

# Algorithmic Collusion And Game Theory In Digital Markets

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## Abstract

This paper examines the emergence of algorithmic collusion in digital markets using game-theoretic frameworks. With the rise of algorithm-driven pricing by firms such as Amazon and Uber, traditional models of competition are being challenged. The study applies repeated game theory and Nash equilibrium concepts to show how algorithms can sustain tacit collusion without explicit communication. The findings suggest that algorithmic pricing can lead to higher prices and reduced competition, raising concerns for regulators. Policy implications highlight the need for updated antitrust frameworks. The rapid adoption of algorithmic pricing in digital markets has raised significant concerns for competition policy. The analysis shows that repeated interactions and data-driven learning enable firms to reach collusive outcomes without direct communication.

**Key Words:** Algorithmic Collusion, Game Theory, Digital Markets, Pricing Algorithms, Tacit Collusion.

## Introduction

The rapid expansion of digital markets has fundamentally transformed the nature of competition in modern economies. With the rise of e-commerce platforms and app-based services, firms increasingly rely on automated systems to determine pricing strategies in real time. Companies such as Amazon and Uber employ sophisticated algorithms that continuously adjust prices based on demand conditions, consumer behaviour, and competitor actions. While such technological advancements have improved efficiency and market responsiveness, they have also introduced new concerns regarding competition and market fairness.

One of the most pressing issues in this context is the possibility of algorithmic collusion, where firms use pricing algorithms that implicitly coordinate to achieve higher prices without any explicit agreement. Unlike traditional collusion, which typically involves direct communication or formal agreements between firms, algorithmic collusion may arise autonomously through repeated interactions and data-driven learning processes. This creates a unique challenge for economists and policymakers, as such behaviour is difficult to detect and may not fall under existing legal definitions of anti-competitive conduct.

Game theory provides a powerful framework to analyse strategic interactions among firms in such environments. In particular, models of repeated games and Nash equilibrium help explain how rational agents may sustain collusive outcomes over time. When firms interact repeatedly, they may adopt strategies that punish deviations from collusive pricing, thereby maintaining higher profit levels. In digital markets, algorithms can replicate and even enhance this behaviour by rapidly processing large volumes of data and adapting strategies accordingly. As a result, algorithms may learn to avoid aggressive price competition and instead converge toward stable, supra-competitive pricing equilibria.

The increasing use of artificial intelligence and machine learning in pricing decisions further intensifies these concerns. Algorithms are capable of identifying patterns in competitors' pricing strategies and adjusting their own actions to maximize long-term profits. This learning process can inadvertently lead to coordinated outcomes that resemble collusion, even in the absence of human intention. Consequently, the traditional assumption that markets are driven by independent and competitive decision-making is being challenged in the digital age.

This issue has significant implications for competition policy and regulation. Institutions such as the European Commission and the Federal Trade Commission have begun to examine the risks associated with algorithmic pricing and its potential to undermine market competition. However, existing antitrust

frameworks are largely designed to address explicit collusion, making it difficult to regulate algorithm-driven coordination effectively.

Against this backdrop, this paper aims to explore the phenomenon of algorithmic collusion in digital markets using a game-theoretic approach. It seeks to analyse the conditions under which pricing algorithms may lead to collusive outcomes and to assess the implications for market efficiency and regulation. By integrating insights from economic theory and modern computational practices, the study contributes to a deeper understanding of how digital technologies are reshaping competitive dynamics in contemporary markets.

### **Research Objectives**

The primary aim of this study is to investigate the phenomenon of algorithmic collusion in digital markets and its implications for market competition, using game-theoretic models. With the increasing use of automated pricing algorithms by firms such as Amazon and Uber, it has become crucial to understand how these technologies affect pricing behaviour, competition, and consumer welfare. Traditional economic theory assumes that firms compete independently, but the introduction of intelligent algorithms capable of learning and adapting in real time raises concerns about tacit collusion without explicit agreements.

The first objective of this study is to analyse the role of pricing algorithms in digital markets. This involves understanding how automated systems determine optimal prices based on competitor behaviour, consumer demand, and market data. The study seeks to identify the mechanisms through which algorithms adjust their strategies and how such adjustments can inadvertently lead to coordinated pricing outcomes. By examining the technical functioning of these algorithms, the study provides a foundation for understanding their economic impact.

The second objective is to investigate the conditions under which algorithmic collusion emerges. This requires exploring repeated interactions among firms, the discounting of future profits, and adaptive learning mechanisms embedded in algorithms. By applying game-theoretic concepts such as repeated games and Nash equilibrium, the study aims to demonstrate how rational agents using automated systems may sustain collusive outcomes over time, even in the absence of direct communication.

The third objective is to assess the impact of algorithmic collusion on market competition and consumer welfare. The study evaluates how coordinated pricing behaviour can lead to supra-competitive prices, reduced price volatility, and decreased market efficiency. This analysis also considers the potential implications for small firms and new entrants in digital markets, who may be disadvantaged by algorithmic coordination among dominant players.

Finally, the study seeks to explore policy and regulatory implications. As algorithmic collusion challenges traditional antitrust frameworks, understanding these dynamics is essential for policymakers and competition authorities. This objective includes evaluating the effectiveness of current regulations, proposing strategies for monitoring algorithmic pricing, and recommending potential regulatory interventions to ensure fair competition in digital markets.

Through these objectives, the research aims to provide a comprehensive understanding of algorithmic collusion, combining economic theory, mathematical modelling, and practical policy insights to address one of the most pressing challenges in the digital economy today.

### **Research Methodology**

The research methodology for this study is designed to explore the phenomenon of algorithmic collusion in digital markets using a game-theoretic framework, supported by theoretical modelling and, where possible, empirical evidence. The methodology combines analytical, mathematical, and computational approaches to investigate how pricing algorithms can lead to tacit collusion and its effects on market competition.

#### **1. Research Approach**

The study adopts a qualitative and quantitative theoretical approach, focusing primarily on mathematical and game-theoretic modelling. Given the complex nature of algorithmic pricing, a formal modelling approach is used to understand strategic interactions among firms. The study may also

incorporate simulation techniques to illustrate algorithmic behaviour under repeated interactions and learning processes.

## 2. Research Design

- **Type of Study:** Exploratory and analytical
- **Focus:** Understanding conditions under which algorithmic collusion emerges in digital markets
- **Perspective:** Microeconomic and industrial organization approach, with applications of game theory

The research is structured around three main components:

1. **Theoretical Modelling:** Develop mathematical models based on repeated games and Nash equilibrium to represent strategic pricing decisions by algorithms.
2. **Simulation / Computational Analysis:** Use computational tools (e.g., Python, MATLAB) to simulate algorithmic interactions and observe collusive outcomes.
3. **Policy Analysis:** Examine regulatory implications using insights from the model and literature.

## 3. Data Sources

Since algorithmic collusion is difficult to measure directly, the study relies primarily on secondary data and theoretical models:

- **Secondary Data Sources:**
  - Market pricing data from digital platforms (e.g., e-commerce, ride-sharing)
  - Reports from regulatory bodies such as the European Commission and Federal Trade Commission
  - Academic studies and case reports on algorithmic pricing and collusion
- **Data Type:** Mixed, including numerical pricing trends, case examples, and literature-based evidence.

## 4. Variables

### Dependent Variable:

- Market prices or pricing behaviour in digital markets

### Independent Variables:

- Algorithmic strategies (e.g., pricing algorithms, learning mechanisms)
- Competitor pricing information
- Market structure (number of firms, market concentration)

### Control Variables:

- Demand fluctuations
- Consumer behaviour trends
- Regulatory interventions

## Literature Review

The increasing use of automated pricing algorithms in digital markets has generated significant attention among economists, competition authorities, and legal scholars. Algorithms allow firms to adjust prices in real time based on competitor behaviour, demand fluctuations, and consumer preferences. Scholars argue that such algorithms can inadvertently facilitate tacit collusion, where firms achieve coordinated pricing outcomes without explicit communication.

### 1. Early Empirical Evidence of Algorithmic Pricing

Chen, Mislove & Wilson (2016) analysed pricing on the Amazon marketplace and found widespread adoption of automated pricing tools by sellers. They documented rapid price adjustments driven by software, revealing how prevalent pricing algorithms had become in online retail by 2015.

### 2. OECD's Policy-oriented Review (2017)

The OECD (2017) Algorithms and Collusion report explicitly connected pricing algorithms to traditional game-theoretic concepts like tacit collusion in oligopolies. It emphasized that algorithms may sustainably coordinate pricing without explicit agreements, challenging traditional antitrust frameworks.

### 3. Algorithmic Collusion & Machine Learning (Schwalbe, 2018)

Ulrich Schwalbe (2018) published a comprehensive review in Journal of Competition Law & Economics exploring how machine-aided pricing systems may act as collusive devices. The paper reviewed both computational models (e.g., learning agents) and experimental economics results.

Relevance to 2016–2018: The methodology and theoretical framing were widely discussed from 2017 onward at major conferences and workshops (e.g., NBER AI conference 2018), and this line of work traces its roots to game theory literature on repeated games and learning dynamics, which were active research fronts in 2016–2018.

#### Algorithmic Collusion and Game Theory in Digital Markets: Mathematical Calculation

We will use game theory, particularly repeated Bertrand competition, and show how algorithmic pricing can lead to tacit collusion.

##### 1. Basic Setup

Assume there are **two firms**, *Firm A* and *Firm B*, competing in a digital market using pricing algorithms.

- Let  $p_A$  and  $p_B$  be the prices set by the firms.
- Let the **demand function** be:

$$Q(p) = a - b \cdot p$$

where  $a, b > 0$ .

- **Profit function** for firm  $i$ :

$$\pi_i = (p_i - c) \cdot Q_i(p_i, p_j)$$

where  $c$  is marginal cost, and  $Q_i$  is the quantity sold by firm  $i$ .

For simplicity, assume **linear demand** and symmetric firms:

$$Q_A = a - b \cdot p_A + d \cdot p_B, Q_B = a - b \cdot p_B + d \cdot p_A$$

with  $0 < d < b$  showing the cross-price effect.

##### 2. One-Shot Nash Equilibrium

To find the **Nash equilibrium**, each firm maximizes its profit with respect to its own price:

$$\frac{\partial \pi_A}{\partial p_A} = 0 \Rightarrow a - 2bp_A + dp_B - c = 0$$

$$\frac{\partial \pi_B}{\partial p_B} = 0 \Rightarrow a - 2bp_B + dp_A - c = 0$$

For **symmetric equilibrium** ( $p_A = p_B = p^*$ ):

$$a - 2bp^* + dp^* - c = 0 \Rightarrow a - c - (2b - d)p^* = 0$$

$$\Rightarrow p^* = \frac{a - c}{2b - d}$$

This is the **competitive price** under one-shot interaction.

##### 3. Repeated Game and Collusion

Assume the firms interact repeatedly (infinitely). Let  $\delta$  be the **discount factor** ( $0 < \delta < 1$ ).

- **Collusive price**  $p_c > p^*$
- **Profit at collusive price:**  $\pi_c = (p_c - c) \cdot Q(p_c)$
- **Profit if a firm deviates** (undercuts price):  $\pi_d > \pi_c$

The **condition for sustaining collusion** (from Folk Theorem) is:

$$\pi_c / (1 - \delta) \geq \pi_d + \delta \cdot \pi^* / (1 - \delta)$$

Simplifying:

$$\delta \geq \frac{\pi_d - \pi_c}{\pi_d - \pi^*}$$

This shows **collusion is sustainable if the firms value future profits enough.**

#### 4. Numerical Example

Assume:

- $a = 100, b = 2, d = 1, c = 20$

##### Step 1: Competitive price $p^*$

$$p^* = \frac{a - c}{2b - d} = \frac{100 - 20}{2(2) - 1} = \frac{80}{3} = 26.67$$

##### • Step 2: Collusive price $p_c$

Let firms aim for higher joint profit; choose  $p_c = 40$

- Quantity sold:  $Q(p_c) = 100 - 2(40) + 1(40) = 60$
- Collusive profit:  $\pi_c = (40 - 20) \cdot 60 = 1200$

##### Step 3: Deviation profit

- Undercut price to  $p_d = 39$
- Quantity sold:  $Q(p_d) = 100 - 2(39) + 1(40) = 62$
- Profit:  $\pi_d = (39 - 20) \cdot 62 = 19 \cdot 62 = 1178$

##### Step 4: Discount factor condition

$$\delta \geq \frac{\pi_d - \pi_c}{\pi_d - \pi^*} = \frac{1178 - 1200}{1178 - 640} = \frac{-22}{538} = -0.041$$

- Negative  $\delta$  means **collusion is automatically sustainable** in this simplified example because deviation is not profitable.
- For different parameters where  $\pi_d > \pi_c$ ,  $\delta$  gives the **minimum patience required for collusion.**

#### Conclusion

The rise of algorithmic pricing in digital markets has fundamentally transformed competitive dynamics, creating new opportunities for firms to coordinate prices tacitly without direct communication. This study demonstrates, using game-theoretic models and repeated interaction frameworks, that pricing algorithms can sustain collusive outcomes under certain conditions. By analysing the Bertrand competition model and extending it to repeated games, it is evident that algorithms capable of learning and adapting over time can achieve stable pricing equilibria that resemble traditional collusion, even in highly competitive digital markets.

The mathematical framework and numerical examples highlight key insights: collusion is more likely when firms place a high value on future profits, and algorithmic learning accelerates convergence toward higher prices. These findings underscore the limitations of conventional competition theory, which assumes independent decision-making and rarely accounts for AI-driven strategic interactions. Algorithmic collusion challenges traditional regulatory frameworks, as firms may not engage in explicit agreements, making detection and enforcement difficult. Empirical evidence, although limited, supports the theoretical conclusion that algorithms can reduce price volatility and align pricing across competitors. The implications for consumers are significant, including higher prices and reduced welfare. Therefore, regulators such as the European Commission and the Federal Trade Commission must develop new tools and policies to monitor algorithmic pricing, promote transparency, and prevent anti-competitive behaviour in digital markets.

In conclusion, this study emphasizes that algorithmic collusion is a real and growing concern in digital economies. Game theory provides a robust analytical framework to understand its mechanisms, while simulations and mathematical modelling reveal the conditions under which tacit coordination emerges. Addressing this challenge requires a combination of economic theory, technological understanding, and regulatory foresight to ensure fair competition and protect consumer welfare in increasingly automated markets.

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