Artificial intelligence refers to the broad branch of computer science that studies and designs intelligent agents, who should be able to carry out tasks of significant difficulty in a way that is perceived as "intelligent" (Swarup, 2012). This concept was coined by John McCarthy in 1956, who defined it as "the science and engineering of making intelligent machines". At the initial stages of AI, machines were programmed with extensive lists of detailed rules in order to attempt to replicate human thoughts, which could easily become a burdensome process. AI became a more effective tool after the development of algorithms that teach machines to learn, an idea that evolved from the study of pattern recognition and learning theory, and which would establish the new branch of machine learning.

Machine learning (ML) is a subfield of AI which designs intelligent machines through the use of algorithms that iteratively learn from data and experience. According to Samuel (1959), machine learning gives "computers the ability to learn without being explicitly programmed". Machine learning algorithms can be classified into three broad categories, depending on their learning pattern (Anitha et al., 2014):

- **Supervised learning**, where the algorithm uses a sample of labelled data to learn a general rule that maps inputs to outputs.
- **Unsupervised learning**, where the algorithm attempts to identify hidden structures and patterns from unlabelled data.
- **Reinforcement learning**, where the algorithm performs a task in a dynamic environment, such as driving a vehicle or playing a game (Box 1), and learns through trial and error.

Regardless of the learning method, conventional machine learning systems have some limitations in their ability to process raw data (LeCun et al., 2015). Indeed, raw databases can have such a large dimension that, before running a machine learning algorithm, it is often necessary to extract from the raw data the features that are relevant for the underlying problem – a process known as "feature engineering". Features can be numerical variables or strings that are either a subset of the original dataset or a construction made from combinations of the original variables. Identifying and constructing the relevant features can be a time-consuming and expensive process that must be manually executed by humans. Alternatively, automatic feature extraction can be performed through deep learning models (Figure 1).

Figure 1. Machine vs deep learning algorithms

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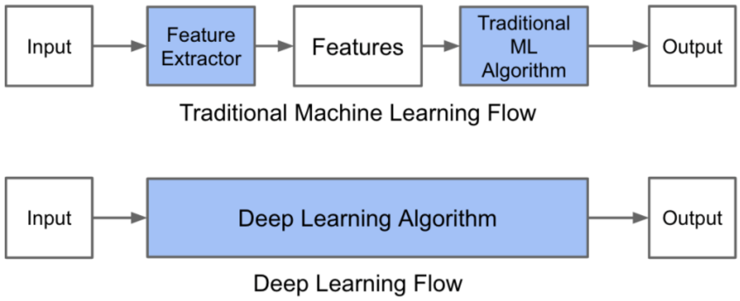


Source: Moujahid (2016).

Box 1. Libratus, the poker playing robot

Libratus is a machine learning program designed by Tuomas Sandholm and Naom Brown from Carnegie Mellon University (CMU) to play a complex version of poker, the no-limit Texas hold'em. In order to master poker strategy, the algorithm behind Libratus uses a reinforcement learning method that can be decomposed into a three stage process:

In a first stage, after entering into the program the rules of the game, Libratus plays against itself trillions of poker hands. While the first hands are played randomly, Libratus starts improving the algorithms at fast speed based on a method of trial and error. This means that Libratus does not actually rely on observed data to learn.

In a second stage Libratus plays against other humans and, taking into consideration their particular actions and behaviours, it selects the strategies learned during the first stage that are best suited to beat the opponents.

Finally, in a third stage, as human players start finding patterns in the behaviour of the machine and adapting their strategies, Libratus removes those patterns by randomising some actions. In other words, Libratus learns how to bluff.

Libratus was put to the test in January 2017, when it played a total of 120 000 hands in a tournament against top world players. In the course of the tournament, the machine was competing against the human players by day and, based on the new collected data, it improved its strategy overnight, by correcting any imperfections that the human players were able to figure out. The success of the machine was unprecedented, earning a total of USD 1.776.250 in chips, as compared to all the other players who ended the game with a negative balance.1 Given that the big blind of the game was set to USD 100, Libratus had a winning rate of 14.7 big blinds per 100 hands, which is very high and statistically significant.

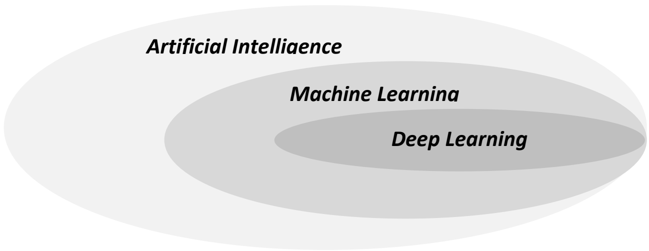
Games have long served as useful tools to improve and measure new developments in artificial intelligence. Yet, the particular application of AI to poker might enable also alternative applications. As a dynamic game of imperfect information with million hand combinations, poker partially reflects the complexity and uncertainty of real world problems. In particular, the ability of Libratus to undertake complex reasoning in an uncertain scenario, to interpret past information that might be intentionally misleading and to anticipate the impact of its own actions of the other players' decisions suggests that AI can be also used to solve more complex "human-like" interactions and decision making.

1. Spice and Allen (2017)
Source: Metz (2017).

Deep learning is a subfield of machine learning (Figure 2) that enables computer systems to learn using complex software that attempts to replicate the activity of human neurons by creating an artificial neural network. Goodfellow et al. (2016) point out that deep learning is able to model powerful abstractions in data. While traditional machine learning algorithms are linear, deep learning algorithms are structured in a hierarchy of increasing complexity and abstraction. As a result, deep learning enables computers to learn faster and more accurately than conventional machine learning.

Despite recent advances and the enormous potential of deep learning to solve the most complex problems, the lack of feature extraction implies that there is no way to know which features or information were used by the algorithm to convert inputs into outputs. In other words, regardless of the quality of the results produced, deep learning algorithms do not provide programmers with information about the decision-making process leading to such results.[4]

Figure 2. Relationship between artificial intelligence, machine learning and deep learning



2.2 Applications of algorithms by businesses

The growing importance of algorithms for society is a direct consequence of their enhanced adoption by companies, not only in online markets, but also in many other high-tech industries. In this context, Stucke and Ezrachi (2016) have introduced the concept of "algorithmic business" to refer to the use of complex algorithms to improve business decisions and automatise processes for competitive differentiation. Although some businesses are still at the very early stages of adopting algorithms, an increasing number of companies nowadays rely on them for predictive analytics and optimisation of business processes.

- **Predictive analytics** involves the development of algorithms to measure the likelihood of future outcomes based on the analysis of historical data. Predictive models can be used to estimate demand, forecast price changes, predict customer behaviour and preferences, assess risks and forecast endogenous or exogenous shocks that might affect the market environment, such as the entry of new firms, variations in exchange rates or even natural disasters. All this information can be extremely valuable to improve decision-making, enabling companies to plan more efficiently their business strategies and to develop innovative and customised services that would not be possible otherwise.

- Algorithms can also be implemented to **optimise business processes**, allowing businesses to gain a competitive advantage by reducing production and transaction costs, segmenting consumers or by setting optimal prices that effectively respond to market circumstances. The particular ability of algorithms to optimise processes is a result of their automated nature and great computation power, which allows them to process large datasets, react fast and incur in a lower cost than what would be observed if the same tasks were performed by humans.

The employment of algorithms for predictive analysis and optimisation of business processes has multiple practical applications that are observed across many industries, such as fraud prevention, supply-chain optimisation, targeted advertising, product recommendation, corporate security and dynamic pricing. In addition, there are peculiar industry-specific applications of algorithms that, particularly when based on machine and deep learning principles, are bringing breakthrough data-driven innovations and are revolutionising existing markets (Box 2).

Box 2. Modern applications of deep learning

While the initial attempts to develop the first deep learning algorithms can be traced back to the mid-twentieth century,[1] for many decades the practical applications of deep learning were very limited, possibly due to the insufficient processing speed of computers and the lack of funding to support research. However, as digitalisation made computers faster and more data became available in recent years, computer scientists have come up with algorithms that outperform humans in tasks that were once thought impossible to be carried out by a machine. Some of the areas where state-of-the-art applications of deep learning have been recently developed include:

Health: In the health sector, image recognition algorithms were created to detect the melanoma cancer at an early stage from the analysis of moles and lesions, as well as to assist in brain cancer surgery by detecting cancerous cells to be removed.[2] Additional applications in health include the analysis of foetal ultrasound images to assist in pre-natal care[3] and the examination of radiographs to quantify the severity of knee osteoarthritis.[4]

Civil and mechanical engineering: Artificial neural networks have been applied for multiple purposes, such as to predict the dispersion of dust in drilling operations, [5] to forecast the structural response of buildings under earthquakes,[6] as well as to predict traffic speed conditions.[7]

Finances: In financial markets, neural networks and genetic algorithms have been designed to generate buy and sell signals for portfolios of stocks[8] and to predict corporate bankruptcy,[9] where they were shown to be more accurate and sometimes even easier to implement than traditional techniques.

Biology: Some scientists have been deploying and testing complex algorithms in order, for instance, to automate the detection and classification of deep-sea animals[10] or to estimate the concentration of chlorophyll in the leaves of medicinal and aromatic plants.[11]

Sound and image: Deep learning can be used to automatically colour black and white images by recognising the objects and their context in the photograph and, more impressively, to add sounds to silent movies by analysing what is happening in the scenes. [12]

1. Foote (2017); 2. Hemsoth (2016); 3. O'Shea et al. (2016); 4. Anthony et al. (2016); 5. Nagesha et al. (2016); 6. Suryanita et al. (2016); 7. Lee and Teknomo (2016); 8. Er and Hushmat (2016); 9. Jones et al. (2016); 10. Hollis et al. (2016); 11. Odabas et al. (2016); 12. Brownlee (2016).

The widespread adoption of algorithms by businesses is not only transforming the way in which companies operate and interact with each other, but it is also significantly affecting the evolution of markets towards global digitalisation triggering a domino effect that promotes a wider use of algorithms in an industry. As argued by Stucke and Ezrachi (2016), as companies use algorithms to become more efficient, other companies feel pressure to digitalise their operations and to develop similar algorithms themselves. In turn, as more companies rely on automated systems, computer scientists are encouraged to develop new technologically-advanced programming principles and companies have strong incentives to come up with novel business applications for algorithms.

2.3 Applications of algorithms by governments

In addition to the rapid spread of algorithms in the business world, there is a growing interest towards the application of algorithms by government agencies, especially for detecting crimes. In some countries, like the United States, there have been developments towards a more data-driven approach to detect patterns of criminal behaviour (Rudin, 2016). In a recent initiative, PhD students from MIT have collaborated with crime analysts to design a machine learning algorithm called “Series Finder”, which uses historical criminal data to detect housebreak patterns and build a *modus operandi* (Umamaheswari et al., 2016). This algorithm was considered a powerful tool to assist the police detecting series of crimes and identifying likely suspects.

Box 3. The Korean bid-rigging indicator analysis system (BRIAS)

The BRIAS is an automatic quantitative analysis system that predicts the probability of bid rigging, by analysing large amounts of bidding data from public agencies in Korea. Since 2013, the system collected bidding information from 51 central government agencies, 246 local governments and 26 public enterprises. The system is designed to quantify the possibility of bid rigging by weighting different types of information, such as the rate of successful bids, the number of companies that participated in the auction and the bid prices. The BRIAS operates in three phases, from the gathering of the data and input, to the generation of the results:

In a first phase, BRIAS collects all bid-related data and information concerning large scale bidding contracts awarded by central and local administrations. All data and information are collected within 30 days of the tender award.

In a second phase, the system analyses the data received and it automatically generates scores on the likelihood of bid rigging, by assessing each relevant factor for the analysis. To each of these factors a weighted value is assigned and the scores of each evaluation item are then added up.

In a last step, the bidding opportunities are screened by BRIAS according to their score. Tenders which score above a certain threshold are flagged by the system for in-depth review by the Korean Fair Trade Commission (KFTC).

In order to design the system and to identify the criteria to detect possible bid rigging conspiracies, the KFTC relied on its past enforcement experience and used pre-determined red flags for collusion as a benchmark. On the basis of these markers, the system was designed to give a higher score when: (1) the successful winning rate of a company is high; (2) there are few bidders in the tender process; (3) there are several bidders whose bid is higher than the estimated price; (4) non-competitive bidding processes are used; and (5) there is a large gap between the winning and the losing bids. The system, however, is effective only if the weighting system is correctly balanced.

Source: Korea’s submission to the Roundtable on Ex officio Cartel Investigations, www.oecd.org/daf/competition/exofficio-cartel-investigation-2013.pdf, Report to the OECD Council on the implementation of the Recommendation of the Council on Fighting Bid Rigging in Public Procurement.

Similarly to catching criminals, data-driven approaches have been proposed and sometimes applied to detect collusion, particularly through the use of screening methods. Although competition authorities generally rely on reactive detection tools to detect and investigate cartels, such as leniency programmes, a combination of both reactive and proactive detection measures – including screens – is considered to be more effective.[5] A number of competition agencies have already reported using screens to detect bid rigging cases, which has only been possible due to the availability of extensive and reliable bidding data on public tenders, as well as algorithms able to detect bidding anomalies and suspicious bidding patterns across large data sets.[6] That is the case, for instance, of the Korea Fair Trade Commission (KFTC), which has in several occasions succeeded in detecting bid rigging conspiracies by screening procurement bidding data (Box 3).

Despite some difficulties observed, it is likely that there will be significant developments in this area in the near future, as screening technology improves and data are more readily available. For example, Akhgar et al. (2016) describe the potential of applying machine learning algorithms to identify hidden relationships as a possible indicator of collusion in public tenders. They argue that through feature engineering it is possible to provide a sufficiently rich set of attributes for machine learning methods to detect even sophisticated collusive tendering schemes. This involves labelling collusive bidding patterns and associating to each of them a corresponding set of features (Table 1) that can be computed and used by the machine learning algorithm. The use of algorithms to detect collusive bidding, and more generally possible cartel conduct, will open unprecedented possibilities to put technology at the service of public antitrust enforcement.

Table 1. Collusive patterns and corresponding feature engineering technologies

Collusive Pattern	Numeric or Nominal Feature
Same company wins most of the time	Number and fraction of wins, by region, by sector, etc.
Bid rotation	Time series descriptors of winners
Few or no new participants	Histogram of participation distribution
Bidding does not erode target price	Bid to reserve prize statics
Participant withdraw	Withdraw count by bid and participant

Source: Akhgar et al. (2016).

3. Pro-competitive effects of algorithms

Data-driven marketplaces are generally associated with significant efficiencies both on the supply and demand side. Algorithms are no exception.

On the **supply side**, algorithms help increasing transparency, improving existing products or developing new ones. The OECD’s work on disruptive innovation has shown how market entry has been promoted by the ability of firms to develop new offerings based on algorithms (OECD, 2016e; OECD, 2016f and OECD, 2016g). This triggers a virtuous mechanism whereby companies are under constant pressure to innovate, thus promoting dynamic efficiencies (OECD, 2015a). The rise of algorithms on the supply side can also promotes static efficiencies by reducing the cost of production, improving quality and resource utilisation, as well as streamlining business processes.

On the **demand side**, algorithms may significantly affect the dynamics of the market by supporting consumer decisions: they better organise information so that it can be accessed more quickly and more effectively and they provide new information on dimensions of competition other than prices, such as quality and consumers' preferences. Thus, algorithms have the potential to create positive effects on consumers and social welfare.

3.1 Algorithms and supply-side efficiencies

Supply-side efficiencies allow firms to lower their production costs by improving the allocation of resources. This is reflected in lower prices to consumers. In the past, it could take time to find patterns and create data trends in order to determine the optimal decisions. Now algorithms can perform this task in a matter of seconds. Deep learning techniques enable companies to optimise their commercial strategies instantaneously following trials and feedback. There is a rapid progress in self-learning algorithms to assist in almost every field of business operations, especially planning, trade and logistics (Box 4).

Box 4. Artificial intelligence in the insurance industry

For many years, insurance markets have been unable to keep up with technological developments,[1] being frequently perceived as a sector where traditional business practices prevail. Indeed, according to a survey by Willis Towers Watson (2017), "[a]lmost three-quarters of global insurers (74%) believe their sector has failed to show leadership in digital innovation". This lack of innovation, along with the moral hazard traditionally observed in insurance business models, may result in high premiums, as well as in slow and bureaucratic claiming procedures in case of an event. Nonetheless, digitalisation appears to have recently started reaching the insurance industry, as new start-ups attempt to disrupt the market and incumbents are pressured to make substantial investments in research and development.[1]

One of these new online start-ups, Lemonade, is attempting to transform the industry by providing insurance services exclusively through a mobile app and a website, while successfully introducing AI in several phases of its business model. This allows the company to save resources and run its operation more efficiently. In order to acquire an insurance policy, a new customer must interact and provide personal information to a "chatbot", while algorithms are being run in the background to cross that information with other databases, assess the risk of the customer and make an automatic offer. If any eventuality occurs, the claim is either rapidly addressed by another AI bot or, in more complex cases, it is addressed by a human. The speed at which claims are handled is also a result of Lemonade charging a flat fee to consumers and donating any unclaimed premiums to charity causes, therefore eliminating corporate incentives to delay or deny claims.[2]

Late last year a customer called Brandon claimed for a stolen coat. He answered a few questions on the app and recorded a report on his iPhone. Three seconds later his claim was paid – a world record, says Lemonade. In those three seconds 'A.I. Jim', the firm's claims bot, reviewed the claim, cross-checked it with the policy, ran 18 anti-fraud algorithms, approved it, sent payment instructions to the bank and informed Brandon. The real-life Jim (Hageman), Lemonade's chief claims officer, was driving home for Christmas at the time.[3]

1. Ralph (2017).
2. More information about Lemonade's business model can be found at their corporative website www.lemonade.com/faq#service.
3. The Economist (2017).

Certain algorithms can offer a wide range of quality effects. They can assist in improving, refining or developing products and services in a number of ways. Search engines, for example, use data to deliver more relevant and high-quality search results. By learning from user search queries and clicks, search engines can identify the most relevant results for a particular query and can also use the data to provide additional "value-added" services to users. Some e-commerce sites use past purchase information and browsing history to make personalised shopping recommendations for users. Online media outlets use browsing history and personal information to recommend other articles that may interest a reader.

The perceived benefits from algorithms are also due to the fast growing use of **dynamic pricing**, which enable consumers and providers alike to see and act on fast changing prices in many business areas, such taxi fares, sports tickets or hotel rooms, to name just a few. Pricing algorithms allow for constant adjustment and optimisation of individual prices based on many factors, including available stock and anticipated demand (Box 5). Pricing algorithms learn through trial and error and through finding patterns from a great volume and variety of data, leading to optimal pricing. As companies collect more user data and algorithms have more opportunities to experiment (such as presenting items and suggesting other purchases), pricing becomes more dynamic, differentiated and personalised (Schumpeter, 2016).

Box 5. Pricing algorithms and dynamic pricing

Pricing algorithms are commonly understood as the computational codes run by sellers to automatically set prices to maximise profits,[1] being particularly common in the airline, hotel booking, road transport, electricity and retail industries. As compared to standard pricing strategies, pricing algorithms have the advantage of processing large amounts of data that are incorporated into the optimisation process, allowing them to react fast to any change in market conditions. Given their automated nature, pricing algorithms are particularly useful to implement continuous price changes over time – dynamic pricing – or to charge different price to consumers based on their personal characteristics – price discrimination.

Dynamic pricing algorithms have been recognised to improve market efficiency,[2] by allowing companies to react instantaneously to changes in supply conditions – such as stock availability, capacity constraints or competitors' prices – as well as to fluctuations in market demand. This way, by guaranteeing that the market is constantly in equilibrium, dynamic pricing does not only prevent unsatisfied demand and excess of supply, but under certain competitive conditions it also guarantees that all mutually beneficial transactions between consumers and suppliers are exhausted. Still, dynamic pricing strategies can be so successful for algorithmic sellers, that they have been criticised to make it challenging for non-algorithmic sellers to compete and for consumers to make decisions under constant price fluctuations, unless they also use algorithms to facilitate decision-making.[3]

The implementation of algorithms in digital markets has also been argued to facilitate first degree or 'perfect' price discrimination, by allowing companies to price consumers based on their location, browsing history, previous purchases and other private information.[4] First degree price discrimination is recognised to improve efficiency, by allowing companies to supply services at lower prices to underserved consumers with low willingness to pay. Still, there are also concerns that implementing algorithmic price discrimination to such an extent could result in a lower consumer surplus overall, as well as in undesirable forms of discrimination based on gender or race.[5]

1. Chawla et al. (2007).
2. Weiss and Mehrotra (2001).
3. Chen et al. (2016).
4. OECD (2016a) and OECD (2016b).
5. OECD (2016b).

3.2 Algorithms and demand-side efficiencies

Algorithms do not only help companies improving their business processes, but also assist consumers in their purchasing decisions, resulting thereby in significant demand-side efficiencies. Gal and Elkin-Koren (2017) introduced the concept of "algorithmic consumers" to describe the shift in the decision-making process allowing consumers in data-driven ecosystems to outsource purchasing decisions to algorithms. Due to the fact that algorithms can be used to compare prices and quality, to predict market trends and to make fast decisions, they can significantly reduce search and transaction costs, help consumers to overcome biases and make more rational choices, strengthening buyer power. While a wide variety of algorithms are available to assist in purchasing decisions, a new generation of algorithms can be used to make and execute decisions for the consumer by directly communicating with other systems through the internet. In this case, the algorithm automatically identifies a need, searches for an optimal offer and executes the transaction. These algorithms are known as "digital half" or "digital butlers".

The speed, level of information and analytical sophistication that can be provided by digital butlers can also relate to parameters other than the price of the offer; their ability to rely on additional competitive variables can be very important in the decision-making process that consumers go through. Such algorithms allow consumers to access not only comparative price information (Box 6), but also a wider set of other quality dimensions of the offers that can be compared for competitive purposes. Gal and Elkin-Koren (2017) also point out that, by avoiding consumer biases that could otherwise result in non-optimal decisions, algorithms help consumers overcome manipulative marketing techniques. Algorithms may also increase the equality among consumers, due to their autonomous operation: consumers who do not know how to take advantage of online purchasing tools can easily rely on digital butlers to optimise purchasing strategies on their behalf.

Besides pure demand-side efficiencies, algorithmic consumers also have an effect on suppliers' incentives to innovate and compete. By allowing consumers to compare a larger number of offers, algorithms can potentially lead to consumers switching and therefore increase the competitive pressure on suppliers. Furthermore, algorithms can expand the sets of variable on which competition takes place, since they can check and compare many more variables. For example, algorithms are able to cover considerations such as effects on market structures and collective action problems; they can recognise forms of co-ordination between suppliers (i.e. potentially identifying instances of collusive pricing) and diversify purchasing proportions to strengthen incentives for entry (i.e. help sponsoring new entrants). Another possible use could be the aggregation of demand by pooling consumers and creating buying platforms, which could increase buyer power and solve some collective action problems on the demand side.

Box 6. Price comparison websites

The development of algorithms has improved the ability to offer price comparison services either via search engines or comparison platforms. Price comparison websites (PCW) make it easier for consumers to compare the available offers and find the best alternative. Comparison platforms can also contribute to level the playing field and intensify competitive pressure. In order to produce such benefits, consumers must be aware of the availability of alternative options, understand their needs, have low switching costs, and have the incentives to search and switch. When this is the case, PCWs can facilitate a transparent market environment in which customers obtain comparable information on the available offers. By collecting and aggregating information on products and services, PCWs can reduce the asymmetry of information and improve information flows. This can make it harder for suppliers to take advantage of ill-informed customers. PCWs can also weaken the power of sellers to segment and price discriminate.

PCWs can significantly reduce search cost when shopping for a product or service. Likewise, in the case of switching between providers, using interactive tools to compare offers can result in notable savings. Research conducted by the Financial Conduct Authority revealed that, in recent years, there has been a significant growth in the use of PCWs in real estate, travel and motor insurance industries. Apart from easy and fast access to information and cost savings, consumers identified the awareness-raising of new brands or providers among the significant benefits from using PCWs.[1]

By reducing the search cost for finding the best possible product or service, PCWs have the potential to bring a non-negligible increase in consumer surplus. Moreover, being informed about available products or services and their characteristics – especially price and quality – allows customers to make well-informed purchasing decisions, which can result in increased competition among suppliers.[2]

1. Financial Conduct Authority, Price Comparison Website: Consumer Market Research (June 2014), 7, prepared by Atticus Market Research Consultancy www.fca.org.uk/publication/research/price-comparison-website-consumer-research.pdf.
2. While there is a lot of information available online this still involves search costs and consumers may suffer from information overload. On the limited ability of consumers to process too much information and on why information intermediaries may not always be the perfect solution to information asymmetries (Armstrong, 2008).

4. Algorithms and the risk of collusion

There is no doubt that automated computer algorithms can be a powerful tool to extract value from the increasing amount of data collected in the digital economy, potentially fostering market efficiency, innovation and even promoting competition. Nonetheless, whenever new technological tools revolutionise deeply the way companies operate and interact with each other, there is the risk that some market players use their enhanced power to achieve private interests that are not aligned with social goals. The discussion that follows will focus on the risks that algorithms can raise for competition without disregarding the great benefits that they have brought to society. The question is not whether algorithms should be banned, but rather to understand the risk they may pose to the competitive process and to identify solutions which are compatible with incentives to innovate.

While algorithms might be used to implement virtually any anti-competitive conduct that is typically observed in traditional markets, a particular concern highlighted in the literature is the risk that algorithms may work as a facilitating factor for collusion and may enable new forms of co-ordination that were not observed or even possible before. This is referred to as "algorithmic collusion".

This section introduces traditional definitions of collusion that are fundamental for the discussion and evaluates the impact of algorithms on market conditions identified in the economic literature that affect the likelihood of collusion. The section then looks at several ways in which algorithms might be used to actually facilitate the implementation of an anti-competitive agreement.

4.1 Collusion - concepts and definitions

In the literature, the term "collusion" commonly refers to any form of co-ordination or agreement among competing firms with the objective of raising profits to a higher level than the non-cooperative equilibrium,[7] resulting in a deadweight loss. In other words, collusion is a joint profit maximisation strategy put in place by competing firms that might harm consumers. In order to reach and sustain a collusive equilibrium over time, competitors must put in place a structure to govern their interaction, enabling them (1) to agree on a "common policy"; (2) to monitor the adherence to this common policy; and (3) to enforce the common policy by punishing any deviations.[8]

Economists usually distinguish between two forms of collusion, explicit and tacit.[9]

- **Explicit collusion** refers to anti-competitive conducts that are maintained with explicit agreements, whether they are written or oral. The most direct way for firms to achieve an explicit collusive outcome is to interact directly and agree on the optimal level of price or output.
- **Tacit collusion,** on the contrary, refers to forms of anti-competitive co-ordination which can be achieved without any need for an explicit agreement, but which competitors are able to maintain by recognising their mutual interdependence. In a tacitly collusive context, the non-competitive outcome is achieved by each participant deciding its own profit-maximising strategy independently of its competitors. This typically occurs in transparent markets with few market players, where firms can benefit from their collective market power without entering in any explicit communication.[10]

Contrary to the economic approach, which considers collusion a market **outcome**, the legal approach focuses on the **means** used by competitors to achieve such a collusive outcome. For this reason, competition laws generally do not prohibit collusion as such, but prohibit anti-competitive agreements. If collusion is the result of such as agreement then an infringement of the law can be successfully established. Although there is great variance in how jurisdictions interpret the notion of agreement, they traditionally require some sort of proof of direct or indirect contact showing that firms have not acted independently from each other (the so-called "meeting of the minds").

The distinction between explicit and tacit collusion shows how, under certain market conditions (i.e. transparent markets with few sellers and homogenous products), supra-competitive price strategies may be the normal outcome of rational economic behaviour of each firm on the market. It is for this reason that tacit collusion or conscious parallelism falls outside the reach of competition laws on agreements between competitors. However, from a policy perspective, such a tacitly collusive outcome may not be desirable, as it confers firms the ability to significantly suppress output or raise prices to the detriment of consumers as much as an explicit agreement would.[11]

Rules on anti-competitive agreements generally are not designed to tackle individual and rational market strategies of a single firm, even if the overall result of similar individual strategies has an equivalent outcome to a cartel. However, between explicit collusion (which should always be regarded as illegal under competition rules) and mere conscious parallelism (which should fall outside the reach of competition law as it does not entail any form of co-ordination between competitors), there is a grey area of business behaviour which goes beyond conscious parallelism but at the same time does not involve an express agreement between competitors. This is a situation which may arise particularly in oligopolistic markets where competitors are able to coordinate on prices and increase the likelihood of a tacitly collusive outcome by engaging in facilitating practices which make co-ordination easier (e.g. by facilitating communications) and more effective (e.g. by facilitating detection of cheating and the administration of punishment of deviations) (OECD, 2007).

In order to address these intermediate forms of co-ordination, some jurisdictions have stretched the concept of "agreement" for antitrust purposes and looked at whether an agreement can be inferred from evidence suggesting that competitors have not acted independently. Even in the absence of an explicit agreement, for example, courts have established an infringement of the competition law if evidence of parallel conduct was accompanied by other factors (so called "plus factors"), which indicated that the parallel conduct was indeed inconsistent with unilateral behaviour and rather the result of co-ordination among the parties. Examples of such plus factors include communications revealing an intention to collude or engagements in facilitating practices, such as information exchanges. Some jurisdictions, in particular those in the European Union, also rely on the concept of "concerted practice", which allows them to deal with practices that do not amount to an agreement but nevertheless have the effect of replacing effective competition with practical co-operation between competitors.

4.2 Impact of algorithms on the relevant factors for collusion

Regardless of the means used by companies, there is a concern that algorithms make collusive outcomes easier to sustain and more likely to be observed in digital markets. This section discusses how the use of algorithms and the increasing availability of business data online are changing market conditions and how that may potentially enhance the likelihood of collusive outcomes. Section 5 will then discuss in further detail what this means for competition enforcement and the challenges algorithms pose under the legal framework that most jurisdictions use to assess competitors' co-operation.

Economists have identified the most relevant factors that may increase the likelihood of collusion in a given market.[12] These factors can be divided into structural characteristics, demand-side characteristics and supply-side characteristics. This section discusses how computer algorithms are changing in particular the structural and supply characteristics, so as to make digital markets and some traditional markets more prone to collusion.

4.2.1 Structural characteristics of the industry

The **number of firms** and **barriers to entry** are traditionally identified as two of the most important structural characteristics that affect the risk of collusion. A large number of firms not only makes it harder to identify a "focal point" for co-ordination, but it also reduces the incentives for collusion as each player would receive a smaller share of the supra-competitive gains that an explicit or tacit collusive arrangement would be able to extract. Similarly, in the absence of entry barriers, collusion can hardly be sustained over time, as any increase in profits will increase the incentives to deviate from the collusive equilibrium and will attract new entrants. Supra-competitive profits will therefore be rapidly eroded.

It is unclear how algorithms may affect these two structural characteristics.

- Some of the most typical industries, where algorithms are used to set dynamic prices, segment consumers or improve product quality, have a small number of large players, as it is the case of search engines, online marketplaces, discount stores, booking agencies, airlines, road transport and social networks. However, many of these industries are also characterised by natural barriers to entry, such as economies of scale, economies of scope and network effects, which allow companies to grow, collect large amounts of data and develop more accurate algorithms. Therefore, it is difficult to assert whether algorithms are the cause or the effect of barriers to entry.
- Also the impact of algorithms on the likelihood of entry is not univocal. On the one hand, as discussed in OECD (2016a), algorithms can be used to identify any market threats very fast, for instance through a phenomenon known as now-casting, allowing incumbents to pre-emptively acquire any potential competitors or to react aggressively to market entry. On the other hand, the increasing availability of online data resulting from the use of algorithms may provide useful market information to potential entrants and improve certainty, which could reduce entry costs.
- Finally, one peculiar aspect of algorithms is that it makes the number of competitors in the market a less relevant factor for collusion. In traditional markets, collusion is more easily sustainable if there are few competitors, as it is easier to find terms of co-ordination, to monitor deviations and implement effective punishment mechanisms among fewer firms. Algorithms can allow co-ordination, monitoring and punishment to take place also in less concentrated markets as their ability and speed in collecting and analysing data makes the number of firms to monitor and agree with less relevant. In other words, the small number of firms is an important but not a necessary condition for algorithmic collusion to take place.

Other two important structural characteristics are **market transparency** and **frequency of interaction**, both of which make industries more prone to collusion. While transparent markets allow companies to monitor each other's actions and detect deviations from an agreement, frequent interactions enable them to retaliate fast and punish aggressively any deviators. Unlike with the number of firms and entry barriers, algorithms are very likely to enhance these two factors for collusion, posing therefore a threat to competition.

Focusing first on market transparency, the effective implementation of algorithms as a central component of a business model requires the collection of detailed real-time data that can be automatically analysed and converted into action. Therefore, in order for firms to benefit from the strong predictive capacity and efficient decision-making rules of algorithms, they have an enormous incentive not only to gather market information, but also to actually develop automated methods that allows them to collect and store the data into computer systems, ready to be processed, without the need for human action. This can be done using online cookies, smart cards, bar codes, voice recognition, radio frequency identification and other technologies.

Then, as soon as a few market players make an investment in technology to benefit from an "algorithmic competitive advantage", the remaining firms of the industry have a strong incentive to do the same, risking otherwise being driven out of the market. The result is an industry where all market participants constantly collect and observe in real-time rivals' actions, consumers' choices and changes in the market environment, creating thus a transparent environment that is prone to collusion. Also, as Ezrachi and Stucke (2016) suggest, the realisation of this fact may encourage firms to share their data stream online, allowing all players to have access to the same information set.

The increase of market transparency is not only a result of more data being available, but also of the ability of algorithms to make predictions and to reduce strategic uncertainty. Indeed, complex algorithms with powerful data mining capacity are in a better place to distinguish between intentional deviations from collusion and natural reactions to changes in market conditions or even mistakes, which may prevent unnecessary retaliations.

With respect to the frequency of interaction, the advent of the digital economy has revolutionised the speed at which firms can make business decisions. Unlike in a brick and mortar business environment where price adjustments are costly and take time to implement, in online markets prices can in principle be changed as frequently as the manager wishes. If automation through pricing algorithms is added to digitalisation, prices may be updated in real-time, allowing for an immediate retaliation to deviations from collusion. In fact, the combination of machine learning with market data may allow algorithms to accurately predict rivals' actions and to anticipate any deviations before they actually take place.

The joint report of the French and German competition authorities clearly identifies the risks for competition caused by an artificial increase in market transparency and in the frequency of interaction that is possible thanks to algorithms:

> Even though market transparency as a facilitating factor for collusion has been debated for several decades now, it gains new relevance due to technical developments such as sophisticated computer algorithms. For example, by processing all available information and thus monitoring and analysing 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. Autorité de la Concurrence and Bundeskartellamt (2016)

4.2.2 Demand and supply factors

The likelihood of collusion in a given industry can be also affected by demand factors. In particular, market stagnation characterised by declining demand and the existence of business cycles may hinder collusion. This is because firms have strong incentives to profitably deviate when demand is high and reducing the costs of retaliation in future periods when demand is low.

The use of algorithms by consumers can enable them to improve their decision-making process and buy products at periods of low demand (when they are usually cheaper). However, this section is specifically focused on the risks associated with the use of algorithms by firms which should not directly affect market demand. Therefore, it is considered here that the use of algorithms as part of business practice does not affect significantly collusion through demand factors.

Supply factors, on the other hand, can play a major role in the sustainability of collusive arrangements. One of the most relevant supply-side characteristics is **innovation**. The innovative nature of the market reduces the present value of collusive agreements, as well as the ability of less innovative firms to retaliate. In this matter, algorithms are naturally an important source of innovation, allowing companies to develop non-traditional business models and extract more information from data, in order to improve product quality and customisation. In industries where the algorithm is a source of competitive advantage, as it may be the case for search engines, navigation apps and matching platforms, companies may actually face a greater competitive pressure to develop the best-performing algorithm.

Similarly, if algorithms allow companies to differentiate their services or the production process in such a way that leads to **cost asymmetry**, collusion might be again harder to sustain, due to the inherent difficulties of finding a focal point to coordinate and as a result of the low incentives for the low-cost firms to collude. This suggests that some supply characteristics of digital markets may somehow counterbalance the enhanced risk of collusion resulting from more transparent markets where companies react fast.

4.2.3 The impact of algorithms on the likelihood of collusion

The previous analysis suggests that it may be quite hard to evaluate whether algorithms increase or reduce the likelihood of collusion, as they have changed structural market conditions and supply side factors that, all together, could have a positive, negative or ambiguous impact on the sustainability of collusion. Table 2 summarises the main relevant factors for collusion and identifies, for each, the expected impact of algorithms.

Table 2. Impact of algorithms on collusion

Relevant factors for collusion		Impact of algorithms on the likelihood of collusion
Structural characteristics	Number of firms	±
	Barriers to entry	±
	Market transparency	+
	Frequency of interaction	+
Demand variables	Demand growth	0
	Demand fluctuations	0
Supply variables	Innovation	-
	Cost asymmetry	-

Note: + positive impact; - negative impact; 0 neutral impact; ± ambiguous impact.

There are other considerations that make the impact of algorithms on the likelihood of collusion uncertain. For example, in highly dynamic markets where companies have distinct sizes, sell differentiated products and play heterogeneous business strategies, tacit collusion might be very hard to achieve due to the lack of a natural focal point. Algorithms have no impact at all on some of the other factors that the economic literature has identified as making markets more prone to collusion and which are related to the nature of the product, the characteristics of the firms and the existence of alternative competitive constraints. For instance, collusion is likely to arise not only in concentrated markets, but also in markets which involve homogenous products. If products are differentiated, co-ordinating prices and other keys terms of sale must be quite difficult despite the use of algorithms by the participating firms. Likewise, if competitors have different cost levels, different capacity utilisation ratios, market shares and customer loyalty, collusion is harder to achieve and sustain over time regardless of the fact that competitors may be using algorithms. Finally, the existence of fringe competitors and buyers with strong buying power, all of whom may also be using their own pricing algorithms to disrupt any attempt to reach terms of coordination may make algorithmic collusion an unlikely outcome.

Despite the apparently ambiguous effects, algorithms appear to have changed more substantially the structural characteristics that raise competition concerns, namely market transparency and frequency of interaction, as compared to other structural characteristics or demand and supply factors. Annex 1 proposes a simple exercise using the standard modelling of collusion in the economic literature, which mathematically shows that, in a perfectly transparent market where firms interact repeatedly, when the retaliation lag tends to zero, collusion can always be sustained as an equilibrium strategy.

The consequence from this model is the following: if markets are sufficiently transparent and firms can adjust their decisions very fast, for instance by changing prices in real time, collusion is always sustainable, regardless of the potential counter-balancing effect of other factors, such as the number of firms in the industry or the risk that innovations will disrupt the market in the future. The intuition for this result is straightforward, as the combination of perfect market transparency with very frequent interaction entirely eliminates the profitability of deviations, which can be easily identified and immediately retaliated.

Naturally, the assumptions underlying the model are strong and not necessarily verified in reality, as it may be quite difficult to observe perfect market transparency and instantaneous retaliation. In addition, the fact that collusion can be sustained as an equilibrium strategy does not necessarily imply that it will. As Selten (1973) has shown, in industries with a high number of firms each player has an incentive to stay out of the cartel and benefit from the so-called ‘cartel umbrella’. This may give companies an incentive to wait for others to initiate an agreement and ultimately result in failure to coordinate.

Still, there is a clear risk that current changes in market conditions may facilitate anti-competitive strategies, such as collusion and other market manipulations. The stock exchange is a particularly good example of market where stock prices are transparent, securities are transacted at high speed and, accordingly, market manipulations have been observed despite the existence of strong regulatory institutions (Box 7).

4.3 Role of algorithms as facilitators of collusion

Taking into consideration the recent evolution of the digital economy and previous experience in some markets, competition law enforcers should be at least alerted to the risk that collusion might become easier to sustain and more likely to be observed when algorithms are involved. Once it is asserted that collusion might be easier to sustain in digital markets characterised by high transparency and frequent interaction, the natural question that follows is how companies can actually establish collusion and put in place the necessary structures to coordinate strategies, allocate gains and enforce the agreement.

Box 7. The 2010 "Flash Crash" in financial markets

On 6 May 2010 financial markets suffered one of the fastest and strongest shocks in history that would become known as the "Flash Crash", when several stock indices such as the S&P 500, Nasdaq 100 and Dow Jones deeply collapsed and rebounded in the short time frame of 36 minutes.1 During that period, more than 8000 securities temporarily dropped between 5% and 15%, and 300 other securities were transacted at prices more than 60% away from their original value, with the market closing at losses around 3% from the previous day.2 Although the exact cause of the Flash Crash is still subject of enormous debate, most theories suggest that algorithmic trading activity and automated execution programs had a fundamental role in setting up the conditions that would eventually lead to the crash.

According to a joint report by the US Commodity Futures Trading Commission and the US Securities & Exchange Commission,2 the Flash Crash was triggered by a mutual fund company that used an automated execution algorithm to sell 75.000 E-Mini S&P 500 contracts (E-Minis) valuated in nearly USD 4.1 billion, in a market context of high price volatility and reduced liquidity during the European debt crisis. The execution algorithm was programmed to sell the E-Minis at an execution rate proportional to the trading volume in the market, regardless of the price or timing of the transactions. Most sell orders were absorbed by high frequency traders who, using automated algorithms themselves, rapidly accumulated E-Mini contracts that they started aggressively selling and rebuying among each other. As the trading volume increased in the market, the algorithm of the mutual fund company submitted more sale orders and fostered a liquidity crisis, until an automatic mechanism of the stock market interrupted transactions for five seconds, apparently allowing algorithms to reboot and prices to recover.

Five years after the event, the US Department of Justice charged an independent British trader, Navinder Singh Sarao, who may have also contributed to the Flash Crash by designing "spoofing" algorithms to manipulate the market.3 According to a press release of the Department of Justice,4 Sarao used the automated trading program to bid large sale orders of E-Minis and to cancel them just before execution, sending a pessimistic signal to the market and making prices temporarily drop. By purchasing the E-Minis at low prices and selling them after the prices recovered, Sarao gained USD 900 thousand during the Flash Crash and, using similar illegal strategies over four years, he made around USD 40 million in profit.5

Despite the lack of consensus about what actually triggered the Flash Crash, an empirical study by Kirilenko et al. (2010) suggests that the incident was at least facilitated by high frequency trading, which "contributes to flash-crash-type events by exploiting short-lived imbalances in market conditions" and is a root cause of fragility of automated markets. This case certainly illustrates how certain market conditions, such as high frequency trading, may enable automated execution algorithms to distort and manipulate markets.

1. Kirilenko et al. (2010).
2. CFTC and SEC (2010).
3. Brush et al. (2015).
4. DOJ (2015b).
5. Stafford and Croft (2016).

One of the main risks of algorithms is that they expand the grey area between unlawful explicit collusion and lawful tacit collusion, allowing firms to sustain profits above the competitive level more easily without necessarily having to enter into an agreement. For instance, in situations where collusion could only be implemented using explicit communication, algorithms may create new automatic mechanisms that facilitate the implementing of a common policy and the monitoring of the behaviour of other firms without the need for any human interaction. In other words, algorithms may enable firms to replace explicit collusion with tacit co-ordination.

This section describes in more detail how the use of algorithms might increase the risk of tacit collusion and discusses a non-exhaustive list of the possible roles of algorithms in governing such structures and achieving the collusive outcome.[13]

4.3.1 Monitoring algorithms

The most obvious and simple role of algorithms as facilitators of collusion is in monitoring competitors' actions in order to enforce a collusive agreement. This role may include the collection of information concerning competitors' business decisions, data screening to look for any potential deviations and eventually the programming of immediate retaliations.

The collection of data might be the most difficult step out of this process. Even if pricing data is publicly available it does not necessarily mean that a market is transparent. Companies that take a part in a conspiracy still need to aggregate that data from all competitors in an easy-to-use format that can be regularly updated. This is already done by some price comparison websites, also known as aggregators, which either receive data directly from online companies or, instead, use web scraping, an automated process to extract data from websites using software applications such as internet bots. As new automatic data collection processes become available, these technologies will likely be extended from electronic commerce to traditional markets (Box 8). As a result, colluding companies will be able to increasingly monitor each other's actions using sophisticated algorithms.

Box 8. Monitoring fuel prices with computer vision algorithms

The petrol industry is a notable example of a highly studied market where, despite firms transacting a relatively homogeneous product, price dispersion tends to be observed across competing petrol stations.[1] While fuel price comparison websites already exist in many jurisdictions, these aggregators often incur in significant costs related to collecting manually prices from different petrol stations. However, Dong et al. (2008) have proposed and tested a new application for "wireless sensor network" (WSN) technologies, which could be used to implement an automatic data collection system that would allow consumers and firms to monitor fuel prices in close-to-real time.

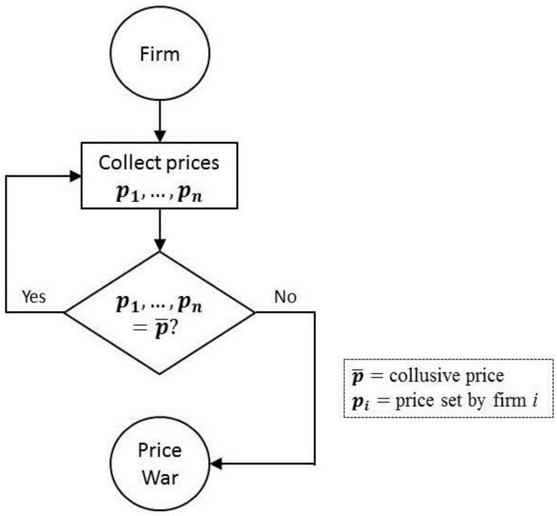
WSNs consist of networks of a large number of distributed nodes or devices, which are equipped with sensor technology to detect physical phenomena, such as light or heat.[2] The system proposed by Dong et al. (2008) involves using a network of mobile phones equipped with GPS and video cameras owned by individuals who would voluntarily share information through a mobile application. In order to achieve this purpose, Dong et al. (2008) developed a prototype computer vision algorithm that is automatically triggered when a mobile phone is close to a petrol station and which is able to detect and read fuel prices from the images of price boards collected by the mobile camera. After testing the computer vision algorithm using 52 images, the system was shown to achieve "a hit rate of 92.3% for correctly detecting the fuel price board from the image background" and to read "the prices correctly in 87.7% of them."

Although the system in Dong et al. (2008) ultimately relies on the willingness of a sufficient number of users to provide access to their mobile cameras and GPS signals, similar algorithms can be developed in the future to take advantage of existing networks of devices, such as cameras in public places. As wireless sensor networks become more common, it will be increasingly easier to use algorithms to monitor prices even in brick and mortar industries as it was never possible before.

1. Yilmazkuday and Yilmazkuday (2016) and Haucap et al. (2015).
2. IEC (2014).

The data collected by automatic collection methods can then be monitored and combined with a pricing algorithm that automatically retaliates to deviations from an agreed price. For instance, companies may program pricing algorithms to effectively execute trigger strategies, which consist in setting the agreed price as long as all the rivals do the same, but reverting to a price war as soon as any firm deviates (see Figure 3). Naturally, because algorithms are very fast at detecting and punishing deviations, firms do not have any incentive to actually deviate. Hence, unlike traditional cartels, it is very unlikely that price wars between algorithms will be actually observed, except if triggered by algorithmic errors.

Figure 3. Illustration of monitoring algorithm



> Recently, one of these algorithms malfunctioned. The matching led to a price war, fuelled by algorithms and proceeding at breakneck speed. Before it was detected, some vendors had lost thousands of dollars. Fortunately, the vendors noticed a huge spike in traffic as consumers attempted to buy large screen TVs worth thousands – for mere pennies. Love, 2015

In conclusion, monitoring algorithms may facilitate illegal agreements and make collusion more efficient, by avoiding unnecessary price wars. Still they do not eliminate the need for explicit communication during the establishment and implementation of the cartel. Therefore, while competition law enforcers should certainly be vigilant and alerted to the role of monitoring algorithms, as long as prices and other trading conditions are concerted by human beings, this behaviour could be prevented using traditional antitrust tools.

4.3.2 Parallel algorithms

One of the difficulties of implementing a cartel in highly dynamic markets is the fact that continuous changes in supply and demand require frequent adjustments of prices, output and other trading conditions. As a result, companies have to frequently renegotiate the collusive agreement through meetings, phone calls, emails or using third-parties, all of which pose a risk of detection. An alternative solution for colluding companies is to automatise their decision process so that prices react simultaneously to any changes in market conditions, replicating thereby a scenario of conscious parallelism.

As already discussed, dynamic pricing algorithms have been implemented, for instance, by airlines, hotel booking services and transportation network companies to efficiently adjust supply to periods of lower or higher demand, resulting in pro-competitive effects. However, concerns for competition might arise if companies start sharing the same dynamic pricing algorithm, which may be programmed not to compete against other firms, but to set anti-competitive prices (Box 9). Such algorithms would allow companies not only to collude, but also to have their prices automatically reacting to market changes without the need to engage in further communications.

Box 9. Algorithmic collusion in the Amazon marketplace

In 2015, the US Department of Justice (DOJ) charged a seller in the Amazon marketplace, David Topkins, for coordinating with other sellers the prices of posters sold online between September 2013 and January 2014. According to the details of the investigation released by the DOJ, David Topkins and the other conspirators designed and shared among each other dynamic pricing algorithms, which were programmed to act in conformity with their agreement. As stated by the Assistant Attorney General Bill Baer:

> Today's announcement represents the Division's first criminal prosecution against a conspiracy specifically targeting e-commerce (…) We will not tolerate anticompetitive conduct, whether it occurs in a smoke-filled room or over the Internet using complex pricing algorithms. American consumers have the right to a free and fair marketplace online, as well as in brick and mortar businesses.[1]

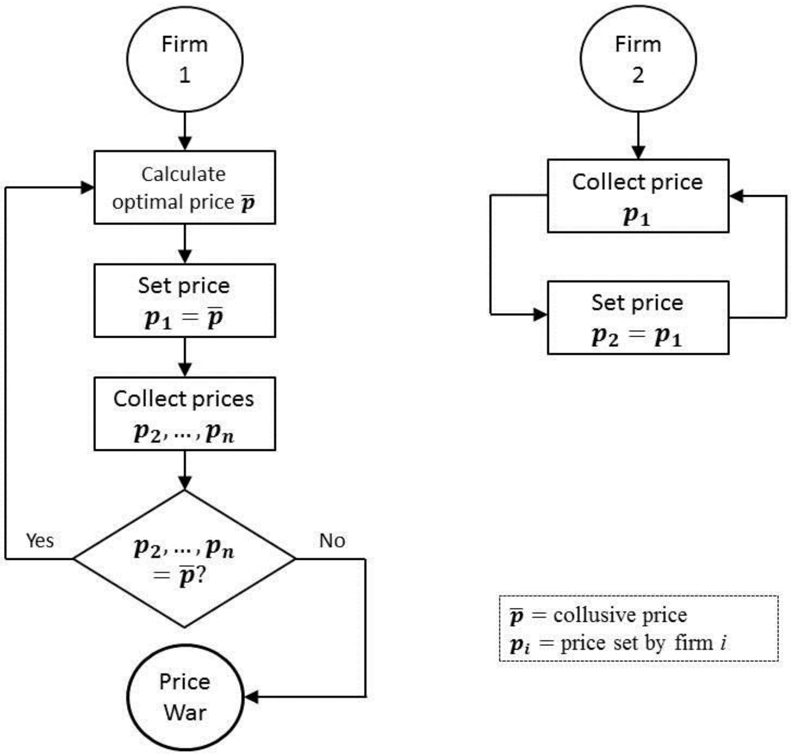
Although algorithmic pricing is not illegal and is a common practice in many industries, it was the existence of an agreement to jointly implement the algorithm that made the case for the DOJ. Since then, researchers have been able to detect many other algorithmic sellers in the Amazon marketplace by using target price times series,[2] but no new cases of collusion have been identified. Indeed, to the best of our knowledge, this is so far the only competition case of algorithmic collusion being detected by any competition authority and resulting in criminal prosecution, having thus a fundamental role in the growing interest by academic and practitioners in the risks of algorithms for competition.

1. DOJ (2015a).
2. Chen et al. (2016).

While sharing pricing algorithms with rivals is a more clear-cut violation of competition rules, there may be more subtle ways to coordinate parallel behaviour without actually engaging in explicit communication. For instance, concerns of co-ordination could arise if firms outsourced the creation of algorithms to the same IT companies and programmers. This might create a sort of "hub and spoke" scenario where co-ordination is, willingly or not, caused by competitors using the same "hub" for developing their pricing algorithms and end up relying on the same algorithms, or very close versions of them, to develop their pricing strategies (Ezrachi and Stucke, 2015). Similarly, a collusive outcome could be achieved if most companies were using pricing algorithms to follow in real-time a market leader (tit-for-tat strategy), who in turn would be responsible for programming the dynamic pricing algorithm that fixes prices above the competitive level (see Figure 4).

Despite the simplicity of tit-for-tat strategies, they have proved to be very effective in solving the iterated Prisoner's Dilemma game, where players have to repeatedly select a cooperative or non-cooperative choice on each move. In a computer tournament organised by Axelrod (1984), professional game theorists were invited to write an algorithm that would play the iterated Prisoner's Dilemma game against all the other algorithms submitted and against its own twin. The winner of the tournament, achieving co-operation most often, corresponded precisely to the simple version of the tit-for-tat strategy. More importantly, this algorithm was successful despite the fact that participants in the tournament did not communicate with each other or coordinated in any way the programmed decision rules.

Figure 4. Illustration of parallel algorithms



Note. Firm 1 is the leader and firm 2 is the follower.

4.3.3 Signalling algorithms

In highly dynamic markets where companies have distinct sizes, sell differentiated products and play heterogeneous business strategies, tacit collusion might be very hard to achieve due to the lack of a natural focal point. In order to avoid explicit communication, companies may attempt to reveal an intention to collude and coordinate more complex cooperative strategies through signalling and unilateral price announcements.[14] As recognised by Judge Posner during the course of an antitrust litigation:

> If a firm raises price in the expectation that its competitors will do likewise, and they do, the firm's behaviour can be conceptualized as the offer of a unilateral contract that the offerees accept by raising their prices.[15]

It is difficult to establish bright lines on how to treat signalling under competition laws, given the potential pro and anti-competitive effects of such conduct which obliges competition agencies to assess if, on balance, the anticompetitive effects of unilateral disclosure of information outweigh any efficiency enhancing effects (OECD, 2012). Greater transparency in the market is generally efficiency enhancing and, as such, welcome by competition agencies. But it can also produce anticompetitive effects by facilitating collusion or providing firms with focal points around which to align their behaviour if transparency only goes to the benefit of suppliers.

Box 10. The airline tariff publishing company case

During the early 1990's, the US DOJ investigated tariff fixing activities in the airline industry, where the cartel members were able to implicitly coordinate tariffs using a third party centre and sophisticated signalling mechanisms. The case is described in detail in Borenstein (1999).

In the US airline industry, airline companies send fare information on a daily basis to the Airline Tariff Publishing Company (ATPCO), a central clearinghouse that compiles all the data received and shares it in real time with travel agents, computer reservations systems, consumers and even the airline companies themselves. The database published by ATPCO includes, among other things, information about prices, travel dates, origin and destination airports, ticket restrictions, as well as first and last ticket dates, which indicate the time range when the tickets at a particular fare are for sale.

According to the case presented by the DOJ, airline companies were using first ticket dates to announce tariff raises many weeks in advance. If the announcements were matched by the rivals, when the first ticket date arrived all companies would simultaneously raise the tariff. Some of the co-ordination strategies were more complex, involving the use of fare code numbers and ticket date footnotes to send signals or negotiate multimarket co-ordination.

According to the DOJ's case it was the existence of a fast data exchange mechanism to monitor tariffs and react rapidly to price changes that enabled companies to collude without explicitly communicating. As tacit collusion is not forbidden by competition law and any explicit co-ordination was very hard to prove in a criminal case, eventually the DOJ reached a settlement agreement with the airline companies, under which the latter agreed to stop announcing most price increases in advance, with the exception of a few circumstances where early announcements could enhance consumer welfare.[1] All of the airline defendants' fares had to be concurrently available for sale to consumers.

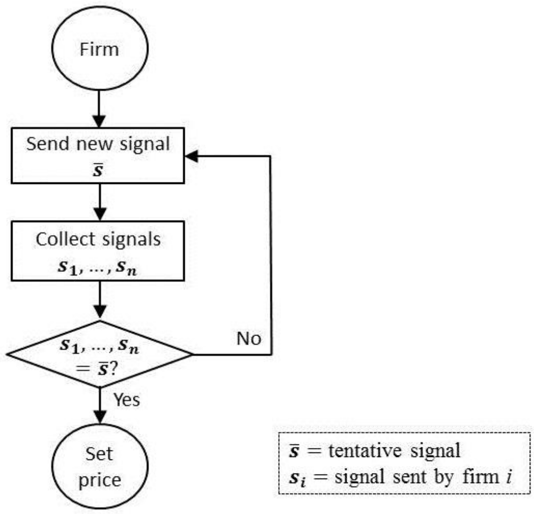
1. United States v. Airline Tariff Publishing Co., 1994-2 Trade Cas. (CCH) ¶70,687 (D.D.C. Aug. 10, 1994).
Source: Extract from OECD (2016a).

Although signalling may be observed virtually in any market, it usually does not come without a cost. Whenever a firm increases the price to indicate an intention to collude, if most competitors do not receive the signal or intentionally decide not to react, the signalling firm loses sales and profits. This risk might encourage firms to wait for other competitors to signal, eventually leading to delay or even failure to coordinate (Harrington and Zhao, 2012). Algorithms might reduce or even entirely eliminate the cost of signalling, by enabling companies to automatically set very fast iterative actions that cannot be exploited by consumers, but which can still be read by rivals possessing good analytical algorithms. There may be several ways to achieve this. For instance, firms may program snapshot price changes during the middle of the night, which won't have any impact on sales but may be identified as a signal by rivals' algorithms. Or, alternatively, companies may use algorithms to publicly disclose a lot of detailed data that is used as a code to propose and negotiate price increases, as it was observed in the US case on Airline Tariff Publishing Company (Box 10).

The evidence from the ATPCO case shows that signalling can be very effective not only in establishing an informal cartel, but particularly in supporting negotiation between companies whose interests are not necessarily aligned. When empowered with technologically advanced algorithms, this informal negotiation process may become even faster and more efficient. Similarly to the study conducted by Axelrod (1984), Henderson et al. (2003) used a tournament-based approach to evaluate the performance of alternative negotiation algorithms, some of which interacted autonomously to obtain the best deal while at the same time accommodating the interests of the other part.

Figure 5 illustrates how a general signalling algorithm could be set in order to establish and negotiate the terms of collusion before actually engaging in price co-ordination. As portrayed in the flowchart, each firm continuously sends new signals (for instance, offers to raise prices) and monitors the signals sent by the other competitors. When all players finally reach an agreement by sending the same signal, they fix the agreed price until a new successful negotiation takes place.

Figure 5. Illustration of signalling algorithms



4.3.4 Self-learning algorithms

Finally, the most complex and subtle way in which algorithms can achieve collusive outcomes is through the use of machine learning and deep learning technologies, which may potentially enable a monopoly outcome even without competitors explicitly programming algorithms to do so. In other words, there is the risk that some algorithms with powerful predictive capacity, by constantly learning and readapting to the actions of other market players (who may be human beings or artificial agents themselves), will be able to collude without the need for any human intervention.

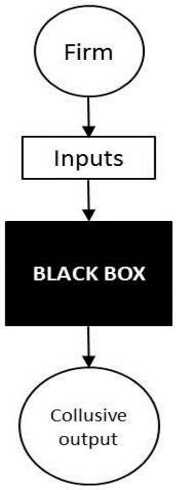
It is still not clear how machine learning algorithms may actually reach a collusive outcome. But once it has been asserted that market conditions are prone to collusion, it is likely that algorithms learning faster than humans are also able through high-speed trial and error to eventually reach a cooperative equilibrium. Even when an infinite number of anti-competitive prices can be sustained, it is also likely that self-learning algorithms can more easily determine the price that maximises joint profits and which harms consumers the most.

Some studies in game theory have analysed the ability of machine learning to achieve cooperative outcomes. In particular, Hingston and Kendall (2004) simulated an evolutionary game scenario where a population of model-based adaptive agents and non-adaptive agents play the Iterated Prisoner’s Dilemma. In their simulation, the adaptive players that learn fast perform better than non-adaptive agents. More recently, Agrawal and Jaiswal (2012) proposed also a machine learning algorithm for the Iterated Prisoner’s Dilemma that is shown to perform strictly better than the tit-for-tat strategy discussed before.

It is hard to know whether self-learning algorithms are already leading to collusive outcomes in digital markets or to detect when that happens, as machine learning may result in collusion being observed in effect and substance, but not in format – designated here as virtual collusion. Indeed, by relying on machine learning to move business decisions from humans to computers, managers do not only avoid any explicit communication during the initiation and implementation stages of collusion, but are also released from the burden of creating any structures, such as signalling mechanisms, that could be seen by authorities as facilitating practices of collusion (OECD, 2007).

If companies go one step further and implement deep learning algorithms to automatically set prices and other decision variables, collusion becomes even harder to prevent using traditional antitrust tools. The way a deep learning algorithm works can be simplistically illustrated with the concept of a "black box" (see Figure 6), as it processes raw data in a complex, fast and accurate way, resembling the human brain, and delivers an optimal output without revealing the relevant features that were behind the decision process. Therefore, by relying on deep learning, firms may be actually able to reach a collusive outcome without being aware of it, raising complex questions on whether any liability could ever be imposed on them should any infringement of the law be put in place by the deep learning algorithm.

Figure 6. Illustration of collusion as a result of deep learning algorithms



In conclusion, this section describes a non-exhaustive list of algorithms that pose multiple different risks for market competition. Table 3 summarises the main characteristics of each type of algorithm and the role they may play in implementing a collusive arrangement. The next section addresses these challenges in more detail and discusses how they could affect competition policy in the future.

Table 3. Summary of the roles of algorithms in implementing collusion

	Role in implementing collusion
Monitoring algorithms	Collect and process information from competitors and eventually punish deviations.
Parallel algorithms	Coordinate parallel behaviour, for instance by programming prices to follow a leader; sharing pricing algorithms; or using the same third party algorithm.
Signalling algorithms	Disclose and disseminate information in order to announce an intention to collude and negotiate the common policy.
Self-learning algorithms	Maximise profits while recognising mutual interdependency and readapting behaviour to the actions of other market players.

5. Algorithms and challenges for competition law enforcement

The current growth in the use of algorithms combined with developments in machine learning have induced many changes in digital markets and fuelled a wide debate on what such developments may mean for competition agencies and their enforcement activities.[16] Without disregarding the many pro-competitive efficiencies which are commonly associated with automation, such as cost reduction, quality improvement and better allocation of resources, the analysis of the previous section alerts to the risk that algorithms might distort digital markets by creating incentives and mechanisms to collude that did not exist otherwise. This is not only the case for oligopolistic markets where algorithms can concur to make collusive outcomes more likely and stable over time, but also for non-oligopolistic markets where collusion was not considered a significant risk that competition law should be too concerned with.

Although the use of algorithms by companies is widespread in certain industries, the use of complex algorithms based on deep learning principles may still be relatively rare across traditional sectors of the economy. At the moment, there is still no empirical evidence of the effects that algorithms have on the actual level of prices and on the degree of competition in real markets. This is an area where future research will be certainly welcomed to inform policy choices that governments will be facing. However, as more processes become automated and more transactions digitalised, one could expect the use of algorithms to be increasingly more common in the future. And with that, one could also expect challenges will arise for agencies when enforcing standard antitrust tools (Box 11) as well as an increase in the risks associated with collusion.

Before addressing some of the open questions for enforcement in an algorithmic business environment, it is important to make a distinction between instances where algorithms amplify conduct which is already covered under the current legal framework and algorithms which to some extent create new risks related to behaviours not covered by the current antitrust rules. Under the first scenario, the discussion is rather straightforward, as algorithms ought to be assessed together with the main infringement that they help enforcing. While detecting the existence of an infringement[17] and proving such an infringement might still be complex because of the presence of an algorithm, agencies can nevertheless rely on existing rules on anti-competitive agreements, concerted practices and facilitating practices, which offer agencies a framework to assess algorithms either on their own or as practices ancillary to a main infringement. As such, the challenges for agencies are left to understanding how the technology works and how the algorithm can facilitate or support the main antitrust infringement.

On the other hand, the discussion on what competition agencies can do in order to address algorithms' risks for competition is more complex under the second scenario, when such conduct is not covered by standard antitrust rules on co-operation between competitors. This is the issue of algorithms achieving a tacitly collusive equilibrium without any need for contact between competitors or without putting in place any facilitating practice.

Algorithms can amplify the so called "oligopoly problem" and make tacit collusion a more frequent market outcome.[18]

Accordingly, this section focuses on the more complex challenges brought by algorithms under the second scenario. After discussing the relationship between algorithms and tacit collusion, this section questions whether the notion of agreement (which does not cover pure unilateral business conduct) should be revisited and debates the scope for antitrust liability. Finally, this section debates the antitrust tools that could be used to address, at least partially, the competition concerns brought by algorithms. While it is still uncertain how competition policy can be adapted to react to algorithmic collusion, it is the purpose of this paper to frame the ongoing debate by identifying the main challenges raised by algorithms for antitrust enforcement and to anticipate possible solutions for future discussion.

Box 11. Individualised pricing and standard antitrust tools

Algorithms can raise specific challenges for enforcers which go beyond proving an anti-competitive agreement. The ability of pricing algorithms to discriminate between buyers based on a number of pre-determined variables may have important consequences on the general application of economic competition tools in markets where pricing algorithms are used by suppliers to establish individualised prices.

Current antitrust analysis largely depends on the ability of the enforcer to observe prices and to infer conclusions from the way in which companies price goods and services. An analysis that is often crucial in an antitrust case consists in looking at whether the supplier has the incentive and ability to raise prices above a competitive level; this is a key question, for example, when trying to define markets based on a standard SSNIP (Small but Significant and Non-Transitory Increase in Price) test, measure market power of a firm or assess the impact of a merger based on a unilateral effects analysis. Typically this requires a comparison between the market price given the conduct under review and a hypothetical (or pre-conduct) competitive market price.

However, it is not clear how these standard economic antitrust tools will be applicable when individualised prices are made possible by algorithmic pricing. These pricing mechanisms are capable of changing prices based on supply and demand at such a speed and with so many interactions between them that a standard price comparison will be quite a difficult exercise. The challenges that these new forms of pricing mechanisms present to agencies are still largely unexplored, as enforcement has not yet been confronted with such questions, but they can arise more frequently in the future as cases involve more often automatic individualised pricing models by the firms under investigation.

5.1 Algorithms and tacit collusion

If assessing algorithms ancillary to a main infringement is a rather straightforward case from a legal perspective, the analysis of algorithms which escape the traditional legal framework is more complex, because they allow collusion to take place without the need for any communication or contact between competitors. Algorithms are changing the characteristics of digital markets, increasing transparency, the velocity of business decisions and the ability of companies to immediately respond to rivals' actions. Under these circumstances, algorithms may make firms' actions interdependent without the need for explicit communication or interaction, increasing thereby the risk of tacit collusion and subsequently leading to higher price levels.

Box 12. The "oligopoly problem"

The "oligopoly problem", an expression sometimes attributed to Posner (1969), refers to the concern that high interdependence and mutual self-awareness in oligopolistic markets might result in tacit collusion, an outcome which is socially undesirable but that falls out of the reach of competition law. Competition authorities in some jurisdictions have attempted to extend antitrust tools to address the oligopoly problem, using in particular two distinct solutions:

- *Ex ante* merger control rules to prevent structural changes which favour coordinate effects.
- *Ex post* rules to prevent unilateral conducts that promote oligopolistic interdependence, such as facilitating practices, under the notion of joint dominance.

On the other hand, some critics of the oligopoly problem argue that it is rather unlikely that oligopoly structures unavoidably lead to tacit collusion, questioning therefore the need for antitrust intervention in this area. Whish and Bailey (2012) identify some of the counter-arguments to the oligopoly problem:

- The interdependence of oligopolists is frequently overstated. Even in symmetrical oligopolies a firm might be able to raise profits by cutting its price, as rivals may take time to react or might be unable to expand their capacity in order to meet the increased demand.
- Oligopolists frequently have different cost levels, produce differentiated goods, have different market shares and can build customer loyalty, which makes tacit collusion harder.
- Competitive edges of small market players may act as a competitive constraint on the oligopolists.
- Even if oligopolists are able to sustain tacit collusion and earn supra-competitive profits over a short period that would attract new entrants to the market and increase competition in the long run, unless there are significant barriers to entry.

Note. For a general discussion on competition policy in oligopoly markets, see OECD (2015b).

As a result, one can identify similarities between the concerns raised by algorithms and the ones posed by the classical oligopoly problem (Box 12). It has been for long recognised that in highly concentrated, stable and transparent markets the actions of firms have a significant impact upon those of rivals. Therefore, after a period of repeated interactions, firms become conscious that their respective strategic choices are interdependent and that, by matching each other's conduct, they can set prices at a supra-competitive level, without actually communicating. In other words, the structure of some markets is such that, through interdependence and mutual self-awareness, prices may rise towards the monopoly level (Whish and Bailey, 2012).

So far, competition policy has provided limited solutions to the oligopoly problem, as it is commonly understood that the particular conditions required to sustain tacit collusion are rarely observed, with the exception of a few markets with a very small number of competitors (possibly even only in a duopoly context), high degree of transparency and high barriers to entry (Potters and Suetens, 2013). However, algorithms might affect some characteristics of digital markets to such an extent that tacit collusion could become sustainable in a wider range of circumstances possibly expanding the oligopoly problem to non-oligopolistic market structures.[19]

In addition to the concerns typically evoked in the oligopoly problem, algorithms might directly facilitate a non-competitive equilibrium by working as instruments that eliminate the need for explicit communication or interaction between competitors. Indeed, algorithms function as an "intermediary" between firms, by collecting and processing market data, and rapidly responding to rivals' actions. As noted by Mehra (2015), algorithms might actually succeed in governing collusive structures better than humans, given their greater accuracy in detecting price changes, the elimination of the element of irrationality and the reduction of the chance that the collusive scheme is undermined by mistake.

In light of all these considerations, one should question whether, with the recent developments of algorithms, tacit collusion is likely to become a more common phenomenon in digital markets. If that is the case this could ultimately result in substantial consumer harm given the difficulties to address tacit collusion under the current competition law frameworks. If future research supports this hypothesis, competition law enforcers might want to consider if their current approach to the legal treatment of tacit collusion needs adjusting.

5.2 The notion of agreement: does it need revisiting?

Because of the way in which competition laws are designed, identifying an "agreement" between competitors is a prerequisite to enforce the law against collusive outcomes. In most cases, the term agreement is broadly defined to ensure the widest possible reach of the competition rules (Box 13).

In practice, the definition of agreement may still provide little guidance on whether more subtle forms of communication fall in the scope of application of the competition rules. For instance, signalling mechanisms such as unilateral public price announcements could be seen as an invitation to reach a common policy, but it is questionable under the law of many jurisdictions if they can amount (and under which circumstances) to an agreement. In the absence of communication and explicit co-ordination, the applicability of provisions on agreements is not straightforward. Mere parallel conduct, such as simultaneous price increases by competitors, is insufficient to indicate co-ordination since it can result from independent and rational behaviour.

This raises the concern of whether the need to address algorithmic collusion should require a new definition of what is an agreement for antitrust purposes. This is not a new question for antitrust scholars[20] but the question has come up again in recent times in a "renewed debate about whether classic oligopoly behaviour can be prosecuted as an unlawful agreement" (Hay, 2013).

Box 13. The notion of "agreement" for antitrust purposes

In the European Union, the Article 101 of the TFEU applies to all "agreements" and "concerted practices", although the TFEU does not provide clear-cut definitions of what is an agreement or a concerted practice. According to the courts, an agreement reflects "a concurrence of wills between economic operators on the implementation of a policy, the pursuit of an objective, or the adoption of a given line of conduct on the market, irrespective of the manner in which the parties' intention to behave on the market in accordance with the terms of that agreement is expressed."[1] In other words, the concept of agreement simultaneously involves the existence of a common will and some form of manifestation, whether it is implicit or explicit. In the absence of a formal agreement, the category of concerted practices can be applied. This involves, among other factors, direct or indirect contacts intended to deliberately influence the conduct of other firms.

In the United States, the section 1 of the Sherman Act uses multiple terms to refer to an agreement, including "contract", "combination in the form of trust" and "conspiracy". According to the Supreme Court of the US, an agreement does not necessarily need to be explicit or formal, as long as it involves "a unity of purpose or a common design and understanding, or a meeting of minds",[2] as well as "a conscious commitment to a common scheme".[3] This definition is, in principle, very broad and could potentially cover parallel conduct. In practice, courts have required evidence that observed parallel conduct is indeed the result of co-ordination among the parties and not mere oligopolistic interdependence (so-called "plus factors"). An example of a "plus factor" required by courts is that the parties have communicated their intentions to act in a certain way.

1. Case T-41/96, Bayer AG v Commission, [2000] ECR II-3383, para 173.
2. Interstate Circuit Inc v United States, 306 US 208, 810 (1939); Am. Tobacco Co. v. United States, 328 U.S. 781, 809–10 (1946), at 810.
3. Monsanto Co. v. Spray- Rite Serv. Corp., 465 U.S. 752, 768 (1984); In re Flat Glass, 385 F.3d at 357.

Kaplow (2011) argues that the current approach to horizontal agreements may be too formalistic and incapable of addressing harmful interdependence among firms. He also argues that a narrow view of the meaning of agreement is in contrast with a more economically-based approach to competition law, stating that "successful interdependent coordination that produces supra-competitive pricing leads to essentially the same economic consequences regardless of the particular manner of interactions that generate this outcome." He has highlighted limitations of this approach, such as the reliance of US doctrine on communication as an important condition to define the concept of agreement, advocating thus for a broader interpretation of what constitutes an agreement. However, the suggestion that competition law should capture standard oligopoly behaviour is not without critics, as it is the case of Judge Posner who has recently warned against the danger of the laws "treating tacit collusion as if it were express collusion."[21]

Similar challenges can arise with algorithms. As the development of algorithms increasingly allows for rapid and sophisticated interactions between competitors, who might use complex codes as intermediates to reach a common objective, the notion of agreement and its applicability to the digital economy becomes more unclear:

> While an agreement among competitors to fix prices is per se illegal, computer technology that permits rapid announcements and responses has blurred the meaning of 'agreement' and has made it difficult for antitrust authorities to distinguish public agreements from conversations among competitors. Borenstein (1997)

In light of the role of algorithms in reaching and enforcing a common policy, some have raised the question of whether the concept of agreement should be revisited in order to incorporate other "meetings of minds" that are reached with the assistance of algorithms. For instance, the signalling algorithms discussed above might result in very fast iterative change of prices that eventually converge to a common value, resembling an actual negotiation process between businessmen to implement a collusive agreement. Could therefore be concluded that the fast adjustment of prices in reaction to competitors until convergence is reached is tantamount to an agreement?

Likewise, the parallel algorithms mentioned above could potentially be seen as an alternative automatic mechanism to implement an agreement. For instance, in a "follow-the-leader" strategy, a firm could make an offer to collude by implementing an algorithm that imitates in real-time the price of the market leader, while the leader could accept the offer by increasing the price in reaction to the competitor's algorithm. Alternatively, a firm may make an invitation to collude by publicly releasing a pricing algorithm, while competitors would accept the offer by using the same algorithm as part of their business strategy.

Box 14. Unfair competition standards and Section 5 US FTC Act

In the United States, under Section 5 of the FTC Act, the US Federal Trade Commission (FTC) has the power to prohibit "unfair methods of competition". The Supreme Court has held that Section 5 extends beyond the Sherman Act and other US antitrust laws,[1] and over time the FTC has relied on this power to tackle various conducts that have anti-competitive effects, but would be challenging to pursue under cartel or monopolisation provisions. An example is unilateral communications of information to competitors with anti-competitive effects, or the so-called "invitations to collude".[2]

Section 5 is broadly constructed and offers flexibility to the FTC on which practices to tackle, as it is a provision which is "principle-based" rather than "rule-based".[3] Under the current legal standard, the FTC would need to show that a practice (e.g. the use of an algorithm) is unfair because (1) it causes or is likely to cause substantial injury to consumers; (2) it cannot be reasonably avoided by consumers; and (3) is not outweighed by countervailing benefits to consumers or to competition.

It has been suggested that statutes like Section 5 could be used to tackle algorithmic collusion if the agency could show that, when developing the algorithms, defendants were either motivated to achieve an anticompetitive outcome or were aware of their actions' natural and probable anticompetitive consequences.[3]

1. FTC v. Sperry & Hutchinson Co., 405 US 233 (1972) (Finding that the statute, its legislative history, and prior cases empower the Commission under Section 5 to define and proscribe an unfair competitive practice, even though the practice does not infringe either the letter or the spirit of the antitrust laws); and FTC v. Indiana Federation of Dentists, 476 US 447 (1986) ("The standard of 'unfairness' under the FTC Act is, by necessity, an elusive one, encompassing not only practices that violate the Sherman Act and the other antitrust laws […] but also practices that the Commission determines are against public policy for other reasons") (dictum).
2. OECD (2015b) also notes that, because Section 5 can only be enforced by the FTC, an expert administrative body, it limits the potentially burdensome combination of class actions and treble damages that could result from private antitrust enforcement in this area. In stand-alone cases violating Section 5 (i.e. cases that have not been alleged to violate the other antitrust laws) the FTC has tended to restrict its remedies to prohibiting future recurrence of the conduct (e.g. prohibiting future unilateral communications of the type that gave rise to concerns) rather than seeking damages or punitive sanctions.
3. For example, see Ethyl Corp v FTC, 729 F.2d 128, 136 (2d Cir. 1984) ("Congress, in the process of drafting Sec. 5, gave up efforts to define specifically which methods of competition and practices are competitively harmful and abandoned a proposed laundry list of prohibited practices for the reason that there were too many practices to define and many more unforeseeable ones were yet to be created by ingenious business minds.").
4. Ezrachi and Stucke (2017).

At this point it is still very hard to draw firm conclusions on whether algorithmic interactions (or a "meeting of algorithms") should be treated similarly to a "meeting of minds" under the definition of agreement covered by competition rules. However, a more clear definition of agreement could not only reduce uncertainty by helping businesses understanding which practices are illegal and which ones are acceptable, but also to potentially address some of the concerns related to algorithmic collusion.

Because proving that a pure unilateral conduct such as conscious parallelism constitutes an agreement restricting competition can be difficult under the legal standards, in particular in jurisdictions where the concept of agreement has been interpreted narrowly, some agencies may have the possibility to rely on legal standards such as "unfair competition" which provide the enforcement agency with more flexibility (Box 14).

5.3 The scope for antitrust liability

A question discussed in the literature on algorithms and competition is whether antitrust liability can be established when pricing decisions are made by a machine using an algorithm rather than by human beings.

As Mehra (2016) puts it, "[i]n dealing with a robo-seller that takes anticompetitive actions there are three choices in attributing responsibility: to the robo-seller itself, to the humans who deploy it, or to no one." While the third option (no liability) cannot be considered a realistic one, as it would *de facto* provide impunity for anti-competitive conduct put in place through the intermediary of an algorithm, the debate has highlighted the challenges of attributing antitrust liability to individuals when commercial strategies are delegated to an algorithm and humans have no ability to influence the way in which such decisions are taken. Of course, most algorithms today still operate based on instructions designed by human beings and there is no doubt that humans will be in most cases responsible for the decisions made by algorithms. Based on the current stand of the law, computer programs and algorithms are to be considered simply as tools, implying that their decision can be directly attributed to their human operators.

As the European Commissioner Vestager stated in a recent speech:

> The challenges that automated systems create are very real. If they help companies to fix prices, they really could make our economy work less well for everyone else. (…) So as competition enforcers, I think we need to make it very clear that companies can't escape responsibility for collusion by hiding behind a computer program. Vestager (2017)

However, as AI develops further, the links between the agent (the algorithm) and its principal (the human being) become weaker and the ability of algorithms to act and price autonomously puts in question the liability of the individuals or firms who benefit from the algorithm's autonomous decisions. In such cases, determining liability mainly depends on the facts at hand. As noted by Ezrachi and Stucke (2016), defining a benchmark for illegality can be challenging since it requires assessing whether any illegal action could have been anticipated or predetermined by the individuals who benefit from the algorithm. Such assessment includes, for example, a careful consideration of the programed instructions of the algorithm, available safeguards, reward structure and the scope of its activities.

Furthermore, agencies should consider the extent to which humans can control the activities of algorithms. It can be obvious that algorithms are designed by humans, but do they intentionally create algorithms to harm consumers? Could liability be automatically charged jointly and severally on the person who designed the algorithm, on the individual who used it and on the person (or entity) who benefitted from the decision made by the algorithm?[22] These questions do not have clear-cut answers at the moment, but will likely arise in courts of law as more antitrust cases involving independent algorithmic activities will be litigated.

5.4 Possible alternative approaches to algorithmic collusion

Aside from more radical interventions (possibly of a legislative nature) that involve reconsidering the legal approach to tacit collusion, revisiting the notion of agreement that would fit algorithmic collusion or determining the scope of liability for AI systems, there are some traditional measures that antitrust agencies can put in place to address at least some of the competition concerns. Possible alternative approaches could include *ex ante* measures such as the use of market studies, merger control enforcement, the use of remedial actions or even a regulatory approach. This section briefly exposes the first three approaches, while the last section of this paper focuses on the scope for market regulation in more detail.

5.4.1 Market studies and market investigations

In general, a prerequisite for antitrust intervention against an anti-competitive agreement is the existence of evidence of some form of competitors' co-ordination which has a negative impact on competition and poses a risk of consumer harm. Yet, when there are signs that the market is not functioning well, but there are no indications of any co-ordination among the market players, competition agencies may decide to engage in market studies or sector inquires in order to understand why the market is failing and to identify possible solutions.[23] Hence, the use of market studies typically precedes other enforcement actions.

Box 15. Findings on pricing software of the EC sector inquiry on e-commerce

An example of how market studies can assist agencies and governments identifying possible concerns from algorithmic pricing for competition, as well as possible policy solutions, can be found in the final Report of the European Commission to the Council and European Parliament on the E-Commerce Sector Inquiry. Among the main findings, the Report concludes that

> (…) increased price transparency allows companies to monitor more easily their prices. A majority of retailers track the online prices of competitors. Two thirds of them use automatic software programmes that adjust their own prices based on the observed prices of competitors. With pricing software, detecting deviations from 'recommended' retail prices takes a matter of seconds and manufacturers are increasingly able to monitor and influence retailers' price setting. The availability of real-time pricing information may also trigger automatised price co-ordination. The wide-scale use of such software may in some situations, depending on the market conditions, raise competition concerns.[1]

1. European Commission (2017).
Source. Ezrachi and Stucke (2017).

With respect to algorithmic collusion, agencies could seek to examine whether algorithms commonly result in coordinated effects and, if so, to attempt to identify the circumstances and sectors under which algorithmic collusion is more likely to be observed. In this sense, market studies (or sector inquiries) may support agencies' efforts to understand the market characteristics that can lead to collusive outcomes, whether they consist in high transparency, predictability and frequent interaction or in any other structural characteristics that have not been identified yet. Ezrachi and Stucke (2017) suggest that "[s]uch approach may prove useful in helping agencies understand the new dynamics in algorithm-driven markets and the magnitude of any competitive problems."

The use of market studies can lead to recommendations for the government to engage in regulatory interventions to address legal or structural restrictions to competition, as well as to the opening of investigations when the cause of the concern is behavioural. Market studies could also lead to advocacy efforts and recommendations to the business community itself with the objective of fostering stronger compliance with competition principles. This could result, for instance, in the adoption of self-regulation in the form of codes of conduct, which companies would agree to comply with when designing and using pricing algorithms.

Finally, in some jurisdictions, such as the United Kingdom, Iceland and Mexico, competition authorities can go beyond market studies and engage in so-called market investigations. These tools allow them to go a step beyond by issuing non-binding recommendations (which is the typical outcome of a market study) and eventually to impose structural or behavioural remedies. The advantage of market investigations is that they offer the agency a degree of flexibility in restoring competition in the market that would not be possible through other means.

5.4.2 Ex ante merger control

Another possible ex-ante approach consists in establishing a system capable of preventing tacit collusion, through the enforcement of merger control rules in markets with algorithmic activities. This may require agencies to consider lowering their threshold of intervention and investigate the risk of coordinated effects not only in cases of 3 to 2 mergers, but potentially also in 4 to 3 or even in 5 to 4. Such an approach would allow agencies to assess the risk of future co-ordination, going beyond the traditional duopolies where tacit collusion is more easily sustainable, to include also cases where the use of algorithms may facilitate collusion even in less 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. Ezrachi and Stucke (2017)

In order to effectively prevent algorithmic collusion, competition agencies should focus their analysis particularly on the impact of the transactions on market characteristics such as transparency and velocity of interaction, which are the factors that are mostly affected by the use of algorithms. Ezrachi and Stucke (2017) also suggest that agencies may need to reconsider the approach to conglomerate mergers when tacit collusion can be facilitated by multimarket contacts. In particular they note that "one aspect of machine learning is to discover correlations in large data sets. Thus, the algorithms can ascertain and respond to punishment mechanisms in distinct product markets, which to the human may appear unrelated."

5.4.3 Commitments and possible remedies

Lastly, competition law enforcers could make tacit collusion harder to sustain through a behavioural approach, by preventing oligopolists from putting in place harmful mechanisms for the competitive process in so far as they facilitate collusion. Although this has not been tested yet, one could argue that relying on certain types of algorithms may amount to a facilitating practice that could trigger competition law enforcement. This could be the case, for instance, if competitors facilitated a collusive equilibrium by relying on monitoring, parallel or signalling algorithms.

In many jurisdictions, enforcement actions can also lead to the adoption of remedies in the form of commitments (OECD, 2011a and OECD, 2016i). Remedies can resolve and prevent the harm to the competitive process that may result from a unilateral conduct, such as a facilitating practice. Although it could be a delicate task to find an adequate remedy in case of algorithm-driven conducts, it is worth considering the use of remedies to introduce special compliance or monitoring programs. A similar procedure should be introduced for the so-called "notice-and-take-down" process, under which the online hosts should post a notice and remove the content in response to court orders. This way, if as a result of the use of algorithms any anti-competitive behaviour is detected, an appropriate action can immediately be taken.

Another possible remedy could be the introduction of auditing mechanisms for algorithms, which could guarantee that algorithms are programmed in a way to steer clear of any competition concerns. However, as noted by Ezrachi and Stucke (2016), this can fail in leading to a meaningful tool, since (1) algorithms do not necessarily include instructions to collude, but rather to maximise profit; (2) auditing is not likely to keep pace with the development of the industry, especially given the self-learning nature of algorithms and (3) it may be hard to prevent algorithms from ignoring information that is publicly available ("cheap talk" problem).

6. Algorithms and market regulation

From the previous discussion there seems to be scope for competition law enforcers to tackle some of the anti-competitive effects of algorithms. Yet, as computation methods become more complex and a phenomenon of "governance by algorithms" is increasingly observed, this section debates whether competition law is enough to address most of the existing concerns or whether some form of regulatory intervention is necessary.

In what follows, the general risks of algorithms for society are identified, as well as the market failures that might prevent such risks from being addressed by self-correcting mechanisms, therefore serving as arguments in favour of market regulation. Then, some alternative regulatory approaches are presented, alerting to the risks that over-enforcement could pose on market competition and innovation. Finally it is discussed the challenge of designing market regulations with the specific purpose of preventing algorithms from reaching collusive outcomes.

Many of the considerations touched upon in the next sections go well beyond the issue of collusion and even competition law enforcement in general. Discussions on the viability and advisability of any regulatory options would also require a comprehensive and careful consideration of a whole host of other policy areas. While such an exercise goes far beyond the scope of this paper, these sections frame the competition concerns raised by the spread use of algorithms in such a wider policy context.

6.1 Arguments in favour of regulating algorithms

The ongoing debate about regulating the digital economy seems a result, at least in part, of the exponential growth of a few players in digital markets, which include some of the biggest companies in the world by market capitalisation. The internet giants, as they have become known, are responsible for the provision of multiple information goods, such as operating systems, browsers, search engines, email and messaging, navigations maps, electronic books, music distribution and social networks. In turn, the value added of these services partially relies on complex proprietary algorithms that are implemented for multiple ends: dynamic pricing, data mining, result ranking, user matching, product recommendations and ads targeting, among others.

Despite the immeasurable value that the internet giants have brought to society in the form of innovative technology and high-quality online services, their increasing dimension and presence across multiple fundamental markets have attracted not only the attention of the general public, but also of regulators and policy makers.[24] The increasing reliance of big online companies on secret algorithms poses a concern that the organisation of the world's information is, to some extent, controlled by automated systems in the hands of a few market players.

6.1.1 Risks of "algorithmic selection" beyond collusion

Algorithms can determine the news that online users read, the multimedia content they access, the products that they purchase and even the individuals that they meet or interact with socially. As Domingos (2016) puts it, "these days, a third of all marriages start on the Internet, so there are actually children alive today that wouldn't have been born if not for machine learning."

The use of automated computer systems to organise and select relevant information – "algorithmic selection" – is not necessarily undesirable, particularly if the decisions and predictions determined by machines are considerably more efficient, accurate and objective than those that any human being could make. Nevertheless, due to their vast potential in supporting decision-making, algorithms are starting to be implemented in fundamental areas that govern the structure of society, where computer errors or bias could have major implications. Indeed, in the same way that algorithms perform actions that cannot be feasibly executed by humans, computers are not infallible and may also result in errors that are typical of automated systems, leading to a whole new range of policy concerns. Saurwein et al. (2015) identifies multiple risk categories of algorithmic selection, some of which are summarised in Table 4.

The risk categories in the table do not only pose social concerns, but can actually have severe implications for the good functioning of the digital economy. Some of the risks, such as the potential of algorithms as a tool for abuse of market power, have a direct impact on competition. Other risks, including information bias, market manipulations and violations of property rights, may also indirectly affect competition by creating barriers to new entrants and reducing incentives to innovate:

> The way that algorithms are used to make decisions automatically could even undermine our democracy. These days, social media is a vital source of news. (…) So the scope for social media algorithms to create an alternative reality, by showing people one story after another that just isn't true, is a concern for us all.
> Vestager (2017)

Table 4. Risk categories of algorithmic selection

Risk	Description	Examples
Abuse of market power	Algorithms programmed to facilitate anti-competitive practices, such as collusion, as well as exclusionary and exploitative abuses.	• Allegations that search engines manipulate search results in order to disadvantage competitors[1] • Algorithmic co-ordination to fix prices in internet marketplaces
Bias	Information filters that reduce variety and bias information according to the preferences of online users, leading to "echo chambers"[2] and "filter bubbles".[3]	• Search engines that provide online readers with news that match their own believes and preferences • Product recommendations for books and movies with similar content to the ones previously acquired • Social networks' updates about the closest contacts
Censorship	Restrictions programmed to control or block the content that certain users are able to access.	• Content-control software used by companies to block sites with particular religious, political and sexual orientations • Content-control software implemented by governments in certain jurisdictions
Manipulation	Manipulation of algorithms to select information according to business or political interests, instead of its relevance or quality.	• Creation of multiple accounts or repetitive transactions in internet marketplaces in order to manipulate feedback scores and influence rating • Design of internet links to bias search engine results in order to rank certain websites higher[4]
Privacy rights	Automated systems that collect personal data from users (sometimes shared with third parties), posing concerns for data protection and privacy.	• "Instant Personalization" model adopted by Facebook in 2010, which allowed service providers to access users' profiles[5] • Collection of user's location data in order to better target advertisement
Property rights	Use of algorithms to collect, aggregate, display and share information goods protected by Intellectual Property rights.	• News aggregator services that redistribute fragments of copyrighted articles[5] • Unlicensed streaming sites for music and video
Social discrimination	Automated data-decision processes that, by considering personal information in their formulas, can result in discriminatory outcomes.	• Pricing algorithms that discriminate based on social and demographic characteristics, such as location • Recidivism algorithms that could result in racial discrimination

1. Patterson (2013).
2. Sunstein (2009).
3. Pariser (2011).
4. Bar-Ilan (2007).
5. Helft and Wortham (2010).
6. Quinn (2014).

6.1.2 Market failures

In light of the risks brought by algorithms, a central question for policy makers is whether market competition combined with existing laws on privacy, intellectual property and fundamental human rights will suffice to dissipate such concerns, or whether some form of regulatory intervention in necessary. In other words, will competition be sufficient to drive out of the market fallible and erratic algorithms, while preserving those that are efficient and enhance social welfare? While the answer to this question may depend on the particular risk addressed, it is possible to identify at least three market failures that could eventually compromise the ability of digital markets to self-correct:

1. **Imperfect information resulting from lack of algorithmic transparency:** The lack of transparency in the way algorithms are programmed and run may limit consumers' ability to make valid and conscious choices among competing products. Likewise, law enforcers may lack the necessary information or even expertise to make sure that automated systems comply with existing regulations. In part, this lack of transparency results from the fact that most algorithms are trade secrets. Yet, even if companies publicly release or share their secrets with some regulators, their long and complex program codes would be still extremely hard to interpret. The effects of algorithms can be also particularly difficult to evaluate when outcomes are highly variable and depend on individual characteristics (Sandvig et al., 2014).

2. **Data-driven barriers to entry:** The development of good predictive algorithms requires expensive complementary assets such as advanced data-mining and machine learning software, as well as physical infrastructures such as data centres, whose investment is subject to economies of scale. The ability of algorithms to find new relations and patterns of behaviour also requires access to a variety of data collected from multiple sources, resulting in economies of scope. Thereby, small firms that do not have the necessary complementary assets or that are not simultaneously present in multiple markets might face barriers to entry, preventing them from developing algorithms that can effectively exert competitive pressure (OECD, 2016a).

3. **Spill-overs associated with information and knowledge:** By being programmed to select only the most relevant and useful information, algorithms might reduce the variety of ideas and views that individuals are confronted with. Sunstein (2009) and Pariser (2011) alert to the danger that algorithms tend to bias information in a way that reinforces our own beliefs, leading to a phenomenon known as 'echo chambers'. This could arguably lead to an environment where static efficiency is optimised but which is less prone to human creativity and innovation. In the process of research and development, many great discoveries were made by accident when scientists were confronted with data that were not relevant for the objectives that they initially had in mind; or when they broke with established knowledge and tested hypothesis that could appear risky or ill-advisable for a machine. In economic terms, algorithms might fail to internalise the spill-overs that a variety of knowledge and multi-disciplinary approaches could have on the process of innovation.

6.2 Possible regulatory interventions

Recognising the prominent role of algorithms in the organisation and processing of the world's information, with consequences that go far beyond the limits of the digital economy, academics and policy makers have engaged in a growing debate concerning the need for new forms of regulatory intervention. Some of the central topics debated include the institutional options to govern algorithms, alternative regulatory measures and the risks associated with excessive regulation, all of which are addressed in turn.

6.2.1 Institutional options to govern algorithms

Saurwein et al. (2015) identify several options that have been either proposed or implemented to govern algorithms, ranging from a continuum between market solutions and state regulations. Each option has different limitations and might be more or less appropriate to address each of the risk categories of algorithms identified in the last section.

In one extreme of the continuum of governance options there are supply and demand-side market solutions. The first consist in suppliers competing to provide better algorithms across several dimensions, for instance by using machine learning to reduce bias or to prevent algorithms from being manipulated. The second correspond to consumers taking active actions, such as refusing to use certain services or relying on advanced technology to protect themselves from algorithmic risks (for example, with tools for anonymisation or to prevent censorship). Whenever possible, market solutions should be applied as they are less likely to hamper innovation or to deter new entry.

Nonetheless, the market failures previously identified could serve as an argument for alternative solutions, which include self-organisation (companies committing to good principles and standards to improve their reputation), self-regulation, co-regulation and state intervention. Along this range of governance options, many regulatory measures have been proposed, including information measures, principles of "search neutrality", cybercrime regulations, data protection certification schemes, etc.

In the scope of state intervention options, some academics are currently advocating for the establishment of new regulatory institutions to govern the digital economy. For instance, Gawer (2016) has suggested the creation of a global digital regulator, a central and independent agency that would be responsible for coordinating and supervising the different regulatory aspects of internet and data. On the other hand, in order to address the risks associated with algorithms and artificial intelligence, others have proposed the establishment of a new AI regulatory regime:

> (…) the scheme outlined (…) proposes legislation, the Artificial Intelligence Development Act ('AIDA'), that would create an agency tasked with certifying the safety of AI systems. Instead of giving the new agency FDA-like powers to ban products it believes to be unsafe, AIDA would create a liability system under which the designers, manufacturers, and sellers of agency-certified AI programs would be subject to limited tort liability, while uncertified programs that are offered for commercial sale or use would be subject to strict joint and several liability. Scherer (2016)

Whether the establishment of such regulatory agencies is feasible and socially desirable is still an open question and one that spans a number of policy areas. So far governments have adopted a market-oriented approach towards the digital economy, which has greatly contributed to the fast growth of online commerce and encouraged the development of innovative services, as well as efficient and fast transactions. This market approach has prevailed since the early stages of the internet, when the White House recommended a set of principles to expand internet markets through private-sector leadership and minimum regulatory restrictions on competition:

> Unnecessary regulation of commercial activities will distort development of the electronic marketplace by decreasing the supply and raising the cost of products and services for consumers the world over. (…) Accordingly, governments should refrain from imposing new and unnecessary regulations, bureaucratic procedures, or taxes and tariffs on commercial activities that take place via the internet. White House (1997)

Before taking any actions, policy makers should cautiously evaluate the risks of over-enforcement, as excessive regulatory interventions could result in new barriers to entry and reduce the incentives of companies to invest in proprietary algorithms, which so far have brought a great value for society. In this matter, the OECD (2009) recommends governments to evaluate the competitive impact of market regulations, emphasising that "competition assessment of proposed public policies should be integrated in the policy making process at an early stage."

Keeping these important principles in mind, this section questions whether there is scope to tackle algorithmic risks through market regulation, identifying a few alternative forms of intervention and the respective risks for competition.

6.2.2 Measures on algorithmic transparency and accountability

Some of the regulatory interventions discussed in most recent debates appear to focus on making algorithms more transparent and accountable for their effects. In the United States, the FTC's Bureau of Consumer Protection established the brand-new Office of Technology Research and Investigation, which is responsible for conducting independent studies and providing guidance in several topics, including algorithmic transparency. In addition, the US Public Policy Council of the Association for Computing Machinery (USACM) published a statement proposing a set of principles for algorithmic transparency and accountability, which are intended to minimise harm while at the same time realising the benefits of algorithmic decision-making (Box 16).

Recent developments in Europe seem to indicate a similar movement to make algorithms more transparent and accountable for law infringements. In a recent speech at the Bundeskartellamt, the EU Commissioner Vestager (2017) stated that businesses have the obligation of programming algorithms to deliberately comply with data protection and antitrust laws, which can be denominated as "compliance by design". The German Chancellor Angela Merkel made also a public statement calling for companies like Facebook and Google to publicly disclose their proprietary algorithms:

> The algorithms must be made public, so that one can inform oneself as an interested citizen on questions like: what influences my behaviour on the internet and that of others? (…) These algorithms, when they are not transparent, can lead to a distortion of our perception, they narrow our breadth of information. Agerholm (2016)

One way to empower the public with a watchdog function is to have regulators reverse-engineering algorithms in order to understand how their decision-making process functions. However, enforcing algorithmic transparency and accountability might turn out to be a challenging task in practice, especially when facing black box algorithms that make inherently autonomous decisions and might contain implicit or explicit biases. The sensible reaction to demand for more transparency about how these algorithms work may not achieve the intended purpose, as making these complex algorithms fully transparent can be extremely challenging. Merely publishing (or disclosing to a regulator) the source code of the algorithm may not be a sufficient transparency measure. Complete transparency would require that someone could explain why any particular outcome was produced, but that might be an impossible task when machine learning systems have made autonomous decisions that have not been instructed by anyone.

Box 16. USACM's principles for algorithmic transparency and accountability

"1. **Awareness**: Owners, designers, builders, users, and other stakeholders of analytic systems should be aware of the possible biases involved in their design, implementation, and use and the potential harm that biases can cause to individuals and society.
2. **Access and redress**: Regulators should encourage the adoption of mechanisms that enable questioning and redress for individuals and groups that are adversely affected by algorithmically informed decisions.
3. **Accountability**: Institutions should be held responsible for decisions made by the algorithms that they use, even if it is not feasible to explain in detail how the algorithms produce their results.
4. **Explanation**: Systems and institutions that use algorithmic decision-making are encouraged to produce explanations regarding both the procedures followed by the algorithm and the specific decisions that are made. This is particularly important in public policy contexts.
5. **Data Provenance**: A description of the way in which the training data was collected should be maintained by the builders of the algorithms, accompanied by an exploration of the potential biases induced by the human or algorithmic data-gathering process. Public scrutiny of the data provides maximum opportunity for corrections. However, concerns over privacy, protecting trade secrets, or revelation of analytics that might allow malicious actors to game the system can justify restricting access to qualified and authorized individuals.
6. **Auditability**: Models, algorithms, data, and decisions should be recorded so that they can be audited in cases where harm is suspected.
7. **Validation and Testing**: Institutions should use rigorous methods to validate their models and document those methods and results. In particular, they should routinely perform tests to assess and determine whether the model generates discriminatory harm. Institutions are encouraged to make the results of such tests public."

Source. Quoted from USACM (2017).

On top of this, it is still not clear which authority or regulator would be best placed to review and supervise algorithms in order to ensure transparency and accountability. And if multiple agencies should be involved in this role, questions remain on how co-ordination and co-operation between regulators would work to reconcile possibly conflicting objectives of different policies. Indeed, one of the main difficulties of regulating the digital economy is precisely the fact that online companies operate at the interface of existing laws, such as privacy law, transparency law, data protection, intellectual property rights, consumer protection and competition law. This may require regulatory interventions under different policy areas (Box 17), which are enforced by multiple different agencies (Strowel and Vergote, 2016). Moreover, many online companies operate beyond national borders, posing thereby a territorial challenge in the design of regulations.

6.2.3 Regulations to prevent algorithmic collusion

It is still unclear at this point whether any regulations can be created to prevent machine learning algorithms from autonomously reaching tacit co-ordination, at least not without harming the competitive process in other ways. To the best of the Secretariat's knowledge, no solutions have been proposed so far in the antitrust literature to tackle this conduct. Moreover, there are no competition cases or investigations providing supportive evidence of this "virtual" form of collusion, making it hard to justify the creation of regulations to prevent the negative impact of conducts that have not been observed yet.

Box 17. Accountability and the "right to explanation" in the European GDPR

In April 2016, the European Parliament adopted a comprehensive set of rules for the collection, storage and use of personal information, the General Data Protection Regulation (GDPR). Among the different regulatory measures adopted, which deal in particular with data protection, the GDPR also introduces the right of citizens to seek and receive an explanation for decisions made by algorithms, especially if they are using profiling techniques (Art. 22). In particular Article 13, 14 and 15 GDPR (which regulate the right of access in specific circumstances) specify that individuals have a right to ask for "the existence of automated decision-making, including profiling, […] and, at least in those cases, meaningful information about the logic involved, as well as the significance and the envisaged consequences of such processing for the data subject."

This regulatory framework highlights the importance that the EU legislator places on the ability of humans to interpret decisions made by algorithms and provides a strong indication to algorithm designers that they should be in a position to provide meaningful information about the logical process involved in the algorithm itself. This form of transparency and accountability is associated with the right of individuals "to obtain human intervention" and to express their points of view if they wish to contest the decision made by an algorithm. The GDPR is an attempt to use regulation to ensure that humans can intervene in algorithmic decision-making and to promote forms of algorithmic design that can ensure compliance with the regulatory framework.[1]

1. Goodman and Flaxman (2016).
Source. Regulation 2016/679 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation), OJ L119/1 of 4.5.2016.

Nonetheless, recognising that collusion among machine learning algorithms might be very hard to detect, and given the fast speed at which digital markets have evolved in the last years, it is important to anticipate what kind of regulations could be considered in the future if this peculiar form of collusion ever becomes part of the market reality. Three potential types of regulatory intervention are briefly mentioned here, as well as the risks they could pose for competition.

1. **Price regulation:** Given that algorithms may lead to anti-competitive prices even in the absence of traditional conducts that could amount to "plus factors" – such as communication or signalling – policy makers could be tempted to introduce maximum price regulations. Maximum prices are considered to pose significant barriers to competition and, whenever possible, should be replaced with more efficient alternative policies.[25] Indeed, price regulations not only reduce

incentives to innovate or to provide high-quality products, but could actually result in higher prices by creating a focal point for collusion in digital markets that would otherwise be competitive.

2. **Policies to make tacit collusion unstable:** Policy makers might come up with policies to change the structural characteristics of digital markets that most facilitate collusion.[26] For instance, in order to make markets less transparent, policy makers could enforce systems of secret discounts or impose restrictions on the information that can be published online; likewise, in order to reduce the high frequency of interaction in digital markets, they could enforce lags on price adjustments or require companies to compromise to any new offer for a minimum time period (Ezrachi and Stucke, 2017). Unfortunately, such policies would also be likely to result in severe restrictions to competition, by reducing the amount of information available to consumers[27] and by preventing fast price adjustments from efficiently matching demand and supply.

3. **Rules on algorithm design:** Thirdly, policy makers could eventually consider the creation of rules that restrict the way algorithms are designed, i.e. an algorithmic version of Asimov's Three Laws of Robotics. If the purpose is to prevent companies from independently coordinating anti-competitive prices, regulations could inhibit algorithms from reacting on particular features or market variables that are necessary to sustain tacit co-ordination.[28] As an example, algorithms could be programed not to react to most recent changes in prices; or, instead, to ignore price variations of individual companies, while still accounting for average prices in the industry. This solution might also constrain the ability of firms to develop innovative algorithms, though it is probably less restrictive for competition than the two previous forms of intervention. On the other hand, regulating algorithm design could also pose on some agencies the additional burden of supervising whether companies are effectively complying with the rules.

The list of potential regulatory interventions discussed here is not intended to direct policy in any particular direction, but merely to set a framework for discussion and promote future debate. In fact, if any regulations must be designed to make markets less prone to collusion, policy makers should adopt a conservative approach, since such rules could have many other unpredictable implications that could ultimately compromise the good functioning of digital markets.

7. Conclusions

Recent developments of the digital economy are challenging the established approaches on which law enforcers and regulators rely to protect competition, secure market trust and promote social wellbeing. At the frontline of most discussions by current practitioners is the concern that the generalised integration of computer algorithms in modern business models might create risks for competition that should not be underestimated. Without disregarding the significant benefits that automated systems have brought to society, this paper attempted to frame the debate around the potential impact of algorithms on collusion, identifying some preliminary possible responses that competition law enforcers could pursue and possible areas for further research.

This paper recognises, in particular, two major mechanisms through which algorithms could challenge antitrust investigators. Firstly, algorithms are fundamentally affecting market conditions, resulting in high price transparency and high-frequency trading that allows companies to react fast and aggressively. These changes in digital markets, if taken to a certain extent, could make collusive strategies stable in virtually any market structure. Secondly, by providing companies with powerful automated mechanisms to monitor prices, implement common policies, send market signals or optimise joint profits with deep learning techniques, algorithms might enable firms to achieve the same outcomes of traditional hard core cartels through tacit collusion.

From an enforcement perspective, one has to distinguish between cases where algorithms are used by competitors as an ancillary tool to a wider collusive arrangement falling within the traditional reach of competition rules on anti-competitive agreements, and cases where algorithms allow firms to align business conduct in what looks very much like conscious parallelism, a conduct with is not illegal under competition rules. While in the first case the challenges for agencies are related to detecting possible anti-competitive cases, understanding the technology and collecting evidence to meet the required legal standard, the second scenario raises more difficulties because the current legal standard does not allow intervention with the traditional rules on anti-competitive agreements between competitors.

In light of these difficulties, competition law enforcers can take alternative courses of action. Using traditional antitrust tools, they could firstly conduct market studies in order to evaluate whether algorithmic collusion is a phenomenon commonly observed and, if so, under which conditions and in what industries it should be expected. Then, if a competition problem is actually identified, some solutions might involve the adaptation of merger review to account for the impact of algorithms on coordinated effects; or the design of behavioural remedies to prevent companies from using algorithms for collusion. Finally, as research progresses and delivers consistent evidence that algorithms are indeed significantly contributing to price increases through tacitly collusive interdependence, policy makers might need to consider if more substantial revisions are needed to address algorithmic collusion, including revisiting the concept of “agreement” as well as the current legal treatment of tacit collusion.

Since algorithms can result in multiple other market failures and affect substantially the selection and organisation of the world’s information, some commentators have been giving an increasing attention to the potential need for a regulatory reform in the digital economy, whose governance has so far been left to the market. This paper mentions a few regulatory approaches that might be considered in the future to tackle algorithmic collusion, such as price regulation, policies to make tacit collusion unstable and rules on algorithm design. However, at this stage, there are still concerns that any regulatory interventions might have severe negative impacts on competition that could outweigh their potential benefits. If regulatory solutions are to be considered, competition concerns would only be an element of such discussion and considerations going beyond the risk of collusion would have to be factored in such discussions.

Given the multi-dimensional nature of algorithms, policy approaches should be developed in co-operation with competition law enforcers, consumer protection authorities, data protection agencies, relevant sectorial regulators and organisations of computer science with expertise in deep learning. In conclusion, despite the clear risks that algorithms may pose on competition, this is still an area of high complexity and uncertainty, where lack of intervention and over regulation could both pose serious costs on society, especially given the potential benefits from algorithms. Whatever actions are taken in the future, they should be subject to deep assessment and a cautious approach.

Notes

1. The full text of the letter is available at https://futureoflife.org/ai-open-letter/.

2. For an analysis of the impact of data-driven innovation on growth and well-being, see OECD (2015a).

3. Although it cannot be excluded that algorithms may have an impact on how competition laws are enforced outside the area of collusion, this paper only deals with the potential risk that algorithms and AI can have on co-ordination of business behaviour between competitors.

4. It is not unusual for companies to run simultaneously deep learning and traditional machine learning algorithms, so that they can identify the best course of actions and, simultaneously, to be aware of the features that were relevant for the final decision.

5. See OECD (2013) and International Competition Network (2010) for more information about reactive methods (generated by an event, such as a complaint or leniency application) and proactive methods (initiated by the competition authority) to detect bid rigging.

6. Screening algorithms can be *structural*, involving the analysis of markets characteristics and identifying those where collusion is more likely; or *behavioural*, involving the analysis of market conduct to assess whether companies' actions are consistent with collusion. While structural and behavioural approaches are both useful to detect collusion and can actually complement each other, they face some common challenges, such as the lack of sufficiently detailed and validated data to identify suspicious signs of collusion. Relevant and accurate data is necessary for all stages of the screening exercise, from its design, to its implementation, up to the interpretation of its results. Accessing this information is a key issue in any empirical methodology and lack of it exposes screens to a serious risk of failure. For more information about behavioural and structural screens, see OECD (2013).

7. Common definitions of collusion can be found in OECD (1993), O'Sullivan and Sheffrin (2003) and Green et al. (2013).

8. Firms can collude on a variety of competitive variables. In most cases, co-ordination involves keeping prices above the competitive level, but in other occasions collusion may aim at limiting production or capacity investments. Firms may also co-ordinate by dividing the market (for instance, by geographic area or customer characteristics) or by allocating contracts in bidding markets. Usually, traditional concepts of collusion excludes agreements that are pro-competitive in nature, such as some vertical agreements or joint ventures in R&D. See OECD (2012b) and OECD (2015b).

9. See Green et al. (2013), Harrington (2012), Ivaldi et al. (2003), Tirole (2002), Posner (2001) and Turner (1962).

10. The role of transparency as a relevant factor for collusion is more extensively discussed in Ezrachi and Stucke (2016), Whish and Bailey (2012), OECD (2012b), OECD (2010), Ivaldi et al. (2003) and Stigler (1964).

11. This is the so-called "oligopoly problem", which has generated a large debate on whether competition policy should be concerned with tacit collusion or not (see also Section 5 in this paper and OECD, 2015b).

12. Relevant factors for collusion are discussed, for instance, in Ivaldi et al. (2003), Levenstein and Suslow (2006), OFT (2005), Canoy et al. (2004), Jacquemin and Slade (1989) and Stigler (1964).

13. See Ezrachi and Stucke (2016) for a detailed description of alternative collusive scenarios, where the roles of algorithms identified here might apply.

14. Such strategies are not only used in more complex scenarios of differentiated products and heterogeneous businesses but also when firms are trying to reach co-ordination in more homogeneous and straight forward market contexts

15. In Re High Fructose Corn Syrup Antitrust Litigation Appeal of A & W Bottling Inc. et al., United States Court of Appeals, Seventh Circuit, 295 F3d 651, 2002, p. 2.

16. For a more detailed discussion see Mehra (2015), Ezrachi and Stucke (2015 and 2017) and Graef (2016).

17. Detection may be in practice very challenging as enforcers would not be in a position to determine if a particular pricing would be the 'natural' outcome of market dynamics or if it was 'artificially' enhanced or created by algorithms. Ezrachi and Stucke (2017) suggest that detection could be enhanced through auditing of algorithms by agencies or regulators to "*assess whether an algorithm 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 authors themselves recognise the challenges linked to auditing of algorithm, first and foremost because of the sheer number of algorithms that would require auditing and because the degree of technical expertise required to understand their functioning and effects. Today agencies are not equipped for such an analysis, especially if the algorithm to audit falls into the deep learning type of algorithm.

18. Mehra (2015) notes that the competition concerns related to the use of algorithm are not just similar to the oligopoly problem, but they can aggravate it by giving individual firms the incentive to raise the price above the competitive level in the absence of co-ordination, which can also contribute to the stability of this action in the long run. He emphasises a number of factors to support his thesis: algorithm ensure greater accuracy in detection of price changes; the minimal level of human collaboration can remove the element of irrationality and reduce the chance that the collusive scheme is undermined by mistake; and due to mass data collection and processing, price cuts are become more detectable and also lower the possibility of price wars.

19. Apart from increasing the internal stability of markets, which relates to the strategic interaction between existing incumbents, algorithms may also foster external stability, which refers to the entrance of potential entrants who are not present in the market yet. For that purpose, colluding companies can use algorithms to instantaneously target new competitors with exclusionary practices, eliminating thereby the threat of entry, which is the main poison of collusion.

20. The debate on the most appropriate notion of "agreement" for antitrust purposes is not recent. Indeed in the United States this debate that goes back to arguments in the sixties by Posner and Turner. Posner (1968) favoured a broad interpretation of the notion of agreement that would reach interdependent pricing by oligopolists, even where they did not enter into an agreement in the common sense of the term. Turner (1962), on the other

hand, agreed that the term “agreement” could not be limited only to an classic explicit agreement. However, he disagreed with Posner’s approach and believed that punishing businesspeople for interdependent oligopolistic pricing would be problematic, since, as in a competitive industry, they were simply rationally optimising their prices given market realities.

21. See *Aircraft Cheque Services et al. v. Verizon Wireless et al.*, No. 14-2301 (7th Cir. 2015).

22. A strict liability standard (i.e. business will *always* be responsible for what their algorithms do) may induce counterproductive (chilling) effects on incentives to develop new and more performant algorithms which have the potential to play an important role in promoting innovation and a greater role in modern society. On the other hand, a strict liability standard would promote incentives of developers and users of algorithms to understand how algorithms (including deep learning algorithms) work and build in safeguards to prevent algorithms from reaching anticompetitive outcomes. Such an approach seems to be implicitly suggested by Vestager (2017): “*[...] businesses also 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 works.*”

23. According to OECD (2016d), market studies and sector inquiries are useful tools to understand the dynamic of the market and to promote competition. Market studies are used primarily for the assessment of markets and their competitive conditions. They are mainly considered as an advocacy tool to issue recommendations to change laws and regulations or as a pre-enforcement tool in case they reveal constraints to competition of a behavioural nature.

24. See for instance Miller (2016), The Economist (2016) and Teffer (2016).

25. For a more detailed discussion about the barriers to competition resulting from price regulations, see paragraph B1 of the checklist of the Competition Assessment Toolkit (OECD, 2016c).

26. As discussed in detail in Section 4.2, collusion in digital markets might be facilitated by market transparency and high frequency of interaction.

27. For further details about restrictions that limit the choice and information available to customers, see paragraph D of the checklist of the Competition Assessment Toolkit (OECD, 2016c).

28. According to Vestager (2017): “What businesses can – and must – do is to ensure antitrust compliance by design. That means pricing algorithms need to be built in a way that doesn't allow them to collude. Like a more honourable version of the computer HAL in the film 2001, they need to respond to an offer of collusion by saying “I’m sorry, I’m afraid I can’t do that.”

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Annex 1. Mathematical derivation of collusion

Proposition

In a perfectly transparent market where firms interact repeatedly, if collusion does not decrease the payoff of any player and the retaliation lag tends to zero, collusion can always be sustained as an equilibrium strategy.

Proof

This formal demonstration applies standard techniques usually used in the literature to analyse the relevant factors for collusion (see, for instance, Ivaldi et al. 2003). However, in order to incorporate the fact that algorithms allow companies to adapt their strategies very fast, the inter-temporal stream of profits are represented in continuous time, in opposition to the economic literature where collusion is commonly model in discrete time.

Collusion is a super game Nash equilibrium if, at any moment of time, the present discount value of the profits of an arbitrary firm under the collusive path is greater than or equal to the present discount value of the profits that the firm would earn by deviating from collusion. The value of the collusive path is given by:

$$V^M = \int_0^{\infty} e^{-rt} \pi_t^M . dt, \tag{1}$$

where π_t^M is the profit of the firm at moment t under collusion and r is the discount rate. The definite integral represents the sum of all discounted profits from moment 0 up to infinite.

On the other hand, the value obtained by a firm that deviates from the collusive path is:

$$V^D = \int_0^{T+L} e^{-rt} \pi_t^D . dt + \int_{T+L}^{\infty} e^{-rt} \pi_t^C . dt, \tag{2}$$

where π_t^D is the profit from deviating from collusion, π_t^C is the payoff under competition (in other words, under the punishment phase), T is the number of periods that it takes for other firms to detect a deviation and L is the time lag required to react to the deviation (for instance, by introducing a price change). This way, T is a measure of the transparency in the market and L is a measure of the velocity of response or of the frequency of interaction. In equation (2), the first term of the right-hand side corresponds to the one shot gain from deviation, which takes place between periods 0 and $T + L$, while the second term is the value of the competitive path that takes place after period $T + L$.

Then, collusive is an equilibrium strategy if the following incentive compatibility constraint (ICC) is fulfilled:

$$V^M \geq V^D. \tag{3}$$

Replacing V^M and V^D by equations (1) and (2) respectively:

$$\int_0^{\infty} e^{-rt}\pi_t^M.dt \geq \int_0^{T+L} e^{-rt}\pi_t^D.dt + \int_{T+L}^{\infty} e^{-rt}\pi_t^C.dt. \tag{4}$$

For simplification, the profit functions are considered to be constant over time. However, the same results could be easily demonstrated by considering that profits grow at a constant rate g, as long as $g < r$.

$$\int_0^{\infty} e^{-rt}\pi^M.dt \geq \int_0^{T+L} e^{-rt}\pi^D.dt + \int_{T+L}^{\infty} e^{-rt}\pi^C.dt. \tag{5}$$

Bringing the profits to outside the integrals:

$$\pi^M\int_0^{\infty} e^{-rt}.dt \geq \pi^D\int_0^{T+L} e^{-rt}.dt + \pi^C\int_{T+L}^{\infty} e^{-rt}.dt. \tag{6}$$

Taking into consideration that the indefinite integral $\int e^{-rt}.dt$ is equal to $\frac{-e^{-rt}}{r}$, the defined integrals above can be solved as follows:

$$\pi^M\left[\lim_{t\to\infty}\left(\frac{-e^{-rt}}{r}\right)-\left(\frac{-e^{-r\times 0}}{r}\right)\right] \geq$$
$$\geq \pi^D\left[\left(\frac{-e^{-r(T+L)}}{r}\right)-\left(\frac{-e^{-r\times 0}}{r}\right)\right]$$
$$+\pi^C\left[\lim_{t\to\infty}\left(\frac{-e^{-rt}}{r}\right)-\left(\frac{-e^{-r(T+L)}}{r}\right)\right]. \tag{7}$$

Solving the limits and simplifying some of the terms:

$$\pi^M\left[0-\left(-\frac{1}{r}\right)\right]$$
$$\geq \pi^D\left[\left(\frac{-e^{-r(T+L)}}{r}\right)-\left(-\frac{1}{r}\right)\right]$$
$$+\pi^C\left[0-\left(\frac{-e^{-r(T+L)}}{r}\right)\right]. \tag{8}$$

Finally, using standard algebra, equation (8) can be simplified to the following equation:

$$\pi^M \geq \pi^D - (\pi^D - \pi^C).e^{-r(T+L)}. \tag{9}$$

As a preliminary result, it is possible to conclude from equation (9) that transparency and velocity of interaction facilitate collusion. Indeed, when T and L fall, the right-hand side of equation (9) also falls (notice that the profit under deviation is always greater than the profit under competition), relaxing the incentive compatibility constrain and thus making collusion more likely.

In order to see what happens when markets are perfectly transparent and firms are able to adjust their strategies instantaneously, the limit of the right-hand side of equation (9) is taken when T and L tend to zero:

$$\pi^M \geq \lim_{\substack{T\to 0\\ L\to 0}}\left(\pi^D - (\pi^D - \pi^C).e^{-r(T+L)}\right). \tag{10}$$

Solving the limit:

$$\pi^M \geq \pi^D - (\pi^D - \pi^C) \times 1. \tag{11}$$

Finally, it follows directly that:

$$\pi^M \geq \pi^C. \tag{12}$$

Equation (12) completes the proof: when markets are perfectly transparent, so that firms can immediately identify any deviation from collusion ($T = 0$), and the time lag of response L is zero, collusion can always be sustained as an equilibrium strategy as long as the profit of any firm under collusion is greater than under competition.

The combination of big data with technologically advanced tools, such as pricing algorithms, is changing the competitive landscape in many markets and sectors. While this is producing benefits and efficiencies, it is also raising concerns of possible anti-competitive behaviour. This paper looks at whether algorithms can make tacit collusion easier and discusses some of the challenges they present for both competition law enforcement and market regulation.

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