

ALGORITHMIC COLLUSION IN THE STOCK MARKET

CONLUIO ALGORÍTMICO NO MERCADO DE AÇÕES

COLUSIÓN ALGORÍTMICA EN EL MERCADO DE VALORES



10.56238/revgeov17n1-115

Alan Sousa de Andrade¹, Edson Takeshi Konda Nakamura²

ABSTRACT

This article aims to analyze algorithmic collusion in the stock market and its competitive implications. Recent studies warn that machine learning algorithms may possess the capacity to generate facilitating factors for tacit collusion among market operators. This could lead to unlawful practices such as creating artificial conditions for the demand, supply, or price of securities, price manipulation, fraudulent operations, and inequitable practices. This study intends to contribute to the initial discussions regarding the risks of algorithmic collusion.

Keywords: Antitrust Violations. Algorithmic Collusion. Stock Exchange. High-Frequency Traders (Hfts).

RESUMO

O presente artigo tem por objetivo analisar a colusão algorítmica no mercado de bolsa e suas implicações concorrenenciais. Recentes estudos alertam para o risco de os algoritmos de machine learning possuírem a capacidade de gerar condições ou fatores facilitadores de colusão tácita entre operadores de mercado, com vista a práticas de criação de condições artificiais de demanda, oferta ou preço de valores mobiliários, manipulação de preço, realização de operações fraudulentas e uso de práticas não equitativas. Espera-se com este estudo contribuir para o início de discussões a respeito do risco de colusão algorítmica.

Palavras-chave: Infração à Ordem Econômica. Colusão Algorítmica. Bolsa de Valores. High-Frequency Traders – Hfts.

RESUMEN

Este artículo tiene como objetivo analizar la colusión algorítmica en el mercado de valores y sus implicaciones competitivas. Estudios recientes advierten que los algoritmos de aprendizaje automático pueden tener la capacidad de generar factores facilitadores para la colusión tácita entre los operadores del mercado. Esto podría dar lugar a prácticas ilícitas, como la creación de condiciones artificiales para la demanda, la oferta o el precio de valores

¹ Graduated of Production Engineering. ESEG (ETAPA Group). University of Coimbra. Portugal.
E-mail: alansousa220@gmail.com

² Master's student in Law. Pontifícia Universidade Católica do Paraná (PUC-PR).
E-mail: edson.takeshi@pucpr.edu.br



mobiliarios, la manipulación de precios, operaciones fraudulentas y prácticas inequitativas. Este estudio pretende contribuir a las discusiones iniciales sobre los riesgos de la colusión algorítmica.

Palabras clave: Infracciones Antimonopolio. Colusión Algorítmica. Mercado de Valores. Operadores de Alta Frecuencia (Hfts).



1 INTRODUCTION

The versatility and flexibility of manufacturing processes, stemming from the migration to cyber-physical systems (KOCSI, OLÁH, 2017) have inaugurated Industry 4.0 (HOFMANN, RÜSCH, 2017). This transition becomes particularly significant as many human activities are increasingly performed by machines powered by Artificial Intelligence (AI), which can learn independently of prior human determination.

This necessary proliferation of process digitalization brings about the subsequent utilization of algorithms by economic agents in their operations. In this context, Stucke and Ezrachi (2016) observed the emergence of a new power driven by self-learning algorithms used to optimize business decisions and automate processes – often in pursuit of economic advantages – thereby impacting traditional market structures.

Naturally, the exponential development of AI in conjunction with Big Data³ and its implementation within business environments will raise complex challenges and increasingly significant antitrust and competition concerns.

Without disregarding the benefits of algorithms for economic activity, the objective of this article is to analyze the risks of tacit collusion – even when facilitated by algorithms – without intending to prohibit their use or hinder the technological advancement of algorithms.

2 ALGORITHMS: PRELIMINARY CONSIDERATIONS

The term algorithm does not have a single established concept, as it is defined according to its specific application (language, code, task, calculation, etc.). For the purposes of this article, an algorithm will be understood within the evolution of computer science:

An algorithm is a recipe, method, or technique for doing something. The essential feature of an algorithm is that it is made up of a finite set of rules or operations that are unambiguous and simple to follow (computer scientists use technical terms for these two properties: definitive and effective, respectively). [...] 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; KEIL, 2001, p. 11).

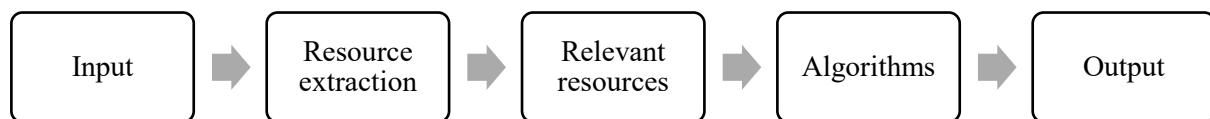
³ According to Frazão (2018, p.1): “A matéria-prima utilizada pelos algoritmos para tais decisões é o big data, ou seja, a enorme quantidade de dados disponíveis no mundo virtual que, com o devido processamento, pode ser transformada em informações economicamente úteis, que servirão como diretrizes e critérios para o processo decisório algorítmico”.



According to Costa (2018, *apud* CORMEN, 2002, p. 18), “*um algoritmo é qualquer procedimento computacional bem definido que torna algum valor ou conjunto de valores como entrada e produz algum valor ou conjunto de valores como saída*”. In this sense, algorithms have been utilized to automatically execute activities that require complex calculations alongside data processing in a more efficient and reliable manner. Traditionally, algorithms constituted a stage of the following process:

Figure 1

Traditional flow of algorithms



Source: Authors (2025)

As noted previously, algorithms lacked the capacity to process raw data owing to infrastructural and processing constraints – namely volume and velocity – necessitating prior manual feature extraction by human agents, who converted such resources into numerical datasets or strings via feature engineering.

The advancement of Artificial Intelligence and its integration with big data⁴ established a paradigm in which machines possess the aptitude to learn (machine learning)⁵ directly from data, independent of prescriptive human programming, thereby positioning algorithms as the primary drivers of the structural transformation within the field of Artificial Intelligence.

Machine learning uses a variety of algorithms that iteratively learn from data to improve, describe data, and predict outcomes. As the algorithms ingest training data, it is then possible to produce more precise models based on that data. A machine learning model is the output generated when you train your machine learning algorithm with data. After training, when you provide a model with an input, you will be given an output. For example, a predictive algorithm will create a predictive model. Then, when you provide the predictive model with data, you will receive a prediction based on the data that trained the model. Machine learning is now essential for creating analytics models. (HURWITZ; KIRSCH, 2018, p. 4).

⁴ For HURWITZ, KIRSCH (2018), the term big data refers to any data source exhibiting at least one of these four characteristics (4 Vs): (i) Volume of data; (ii) Velocity in data extraction; (iii) Variety of aggregated information; or (iv) Value capable of being generated by the data, with integrity.

⁵ Pursuant to Wilson e Keil (2018, p. 11): “*Computational hypothesis of the mind is that thinking itself is an algorithm – or perhaps, the result of many algorithms working simultaneously*”.

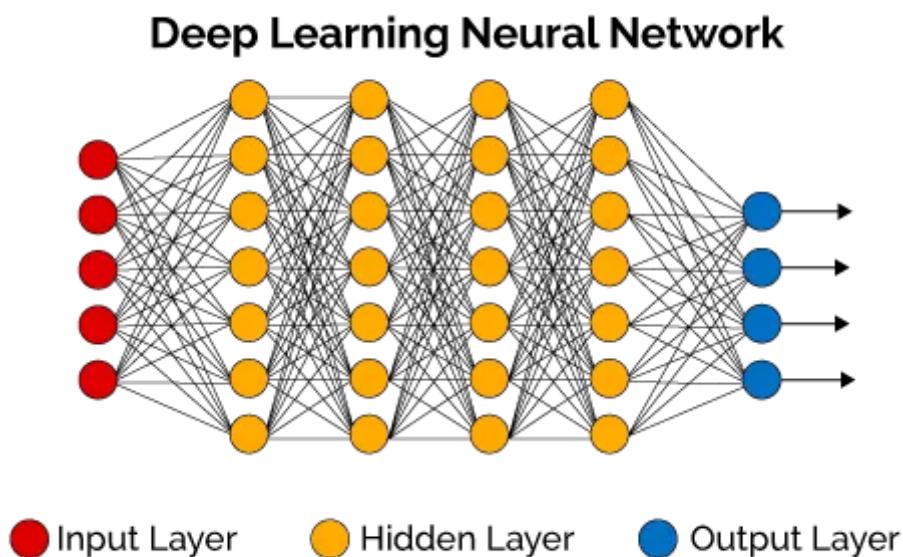


Machine learning algorithms are self-developed by the system, generated from the data to be analyzed and the intended outcomes. These mechanisms enable machines to analyze multiple variables to resolve complex problems, generate projections, and undertake decision-making processes without direct human intervention.

The specific machine learning process in which machines learn by complex software capable of creating an Artificial Neural Network – modeled after human neural networks – is termed deep learning. Furthermore, deep learning does not constitute a form of learning in the strict sense but rather refers to Artificial Neural Networks – ANN (SCHWALBE, 2018), which attempt to emulate the cognitive processing of the human brain.

Figure 1

ANN algorithm



Source: <http://deeplearningbook.com.br/o-que-sao-redes-neurais-artificiais-profundas/>

As illustrated in the figure above, data in an Artificial Neural Network (ANN) is received at the input layer, which reshapes the information. Once a predefined threshold is reached, the data proceeds to the subsequent levels, known as hidden layers. These layers modify the data according to a specific learning rule, functioning analogously to human neurons. Finally, the data reaches the terminal level, generating the output or result (SCHWALBE, 2018).

Consequently, the distinction between Machine Learning and Deep Learning algorithms lies in their learning architecture. While Machine Learning algorithms typically involve linear processes, Deep Learning algorithms are structured through a hierarchy of

complexity and feature extraction (data mining). This structure enables the latter to achieve highly rapid and precise machine learning capabilities

Deep Learning algorithms enhance procedural efficiency and foster the emergence of new business models across both the private and public sectors. However, the unpredictability of the outcomes generated by these algorithms raises significant concerns regarding the risk of improper or illegitimate practices. Such results may lead to potential infringements of the economic order.

3 METAMORPHIC EFFECTS OF ALGORITHMS: FROM EFFICIENCY TO ALGORITHMIC COLLUSION

While Deep Learning algorithms may, on one hand, foster a healthy competitive environment, they may, on the other, produce anti-competitive effects⁶, such as creating conditions that facilitate collusion.

Consequently, international authorities have warned that their implementation may act as a facilitating factor for collusive behavior among market player – a phenomenon known as algorithmic collusion.

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". (OCDE, 2017, p. 18/19).

3.1 ANTI-COMPETITIVE RISKS OF ALGORITHMIC IMPLEMENTATION

In the literature, the term collusion is commonly used to describe a form of economic conspiracy involving the adoption of any coordinated strategy or agreement among vertically or horizontally related firms aimed at joint profit maximization and the reduction of deadweight loss.

When there is an explicitly stated agreement among competing companies intended to secure supernormal profits, it is defined as explicit collusion. Conversely, when firms do not formally agree to form an economic conspiracy but nonetheless achieve profit levels similar to those of a cartel, it is considered tacit collusion.

⁶ As the ADC (2019) warns: "43. Sem prejuízo dos benefícios que o big data e os algoritmos podem trazer para o mercado, o aumento da frequência da sua utilização pode facilitar estratégias de colusão, explícita ou tácita, no mercado. A disseminação da utilização de algoritmos de monitorização e de preços é passível de aumentar a transparéncia no mercado e a frequência de interação entre empresas concorrentes".

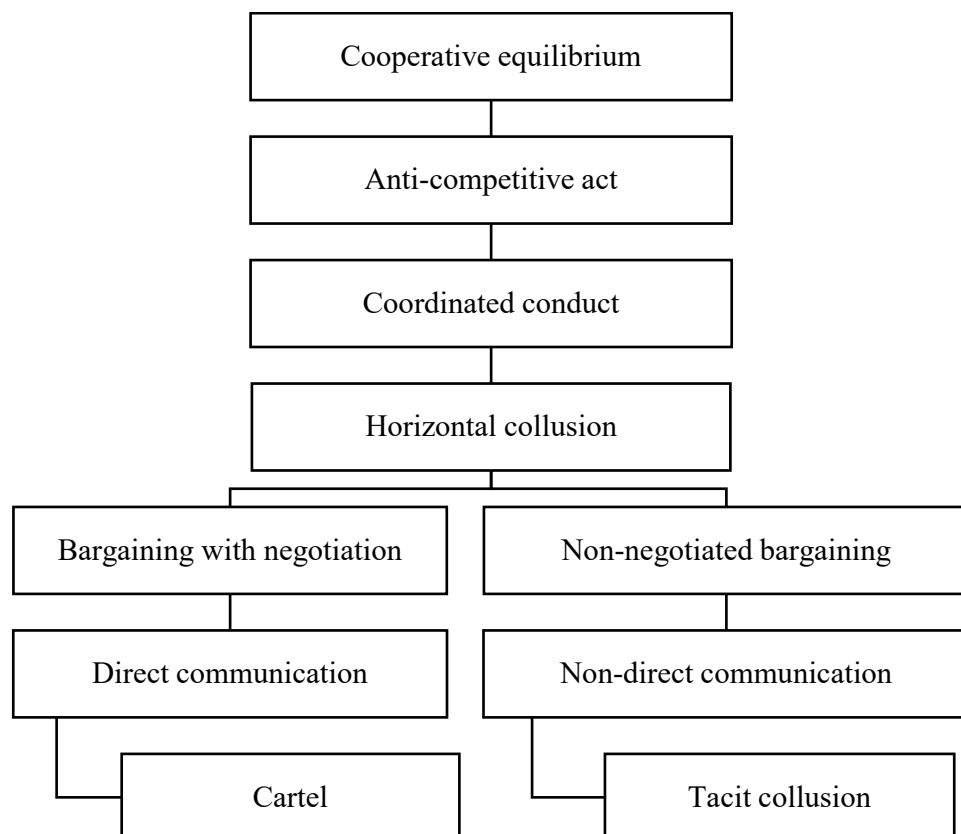


Temos duas explicações possíveis para a colusão tácita: as empresas comunicam-se entre si por meio de seus movimentos mercadológicos, como se utilizassem um código; e a outra explicação é, simplesmente, o reconhecimento da insensatez do comportamento Cournot e as empresas, então, agiriam de maneira mais adequada ao seu pressuposto de racionalidade (GICO JUNIOR, 2007, p. 269/270).

The fundamental distinction between these two forms of collusion lies in the existence of communication or interaction among competitors, as briefly illustrated in the diagram below:

Figure 2

Collusion structure



Source: GICO JUNIOR (2007), adapted

Thus, to maintain and achieve a collusive equilibrium over time, firms have a legal and functional imperative to establish a framework that enables: (i) coordination (a common policy); (ii) monitoring of said common policy; and (iii) the sustainability of the common policy, including enforcement mechanisms or sanctions.

Notwithstanding the economic perspective that distinguishes between explicit and tacit collusion, antitrust law focuses on the anti-competitive outcomes of cooperation among firms, rather than the diverse methods through which cooperative conduct is executed (such as associative contracts (*contratos associativos*), joint ventures, or restrictive practices).



Furthermore, it distinguishes these from commercial strategies that may simply be the natural and expected result of the economic rationality of independent market agents.

For this reason, tacit collusion or conscious parallelism – the outcomes of which may be identical to those of explicit collusion – proves extremely challenging for antitrust law. This difficulty stems from the law's reliance on economic models based on marginal cost analysis or other economic factors to identify a supracompetitive equilibrium (GICO JUNIOR, 2007) achieved without any communication between firms⁷.

Given these practical limitations imposed on the legal system, some jurisdictions provide that evidence of parallel conduct (such as repeated interaction, market power, and interdependence) must be analyzed alongside additional elements, known as plus factors. These include indirect communications revealing an intent to collude, concerted practices that result in reduced competition, or the implementation of facilitating practices for collusion⁸.

In this context, international authorities have warned that the use of algorithms may act as a facilitating factor for new forms of collusive behavior – forms that were previously unobserved or even impossible – conducted by firms without any express agreement or human interaction. This phenomenon, which constitutes a type of tacit collusion, is defined as algorithmic collusion.

3.2. FACILITATING FACTORS FOR COLLUSION AND ALGORITHMIC COLLUSION

Recent discussions and studies highlight the risk that algorithms may be capable of learning to create environments that facilitate collusion. Regarding the algorithms identified to date, the OECD (2017) has, in summary, correlated their use with the implementation of collusion-facilitating environments, as outlined below:

Table 1

Identified categories	Acting as facilitators of collusive factors
Monitoring algorithm	The collection and processing of competitors' information and the punishment of any deviations from the collusion.
Pricing algorithm	Parallel conduct coordination ⁹ .

⁷ As stated by Gico Junior (2007, p. 383): “Nenhum ordenamento jurídico aceitou arriscar propostas nesse sentido, e os poucos experimentos acadêmicos a testar a viabilidade desse tipo de abordagem não obtiveram resultados satisfatórios”.

⁸ Examples of facilitating practices for collusion include advance price announcements, the dissemination of costs and related information, market outlook or future performance predictions, the development of industry technical standards, product standardization, cross-licensing of patents, delivered pricing systems, etc.

⁹ It is worth noting that U.S. authorities (DOJ, 2015) have already secured convictions against poster sellers on the Amazon Marketplace who utilized pricing algorithms to implement an explicit collusion agreement.



Signaling algorithm	Disclosure and dissemination of intentional announcements of collusion.
Self-learning and deep learning algorithms	Profit maximization and readaptation to competitors' actions.

The ADC (2019) issued a report on monitoring and pricing algorithms, in which it warns that: "*Os algoritmos de preços e monitorização podem promover ou reforçar a colusão explícita, aumentando a sua frequência, duração ou extensão, por reforçar as condições de sustentabilidade interna de acordos de colusão explícitos*".

Signaling algorithms are also identified as facilitators of collusion; their objective is to unilaterally signal price announcements from one or more economic agents, in the expectation that such behavior will be mirrored by others. Furthermore, Deep Learning algorithms are distinguished by their ability to learn from and adapt to the actions of economic agents.

A peculiar characteristic of Deep Learning algorithms is their failure to disclose the underlying sources or data points that support their decision-making process. This lack of transparency hinders the detection or prevention of tacit collusion:

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. (OCDE, 2017, p. 32).

Indeed, with the development of signaling and Deep Learning algorithms, it is possible to predict the presence of non- incidental parallel behaviors – a dynamic and complex result optimized by the knowledge acquired by algorithms, including algorithmic collusion.

According to Stucke and Ezrachi (2016), algorithmic collusion can occur in four distinct scenarios:

Table 2

	Collusive conduct	Key features
1	<i>Messenger</i>	Humans agree to engage in collusion and utilize computers to execute such conduct.



2	<i>Hub and spoke</i>	Horizontally related firms use a single pricing algorithm to set their prices. There is a vertically related provider (the algorithm developer) who acts as the hub, orchestrating the collusion previously established by the competitors ¹⁰ .
3	<i>Predictable agent</i>	Developers unilaterally create algorithms with the purpose of predicting market behavior, monitoring, and adjusting prices. There is no agreement between competitors. Each firm utilizes its own pricing algorithm, the result of which is conscious parallelism performed by an algorithm.
4	<i>Digital Eye</i>	Through deep learning, machines independently learn and determine methods for profit maximization, which may result in anti-competitive outcomes regardless of human interaction or collusive agreement. In this scenario, we may not even be aware that something is wrong.

Based on the scenarios projected by Stucke and Ezrachi (2016), legal doctrine has identified market elements that increase the likelihood of algorithmic collusion occurring, categorized into: (i) structural characteristics¹¹; (ii) demand variables; and (iii) supply variables.

The assessment of facilitating factors helps to establish the degree of convergence of interests and the probability of cooperative behavior occurring in the absence of proactive (illicit) conduct, beyond mere strategic behavior (GICO JUNIOR, 2007).

Thus, based on traditional factors that facilitate collusion, the OECD (2017) developed a framework assessing the probability of algorithms enhancing or impacting such factors:

Table 3

Market features	Facilitating factors	Likelihood of algorithmic collusion
Structural characteristics	Number of players	Greater or Lesser
	Entry barriers	Greater or Lesser
	Market transparency	Greater
	Frequency of interaction	Greater
Demand variables	Demand growth	Neutral
	Demand fluctuations	Neutral
Supply variables	Innovation	Lesser

¹⁰ *Hub and Spoke* is characterized when (ADC, 2019): “os spores coordenam as suas estratégias de preços no mercado através de um fornecedor de algoritmos comum – o hub. Num cenário de hub-and-spoke é ainda possível que as empresas deleguem a maximização dos lucros conjuntos a um terceiro. Neste caso, o hub pode combinar no seu processo de determinação dos preços das diversas empresas a informação estratégica que estas lhe transmitam, internalizando o impacto que as mudanças de preço de uma empresa teriam nos seus concorrentes”.

¹¹ As structural characteristics, we have factors relating to the number of firms in a given market, barriers to entry, market transparency, and frequency of interaction.



	Cost asymmetry	Lesser
--	----------------	--------

It is noted that the ambiguous or negative effects of algorithms tend to substantially impact the structural characteristics of the market, such as market transparency and frequency of interaction, fostering an environment where collusion can be sustainable, while remaining neutral or low regarding demand and supply variables.

4 ALGORITHMIC COLLUSION IN THE STOCK MARKET

A prime practical example – characterized by transparency and frequent interactions – impacted by the ambiguous effects of algorithms is in the stock market. It is defined by an intense and constant process of electronification, where prices are transparent and securities are traded at high speeds.

According to Comerton-Forde and Rydge (2006), prior to the implementation of algorithms, an increase in price volatility and trading volume occurred at the end of each trading period during the closing auction¹², which reduced the pricing efficiency of the traded assets.

With the introduction of algorithms, it was observed that during the same closing auction period, there was a reduction in asset price volatility, resulting in overall efficiency of the pricing process.

¹² In Brazil, the closing auction currently takes place during the final five minutes of the regular trading session (from 5:55 p.m. to 6:00 p.m.), with the objective of establishing a fair price for the assets of the regular session, in accordance with the following B3's rules (2020): "*The criteria for establishing the theoretical price are described below:*

I. First criterion: The price assigned to the auction is the one at which the largest quantity of the asset or derivative is traded.

II. Second criterion: In the event of a tie in the first criterion – that is, when there are two or more prices at which the same quantity of assets or derivatives is traded – the prices that generate the minimum buy imbalance and the minimum sell imbalance are selected; within the range between such prices, the theoretical price shall be the one closest to the last traded price or, in its absence, the closest to the adjusted closing price or the settlement price of the trading session, rounded according to the minimum tick size (for derivatives only).

III. Third criterion: In the event of a tie in both the first and second criteria – that is, when there are two or more prices for which the same quantity is traded and the same imbalance is generated on opposite sides – the auction price assigned shall be the one (equal to or between the prices generating the tie in the second criterion) closest to the last traded price or, in its absence, the closest to the adjusted closing price or the settlement price of the trading session, with rounding".

Alongside the efficiency promoted by algorithms, the Brazilian Securities and Exchange Commission (CVM) highlights the risk of abusive practices through algorithms that constitute market manipulation, such as spoofing¹³ and layering¹⁴⁻¹⁵.

This issue gained prominence in 2010 with the phenomenon known as the Flash Crash, where, following an abrupt devaluation of securities in the United States, there was a rapid recovery – both without any apparent reason. U.S. authorities recognized that the actions of high-frequency traders (HFTs) contributed to the event, although they were not held responsible for its occurrence:

Os HFTs por meio de algoritmos e mecanismos tecnológicos sofisticados, processam informações em grande velocidade e operam no mercado na ordem de milissegundos, não raro assumindo posições e nas pontas vendedoras e compradoras, com o intuito de auferir ganhos com as flutuações de mercado. (Administrative Proceeding SEI No. 19957.006019/2018-26. Chairman Marcelo Barbosa. j. 1.10.2019).

HFTs enable investors to maintain “certain profits” without the need for an explicit agreement¹⁶. It is for this reason that Costa (2018) raises the concern that HFTs are not limited to the profitability they provide, but rather “*como se a aliança entre operadores de mercado e desenvolvedores de programas de computador tivesse permitido a descoberta de uma ‘pedra filosofal’ capaz de transformar algoritmos em lucros certos*”.

Beyond the risk of offenses within the scope of the securities market, price fluctuations carried out through algorithms may also constitute an infringement of the

¹³ For BSM (2017), the self-regulatory organization, responsible for the supervision and oversight of the organized markets managed by B3, the definitions are as follows: (i) *Spoofing* como a “*Prática abusiva que cria liquidez artificial com ofertas de tamanho fora do padrão do livro de ofertas com o objetivo de influenciar investidores a superar a oferta artificial e gerar negócios do lado oposto do livro. Após negócio, a liquidez artificial na forma de oferta fora do padrão é cancelada*”, e (ii) *Layering* como a “*Prática abusiva que cria liquidez artificial no livro do ativo via camadas de ofertas em níveis sucessivos de preços com o objetivo de influenciar investidores a superar a barreira criada pela camada e gerar negócios do lado oposto do livro. Após negócio, a liquidez artificial na forma de camadas é cancelada*”.

¹⁴ On March 13, 2018, the CVM issued its first conviction for spoofing (Administrative Proceeding SEI No. 19957.005977/2016-18), and on October 1, 2019, it convicted the first case of layering (Administrative Proceeding SEI No. 19957.006019/2018-26).

¹⁵ The difference lies in the fact that in spoofing, orders occur in large volumes, whereas layering consists of a set of multiple small offers. Furthermore, although these two offenses do not strictly require the use of algorithms, all cases of spoofing and layering analyzed to date involved strategies executed by algorithms, given that the actions occur in milliseconds.

¹⁶ HFTs could favor the price convergence of assets traded on different stock exchanges. While Brazil currently has a single exchange, certain assets from Brazilian or foreign issuers can be traded both in Brazil and abroad (BDRs and ADRs). Furthermore, the CVM (2019) proposed public hearings for its regulations – specifically Public Hearing Notice SDM No. 9/19 regarding the new regulation on the constitution and operation of organized market management entities. This followed expressions of interest from foreign market operators wishing to establish themselves in the country, as well as a 2012 study by Oxera Consulting Ltd. on the feasibility and benefits of potential exchange competition in Brazil.

economic order, whether through collusion between agents or unilateral conduct¹⁷ (such as spoofing and layering).

5 ALGORITHMIC COLLUSION IN LIGHT OF BRAZILIAN COMPETITION LAW

The entire analysis undertaken in this article, for the time being, constitutes a hypothetical scenario rather than a factual case in which algorithms have contributed to an actual situation of harm to the economic order¹⁸.

The apprehension of the international debate regarding the risks of algorithmic collusion within the Brazilian context, while possible, remains abstract and depends on further study and deeper exploration of the subject.

Buchain (2006) states that: “*a própria natureza do comportamento do agente econômico não admite previsibilidade absoluta, de forma a emoldurá-lo numa categoria de comportamentos sociais previamente anunciado*”.

It is no coincidence that the Brazilian Antitrust Law was structured to allow for an interpretation that adapts to the dynamics and tone of economic and social reality, whenever an act produces any of the effects – even if potential – provided for in items I to IV of Article 36 of Law No. 12,529/2011¹⁹, especially, in the case of the stock market, the use of deceptive means to trigger price fluctuations²⁰.

In this sense, in Brazil, the analysis and prosecution of eventual algorithmic collusion that constitutes an infringement of the economic order, or aims to create facilitating conditions for collusion, faces no legal obstacle regarding the application of Brazilian antitrust law.

¹⁷ For the purpose of defining the scope of this essay, analysis of unilateral conduct has been intentionally excluded.

¹⁸ The OECD (2017) highlights that: “*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*”.

¹⁹ “*Article 36. The acts under any form manifested, which have as their object or may produce the following effects, even if they are not achieved, shall constitute an infringement of the economic order, regardless of fault:*

I - to limit, distort, or in any way injure free competition or free initiative;

II - to control a relevant market of goods or services;

III - to arbitrarily increase profits; and

IV - to exercise a dominant position in an abusive manner”.

²⁰ “*Article 36. [...] §3º The following conduct, among others, to the extent that it constitutes the hypothesis provided for in the head provision (caput) of this article and its items, characterizes an infringement of the economic order:*

[...]

VII - to use deceptive means to trigger price fluctuations of third parties”.



Therefore, in the event of algorithmic collusion – whether involving human conduct – Brazilian antitrust law provides that any person²¹⁻²² is strictly liable (“regardless of fault”) for infringements of the economic order.

It must be understood that economic agents bear responsibility when relevant strategies are delegated or assigned to algorithms, even if they lack the capacity to influence the manner in which the algorithms make decisions in pursuit of an objective (e.g., profit maximization).

The challenge of this type of collusion, however, lies not in its legal classification, but in the complexity and difficulty of detecting and producing evidence or indications of the existence of collusion (whether explicit or tacit) to ultimately prove the occurrence of an algorithmic antitrust violation.

Nevertheless, the same movement must be observed within the field of Artificial Intelligence, the catalyst for algorithmic learning – especially deep learning algorithms. What remains uncertain is whether the algorithms' pursuit of an objective will solely follow a path that favors a healthy competitive environment.

6 FINAL REMARKS

The yearning for new models, sources of allocative efficiency, or more efficient methods for economic agents underpins the premise that, with the digitalization of processes, the use of algorithms will become increasingly ubiquitous.

Alongside the advantages provided by algorithms, challenges associated with algorithmic collusion also emerge. In a scenario where algorithms can create artificial price conditions, inequitable practices, and environments conducive to collusion, it is noteworthy that deep learning algorithms are capable of achieving a supracompetitive equilibrium without the need for human intent.

As previously discussed, within the field of administrative law, any algorithmic collusion is subject to enforcement by Brazilian competition authorities, given the strict liability of economic agents. However, the true challenge for authorities and scholars lies in the detection and proof of collusive practices performed or facilitated solely by algorithms, whether analyzed from an administrative perspective or in the context of other legal liabilities, such as civil and criminal.

²¹ “Article 31. This Law applies to individuals or legal entities under public or private law, as well as to any associations of entities or persons, constituted in fact or in law, even if temporarily, with or without legal personality, even if they operate under a legal monopoly regime”.

²² Apart from officers and directors, whether directly or indirectly, of the legal entity responsible for the infringement, in which case their liability shall depend on the conviction of the legal entity and the demonstration of fault or intent (*culpa ou dolo*).



Therefore, understanding algorithmic technology is essential to advancing this debate, emphasizing that tacit collusion remains to this day a subject of economic models and studies attempting to identify its existence.

Proposals aimed at preventing algorithmic collusion must be based on the following premises, among others: (i) algorithms are not necessarily instructed to perform collusion, but rather to pursue an apparently lawful objective; (ii) audit procedures will likely fail to keep pace with the exponential evolution of machine learning, or will face difficulties in obtaining audit trails of algorithmic decision-making processes (the relationship between inputs and outputs); and (iii) it will be impossible to prevent algorithms from accessing implicit, historical, and publicly available data and information.

Thus, whatever actions are taken regarding the application of algorithms in the stock market, they must be subject to thorough assessment and a cautious approach to ensure that technological development remains in harmony with the principles of the economic order.

REFERENCES

ADC. (2019). *Ecossistemas digitais, Big Data e Algoritmos*. Autoridade da Concorrência. http://concorrencia.pt/vPT/Estudos_e_Publicacoes/Estudos_Economicos/Outros/Documents/Ecossistemas%20digitais,%20Big%20Data%20e%20Algoritmos.pdf

B3. (2020). *Regras de pré-abertura/pré-fechamento/fixing*. B3 S.A. – Brasil, Bolsa, Balcão. <http://www.b3.com.br/data/files/61/04/37/49/93E566103811B566AC094EA8/Regras%20de%20Pre-Abertura%20Pre-fechamento%20Fixing.pdf>

BSM. (2017). *Workshop monitoramento de ofertas em spoofing e layering*. BSM – Supervisão de Mercado. <https://www.bsmsupervisao.com.br/Noticias/2017-04-17-Workshop-Monitoramento-de-Ofertas-em-Spoofing-e-Layering>

Buchain, L. C. (2006). *O poder econômico e a responsabilidade civil concorrencial*. Nova Prova Editora.

Comerton-Forde, C., & Rydge, J. (2006). Call auction algorithm design and market manipulation. *Journal of Multinational Financial Management*, 16(2), 184–198.

Costa, I. S. da. (2018). *High frequency trading (HFT) em câmera lenta: Compreender para regular* [Dissertação de mestrado, Fundação Getulio Vargas]. Biblioteca Digital FGV. <http://bibliotecadigital.fgv.br/dspace/bitstream/handle/10438/20720/COSTA%2c%20Isa%20HFT%20-Compreender%20para%20Regular%20%282018%29.pdf?sequence=3&isAllowed=y>

Comissão de Valores Mobiliários. (2019). *Edital de audiência pública SDM 09/2019*. http://www.cvm.gov.br/audiencias_publicas/ap_sdm/2019/sdm0919.html

Comissão de Valores Mobiliários. (2018, 13 de março). Processo administrativo sancionador SEI nº 19957.005977/2016-18 (Rel. Diretor Henrique Machado). Diário Oficial.



Comissão de Valores Mobiliários. (2019, 1 de outubro). Processo administrativo sancionador SEI nº 19957.006019/2018-26 (Presidente Relator Marcelo Barbosa). Diário Oficial.

Department of Justice. (2015). *Decisão de homologação de plea agreement, no caso United States v. David Topkins.* <https://www.justice.gov/atr/case-document/file/628891/download>

Ezrachi, A., & Stucke, M. (2016). *Virtual competition: The promise and perils of the algorithm-driven economy.* Harvard University Press.

Frazão, A. (2018). *Algoritmos e inteligência artificial: Repercussões da sua utilização sobre a responsabilidade civil e punitiva das empresas.* https://professoraanafrazao.com.br/files/publicacoes/2018-05-16-Algoritmos_e_inteligencia_artificial.pdf

Gico Junior, I. T. (2007). *Cartel: Teoria unificada da colusão.* Lex Editora.

Hofmann, E., & Rüsch, M. (2017). Industry 4.0 and the current status as well as future prospects on logistics. *Computers in Industry*, 89, 23–34. <https://isiarticles.com/bundles/Article/pre/pdf/83979.pdf>

Hurwitz, J., & Kirsch, D. (2018). *Machine learning for dummies.* IBM. <https://www.ibm.com/downloads/cas/GB8ZMQZ3>

Kocsi, B., & Oláh, J. (2017). Potential connections of unique manufacturing and Industry 4.0. *LogForum*, 13(4), 389–400. <https://www.yadda.icm.edu.pl>

Organisation for Economic Co-operation and Development. (2017). *Algorithms and collusion: Competition policy in the digital age.* <https://www.oecd.org/daf/competition/algorithms-and-collusion.htm>

Schwalbe, U. (2018). Algorithms, machine learning, and collusion. *Journal of Competition Law & Economics*, 14(4).

Wilson, R. A., & Keil, F. C. (Eds.). (2001). *The MIT encyclopedia of the cognitive sciences.* MIT Press.

