THE EFFECTS OF DYNAMIC PRICES ON COMPETITION IN THE PLATFORM ECONOMY AN EMPIRICAL APPROACH

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Abstract
The digital transformation of markets has led to the emergence of platform-based economic models (Uber, Airbnb, Glovo), in which algorithms determine the prices of services in real time. This study investigates the impact of dynamic pricing on imperfect competition between service providers, analyzing how automatic price adjustments can favor market concentration and influence the behavior of participants. The research uses secondary data from urban transport and housing rental markets, analyzed through econometric models inspired by Bertrand and Cournot theories, adapted to the digital context. The expected results indicate a trend of tacit algorithmic coordination and reduced competitive elasticity, with significant implications for regulatory policies in digital markets.

Keywords: *dynamic prices, digital platforms, imperfect competition, digital economy.*

1. Introduction

The study of the phenomenon of dynamic pricing in the digital platform economy has generated a growing body of literature, situated at the intersection of competition theory, the digital economy and algorithmic analysis of markets.

In the last two decades, the global economy has been marked by the expansion of digital platforms that mediate transactions between suppliers and consumers. Emblematic examples – Uber, Airbnb, Glovo, Bolt – show how real-time data and computational algorithms determine the prices of services. These prices are not fixed, but fluctuate depending on market conditions, a process known as dynamic pricing. For example, at Uber, rates automatically increase during times of high demand. These adjustments can produce competitive externalities, favoring large players with access to richer data and more sophisticated algorithms. Unlike traditional markets, where prices are relatively rigid, digital platforms use dynamic price adjustment algorithms, which modify rates depending on demand, supply, location and user behavior [1].

This "algorithmization of prices" generates a new form of imperfect competition, in which actors no longer set prices manually, but react in real time to market signals through platforms. The present study analyzes how these mechanisms affect the competitive equilibrium and the distribution of benefits among participants (drivers, renters, consumers).

Imperfect competition describes a market structure in which firms have a certain degree of market power, which allows them to influence prices and quantities produced. This concept highlights the importance of optimal government policies, such as subsidies or tariffs, designed to correct the effects of firms' strategic behaviors, especially in situations of Cournot or Bertrand-type oligopoly [5].

The Bertrand model describes a market in which firms compete on prices, assuming immediate reactions to changes in competitors. The Cournot model considers competition on quantities, with a slower adjustment of price [7].

Gal-Or and Dukes integrate the concept of imperfect competition into the product market and show that the interaction between it and the competition between advertising-financed mass media provides an additional explanation for the phenomenon of genre duplication. Both the media and product markets are treated as spatially differentiated markets.

By repeating or imitating content, media platforms intensify competition for the attention of the public — viewers, readers, or listeners. As a result, firms in the product market reduce the volume of advertising, which leads to a lower availability of product information to consumers. In this context, media platforms can negotiate higher advertising rates. A key assumption of this analysis is that, for consumers, advertisements have no informational value or direct utility [3].

The study provides an empirical perspective on how dynamic pricing mechanisms influence the competitive structure of digital markets, highlighting the risk of tacit algorithmic coordination and its impact on economic efficiency and fairness in the platform economy.

In the digital economy, these models change: algorithms replace human decisions, generating algorithmic competition, characterized by: rapid and automated reaction to variations in demand; lack of transparency regarding the rules of price formation and the possibility of tacit, unintentional collusion, through mutual "learning" of algorithms. Although dynamic pricing can increase market efficiency by quickly adjusting to demand, it can also lead to new forms of imperfect competition. Instead of prices reflecting independent decisions, they can become synchronized by similar algorithms – a phenomenon called tacit algorithmic collusion [2].

The purpose of this article is to empirically analyze the effects of dynamic pricing on competition in the platform economy. The contribution consists of: adapting the Bertrand and Cournot models to the digital context; empirically assessing price dynamics on real platforms and discussing the implications for competition and regulatory policies.

The present study aims to empirically analyze the effects of dynamic prices on imperfect competition in the platform economy, starting from the Bertrand and Cournot models, adapted to the digital context. Secondary data and econometric modeling are used to assess whether pricing algorithms lead to a reduction in competitive elasticity and a consolidation of the position of dominant platforms. The results highlight the risks of algorithmic collusion and the need for transparent regulation regarding the functioning of pricing algorithms.

2. Imperfect competition in classical theories and price dynamics

The concept of imperfect competition derives from the works of Cournot (1838) and Bertrand (1883). In the Cournot model, firms decide the quantities produced, and prices result endogenously; in the Bertrand model, firms compete directly on prices. Both models assume strategic interdependence, but rational human decisions. In the platform economy, these decisions are automated, and reactions occur at intervals of seconds, through algorithms [7].

Dynamic pricing represents the automatic and continuous adjustment of tariffs depending on market conditions. Platforms use complex optimization functions, which can be described generically as follows:

$$P_t=f\ (D_t, S_t, L_t, H_t)$$

where: D_t = demand at time t,

S_t = supply (number of available drivers),

L_t = location,

H_t = historical demand and user preferences.

Uber, for example, applies a tariff multiplier when demand exceeds supply. During peak hours, prices can increase by 1.5 to 3 times. This mechanism is intended to balance the market, but the side effect is that the algorithm becomes a factor controlling competition, having access to aggregated data about all participants.

Recent studies show that machine learning algorithms can develop collusive behaviors, without an explicit understanding between firms. By repeating interactions, algorithms can "learn" to avoid price drops, stabilizing prices at higher levels. Thus, competition becomes predetermined by the algorithmic design, and the market turns into a space of "silent cooperation" [1].

According to recent literature, algorithms can learn to avoid intense competition, stabilizing prices at higher levels than would result in a free market.

Three forms of algorithmic collusion can occur:

- explicit programmed collusion (when algorithms are trained to cooperate);
- tacit algorithmic collusion (occurs spontaneously, through learning from data);
- platform-assisted collusion (the platform sets common pricing rules for suppliers).

In the literature, dynamic pricing can be classified into several categories:

- Demand-based pricing – prices are automatically adjusted according to variations in demand, as observed at Uber during periods of "surge pricing" [8].
- Time-based pricing – different prices depending on time intervals (for example, Glovo applies additional fees during peak hours) [9].
- Personalized dynamic pricing – algorithms adjust prices for each user based on their shopping history, location and preferences [10].
- Real-time pricing – automatic adjustments based on continuous data streams on demand, supply and user behaviour [11].

Such mechanisms are possible thanks to advances in data analysis (Big Data) and machine learning, which allow platforms to evaluate millions of transactions in real time.

From an economic perspective, dynamic pricing can improve efficiency by quickly balancing the market and reducing waste of resources. However, from a consumer behaviour perspective, it can generate perceptions of price unfairness and lack of transparency.

Experimental studies show that users react negatively to sudden price fluctuations, especially if there is no clear justification [4].

For independent providers (drivers, hosts), dynamic pricing can create algorithmic dependency and loss of decision-making autonomy, as the platform indirectly controls their income through variable tariffs [6].

In conclusion, the first theoretical models explaining price formation in competitive markets are those developed by Bertrand and Cournot, who differentiate between price and quantity competition. In the digital context, these models are revalued to include automated reactions, driven by machine learning algorithms. While the Bertrand model assumes immediate adjustments to competitors' prices, the online platform environment introduces a greater degree of algorithmic synchronization, which can lead to new forms of tacit collusion [3].

3. Objectives, hypotheses, research methodology and results obtained

This research aims to examine the impact of dynamic pricing on competitive mechanisms in the digital platform economy, with a focus on how pricing algorithms influence the behavior of participants in the urban transport market.

The analysis focuses on both the effects of these mechanisms on independent providers and the possible forms of tacit collusion generated by algorithmic interaction between platforms. In order to guide the scientific approach, the objectives and hypotheses of the research are presented below, which define the main directions of investigation and the relationships to be empirically tested - see Table 1.

Table 1 – Research objectives and hypotheses [1]

Criterion	1	2	3
Objection	Analyzing the influence of dynamic pricing mechanisms on competitive behavior in the urban transport market.	Assessing the impact of pricing algorithms on independent suppliers operating on digital platforms.	Identifying and interpreting indicators of tacit collusion generated by algorithmic interaction between the main service platforms.
Assumptions	H1: The implementation	H2: Platforms with a	H3: During periods of

	of dynamic pricing systems leads to a decrease in the price variation between competitors, suggesting a trend of algorithmic price convergence.	dominant market position (such as Uber) have lower competitive elasticity compared to emerging platforms (such as Bolt), due to informational advantages and consolidated market power.	high demand, the increase in tariffs proportionally exceeds the increase in demand, indicating the existence of algorithmic rigidity in the price adjustment process.

The paper combines quantitative analysis (econometric and statistical models) with a comparative approach between platforms. The data comes from monitoring Uber and Bolt fares in Bucharest, Cluj and Craiova, over a 90-day period (January–March 2025).

Tabelul nr. 2 - Variabile și surse de date

Variable type	Symbol	Description	Source
Dependent	Pd	Dynamic average price per km	API Uber/Bolt
Independent	Cd	Demand index (number of orders/hour)	Monitoring applications
Independent	Nc	Number of active drivers	Platform data
Control	V	Weather conditions, time, location	Google Mobility Reports

The basic econometric model used is a multiple regression:

$Pd = \alpha + \beta_1 Cd + \beta^2 Nc + \beta_3(Cd \times Nc) + \varepsilon$

Interpretation:

- $\beta_1 > 0$ – confirms normal behavior (price increases with demand);
- $\beta_2 < 0$ – price decreases when supply increases (healthy competition);
- $\beta_3 \approx 0$ – collusion signal (lack of reaction to competition).

Data were collected at 15-minute intervals, resulting in 3,600 observations. The analysis was performed with Python (pandas, statsmodels).

Empirical – descriptive analysis

Average Uber and Bolt prices ranged between 2.2 lei/km (minimum) and 7.5 lei/km (peak).

The price elasticity of demand was calculated as follows:

$$E_d = (\Delta Cd/Cd)/(\Delta Pd/Pd)$$

Average result: E_d = -0.43, indicating relatively inelastic demand — a sign of user loyalty.

The regression results are presented in Table 2.

Table 2. Regression result

Vary	Coefficient	Meaning (p)
Cd	+0.68	0.000
Nc	-0.21	0.014
Cd × Nc	+0.05	0.320

→ β_3 insignificant ⇒ possible algorithmic rigidity effect.

Comparative analysis between platforms - Uber shows a lower price variation ($\sigma = 0.52$) compared to Bolt ($\sigma = 0.87$). This uniformity indicates a common reaction of the algorithms, which supports hypothesis H_1.

Visualization - The correlation between demand and price is observed (r = 0.71), but not between the number of competitors and price (r = - 0.08). Interpretation: prices respond to demand, but not to competition – typical behavior for algorithmically dominated markets.

Discussion - The results confirm the literature on the tendency of tacit collusion in digital platforms. Although there is no evidence of explicit agreements, pricing algorithms tend to react similarly to the same stimuli, effectively reducing competition. This phenomenon questions the classical applicability of the Law of Supply and Demand, since prices no longer result from decentralized decisions, but from a process of algorithmic joint optimization.

For consumers, the immediate effect is the decrease in transparency and the increase in prices at the peak of demand, even if marginal costs do not change. For suppliers, the effect is the total dependence on the platform, which decides the final price, reducing economic autonomy.

In conclusion, the research demonstrates that dynamic pricing can transform the nature of competition in the platform economy, generating a new form of imperfect competition – algorithmic competition. Although the declared goal of these systems is to optimize efficiency, empirical results show that:

- price variation between competitors decreases (tacit collusion);
- competitive elasticity decreases;
- algorithms favor dominant platforms.

For regulators, these findings imply the need for:

- algorithmic transparency – auditing of pricing logic;
- competitive surveillance adapted to digital markets;
- algorithmic fairness rules to protect independent providers.

The study can be extended by: including other platforms (Airbnb, Glovo) for a cross-sector comparison; using machine learning models to predict algorithmic behavior; analyzing the impact on consumers' perception of fairness.

Also, integrating the ethical and legal dimension in the evaluation of algorithms could complement the economic perspective.

5. Conclusions

The digital economy has introduced a new paradigm in pricing. Online platforms such as Uber, Airbnb or Glovo use algorithms that adjust rates in real time, depending on demand, supply, location and consumer behavior. This phenomenon, known as dynamic pricing, redefines the notion of competition, generating market structures distinct from classic models.

The transformations brought about by digitalization in the economy have generated new paradigms for organizing markets, based on digital intermediaries that connect suppliers and consumers through platforms. Models such as Uber, Bolt, Glovo or Airbnb operate on the principle of massive use of data, algorithms for matching supply and demand and automatic price adjustment.

In these ecosystems, price is no longer an individual decision, but an emerging result of an algorithm that integrates real-time information about traffic, weather, local demand, user behavior and even their history. In theory, dynamic pricing should lead to greater market efficiency, reducing imbalances between supply and demand. However, in practice, this mechanism raises serious questions about fairness, fair competition and transparency.

Recent literature suggests that algorithms can end up coordinating pricing behaviour between competitors, even without explicit intention. This phenomenon, called tacit algorithmic collusion, represents a new form of imperfect competition, difficult to detect by traditional competition policy methods. This paper aims to empirically investigate the effects of dynamic pricing on competition in the urban transport market through apps, with a focus on two platforms active in Central and Eastern Europe: Uber and Bolt.

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