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Pricing Algorithms and the Risk of Tacit Collusion

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Introduction

The impact that artificial intelligence has on all aspects of today's life is something that goes beyond what anyone could have imagined. Computer algorithms, Big Data, and the Internet have allowed for significant benefits in terms of technology and efficiency of the overall society, including market mechanisms. The unprecedented ability to handle massive amounts of data regarding production, consumers, and market analysis lead to clear innovations: higher quality of goods and services supplied, lower prices, and increased variety of products available in the market. And yet, this promised "increased competition" seems to have significant pitfalls that cannot go unnoticed. Data shows that markets that make substantial use of artificial intelligence are prone to the development of tacit collusion, a phenomenon that is not illegal *per se* but raises a number of concerns for antitrust authorities, as it undermines competition.

Chapter 1 will present some basic notions about algorithms: how they are defined and how they work. This information is useful to understand how they can be applied to businesses and why they are able to outperform humans. Analyzing the different levels of depth and complexity of artificial intelligence, machine learning, and deep learning gives us an insight on why they might raise liability issues. In particular, recognizing that some of these algorithms may go beyond the control of human beings and act on their own leaves us with several ethical and legal questions. What is the relationship between humans and machines? Should it be regulated? Who should we held accountable for the actions of such independent algorithms? Should we be worried at all?

Before examining these issues, Chapter 2 will analyze some of the more evident effects on the market—namely the positive consequences for consumers and producers. On the supply side, firms will be able to increase profits through the maximization of their production process and the use of predictive analytics. On the demand side, consumers may benefit from the lower prices offered and the use of algorithms developed to make better purchasing decisions.

Chapter 3 will instead tackle the negative effects, focusing in particular on pricing algorithms—used in digital markets to automatically set prices of goods and services. To do so, we first explore some basic notions of industrial organization, in order to understand what is collusion, how it works, and why it is detrimental to the economy, putting particular emphasis on tacit collusion and why it cannot be ignored. Then we look at how pricing algorithms affect the relevant market characteristics that allow tacit collusion to happen. With this essential knowledge at hand, we will present the four main types of pricing algorithms that can be identified in digital markets.

The use of these algorithms can be applied to four different scenarios, namely *Messenger*, *Predictable Agent*, *Hub and Spoke*, and *Autonomous Machine*. Each of these algorithmic collusion settings raise different types of concerns. Chapter 4 will display the traditional tools that antitrust authorities use to tackle (tacit) collusion and why the legislative approach may not be enough for some of these scenarios. We will then suggest some alternative approaches, in particular the regulation of market structure and algorithm design in order to prevent *ex-ante* anticompetitive outcomes such as algorithmic collusion.

Through this analysis it will be more clear why algorithms create market conditions that are far more precarious than other traditional oligopolies. The benefits offered by innovative AI technology shall not let competition authorities ignore the perils that come with it. This means that policy makers might need to implement solutions that keep pace with technological improvements.

Chapter 1

A Primer on Algorithms

The concept of algorithm has been around for decades, yet no definition has been accepted universally. Informally we could say that an algorithm is a procedure, a method, or technique useful to complete a certain task or solve a problem. More precisely, we can define algorithms as a series of computational steps that transform a set of values, the input, into another set of values, the output. The essential feature is that there is a precise and unambiguous set of operations to be followed systematically to reach the final state.

Usually they are associated with computer machines that perform calculations or data analysis. They can range from the simple task of organizing a set of numbers in ascending order, to more intricate applications in various fields of science, such as mathematics, engineering, bioinformatics, and data science. In this paper, we will focus on the way they are applied to markets and how they influence the economic landscape, and in particular, we will emphasize the use of pricing algorithms, among others.

1.1 Artificial intelligence, machine learning and deep learning

The different kinds of algorithms can be classified according to their degree of complexity.

Artificial intelligence revolves around the idea of creating intelligent machines, in particular computer programs, used to perform a variety of tasks that mimic human thinking. In this sense, these algorithms are able to recognize patterns and solve problems. AI machines are programmed with long sets of rules used to replicate thought-like behavior. Compiling those lists can be a lengthy and inefficient process; this is why the introduction of self-learning algorithms was a big innovation.

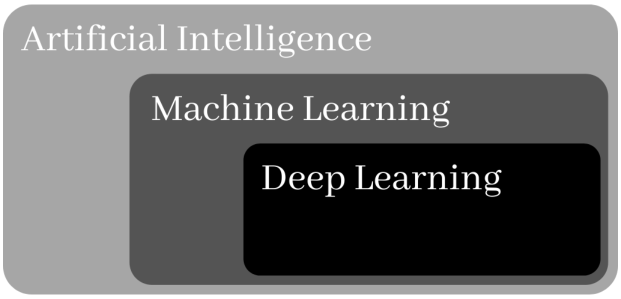

Fig. 1.1: The relationship between AI, ML, and DL

Machine learning is a subset of artificial intelligence (Fig. 1.1) devoted to the creation of machines that learn without being explicitly programmed by humans. What does it mean to learn? It can simply be defined as the ability to change and adapt in accordance to external stimuli while keeping in consideration all past events. Therefore, with the use of machine learning, algorithms can extrapolate general laws and understand their patterns as long as they affect real data, sparing the people working behind them time and energy.

There are three approaches to machine learning. Supervised learning is characterized by the idea of a teacher that supervises the work of a student (the algorithm, in this context). Starting from a set of labeled inputs, the algorithm is expected to provide a solution. Unsupervised learning is when there is no labelled set of inputs. The algorithm will self-organize in order to find underlying patterns and predict the output. Reinforcement learning is not supervised nor unsupervised. It is based on feedback, usually called reward, used to evaluate whether a certain outcome is positive or negative. It is mainly used in dynamic environments.

However, machine learning is often inadequate when raw databases are too large. In this case, it is necessary to organize and divide data into subsets to determine which of those are relevant to solving the original problem. This is where deep learning comes in. It takes a step even further: while simple machine learning algorithms are linear, deep learning algorithms are composed of multiple processing layers. The key characteristic is that deep learning creates an artificial neural network (ANN) that is meant to work like a human brain. As illustrated in Figure 1.2, it is a system made up of billions of connected neurons that interact with each other. Given the complexity of ANNs, deep learning allows algorithms to be very flexible and adapt to very different tasks.

With this knowledge at hand, it is clear that algorithms are not only simple machines that perform the task given by the programmer, but rather they can be so complex that even understanding what they do and how they do it is beyond the capacity of a human brain. For many this is very concerning; the debate regarding the relationship between humans and technology has been fueled by the rise of such sophisticated machines. This is the case also for economists, market analysts, and policy makers that are worried about the changing business landscape.

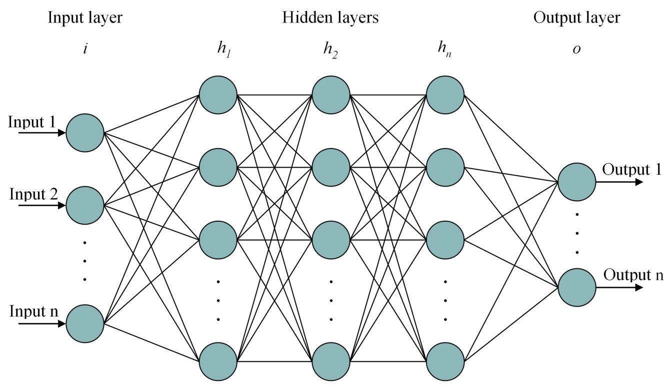

Fig. 1.2: Artificial Neural Network (ANN)

1.2 Pricing algorithms

The use of algorithms by businesses and consumers takes many forms, as we will see in the next chapter. This paper, however, examines in particular pricing algorithms, which are those that either use price as an input or compute price as an output. They are used both in the online and offline market by firms to recommend or set prices, as well as monitor their competitors.

Data is an essential input for the effectiveness of algorithms. The key information that pricing algorithms require regards competitors' prices, past profits and revenues, firms' costs, information about potential buyers, as well as other general information about the market they are operating in. The better the data retrieved, the more efficient the pricing strategies adopted by the algorithms will be. As one can imagine, the significant rise in the quality and quantity of information available, thanks to Big Data, has made it possible for pricing algorithms to become even more relevant. Unlike standard pricing strategies, pricing algorithms can adapt instantly to changes in the market. This has a huge impact on the ability of firms to collude, as we will see in Chapter 3.

Chapter 2

Pro-competitive Effects of Algorithms

The widespread implementation of complex technology in data-driven marketplaces, such as AI algorithms, has lead to significant improvements from the point of view of both producers and consumers. The ability to handle massive data sets about prices, costs, consumer demand, competitors choices, *et cetera*, enabled firms and consumers to achieve results beyond what is possible for human beings. Some of these effects have a positive impact not only on single firms or buyers, but also on competition itself.

2.1 Supply-side efficiencies

On the supply side, producers may exploit algorithms for two purposes, to optimize their business process and to gather predictive analytics. Such technology makes firms more efficient due to the use of optimization algorithms that allow them to reduce production and transaction costs, as well as set the best price to maximize profits. Labor costs can be significantly reduced by replacing human workers with AI algorithms and machines, and by helping managers make faster and better decisions. They can also improve the way in which the available resources are used and improve the management of the inventory.

They also gather information about past events and use it to forecast future events; in particular, they are useful to predict demand, price changes by competitors, evaluate risk, and calculate consumer preferences. Unlike humans, algorithms can manage large sets of data and adjust immediately when there is a shock in the supply or demand in the market. As a result, firms will face lower costs. This will be reflected by a decrease in the prices offered in the marketplace.

Besides the static efficiencies listed above, algorithms may also provide dynamic efficiencies. Algorithms help increase transparency, as they inject massive amounts of data in the market, and improve the quality of existing products and newly developed ones, due to the extremely sophisticated technologies used. This creates a ripple effect that leads to constant innovation in data-driven industries. Overall, there is a positive effect for suppliers, but also for competition itself, as the industry is more efficient in the production and creation of goods and services.

2.2 Demand-side efficiencies

On the demand side, consumers benefit from the lower prices offered due to the efficiencies of the supply side. They can also make use of algorithms that help them make purchasing decisions.

Some basic algorithms provide consumers with information useful to make better decisions. For example Kayak, Expedia, and Skyscanner collect and provide information about flight prices so that consumers know when and where it's cheaper to buy tickets. Others, such as TripAdvisor and Yelp, offer information about the quality of the service. More sophisticated algorithms predict prices based on past events, or even use personal information to narrow down the choices based on personal taste.

Decisions can be made much faster, and algorithms have the ability to compound a much larger set of options and variables than the human brain. This level of sophistication allows for a reduction of information and transaction costs, and helps avoid consumer biases. This leads to a stronger competitive pressure on firms and thus a greater efficiency can be reached overall.

Chapter 3

Anti-competitive Effects of Algorithms

As most economic phenomenons do, innovations in AI technology come at a cost. This cost can be represented by the growing existence of collusion in industries with a high presence of algorithms. Pricing algorithms, which are the main area of concern for competition authorities, raise two potential issues. First, they might facilitate the management of an already existing agreement. Second, they increase the likelihood of tacit collusion, which would not have been possible without such technology.

3.1 Collusion

To understand what is collusion, we start from the assumption that firms seek to maximize their profits. In a perfectly competitive setting, prices are equal to marginal costs, all firms make zero profit, and the economy reaches the efficient outcome. If competitor firms were to act together as a single dominant firm, i.e. form a cartel, they could increase their profits. To achieve such result, competitor firms in the same industry will enter a horizontal agreement.

Cartels work like a monopoly: firms have market power that allows them to decide the quantity and price to fix in the market. This causes a decrease in consumer welfare due to the higher prices charged. However, collusion leads to inefficiencies that are even worse than those caused by monopolies: a monopolist can benefit from economies of scale, whereas coordinated, but independent, firms do not. Furthermore, collusive firms are discouraged to innovate, as creating a new product or improving an existing one is in contrast with the agreement. High prices and little market innovation, therefore, lead to a decrease in society's total welfare which explains why explicitly agreeing to form a cartel is regarded as an illegal activity in most jurisdictions.

There are several ways in which firms can enter such agreement. The most common one is price fixing - when firms agree to set the same supracompetitive price. As we will see later, algorithmic collusion refers only to this kind of agreement, as it is the easiest to manage and control. Firms could achieve a similar outcome by restricting output, i.e. by agreeing to limit the supply of a good or service; having a lower supply allows firms to increase prices and thus increase profits. The third way is through market sharing, which is an agreement on how competitors will split the market or customers among themselves. Lastly, bid rigging allows firms to collude by agreeing on who is going to win an auction. No matter which of these methods firms decide to use to manage the cartel, competition is still going to be weakened.

3.1.1 Tacit collusion

As mentioned before, collusion is regarded as illegal. It is important, nonetheless, to distinguish between explicit collusion, when there is express communication between businesses about the agreement, or implicit (i.e. tacit), when firms coordinate into creating a cartel without explicitly stating it. Although only explicit collusion is illegal, both kinds have the same negative effects on markets and, accordingly, neither should be underestimated. As a matter of fact, tacit collusion might be even more worrisome for competition authorities, as it cannot be sanctioned.

Tacit collusion is not as unrealistic as it sounds: in highly dynamic markets—i.e. when there is repeated interaction between firms—it is a relatively common phenomenon. In order for such agreement between competitors to arise, it is essential to establish a retaliation mechanism that penalizes firms that decide to deviate from the collusive agreement. Such condition comes with two requirements. First, the loss that the cheating firm will incur into must be large enough such that it would prevent deviations. Second, it must be in the non-cheating firms' best interest to finalize the retaliation. Without this kind of mechanism, or without an explicit agreement, it is not feasible to form a cartel.

3.1.2 Relevant characteristics for collusion

One of the crucial steps to understand in which industries there is a high risk of explicit or tacit collusion is by analyzing the relevant market factors. First, we have characteristics related to the structure of the industry, such as the number of firms, barriers to entry, and transparency. Then, we consider the factors related to the demand side the supply side of the market. All of these characteristics are critical because they determine how the market participants will behave in the long run, hence how much emphasis they should put in present and future profits.

Structural characteristics

The number of firms in a market is relevant for collusion in different ways. It is easy to imagine that coordinating many parties is more difficult, especially when the agreement is tacit. In addition, when there are more competitors, each firm has a smaller fraction of the market: this means that each firm has a greater incentive to deviate since the gain will be greater and in the long-run each firm gains a smaller benefit from the collusive profit. Overall we can conclude that as the number of competing firms increases, collusion is less sustainable.

Intuitively, we could think that collusion is more likely to form in industries with symmetric market shares, since firms with low market shares are more likely to gain from deviating. Nonetheless, different market shares among competing firms are often the reflection of asymmetries in marginal costs or differences in the good/service provided. We will look at this later.

With lower entry barriers, it is difficult to sustain collusion. Supra-competitive prices encourage new firms to enter the market offering a lower price, which would make collusion unprofitable. Furthermore, knowing that in the future new firms might enter the industry impacts the long-run sustainability of collusion, since the cost of deviating might be reduced.

Collusion is also facilitated when interactions are repeated and frequent. This is true because firms can react faster in response to a deviation of one of the competitors, and thus the retaliation would take place immediately. Firstly, it is very important to understand that tacit collusion is only possible in a setting where firms compete repeatedly. Second, if the interactions are not frequent, then retaliation would only happen in the far future, hence hindering collusion.

Frequency of interactions is just as crucial as the presence of enough information in the market to understand what the other firms are doing. If firms did not know immediately the price changes of the competitors, then it would be very difficult to sustain collusion and to punish deviation. In particular, it is very important that the market is stable and thus it is easy to detect cheating. The lack of transparency in the market would not make collusion impossible, but only harder to sustain.

Demand-side characteristics

Suppose that the number of market participants is not going to change in the future. If the market is expanding, then this means that each existing firm will earn a higher profit in the future. Therefore, since the profit gains of deviating today are very small with respect to the costs of deviating tomorrow, collusion is more sustainable when demand is growing.

Yet, collusion is less sustainable when there are frequent demand fluctuations in a given market. This can be explained with the opposite example: when the business cycle is at its peak, and demand will soon decrease, the gains from deviating are extremely high while costs of retaliation are minimal. When fluctuations are more significant, collusion is harder to sustain. When business cycles are predictable, for instance they are seasonal, firms know exactly when demand is at its highest and will thus deviate then; conversely, when they are random it is harder for firms to predict the optimal time to deviate. Instead, if demand is stable overtime, there will be no occasions in which firms are prone to cheat more than usual.

Supply-side characteristics

Innovative markets create uncertainty about future profits: firms do not know what to expect or when a firm, newly entering or already in the market, will provide a better or cheaper good than them. When this happens, it is possible that the collusive price is no longer the best choice for consumers, which will switch to the new option available for them. Hence, collusion is less sustainable in innovative markets.

This issue is particularly related to asymmetries. If we consider an industry with substantial cost asymmetry, we can imagine that agreeing on a fixed price can be difficult. Firms that can produce at a lower cost will be more inclined to deviate, considering that they could offer a price that is marginally below the other producers' marginal cost and accordingly cut them all off the market. A possible solution would be sharing the market unequally, but according to the firms' technology and costs. However, this is implausible in a tacit collusion setting.

Usually, in a given industry, the goods and services produced tend not to be homogeneous. In this case, firms can be involved in vertical differentiation or horizontal differentiation. The first refers to a situation in which some products are better than others in terms of quality. Costs and prices tend to be higher for those who produce higher-quality goods, which implies that most likely they would have to settle to a low collusive price that does not reflect their quality: they are in fact incentivized to deviate under this scenario. Collusion is thus less sustainable when high-quality producers have a high competitive advantage. On the other hand, the effect of horizontal differentiation, i.e. differentiation not in terms of price or quality but in terms of characteristics that determine a specific target to sell to, seem ambiguous.

Algorithms and likelihood of collusion

The presence of algorithms in an industry is able to change market conditions. As a result, they may intensify or reduce the effect that market characteristics have on the sustainability of collusion, as illustrated in Figure 3.1.

They have an ambiguous effect on number of firms and barriers to entry. Because in most markets characterized by an intense use of AI technologies there are only few firms, we would imagine that algorithms actually enhance collusion. But it is actually ambiguous, because in most cases it is the presence of natural barriers to entry that allows for such a small number of suppliers. The effect of algorithms on barriers to entry also seem to be unclear. On one hand, this kind of technology allows existing firms to detect market threats immediately; on the

Table 3.1: Algorithms and likelihood of collusion

Relevant factors for collusion		Impact on the likelihood of collusion	Further impact caused by algorithms
Structural characteristics	Number of firms	Negative	Ambiguous
	Barriers to entry	Negative	Ambiguous
	Market transparency	Positive	Positive
	Frequency of interactions	Positive	Positive
Demand-side characteristics	Demand growth	Negative	Neutral
	Demand fluctuations	Negative	Neutral
Supply-side characteristics	Innovation	Negative	Negative
	Cost asymmetries	Negative	Negative
	Product differentiation	Negative	Negative

other hand, potential entrants have plenty of information about market analytics that improves their certainty. The most interesting aspect is probably that, overall, algorithms reduce the relevance that the number of firms has on the likelihood of collusion.

The most alarming effect for policy makers is that algorithms enhance market transparency and frequency of interactions. The former characteristic obviously benefits from the presence of technologies that need massive amounts of real-time data, but also from the ability of AI technologies themselves of understanding what is going on in the market in a way that humans could not do. The latter is enhanced because algorithms are capable of reacting to market shocks automatically, so that there are no time lags between interactions. As Chapter 4 will display, authorities can use innovative tools that alter market conditions to counteract these effects.

Although consumers can benefit from the existence of algorithms, it can be assumed that the effect on the demand side is not strong enough to have a significant impact on market conditions.

On the supply side, algorithms tend to reinforce the effects analyzed above. First, innovation is further pushed by the presence of such complex technology. Second, such innovation allows firms to differentiate their production processes, hence cost asymmetries, and their products.

3.2 Types of algorithms used to collude

Having analyzed the characteristics that facilitate or complicate collusion, we can now understand the four types of pricing algorithms used for collusion, described by the OECD (2017), and why some of them will be used in markets with certain characteristics.

3.2.1 Monitoring algorithms

In a given market it might be a difficult task to manually collect information about each firm. Even when prices are available to the public, there might not be full transparency. For this reason, monitoring algorithms facilitate collusion. As their name suggests, their role is to collect data about competitors, namely the prices they set, and detect any form of deviation, and eventually design immediate retaliation. Unlike traditional cartels, algorithms gather massive amount of data and are able to adjust information in real time. Since these algorithms are very reactive, firms do not have any incentive to cheat. As illustrated in Figure 3.1, firms that implement this kind of algorithm will keep using the collusive price, $\bar{p}$, as long as all the other firms do as well. Otherwise a price war will begin.

Monitoring algorithms can only be implemented when an explicit agreement has already taken place, as they require firm managers to set a specific benchmark, i.e. the collusive price.

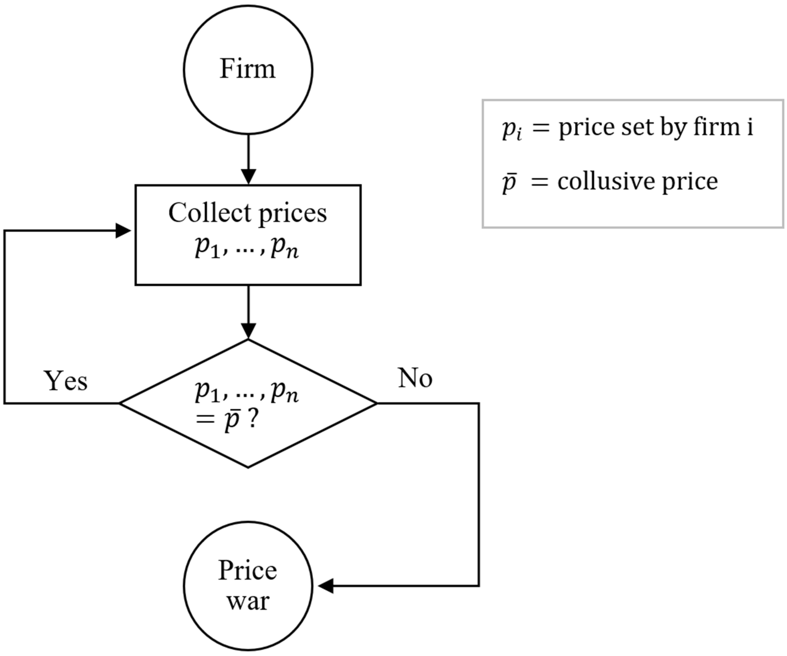

Fig. 3.1: Monitoring Algorithms. (Source: OECD (2017), 27)

3.2.2 Parallel algorithms

In very dynamic markets, where demand and supply adjust frequently, it might be challenging to sustain any form of collusion, as it would require persistent communication between firms. Since this behavior is extremely risky, firms could decide to implement algorithms that automatize the exchange of information. Parallel algorithms can, therefore, help firms in coordinating parallel behavior. This can be achieved in many ways; for instance firms could use the same third-party algorithm (*Hub and Spoke*[1]), or they could automatize their pricing strategies with similar algorithms.

[1]Refer to section 3.3.2

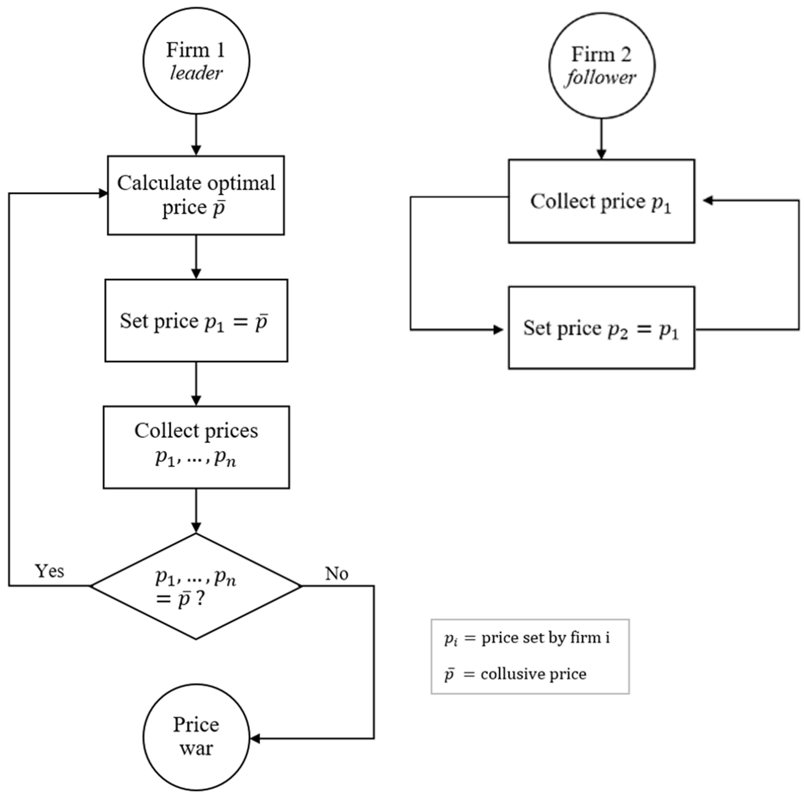

Fig. 3.2: Parallel Algorithms. (Source: OECD (2017), 29)

When firms use analogous algorithms, a simple way to reach the collusive outcome is by using a tit-for-tat strategy[2]. Follower firms would use pricing algorithms to track in real time the movements of the leader, which would be responsible for designing the dynamic pricing algorithm that sets the collusive price, as shown in Figure 3.2.

[2]In game theory, this strategy was analyzed in iterated prisoner's dilemma games. An agent will initially cooperate, then replicate the opponent's reaction. Thus, agents will continue to cooperate as long as the others do as well.

3.2.3 Signalling algorithms

In markets where firms are heterogeneous, namely they have asymmetric market shares, differentiated products, and are of different sizes, it might be challenging to coordinate a cartel. Instead of simultaneously setting the same price to indicate their will to collude, they could decide to reveal their intent by sending signals or price announcements. As illustrated in Figure 3.3, firms would set the supracompetitive price only if every other firm has sent the same signal.

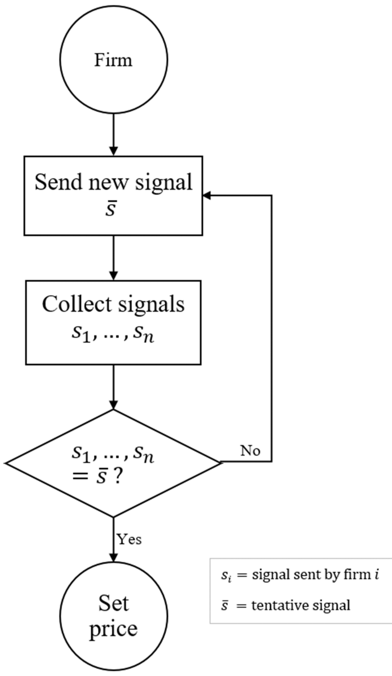

Fig. 3.3: Signalling Algorithms. (Source: OECD (2017), 31)

In traditional markets signalling comes with a cost. Suppose a company decides to raise its price in order to signal its competitors; if they do not receive the signal, or if they willingly decide not to participate, the firm loses profits and sales. The signalling firm might even decide to wait for the competitors' reactions, risking that it will never come. In this context, algorithms may reduce or even eliminate this cost by creating signals that are very quick and could not be exploited by customers.

3.2.4 Self-learning algorithms

Self-learning algorithms use AI technologies, namely machine learning and deep learning, to attain the intended goal[3].

The algorithm is never told specifically how to reach it, in fact it uses experience and results to constantly adjust and improve. As Figure 3.4 shows, raw inputs are processed in a "black box", which works like a faster and more efficient human brain. Very often the result is that the algorithm determines that the best profit maximizing strategy is collusion.

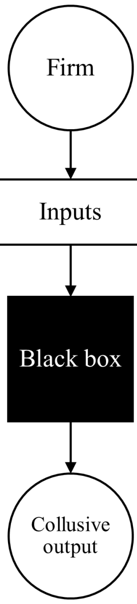

Fig. 3.4: Collusion as a result of deep learning algorithms. (Source: OECD (2017), 32)

[3]This goal is usually to maximize profits, as we will see later in the *Autonomous Machine* scenario.

3.3 Scenarios

According to Ezrachi and Stucke (2017), there are four scenarios in which algorithms are used to collude, each with a different degree of complexity of computer algorithms and each raising different challenges for competition authorities. In the first two situations, *Messenger* and *Hub and Spoke*, computers help to orchestrate a cartel that is either previously arranged, or implicitly agreed on. Contrarily, in the cases of *Predictable Agent* and *Autonomous Machine*, algorithms are used to collude tacitly.

3.3.1 Messenger

In this first basic scenario, algorithms are merely used to assist humans in their will to collude with competitor firms. After an explicit agreement to form such cartel, computers simply execute the instructions that they are given. In this sense, they act as messengers by monitoring and enforcing the agreement designed by the firm owners. This situation is characterized by the use of monitoring algorithms that let firms know if anyone has decided to change their price, which is an indicator of deviation from the agreement.

This is the most simple setting that antitrust authorities have to face, as it is not highly different from any other traditional cartel. The main concern might be that algorithms simplify the management of such agreement.

3.3.2 Hub and Spoke

Under a traditional *Hub and Spoke* scenario, a person or an organization individually contacts all the participants to coordinate in an illicit agreement, as it happens in some drug cartels.

Here the colluding firms (i.e. the spokes) will refer to the algorithm (i.e. the hub) to determine the market price. Each firm is involved in independent transactions with the central algorithm; there is no horizontal agreement, but rather a series of vertical agreements between the single spokes and the hub. Unlike the first scenario, the algorithm is not used merely to facilitate a behavior that could be implemented without it, but it is the algorithm itself that makes collusion possible.

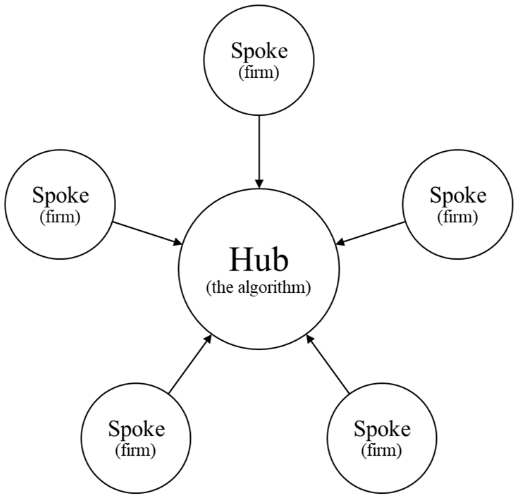

Fig. 3.5: Hub and Spoke Model

In many cases, firms choose not to develop their own pricing algorithm, as it is very expensive and resourceful. Instead, they decide to outsource and use a third-party algorithm. If firms end up using the same algorithm, intentionally or not, it is not hard to imagine that the pricing strategies will align. Even if there is no exchange of data, they use the same "brain" to determine their prices, and thus we end up in a *de facto Hub and Spoke*.

It is also possible that firms know that they are using the same algorithm as their competitors, and they know that their competitors are also aware of it. Therefore they could decide to provide the hub with precise information about their pricing decisions knowing that it will compile their data and their competitors' data to form a cartel. This is an *algorithm and data-fueled Hub and Spoke.*

Furthermore, we could have a platform algorithm that allows suppliers to determine a unique price and result in a *platform Hub and Spoke.* For instance, Uber[4] drivers are brought together by the app, which gives them a fixed price for their service. Although it might enhance competition as it challenges other forms of rides-sharing services, it actually creates a sort of collusion within the independent drivers of the company.

3.3.3 Predictable Agent

Unlike the two scenarios aforementioned, under a *Predictable Agent* setting there is no explicit or implied agreement. Each firm designs its algorithm independently for a specific purpose, for instance to fix the best prices. Among other things, the algorithm will deliver predictable outcomes and react to market changes.

A widespread use of this kind of algorithm in the industry has two effects. First, algorithms will engage in predictive analytics to understand the pricing patterns of their competitors; hence the demand for data and transparency in the market intensifies. Second, when many firms use algorithms the supply of information about prices increases. As the market gets flooded with data and transparency rises, algorithms will be able to simultaneously determine a price and tacitly collude.

[4] Uber Technologies, Inc. provides a variety of services. The company is most notably known for their ride-sharing service, which matches drivers with riders, similar to taxicabs.

3.3.4 Autonomous Machine

In this last possible scenario, competitors unilaterally implement the use of a self-learning algorithm in order to reach a specific target, like maximizing profits. If the algorithm is complex enough, through the use of AI technologies, it will experiment and learn on its own to best way to reach such goal. If it determines that the optimal strategy is tacit collusion, the algorithm will independently pursue it. This scenario is possibly the most complex one, as it assumes that full responsibility for reaching the collusive outcome is to be attributed to independent machines.

Chapter 4

The Role of Competition Authorities

Nowadays most developed countries have a regulatory body that enforces competition policy[1]. Such institutions aim at preserving a healthy competitive environment that allows to maintain static and dynamic efficiencies and foster growth. Competition laws, also known as antitrust laws, ensure that firms do not engage in behavior that is harmful to the economy and society; they establish sanctions that act as a deterrent to future violations. Cartels are one of the main areas of concern for economists and legal scholars because of their effects on prices and welfare as described in Chapter 3.

Algorithmic collusion may raise concern in competition authorities in two ways. On one hand, scenarios such as *Messenger*, *Hub and Spoke*, and possibly *Predictable Agent* see firms as liable in coordinating just like in any other tacit collusion setting[2]. On the other hand, in a *Autonomous Machine* scenario

[1]According to Aydin (2016) more than 130 jurisdictions feature at least some sort of law that protects market competition.

[2]Refer to sections 3.3.1 through 3.3.4

economists and legislators are still unsure on the accountability of firm managers. Whether traditional enforcement tools are suitable for the digital sector is still debated. In the following sections we will go through the conventional approaches, as well as newer proposals.

4.1 Traditional approach to collusion

A traditional approach to this problem signifies redefining what is an agreement, deciding whether tacit collusion should be regulated at all, and questioning who is liable for the behavior of algorithms. Nevertheless, even if competition authorities address all of these issues, it is unclear if it will be enough to counteract the rise in anticompetitive prices among digital markets. The presence of algorithms makes scholars wonder if classic oligopolistic behavior should be regulated as well. Given that algorithms coordinating on their own makes it possible to reach collusion without any agreement between firms, the problem of liability arises: should managers be held responsible for such outcome?

4.1.1 Defining agreements

In order to regulate cartels we need to define precisely what is meant by "agreement". Different jurisdictions provide different definitions.

In the European Union, Article 101 of the TFEU states that "*all agreements between undertakings, decisions by associations of undertakings and concerted practices which may affect trade between Member States and which have as their object or effect the prevention, restriction or distortion of competition within the internal market*" are prohibited. It does not explicitly state what those agreements or concerted practices are, leaving room to interpretation. In practice, courts have expressed in the past that there needs to be a clear intent to collude, as well as manifestation of such intent[3]. Under this approach, both explicit and implicit cartels can be sanctioned.

In the US, under Section 1 of the Sherman Antitrust Act, collusive agreements are defined as "contract", "combination in the form of trust or otherwise", or "conspiracy". The Supreme Court has, however, declared that there must be a common understanding and a shared commitment to pursue a collusive scheme in order to fall under the definition; in addition, courts have stated that there must be proof of coordination between the parties, and that mere oligopolistic interdependence is not enough.

4.1.2 The oligopoly problem and tacit collusion

Literature has long recognized the issue of the "oligopoly problem"[4], which essentially acknowledges the risk that highly concentrated and transparent oligopolies may result into tacit collusion if the firms take advantage of the repeated interactions.

Since it is considered to be mere classic oligopolistic behavior it is not illegal *per se*; however, antitrust authorities do not ignore the negative effects on welfare. Two solutions have been adapted: *ex-ante* merger controls, that ensure that no structural changes facilitating collusion in the market take place, and *ex-post* rules, aimed at inhibiting oligopolistic interdependence.

It is important to realize that the conditions necessary for tacit collusion to be sustainable are rarely detected. However, the presence of algorithms furthers the

[3] "The concept of an agreement (...) centres around the existence of a concurrence of wills between at least two parties, the form in which it is manifested being unimportant so long as it constitutes the faithful expression of the parties' intention". Case T-41/96, Bayer AG v Commission of the European Communities (2000)

[4] This expression seems to appear for the first time in an article of 1969 by Posner.

possibility of such anticompetitive outcome to arise, and it is deemed to increase in the future. In the case of data-driven markets, antitrust authorities could set lower thresholds to impose *ex-ante* merger controls and *ex-post* rules.

4.1.3 Liability

In determining the liability for tacit collusion there are three options. The first is to hold no one accountable for it; it is impracticable as it would essentially give free permission to act in an anticompetitive way. The second and third option are to hold either the pricing algorithms or the firm owners responsible; the issue at hand is that with the growing ability of AI technologies to make decisions on their own, it might be unclear whether humans actually had the intention to reach the collusive outcome. Even if it is determined that humans had absolutely no intent to collude, holding machines liable is illogical: what is the point of sentencing a piece of technology if it cannot pay for damages nor experience any sort of punishment?

Looking at the four scenarios analyzed in the previous chapter it can be said that in the *Messenger* setting, since the firms have agreed on such cartel like in any other traditional setting, the managers and directors who made the decision are liable. In the *Predictable Agent* and *Hub and Spoke* categories, even if there is no evidence of an actual agreement, it is enough to prove that there was an anticompetitive intent in order to hold the firm owners liable. The line becomes blurred in the case of the *Autonomous Machine*, where there is unclear liability since there is no proof of preexisting agreement or anticompetitive intent.

4.2 Alternative tools

The traditional legislative approach is not the only feasible practice to reduce the growing rise of algorithmic collusion. There are several countermeasures to reduce the possibility of such outcome, in particular scholars propose innovative regulation on the market and on algorithms.

4.2.1 Regulating the market

Under this approach, authorities would not make tacit collusion illegal, but rather unfeasible. To do so, they would need to improve the research in markets where they detect some inefficiencies and there is a high concentration of AI technologies. In particular, transparency, frequency of interactions, and market concentration seem to be the most relevant factors to analyze.

Ezrachi and Stucke (2017) propose an "algorithmic collusion incubator" used to better understand under which conditions algorithms tacitly collude. The incubator could test whether decreasing the speed and the number of times firms change prices in a given market has any impact. It could also tackle transparency, to determine which kind of information leads to coordination.

To reduce frequency of interactions, authorities could for instance decide to impose a limit to the amount of times per day that firms can match the competitors' prices. Alternatively, they could decide to impose a time lag that is mandatory for price increases, but not for price decreases. When applying these solutions, it should be important to focus on consumer welfare, in order to not undermine it when setting up such policies.

Policy makers could also decide to reduce transparency in order to make collusion less sustainable. By all means, they should be careful in determining what kind of information is beneficial only to producers. If restrictions involve also knowledge that benefits consumers, this policy could have a detrimental effect to the overall welfare. One way would be to impose restrictions on what kind of information can be published online.

To tackle market concentration, antitrust authorities could decide to reduce entry barriers in order to encourage entry of new firms in the market. One solution would be to sponsor a firm with an unsettling market strategy or technology that would interfere with the normal course of action of the given market, or even sponsor a consumer-owned cooperative that allow for supra-competitive profits to be redistributed to purchases.

4.2.2 Regulating algorithms

Another way to tackle algorithmic collusion is through the regulation of algorithm design[5]. By applying the concept of "compliance by design"[6] the architecture of algorithms themselves would ensure that such technology follows a certain set of guidelines so that they do not end up colluding. For instance, some prerequisites could be that algorithms would need to ignore price changes set by their consumers, or that they could not disclose sensitive information to the public. This implies that algorithms need to be analyzed before they are allowed to be implemented through an auditing system. This solution seems particularly inapplicable to the case of self-learning algorithms, which would be able to bypass these rules.

[5]Such approach can be applied to issues that go way beyond the problem of tacit collusion.
[6]See Vestager (2017)

Conclusion

Innovation, artificial intelligence, and algorithms are starting to disrupt the way in which digital markets operate. They offer a variety of benefits that may deceive us into believing that surely the overall effect is positive: increased profits for firms—thanks to the ability to optimize more efficiently the business process and use predictive analytics to gather information inaccessible by simply using human intelligence—and increased consumer welfare—as a result of lower prices and greater product choice.

In spite of these advantages, market analysts are worried that the way in which pricing algorithms operate may undermine competition. One issue is that, given their use of massive amounts of data and their quickness in responding to market changes, they increase overall transparency and frequency of interaction between firms in the industry, two of the main characteristics that are crucial for the development of tacit collusion. Not to mention that such complex technologies are able to create the conditions for which they collude on their own. This is the case especially for self-learning algorithms, where they are able to collude even without the intent of the firm managers.

At the moment, there is no clear path to solve algorithmic collusion. The traditional legislative approach, already implemented by most developed jurisdictions, stresses the definition of horizontal agreement and the liability for reaching the collusive outcome. This method, however, may not be enough even if antitrust authorities decide to implement the tools already in place for classical tacit collusion, namely *ex-ante* merger control and *ex-post* rules.

Each of the four scenarios presented by Ezrachi and Stucke (2017) needs a different strategy. The *Messenger* scenario and possibly *Hub and Spoke* seem to be less of a concern for competition authorities, as firm owners could be held accountable for deciding to coordinate. This is not the case, however, in the *Predictable Agent* and *Autonomous Machine* categories, where there is no direct proof that firm had decided to implement supracompetitive prices. The latter scenario in particular seem to be the most challenging under antitrust laws, as it raises ethical questions regarding the relationship between humans and machines. The liability of firm managers is unclear in most cases, as machines are able to decide independently that colluding is the profit-maximizing strategy. The most feasible solution seem to be tackling the issue of algorithmic collusion *ex-ante* by regulating markets and algorithms in a way that they do not allow for such collusive outcome, through the modification of market structure and prerequisites necessary in order for algorithms to be approved by an auditing system.

Whether these alternative solutions are enough or not is still unclear. What is for sure is that the way forward seems to be the one of research and improvement of market conditions, through policies that go beyond the traditional legislative approach.

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