How can self-learning algorithmic pricing lead to tacit collusion?*

José María Ramos Chacón

April 2023

Abstract

The use of self-learning pricing algorithms presents numerous benefits to firms and consumers, yet also raises concerns about their potential role in facilitating collusion. This review synthesizes existing literature and examines the market conditions under which self-learning algorithms are more likely to converge on supra-competitive prices. Our analysis concludes that the likelihood of tacit collusion is heavily influenced by the specific context of each market and cannot be broadly applied to different settings. However, considering the rapid development of the artificial intelligence field, is plausible that these autonomous algorithms could instigate collusion in industries where it is currently not prevalent. Consequently, it is imperative for policymakers and regulators to remain vigilant and proactively develop appropriate safeguards and policies to ensure the preservation of competition and protection of consumer interests in the coming years

Contents

*This Literature Review was completed as part of the module (ECON0042) at University College London.

1 Introduction

In recent years, the field of Artificial Intelligence (AI) has witnessed remarkable growth in both discoveries and widespread adoption by businesses and consumers (Figure 1). For instance, in January of this year, ChatGPT achieved a milestone of 100 million monthly active users, becoming the fastest-growing consumer application in history. The best part is, this is just the prelude to an unprecedented technological revolution. This is why it came as a surprise when on March 22^{nd}, a joint statement signed by researchers from prestigious universities and laboratories, as well as tech giants' founders such as Apple and SpaceX, called for a halt to the unbridled race to develop and deploy increasingly powerful AI models observed in recent months. This appeal highlights the other side of the coin: AI presents significant risks to society, including massive job displacement and identity theft, which are growing concerns for many people (Figure 2). Another less-discussed phenomenon is AI's potential to circumvent competition laws by enabling collusion among companies without explicit communication which will be the focus of this review.

This literature review synthesizes the current understanding of how self-learning algorithms may lead to tacit collusion. From an economic perspective, collusion entails an agreement between market participants to coordinate their actions, such as setting prices, output levels, or market shares, for gaining an advantage over competitors and increasing profits (Stigler, 1964). In the case of tacit collusion, also referred to as implicit collusion, firms manage to align their practices without any explicit communication or agreements (Scherer & Ross, 1990).

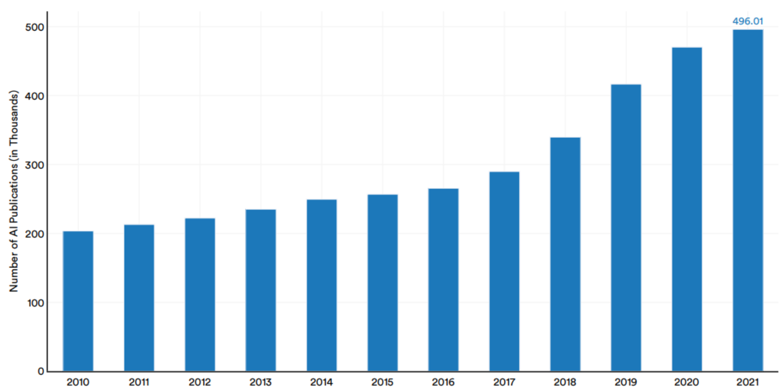

Figure 1: Number of yearly AI publications worldwide.

The detrimental effects of collusion on consumer welfare and market efficiency cannot be neglected, undermining the principles of fair competition, and causing negative consequences. Collusive behavior results in high prices, reduced output, and declining innovation, ultimately leading to lower consumer surplus and a misallocation of resources(Tirole, 1988). One prominent example of the harmful impact of collusion is the European truck cartel, where several major truck manufacturers colluded to fix prices and delay the introduction of more environmentally friendly technology between 1997 and 2011. The European Commission imposed fines of over €2.90 billion on these manufacturers for their anti-competitive behavior (European Commission, 2016). An even more compelling example of the harmful consequences of collusion on consumer welfare can be found in the case of UK hydrocortisone tablets. Tens of thousands in the UK depend on these tablets to treat adrenal insufficiency, including life-threatening conditions. Pharmaceutical companies engaged in anti-competitive practices, causing a price increase of more than 10,000%. The collusion had severe implications for patients and the NHS, with annual spending on hydrocortisone tablets skyrocketing from about £500,000 to over £80 million by 2016 (Competition and Markets Authority, 2018). These two examples underscore the pernicious impact of anti-competitive behavior on overall consumer welfare, as well as on crucial matters such as environmental preservation and public health.

In recent years, technological advancements and rapid digitalization have transformed various aspects of our lives and the global economy. One such development is the increasing prevalence of algorithms in industries such as digital marketplaces and traveling companies. Amazon experienced a significant increase in the pricing algorithms use during late 2012 and 2013, strongly suggesting widespread e-commerce adoption (Competition and Markets Authority, 2018). Furthermore, a 2015-2017 EU survey of online retailers discovered that approximately two-thirds of them employed pricing algorithms (European Commission, 2017).

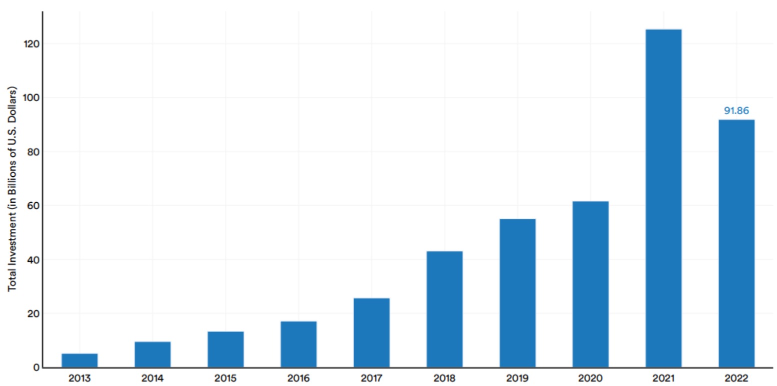

Figure 2: Number of yearly AI incidents and controversies worldwide.

An algorithm can be defined as "a step-by-step procedure for calculations" (Cormen,et al., 2009). Pricing algorithms present numerous benefits to firms and consumers, enabling real-time price adjustments based on demand fluctuations, inventory levels, and competitor pricing (Chen, et al., 2016). This increased efficiency leads to lower operational costs, better resource allocation, and ultimately improved consumer welfare through strategic pricing (Dube & Misra, 2021). However, despite these advantages, the widespread use of pricing algorithms also raises concerns about facilitating collusion. Algorithms may autonomously learn to recognize and react to patterns in competitors' pricing behaviors, ultimately resulting in price coordination (Mehra, 2016). Such unintended collusion could undermine market competition, leading to the same negative consequences associated with traditional forms of collusion (Harrington, 2018). For instance, Ezharachi & Stucke (2015) suggest that by 2014 approximately 25% of the Danish retail fuel market transitioned to using algorithms for pricing purposes, which subsequently led to a 5% increase in profit margins.

By examining relevant research and empirical evidence, this review analyzes factors driving algorithmic collusion, its consequences, and potential future trajectories. While drawing definitive conclusions remains difficult due to scarce empirical research, the rapid artificial intelligence evolution suggests increasing plausibility of algorithmic pricing collusion. Consequently, it is crucial for regulators and researchers to remain vigilant and actively investigate this topic to devise appropriate policies and safeguards that protect competition and consumer interests.

This literature review begins with a synthesis of existing literature in Section 3, discussing how the various research categories collectively contribute to a comprehensive understanding of the likelihood of tacit collusion in markets influenced by self-learning algorithm-driven pricing. Next, in Section 4, we will delve into the market factors and mechanisms affecting tacit collusion likelihood. Finally, Section 5 will present a conclusion summarizing the key findings, implications, and potential directions for future research on the topic.

2 Methodology

2.1 Scope of Review

In this literature review, the primary focus will be on self-learning algorithms, excluding rule-based algorithms from the scope of the study. This decision stems from the distinct characteristics and implications of each type of algorithm in the context of collusion (Figure 3).

Rule-based algorithms, defined as a set of explicit predefined instructions that dictate the behavior of an algorithm, are well-understood in terms of facilitating collusion. As these algorithms require explicit communication and coordination among firms, collusion arising from their use is more easily detectable and can be addressed through existing regulatory frameworks. In contrast, self-learning algorithms, which are based on artificial intelligence techniques such as deep learning and reinforcement learning, pose a unique challenge. These algorithms autonomously learn, adapt, and improve from experience and training data without requiring explicit programming, enabling them to potentially collude without clear communication or human intervention (Ezrachi & Stucke, 2015). The absence of communication complicates identifying and addressing collusion in markets using self-learning algorithms. This is increasingly pressing and intriguing, highlighting the importance of studying their implications for market competition.

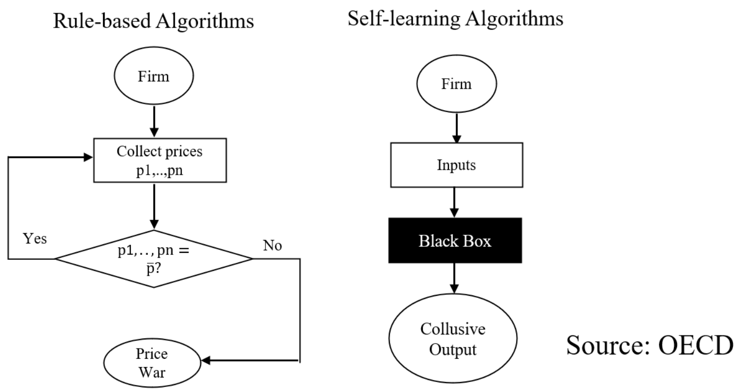

Figure 3: An illustration of a simple rule-based algorithm on the left $\bar{p}$ is the collusive price) and an illustration of a simple self-learning algorithm on the right.

This literature review focuses on getting insights from prior literature and on identifying the market conditions and mechanisms associated with algorithmic collusion likelihood. While this analysis may inform policy and regulatory decisions, it is essential to note that proposing specific regulations or policy measures to prevent collusion is beyond the scope of this review.

2.2 Categorization

Past literature on the likelihood of tacit collusion in markets with self-learning algorithms setting prices can be divided into three categories: theoretical studies, experimental studies, and empirical studies. These categories complement each other by providing a comprehensive understanding of the question. Theoretical studies lay the groundwork for understanding the mechanisms through which collusion may occur. Experimental studies test these mechanisms in simulated environments , while empirical studies validate these findings in real-world settings.

Potential contradictions and differences among the studies may arise due to varying assumptions, methodologies, and data sources. Theoretical studies often rely on simplifying assumptions that may not accurately capture real-world markets complexity. Experimental studies, while valuable in understanding the behavior of algorithms in controlled environments, may face limitations in their external validity. Additionally, empirical studies may have difficulty establishing causal relationships due to confounding factors and limited data availability.

Upon reviewing the literature on tacit collusion likelihood in self-learning algorithm-driven markets, it is crucial to investigate the market factors and mechanisms affecting this potential. The following section examines these factors, categorized into Market Structure Factors, Algorithmic Dynamics and Interactions, and Demand and Cost Factors. This categorization stems from the factors' relationship with the market's organization, firm interaction, and the conditions affecting collusion profitability and sustainability.

3 Synthesis of the current state of the literature

3.1 Theoretical Studies

These research papers focus on building mathematical models, frameworks, and logical arguments to understand the underlying mechanisms that may lead to tacit collusion when firms employ self-learning algorithms. The models often rely on assumptions about firm behavior, market structure, and algorithmic capabilities, which may differ across the different studies. For example, while some papers assume that firms have full knowledge of competitors' algorithms, others argue that complete transparency is unrealistic. These studies have explored various aspects of the problem, and when considered together, they provide valuable insights into the potential for tacit collusion arising from the use of autonomous algorithms in pricing decisions.

Ezrachi & Stucke (2015) contend that algorithms can facilitate tacit collusion by simplifying the process for companies observing and reacting to each other's pricing strategies, reducing the need for explicit agreements. Calvano et al. (2019) underscore the significance of rapidity, learning abilities, and coordination, along with their impact on competition policy. They point out that machine learning algorithms might possess greater proficiency in managing noisy data and synchronizing with other algorithms, contributing to tacit collusion.

Miklós-Thal & Tucker (2019) demonstrated that improved demand forecasting could lead to higher profits for cartels, but this is often counteracted by increasing the temptation to deviate from the cartel price. However, Harrington (2018) suggests that this temptation may not be significant, as the risk of retaliation can deter firms from deviating. Harrington explains that algorithms can effectively detect and punish deviations quickly, maintaining the stability of collusion. This finding complements O'Connor & Wilson (2021), which showed that AI's improved prediction of market shocks could contribute to collusion as it reduces the uncertainty of demand volatility.

Salcedo (2016) explored algorithmic transparency's role in tacit collusion, finding that under certain conditions, such as customers entering the market at a rate that is faster than the time it takes for firms to understand each other's algorithms, collusion is more likely to occur. This result adds another dimension to the previous findings by emphasizing the importance of firms' reaction speed to market information.

In addition, some academics examined scenarios with only a minority of the market using intelligent algorithms. Harrington (2020) studied third-party pricing algorithms' impact on competition, finding prices could rise even with one firm adopting the algorithm. This study highlights the potential for tacit collusion in the form of an implicit hub-and-spoke cartel. Moreover, Zhou et al. (2018) designed a parameterized algorithm that learns to effectively extort the human competitors in the market to engage in collusion.

Bernhardt & Dewenter (2020) argue that communication and transparency are key near-term bottlenecks for intelligent algorithmic collusion. Many algorithms, especially those based on deep learning, can be considered "black-box" models, meaning their internal logic is not easily interpretable. This lack of transparency hinders the ability of algorithms to anticipate and respond to each other's actions, making tacit collusion difficult. In contrast, Azzutti et al. (2021) emphasize the risks associated with deep learning algorithms' "black-box" nature. They argue that the lack of transparency could enable market manipulation and collusion, as participants may exploit complex, opaque algorithms to conceal anti-competitive behavior. While both studies recognize potential challenges posed by "black-box" algorithms, they differ in assessing its implications for collusion, with Bernhardt & Dewenter (2020) viewing it as a barrier and Azzutti et al. (2021) as a potential enabler of anti-competitive behavior.

3.2 Experimental Studies

These research papers focus on creating controlled environments to investigate the potential for tacit collusion in markets with self-learning algorithmic pricing. By employing artificial intelligence techniques, such as reinforcement learning or deep learning, experimental studies can identify specific conditions and algorithmic features that contribute to collusive outcomes.

The most significant and groundbreaking academic article that uses computer simulations to explore tacit collusion potential is Calvano et al. (2020)'s study. The authors created a controlled virtual environment mimicking a market with a small number of competitors selling identical products and assuming no direct communication or knowledge of pricing strategies. The methodology involved training an algorithm, called Q-learning to represent firms, learning pricing strategies in a simultaneous price-setting game. The agents aimed to maximize long-term profits, repeatedly updating decision-making based on observed rewards and actions. A key aspect of the learning process was balancing exploration, which involves trying new pricing strategies to discover potentially better outcomes, and exploitation, which means sticking with the best-known strategy to maximize profits. The authors assumed firms could fully see competitors' past prices, using this information to adjust their pricing decisions.

Calvano et al. (2020) findings revealed that Q-learning agents, trained in the simulated market environment, were indeed able to learn collusive pricing strategies. Interestingly, when a company attempted to undercut competitor prices, other algorithms swiftly retaliated by lowering prices. In over 95% of cases, this "punishment" mechanism made deviation unprofitable. After an initial price war, the algorithms gradually returned to their pre-deviation behavior. In most cases, the punishment ended after 5-7 periods (Figure 4). Furthermore, the punishment harshness strongly correlated (+76.2%) with profit gain, indicating effective collusion maintenance through strategic punishment.

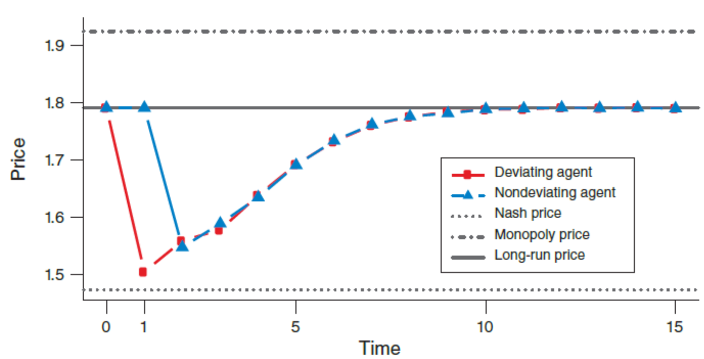

Figure 4: "Punishment" mechanism used by algorithms to make price deviations unprofitable. Source:(Calvano et al., 2020).

While Calvano et al. (2020) examined simultaneous pricing decisions, Klein (2021) focused on sequential pricing in a controlled virtual environment. This difference in the timing of pricing decisions introduces additional complexity for agents learning and coordinating strategies. Klein's research revealed that, under sequential pricing, the Q-learning agents still learned collusive pricing strategies, leading to supra-competitive prices. However, convergence to collusive prices took longer compared to Calvano et al.'s simultaneous pricing scenario.

Hettich (2021) highlights the concern that the slow convergence rate observed by Calvano et al. (2020) questions Q-learning-based collusion's practical relevance. On average, algorithms converged to supra-competitive prices after 850,000 time-steps on learning. Assuming 30 updates per hour, corresponding to Amazon (2020) API's maximum frequency, it would take approximately three years to reach collusive outcomes.

To address this limitation, Hettich (2021) investigates the potential for tacit collusion using Deep Q Networks (DQNs), an advanced technique that combines Q-learning with deep neural networks. Hettich's research demonstrates that, in a similar controlled environment, DQNs achieve collusion significantly faster than their Q-learning counterparts. However, Han (2021) counters Hettich's findings by suggesting that incorporating experience replay with DQNs does not necessarily result in faster collusion. Experience replay is a method that enhances the learning capabilities of reinforcement learning agents by allowing them to store and revisit past experiences during the training process. This counterintuitive finding challenges the assumption that more sophisticated learning techniques invariably lead to quicker, more efficient collusion.

Abada and Lambin (2020) provide a complementary perspective to the aforementioned studies by suggesting that better learning capabilities might make collusion more difficult in certain cases. Therefore, a longer exploration phase can plausibly destabilize collusive outcomes. Additionally, Gautier, et al. (2020) suggest that current (deep) reinforcement learning capabilities might be insufficient to facilitate algorithmic tacit collusion in the near term and firms might not necessarily utilize this type of algorithms. They identify obstacles to tacit algorithmic collusion, including exponential complexity growth for multiple firms, non-stationarity, slow learning speed, and generalization issues.

3.3 Empirical Studies

These studies rely on real-world data to analyze the relationship between self-learning algorithmic pricing and market outcomes, such as prices, and market concentration. Note that it is often unknown whether firms use algorithmic pricing or not, necessitating the identification of algorithmic pricing sellers through indicators such as the number of price changes, the price changes average size, and rival response time. This approach, however, may result in both false positives and negatives, complicating the analysis further. Unfortunately, as the study of algorithmic pricing is still an emerging field, there are limited empirical research papers specifically focusing on real-world settings.

Chen et al. (2016) were the first in analyzing algorithmic pricing on Amazon Marketplace, devising a method to detect such pricing. The authors discovered that non-algorithmic sellers faced difficulties when competing with their algorithmic counterparts. This pioneering work demonstrated that algorithmic pricing could significantly alter the competitive landscape.

Wieting and Geza (2021) sought to address the research gap by examining algorithmic pricing on Bol.com, the leading online marketplace in the Benelux. Building on the methodology developed by Chen et al. (2016), they identified algorithmic sellers and discovered that self-learning algorithmic pricing led to an average price increase of 9% in the marketplace.

Continuing the exploration of the potential for tacit collusion arising from algorithmic pricing in online marketplaces, Mussolf (2021) finds that the average markup on Amazon was 18.62% and identified that merchants frequently adopted collusive cycling strategies. These strategies exhibited Edgeworth-like cycles, with large price increases occasionally, alternating with frequent, stable, and small price decreases. Merchants using pricing algorithms initially lowered prices by marginally undercutting the lowest market price, and then substantially raise prices if they fell below a specific value. The research concluded that the adoption of repricing algorithms could potentially increase profits for sellers, but also significantly raise long-run prices, with average prices approaching monopolistic levels.

Assad et al. (2020) extended the analysis of algorithmic pricing to the German retail gasoline market, where such software became widely available by mid-2017. The study focussed on isolated duopoly markets (geographic markets with only two stations) and compared the outcomes in markets where no stations adopted algorithmic pricing, one station adopted it, and both stations adopted it. In markets where both stations adopted algorithmic pricing, the mean margin increased by roughly 28%. Moreover, margins did not begin to increase until a year after market-wide adoption, indicating that algorithms learned tacitly collusive strategies over time.

Nevertheless, not all studies align on this question. Aparicio et al.(2021) investigated price-matching strategies in online grocery retail, finding that price matching often occurred at lower price levels, with 83% of events taking place below the median price. This behavior led to a 2.7% decrease in prices, suggesting machine-based pricing can sometimes lower prices, supporting the theoretical work from Miklós-Thal and Tucker (2019) discussed in Section 3.1.

4 Market Factors and Mechanisms Affecting the Likelihood of Tacit Collusion

4.1 Market Structure Factors

These factors are related to the overall market organization and the competitive landscape, including the number of competitors, barriers to entry, and market transparency. These factors influence the level of competition and the ease with which firms can monitor and respond to each other's actions.

The number of firms a significant role in determining tacit collision likelihood when using algorithmic pricing. Generally, as the number of firms in a market increases, the complexity of coordinating pricing strategies rises and thus decreasing the chances of tacit collusion (Beneke and Mackenrodt, 2019). The initial experimental research discovered that in laboratory settings, tacit collusion is often observed when there are two sellers, infrequently seen in markets with three sellers, and almost never occurs in markets with four or more sellers (Potters and Suetens, 2013). More recent research from Hettich (2021) found that DQN algorithms exhibit a decrease in the level of collusion as the number of market participants increases, and with seven or more firms, collusion entirely disappears (Figure 5).

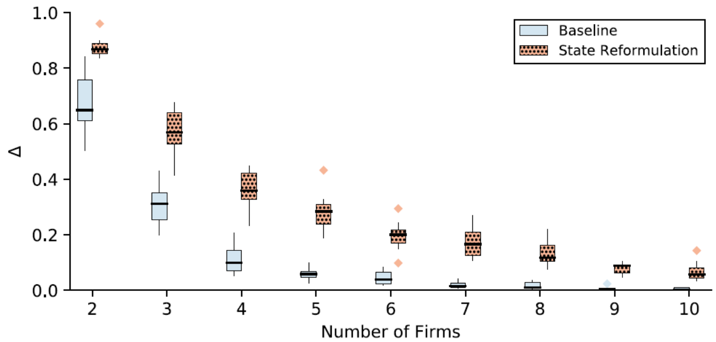

Figure 5: Box plot of the average profit gain of DQN in oligopolies with varying number of firms. Source: (Hettich,2021).

The past literature agrees with the fact that the higher the barriers to entry in a market the greater the incentives to collude. According to Bundeskartellamt et al.(2019), high barriers to entry can strengthen the incentives for firms to collude, as they may perceive greater long-term benefits from supra-competitive pricing, knowing that potential competition is less likely to challenge their market position. This increased incentive further encourages self-learning algorithms to adapt their pricing strategies toward collusion.

Market transparency can be categorized into two main types: data transparency, which refers to the availability and visibility of pricing information from other companies, and decision-making transparency, which pertains to the knowledge about the architecture and variables of other firms' algorithms. On the one hand, greater transparency of data allows firms to easily observe and react to competitors' pricing strategies, which can facilitate the development and maintenance of collusive behavior (OECD, 2017). This monitoring capability enables firms to punish deviations from collusive pricing more swiftly and effectively, thereby reinforcing collusive behavior (Gal, 2019). On the other hand, transparency of decision-making can lead to a deeper understanding of other firms' algorithms, which might either facilitate or impede collusion. Beneke and Mackenrodt (2019) argue that increased transparency of decision-making can potentially undermine collusion by making it easier for regulators and other third parties to detect and punish collusive behavior. However, Ezrachi and Stucke (2017) theorize that increased transparency can support tacit collusion by enabling firms to better coordinate their pricing strategies without explicit communication.

4.2 Algorithmic Dynamics and Interactions

This category encompasses factors related to the specific design and implementation of the self-learning algorithms used by firms and how they interact with each other within the market. This category includes factors such as interaction frequency, discount factor, and competitor algorithm similarity.

The frequency of iterations refers to how often firms adjust their prices. Rapid learning facilitated by frequent iterations can lead to quicker convergence toward collusive pricing strategies. Also, frequent iterations enable swift and precise punishment mechanisms for deviations from collusion, reinforcing the stability of the collusive outcome (Bundeskartellant, 2019). In the most extreme scenario, when retaliation is immediate, the benefits from undercutting vanish and collusion can be achieved regardless of the discount rate (Competition and Markets Authorities, 2018).

The discount factor, which represents the extent to which firms value future profits compared to immediate gains, plays a pivotal role in tacit collusion likelihood. A higher discount factor increases the potential gains from collusion and makes firms more willing to forgo short-term profits in favor of long-term benefits obtained through coordinated pricing strategies (Ezhari and Stucke, 2015). Conversely, a discount factor close to zero would lead to firms setting the competitive price(Mehra, 2016). Calvano et al. (2020) in their simulation found that as the discount factor declines from 0.95 to 0.35, the abnormal profit gains decrease from over 80% to 16% (Figure 6).

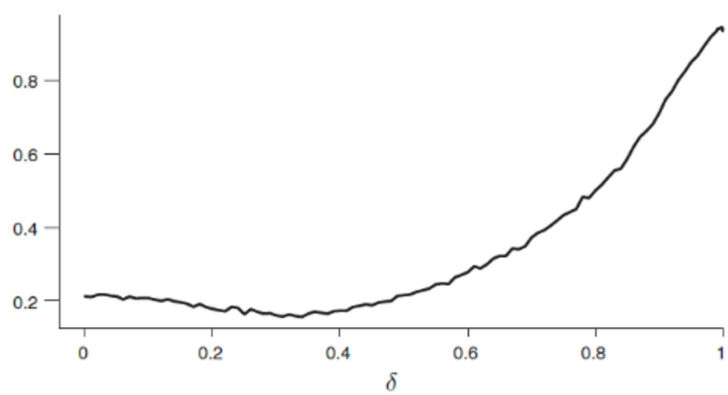

Figure 6: The average profit gain Δ as a function of the discount factor δ in Calvano et al.'s experiment ($\Delta = 1$ represents the monopolistic price).

Ezharachi and Stucke (2017) highlight that when firms in a market utilize similar self-learning algorithms, they tend to learn and converge towards similar strategies, leading to coordinated pricing patterns. This increased alignment of pricing strategies can facilitate tacit collusion among firms. Harrington (2018) suggests that this outcome may arise due to firms outsourcing the development of their pricing algorithms to third-party entities. Hettich (2021) finds similar reasoning in its simulation and also discovers that the presence of rule-based algorithms in the markets does not hinder collusion as their behaviour is completely predictable. However, Gautier et al. (2020) contend that even when algorithms share the same architecture, utilize identical datasets, and employ the same optimization methods, the likelihood of collusion remains uncertain. This is due to the inherently stochastic nature of deep learning techniques, which makes it difficult to determine if the algorithms will collude despite their apparent symmetry.

4.3 Demand and Cost Factors

This category comprises factors related to the underlying market conditions that affect the profitability of collusion, including cost asymmetry, and demand fluctuation. These factors can impact the incentives for firms to engage in collusion and the sustainability of collusive arrangements over time.

Cost asymmetries can impede collusion, as firms with lower costs may be more tempted to deviate from collusive agreements to increase their market share (OECD, 2017). Calvano et al. (2020), in their research on algorithmic pricing, find that greater cost heterogeneity reduces the scope for collusion to a certain extent, hence the abnormal profit earned by the firms decreases as cost asymmetry rises.

In markets with volatile demand, coordinating collusive behavior becomes challenging, potentially undermining the stability of collusive arrangements. Frequent changes in demand conditions can lead to price adjustments that are misinterpreted by algorithms as deviations from the collusive agreement, prompting them to respond with punishment mechanisms (Harrington, 2018). However, as algorithms adapt to demand fluctuations over time, they can learn to anticipate and accommodate changing market conditions, making collusion more sustainable (Hettich, 2021). Additionally, advanced self-learning algorithms can exploit fluctuations to create complex pricing patterns, making it harder for regulators to detect collusion (Ezrachi and Stucke, 2017).

5 Conclusion

This literature review explored the potential for tacit collusion arising from self-learning algorithmic pricing. The motivation behind this research stems from the increasing concern among policymakers and regulators regarding tacit collusion's detrimental effects on consumer welfare, and economic efficiency. The methodology employed in this review consisted of a comprehensive examination of existing literature, and an analysis of the factors affecting tacit collusion likelihood (Figure 7).

The studies outlined in this review collectively demonstrate the significant potential for autonomous algorithmic pricing to facilitate tacit collusion under specific conditions. Theoretical studies highlight the significance of rapidity, learning abilities, coordination, and transparency in the context of algorithmic pricing and tacit collusion. Experimental studies, employing techniques such as Q-learning and Deep Q Networks, demonstrate the ability of self-learning algorithms to engage in collusive behavior in controlled virtual environments. However, these findings are not without limitations, particularly regarding the slow convergence rate to collusion. Empirical studies, though limited in number, provide a glimpse into algorithmic pricing's potential impacts in actual market settings. Some research indicates that algorithmic pricing leads to increased prices and collusion, while other studies suggest that it leads to lower prices under certain circumstances.

Despite the diversity of the literature, some common themes and conclusions emerge. A majoritarian consensus exists on the potential self-learning algorithmic pricing facilitating collusion. We do not have sufficient evidence to guarantee that this potential occurs in the present, but rapid AI advancements might make it a reality sooner rather than later. Also, tacit collusion likelihood in algorithmic pricing depends on a complex interplay of market structure and mechanisms factors like competitors' number, interaction frequency, and demand fluctuation. As such, the potential for tacit collusion in algorithmic pricing is highly context-dependent and not generalizable across different markets and industries.

Relevant Market Factors and Mechanisms		**How these factors are related to algorithmic collusion?**
Market Structure Factors	Number of Competitors	Negatively
	Barriers of Entry	Positively
	Market Transparency on Data	Positively
	Market Transparency on Algorithms	Mixed
Algorithmic Dynamics and Iterations	Discount Factor	Positively
	Frequency of Iteration	Positively
	Competitor's algorithms similarity	Positively
Demand and Cost Factors	Cost Asymmetry	Negatively
	Demand Fluctuation	Mixed

Figure 7: A table that depicts how some relevant market factors and mechanisms are related with the likelihood of algorithmic pricing collusion.

In light of these findings, further empirical and experimental work is needed to identify thresholds for different factors affecting collusion likelihood. For example, at what level of cost asymmetry or demand fluctuation does collusion become unsustainable? Empirical research should be conducted across a broader range of industries, in order to have a more complete perspective of the problem. Also, empirical researchers should study more efficient and suitable real-world settings algorithms than the ones studied so far. A promising candidate for such algorithms is meta-learning, which can generalize learned behavior to new environments (Wang et al., 2018). Additionally, authorities may consider developing mechanisms to monitor and detect potentially collusive behavior in algorithmic pricing, including utilizing advanced analytics and machine learning techniques to identify patterns indicative of collusion.

References

[1] Abada, Ibrahim, and Xavier Lambin. “Artificial Intelligence: Can Seemingly Collusive Outcomes Be Avoided?”. (2020) Available at SSRN 3559308. http://dx.doi.org/10.2139/ssrn.3559308

[2] Alessio Azzutti, Wolf-Georg Ringe, and H. Siegfried Stiehl. “Machine Learning, Market Manipulation, and Collusion on Capital Markets: Why the ”Black Box” Matters”. University of Pennsylvania Journal of International Law Volume 43 (2021). Pages 79-137.

[3] Assad, S., Clark, R., Ershov, D., & Xu, L. “Algorithmic pricing and competition: Empirical evidence from the German retail gasoline market.” CESifo Working Paper No. 8521 (2020). http://dx.doi.org/10.2139/ssrn.3682021

[4] Aparicio D.,Metzman Z., Rigobon R. “The Pricing Strategies of Online Grocery Retailers”. National Bureau of Economic Research (2021). https://doi.org/10.3386/w28639

[5] Beneke F., Mackenrodt, MO. “Artificial Intelligence and Collusion”. IIC-International Review of Intellectual Property and Competition Law. Volume 50 (2019). Pages 109-134. https://doi.org/10.1007/s40319-018-00773-x

[6] Beneke F, Mackenrodt MO. “Remedies for algorithmic tacit collusion”. Journal of Antitrust Enforcement, Volume 9, Issue 1, (2021), Pages 152–176. https://doi.org/10.1093/jaenfo/jnaa040

[7] Bernhardt, Lea, and Ralf Dewenter. “Collusion by code or algorithmic collusion? When pricing algorithms take over.” European Competition Journal 16, Issue.2-3 (2020): Pages 312-342. https://doi.org/10.1080/17441056.2020.1733344

[8] Bundeskartellamt and Autorité de la concurrence, “Algorithms and Competition” (2019).

[9] Dube, Jean-Pierre H. and Misra, Sanjog. “Personalized Pricing and Consumer Welfare”. National Bureau of Economic Research. http://dx.doi.org/10.2139/ssrn.2992257

[10] Calvano, Emilio, Giacomo Calzolari, Vincenzo Denicolò, and Sergio Pastorello. “Artificial intelligence, algorithmic pricing, and collusion.” American Economic Review 110.10 (2020) Pages 3267-97. https://doi.org/10.1257/aer.20190623

[11] Calvano, Emilio, Giacomo Calzolari, Vincenzo Denicolò, and Sergio Pastorello. “Algorithmic Pricing: What Implications for Competition Policy?”. Review of Industrial Organization, 2019, vol. 55, issue 1, No 9. (2019) Pages 155-171 https://doi.org/10.1007/s11151-019-09689-3

[12] Cason, Timothy N., and Arlington W. Williams. “Competitive equilibria in the core of a market with adverse selection.” International Economic Review 31.2 (1990): Pages 283-297.

[13] Chen, L., Mislove, A., & Wilson, C. “An empirical analysis of algorithmic pricing on Amazon marketplace” WWW ’16: Proceedings of the 25th International Conference on World Wide Web(2016)Pages 1339–1349 https://doi.org/10.1145/2872427.2883089

[14] Competition and Markets Authority. “Pricing Algorithms” (2018).

[15] Competition and Markets Authority. “Decision Hydrocortisone tablets”.Excessive and unfair pricing and Anti-competitive agreements, Case 50277 (2021).

[16] Cormen, T. H., Leiserson, C. E., Rivest, R. L., & Stein, C. Introduction to algorithms (3rd ed.). MIT Press. (2009).

[17] European Commision. “Antitrust: Commission fines truck producers € 2.93 billion for participating in a cartel”(2016).

[18] European Commision. “Report from the Commission to the Council and the European Parliament”, Final report on the E-commerce Sector Inquiry” (2017).

[19] Ezrachi A., Stucke ME. “Artificial Intelligence & Collusion: When Computers Inhibit Competition”. Oxford Legal Studies Research Paper. (2015).

[20] Ezrachi A., Stucke ME. “Two Artificial Neural Networks Meet in an Online Hub and Change the Future (of Competition, Market Dynamics and Society)”. University of Tennessee Legal Studies Research Paper No. 323 (2017). http://dx.doi.org/10.2139/ssrn.2949434

[21] Gal, Michal S. “Algorithms as illegal agreements.” Berkeley Technology Law Journal. Volume 34. Issue 1 (2019). Pages 67-118. https://doi.org/10.15779/Z38VM42X86

[22] Gautier, Axel, Ashwin Ittoo, and Pieter Van Cleynenbreugel. “AI algorithms, price discrimination and collusion: a technological, economic and legal perspective.” European Journal of Law and Economics Volume 50. Issue 3 (2020): Pages 405-435. https://doi.org/10.1007/s10657-020-09662-6

[23] Han, Bingyan. “Understanding algorithmic collusion with experience replay.”(2021). Available at arXiv preprint arXiv:2102.091.

[24] Hettich, Matthias. “Algorithmic Collusion: Insights from Deep Learning.” SSRN Electronic Journal (2021). Available at SSRN 3785966. http://dx.doi.org/10.2139/ssrn.3785966

[25] Jason O’Connor, Nathan E. Wilson. “Reduced demand uncertainty and the sustainability of collusion: How AI could affect competition, Information Economics and Policy”, Volume 54, (2021), 100882, ISSN 0167-6245. https://doi.org/10.1016/j.infoecopol.2020.100882

[26] Joseph E Harrington Jr. “Third Party Pricing Algorithms and the Intensity of Competition.” SSRN Electronic Journal (2020). Available at SSRN 3723997.

[27] Joseph E Harrington, “Developing Competition Law for Collusion by Autonomous Artificial Agents”, Journal of Competition Law & Economics, Volume 14, Issue 3, (2018), Pages 331–363. https://doi.org/10.1093/joclec/nhy016

[28] Klein, Timo. “Autonomous algorithmic collusion: Q-learning under sequential pricing.” Amsterdam Law School Research Paper 2018-15 (2021).

[29] Mehra, Salil K., “Antitrust and the Robo-Seller: Competition in the Time of Algorithms” Minnesota Law Review. Volume 100. (2016). Pages 1323-1375.

[30] Miklós-Thal, Jeanine, and Catherine Tucker. “Collusion by algorithm: Does better demand prediction facilitate coordination between sellers?.” Management Science Volume 65.Issue 4 (2019). Pages 1552-1561.

[31] Mussolf L. “Algorithmic Pricing Facilitates Tacit Collusion: Evidence from E-Commerce”. 23rd ACM Conference on Economics and Computation. (2021). https://doi.org/10.1145/3490486.3538239

[32] OECD, “Algorithms and Collusion: Competition Policy in the Digital Age” (2017).

[33] Potters J., Suetens S. “Oligopoly Experiments in the Current Millenium”. Journal of Economic Surveys. Volume 27, Issue 3 (2013). Pages 439-460. https://doi.org/10.1111/joes.12025

[34] Salcedo, Bruno. "Pricing Algorithms and Tacit Collusion." Manuscript, Pennsylvania State University (2016).

[35] Scherer, F. M., & Ross, D. "Industrial Market Structure and Economic Performance" (3rd ed.). Houghton Mifflin Company.(1990).

[36] Stigler, G. J. "A Theory of Oligopoly". Journal of Political Economy, 72, (1964). Pages 44-61.

[37] Tirole, J. "The theory of industrial organization". MIT Press.(1988).

[38] Wang, J. X., Kurth-Nelson, Z., Tirumala, D., Soyer, H., Leibo, J. Z., Munos, R., Blundell, C., & Kumaran, D. "Learning to reinforcement learn". (2018). https://doi.org/10.48550/arXiv.1611.05763

[39] Wieting M., Sapi G., "Algorithms in the Marketplace: An Empirical Analysis of Automated Pricing in E-Commerce". NET Institute Working Paper No. 21-06 (2021).

[40] Zhou, Nan, et al. "Algorithmic Collusion in Cournot Duopoly Market: Evidence from Experimental Economics." (2018). https://doi.org/10.48550/arXiv.1802.08061