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Research Article/Araştırma Makalesi

Algoritmik Anlaşmaların Tespiti: Moment Tarama Yönteminden Çıkarımlar

Detecting Algorithmic Collusion: Insights from Moment Screening Methods

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Abstract

The development of global, automated, and dynamic manufacturing processes is having a growing impact on industries. Virtual machines commonly function behind the scenes, supporting a variety of operations. Algorithms are the essential intelligence of these virtual machines, greatly increasing efficiency and effectiveness within marketplaces. Algorithms have the ability to promote competition and increase efficiency, eventually improving market competitiveness. However, algorithmic collusion can be maintained using "dynamic pricing" techniques, which are typically associated with automated pricing. Algorithmic collusion leads to increases in prices and/or decreases in the quality of products and services. The main objective and the function of competition authorities is to fight against those formations. In this regard, cartel screening is an important first step toward detecting collusive activity. In this paper, we used several moment screens to capture the effects of algorithmic pricing. Our findings suggest that algorithmic pricing exhibits non-collusive behavior within the particular industry and time frame examined in our analysis.

Jel Codes: *L11, L40, L51*
Keywords: *Algorithmic Collusion, Behavioral Screens, Cartel Detection, Dynamic Pricing, Machine Learning, Online Marketplace*

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Öz

Küresel, otomatize ve dinamik üretim süreçlerinin gelişimi endüstriler üzerinde giderek daha önemli bir etkiye sahip olmaktadır. Sanal makineler genellikle sahne arkasında işlev görerek çeşitli operasyonları desteklemektedir. Algoritmalar bu sanal makinelerin temel zekâsıdır ve pazar yerlerinde verimliliği ve etkinliği büyük ölçüde artırmaktadır. Algoritmalar rekabeti teşvik etme ve sonunda pazar rekabetini artırma yeteneğine sahiptir. Ancak, genellikle otomatik fiyatlandırmayla ilişkilendirilen "dinamik fiyatlandırma" tekniklerini kullanarak algoritmik anlaşmalar sürdürülebilir. Algoritmik anlaşma ise, fiyatların artmasına ve/veya ürünlerin ve hizmetlerin kalitesinin azalmasına neden olur. Rekabet otoritelerinin ana hedefi ve işlevi, bu oluşumlarla mücadele etmektir. Bu bağlamda, kartel taraması, anlaşma/ittifak faaliyetlerini tespit etme yolunda önemli bir ilk adımdır. Bu çalışmada, algoritmik fiyatlandırmanın etkilerini yakalamak için moment tarama tekniği kullanılmaktadır. Bulgular, analizde incelenen belirli endüstri ve zaman çerçevesinde algoritmik fiyatlandırmanın anlaşma/ittifak dışı davranış sergilediğini öne sürmektedir.

Jel Kodları: *L11, L40, L51*

Anahtar Kelimeler: *Algoritmik Anlaşma, Davranışsal Tarama, Kartel Tespiti, Dinamik Fiyatlama, Makine Öğrenmesi, Online Pazar*

1. Introduction

Collusion theory has played an important role in a wide range of academic areas, including industrial economics, game theory, competition economics, and antitrust legislation. Indeed, the examination of collusion has predominantly been connected with oligopoly theory following George Stigler's influential article, "A Theory of Oligopoly" (Stigler 1964). In the article, Stigler (1964) states that

"A satisfactory theory of oligopoly cannot begin with assumptions concerning the way in which each firm views its interdependence with its rivals. If we adhere to the traditional theory of profit maximizing enterprises, then behavior is no longer something to be assumed but rather something to be deduced."

Classical market theories start by optimizing utility functions for consumers and profit functions for businesses. It is plausible to suppose that all parties maximizes their goals within the limits of market resources, legislation, and dependencies. However, this does not adequately define real-world marketplaces, which are influenced by human nature and thus prone to errors and suboptimal decisions. (Yalçın 2011). At this juncture, assumptions about market dynamics should represent the best possible alternatives, effectively engaging the appropriate controls.

During the nineteenth century, both the fields of law and economics began to construct theories of competition as well as ideological arguments for the social good. Perhaps due to a lack of confidence, lawyers and economists held exaggerated ideas about the other discipline's ability to identify suitable competition policy boundaries (Hovenkamp 1988, p.1021). Since then, collusion has been one of the most intensively researched topics in competition law and economics. Indeed, collaboration among firms can take many forms, including cartel formation and mergers and acquisitions. The most prevalent kinds of collusion include price agreements or fixing market shares (Stigler 1964). Collusion can be formed to agree on any potential or common interest in a marketplace. Thus, understanding market dynamics is critical for market authorities, whose major purpose is to maintain market competitiveness. These authorities cannot afford to make false allegations (false positive errors) or to fail to act (false negative errors). To avoid these errors, it is critical to comprehend current developments that affect these markets, whether domestically or internationally.

The last decade has seen significant advancements in the electronics sector, particularly within the computer hardware industry. These developments have greatly increased computational and storage capacities, enabling academia, the private sector, and public institutions to develop new tools for storing, managing, and analyzing data. Today, a search for "big data" on Google yields approximately 358 million results, and a search for "collusion" returns about 31.4 million results in less than a second. While "algorithmic collusion" is not as well-known as "big data" or "collusion", with only 21.9 thousand results, its importance is gradually increasing alongside the proliferation of autonomous devices and computer programs.

The development of global, automated, and dynamic manufacturing processes is having a growing impact on industries. Virtual machines commonly function behind the scenes, supporting a variety of operations. Algorithms are the essential intelligence of these virtual machines, greatly increasing efficiency and effectiveness. They cut search costs and improve decision-making processes. Algorithms are critical to the functioning of many technology businesses, including some of the world's most strategically important companies.

These developments raise issues about the effectiveness of established collusion detection methods. Classical screening methods, including structural and behavioral techniques, were developed before the advent of rapid advancements in autonomous decision-making. Given this context, it is reasonable to predict that these classic methodologies may be jeopardized in the face of modern, algorithm-driven environments. Accordingly, Ezrachi and Stucke (2017, p.1777) agree that the translation of such improvements into antitrust implications was unexpected.

Providing a general idea and discussion on the possible new formation of market theories and applications, this paper is organized as follows: Section 2 delves into a detailed understanding of collusion theory, introducing the concept of algorithmic collusion as a recent development. Section 3 outlines classical and contemporary screening techniques for detecting collusion, categorizing them into structural, behavioral, and machine learning (ML) based methods. Section 4 focuses on a novel ML-based approach developed by Yalçın and Öztürk (2024), which analyzes algorithmic pricing in online marketplaces and its impact on market competitiveness. This study will utilize the same dataset to perform classical moment screens and compare the outcomes. Finally, we will discuss our findings and compare the results of both studies.

2. Algorithmic Collusion

In the past, monitoring competitors was a time-consuming and expensive process, with real-time updates difficult to obtain (Calzolari 2021, p.1202). In today's corporate landscape, the availability of big data and associated applications has changed how businesses monitor competitors and make choices. Algorithms have drastically decreased the cost of gathering and integrating data into company decision-making processes. Furthermore, these algorithms have transformed pricing practices by allowing businesses to adjust prices more often and automate the pricing process, enhancing responsiveness to market changes and competitor actions.

The majority of cartel literature focuses on formal agreements between competitors. However, collusion is a more sophisticated type of agreement, similar to the concept of "coordination" in repeated games in game theory. It is vital to note that the goal of this study is not to distinguish between different forms of collusive activities. Instead, we are primarily concerned with tacit collusion, particularly where algorithms may play a significant role in promoting such behavior.

Collusion involves coordination among some or all firms in a market to restrict competition, usually with the intent to raise prices, limit production, or divide markets geographically to increase profits. Tacit collusion, in particular, happens when firms reach an agreement to coordinate their operations without the necessity for direct or indirect communication. In such cases, each company understands that its profits are influenced not only by its own activities, but also by those of its competitors (Green et al. 2014). This understanding frequently results in strategically synchronized behavior across firms, even in the absence of explicit agreements.

There are also structural factors that support or hinder collusion, such as the number of rivals, entry barriers, capacity restrictions, demand stability, market transparency, cost asymmetries, and product differentiation (Grout and Sonderegger, 2005 p.20-37). Algorithmic collusion is most likely to emerge in marketplaces with concentrated and homogeneous products, as algorithms can effectively monitor pricing and other critical criteria. In such circumstances, algorithms may constantly monitor competitive prices and market behaviors and alter their own strategies accordingly (Stucke and Ezrachi 2017, p.4). Indeed, demand stability considerably increases the chance of algorithmic collusion. When demand is predictable and consistent, algorithms can better foresee market circumstances and competitor behavior. This consistency enables algorithms to establish prices with more confidence that competitors will follow suit, lowering the possibility of price wars or moves that could disrupt collusive behavior.

Algorithms provide organizations with automated tools for signaling, implementing uniform policies, monitoring market conditions, and enforcing compliance by penalizing deviations (OECD 2017, p.7). Predictive analytics uses historical data to predict future events. This method is used to estimate demand, forecast pricing, anticipate consumer preferences, assess risk, and predict shocks (OECD 2017, p.11). For example, in the *Topkins case*[3], online retailers selling posters on the Amazon marketplace have decided to use the same algorithm to calculate their product prices. In the *Eturas case*[4], several travel agencies used a specific booking system to engage in collusive actions.

Stucke and Ezrachi (2016) considers four categories in which computer algorithms can promote collusion: (a) 'Messenger': This category includes human actors who agree to collude and use computer algorithms to carry out their agreements. One famous example is the Topkins case, in which human-decided collusion was accomplished via algorithms. (b) 'Hub and Spoke': This scenario usually includes a single pricing algorithm that coordinates the prices of competing agents. Uber's pricing model, for example, is designed to prevent price rivalry among its drivers. (c) 'The Predictable Agent': In this case, each firm has its own pricing algorithm that constantly checks and adjusts to the prices and market data of its competitors. The author refers to this as "tacit collusion on steroids", in which firms covertly coordinate prices using their algorithms. (d) 'Digital Eye': This is the most complex scenario, in which algorithms process massive amounts of data in real time to gain an almost omniscient understanding of the market. By increasing observation capabilities with artificial intelligence, a broader and more thorough market picture is obtained, resulting in a level of tacit collusion that outperforms even the most advanced traditional approaches.

Algorithms have the ability to promote competition and increase efficiency, eventually improving market competitiveness (Descamps et al. 2021, p.35-36). Matching algorithms collect and analyze data to determine which products best match a consumer's preferences. Firms can use these features to improve existing products, reduce transactional and operational costs, and dynamically price their goods more accurately. However there are many concerns regarding the usage of algorithms. The CMA (2021) identifies direct harms to

[3] U.S. v. Topkins, U.S. District Court, Northern District of California, No. 15-cr-00201.
[4] Eturas case (C-74/14).

consumers such as "personalized pricing", "personalized rankings", "algorithmic discrimination", as well as direct harms to rivals through exclusionary practices such as "self-preferencing", and "predatory pricing". Finally, the CMA (2021) identifies "algorithmic collusion" as a different category of harm.

Algorithmic collusion can be maintained using "dynamic pricing" techniques, which are typically associated with automated pricing settings in financial markets, also known as algorithmic-based trading. Furthermore, this strategy is obvious in cases when airline corporations rapidly raise prices in reaction to demand surges, or hotels use individualized pricing tactics for their consumers. An antitrust class action filed in the Western District Court of Washington claims major hotel chains of colluding to control hotel rates by exchanging data via Smith Travel Research, a market analytics platform owned by CoStar Group. On March 1, a similar lawsuit was filed in the Northern District Court of Illinois against hotels' use of Amadeus Hospitality's analytics platform. The lawsuit accused several large worldwide hotel corporations, including Amadeus IT Group and Amadeus Hospitality Americas, of breaking antitrust rules. It claimed that the platform provided hotel companies with insights, including 12 month forward-looking data, to which they did not previously have access (Weinstein 2024). Surprisingly, some vending machines already have sensors that allow them to modify beverage prices based on external temperature (Mehra 2015, p.1336).

Algorithms can help oligopolists impose supra-competitive prices that are greater than the market equilibrium (Mehra 2015, p.1340). These algorithms respond rapidly to changes in demand, identify changes in competitor prices, and minimize unnecessary discounts. As demonstrated by Calvano et al. (2021), advanced algorithms, such as Q-learning algorithms, can learn to collude in environments with imperfect monitoring if given enough time to complete their learning processes, even in the absence of explicit orders to do so.

3. Screening Methods

Cartels, which lead to increases in prices and/or decreases in the quality of products and services, not only captivate researchers but are also of paramount importance to policymakers (Wallimann and Sticher 2024). Policymakers and competition authorities are responsible for the efficient use of public funds, and almost every modern economy has authorities in place to fight potential conspiracies against free market principles. Despite substantial attempts by various regulatory organizations, cartels continue to emerge. This persistence could be attributed to some firms' lack of understanding of the increased regulation, or it may be that the penalties imposed are not severe enough to deter collusion, rendering it still a profitable activity (Harrington and Imhof 2022, p.134). Regardless of the reason, market authorities must use all available tools to detect and deter illegal conduct anytime they believe that market players' actions are damaging the structure of the free market and, as a result, consumers. This proactive approach is vital for ensuring fair competition and protecting consumer interests.

Screening is the ability to discover unlawful activity using economic and statistical analyses. A screen is essentially a statistical test based on an economic model and a theoretical framework relating to the suspected illegal conduct. It is designed to detect instances of manipulation, collusion, fraud, or other types of cheating. (Abrantes-Metz 2013). Cartel screening is an important first step toward detecting collusive activity. It not only saves costs by avoiding unnecessary inquiries, but it also increases the likelihood of correctly identifying and penalizing the right targets. As a result, screening allows regulatory authorities to target their efforts more efficiently and effectively, boosting the efficacy of their anti-competitive practice interventions.

While exploratory screening efforts extend back more than fifty years, it is only in the last decade that competition authorities have widely implemented these procedures (Harrington and Imhof 2022). Historically, the most important tool for competition agencies globally to detect cartels has been leniency applications (Montero 2023). However, the OECD (2023) reports that from 2015 to 2021, the number of leniency applications in OECD countries declined by 58%, a trend that can be seen across most regions. Similar to leniency programs, screening methods are not intended to provide conclusive evidence of unlawful activities. Instead, they serve as a basis for initiating investigations and the collection of non-economic evidence, such as through dawn raids (Harrington and Imhof 2022, p.135).

In general, cartel detection approaches were separated into two categories: reactive and proactive measures (Montero 2023). Reactive methods rely on information provided by third parties, such as whistleblowers, rivals, consumers, or other regulatory bodies. In contrast, proactive methods involve detection activities undertaken by the regulatory bodies themselves. This involves the use of systematic screening strategies that rely on the agencies' own attempts to identify suspected illegal actions before they are publicly disclosed. In the modern economic context, screening activities are anticipated to gain significant importance as a proactive method for detecting illegal activities. It is also expected that regulatory authorities worldwide will increasingly incorporate screening methods into their enforcement toolkits.

Although screening methods have significantly increased in popularity and use in the previous five to eight years, as indicated by successful outcomes such as the detection of the LIBOR conspiracy and manipulation[5], some competition authorities are still unwilling to fully embrace these empirical tools (Abrantes-Metz 2013). Indeed, a research issued by Stanford Computational Antitrust emphasizes the importance of screening approaches to regulatory bodies. This research demonstrates how these technologies are becoming more widely recognized and used in antitrust enforcement (Schrepel and Groza 2022). In this report, partner antitrust agencies discussed their progress in using computational tools. For example, the Australian Competition and Consumer Commission built an algorithm that matches patterns to identify phone numbers and credit card numbers across numerous documents. The Brazilian Administrative Council for Economic Defense (CADE) makes efforts to create data mining and screening tools to improve the detection of signals of bid-rigging and the identification of markets that are more subject to collusion. CADE also stated that they are studying the development of AI-based technologies for detecting cartel activity. Colombia's

[5] In 2013, the European Commission imposed an administrative sanctions of 1.7 billion euros on many of the world's major banking institutions involved in what the media labeled the "Libor Scandal". This cartel was accused of influencing the pricing mechanisms of the Euro Interbank Offered Rate (Euribor) and the London Interbank Offered Rate (Libor), hindering competition in the trading of interest rate derivatives (Samà 2014).

Superintendence of Industry and Commerce (SIC) has been developing three programs, two of which are directly related to screening activities: Sabueso was founded with the goal of leveraging data on products available in online shopping to improve the authority's inspection, surveillance, and control activities. Sherlock intends to assist SIC investigators in identifying signals or patterns that indicate suspected anticompetitive activity using data from public procurement processes. The Czech Office for the Protection of Competition uses both crawling algorithms to collect information (Project Watson) and econometric testing and machine learning algorithms to detect probable bid-rigging activities. The UK Competition and Markets Authority (the CMA) has a unit named the Data, Technology, and Analytics unit (DaTa), which focuses on projects ranging from digital advertising to the use of algorithms in digital marketplaces.

Despite documented improvements in the use of screening techniques, the fundamental principles and methods used to deploy these instruments are often vague. One significant exception is the CMA's free cartel screening tool, which was launched on July 13th, 2017. The final version of this tool, which is available to the public, included twelve tests. It assigned a "suspicion score" to each tender by analyzing the procurement documents and data entered into the system (Beth and Gannon 2022, p.83-85). The tests featured assessments of the number of bids, price patterns, similarities in associated papers, and combination tests; nevertheless, on 13 March 2020, the CMA removed its cartel screen from the public domain (Beth and Gannon 2022, p.85).

3.1. Structural Screening Methods

Structural screening seeks to identify markets with structural characteristics typically associated with collusion. These screens include a combination of qualitative and quantitative assessments that range from market characteristics to regulatory environment. According to theory and empirical evidence, significant characteristics include a small number of companies, homogeneous goods, stable demand, and excess capacity (Harrington and Imhof 2022, p.135). Other factors include high market transparency, frequency of interactions, low demand elasticities, cross-ownerships, and the existence of buyer power in the related markets.

Structural screens have long been employed by competition authorities in mergers and acquisitions, as well as competition rule violations such as cartels, abuse of dominance, and so on. Although these screens can display market features and are commonly used to evaluate the nature of competition within market dynamics, they fail to proactively detect a potential collusive scheme. The rationale for this is the benefit of doubt concept, which protects competing businesses in a marketplace. These signals are prone to false positives, harming the reputations of competition authorities.

Structural screens can be misleading because they are made up of specific prototypes for depicting the marketplace. It is related to people's biases toward people or situations that are influenced by human nature. For example, an airplane tragedy does not necessarily imply that the airline business is the most prone to passenger fatalities. It should be highlighted that these occurrences must be examined in light of the firms' characteristics, as well as the geographic and legal factors that affect their operations. Obliquely, a general grasp of the market structure cannot be considered a sufficient signal for competition authorities to initiate a formal investigative procedure.

3.2. Behavioral Screening Methods

Behavioral screening techniques are focused on determining the market consequences of coordination. Suspicions might originate from firms' pricing or quantity patterns, as well as other aspects of market activity (Harrington 2006). To provide economic evidence of collusion, one must first identify the behavioral patterns that indicate cooperation. Harrington (2006) refers to these markers as collusive markers:

(a) Price markers: Price increases are a common indicator of collaboration. While cartels usually combine the range of distinct prices placed on consumers, analyzing a price marker requires careful study because price increases can occur for a variety of reasons. Harrington (2006) provides some price markers as "A higher list (or regular) price and reduced variation in prices across customers", "A series of steady price increases is preceded by steep price declines", "Price rises and imports decline", "Firms' prices are strongly positively correlated", "A high degree of uniformity across firms in product price and other dimensions including the prices for ancillary services", "Low price variance", and "Price is subject to regime switches".

In their novel article, Abrantes-Metz (2007) proposes a new method of screening based on the coefficient of variation (CV). The screen is supported by observed variations following a cartel's collapse, in which the average price level fell by 16% while the standard deviation of prices increased by 263%. The authors hypothesize that conspiracies in other industries would also display low price variance (second moment) and design a screen based on the standard deviation of price normalized by its mean (first moment). The CV formula is

$$CV = \frac{\sigma}{\mu}$$

where σ is the standard deviation and μ is the mean of the dataset.

Other common price screens are skewness and kurtosis. The third moment is skewness, which assesses the asymmetry of the probability distribution. A distribution with a longer tail on the left side will have negative skewness, whereas one with a longer tail on the right will have positive skewness. Bid manipulations, particularly in cases of bid rigging, can disrupt the symmetry of a tender's bid distribution.

$$\text{Skewness}(S) = \frac{n}{(n-1)(n-2)} \sum_{i=1}^{n} \left(\frac{x_i - \bar{x}}{s}\right)^3$$

where n is the number of observations, x_i represents each element in the dataset, s and x^{-} is the sample standard deviation and mean.

Kurtosis, or the fourth moment, assesses the "tailedness" of the probability distribution. It is most typically used in its "excess" version, which compares the kurtosis of a distribution to that of a normal distribution. Kurtosis is a valuable screening tool for collusive acts because tender participants may impact the convergence of bid distributions.

$$\text{Excess Kurtosis}(K) = \left(\frac{n(n+1)}{(n-1)(n-2)(n-3)}\right)\sum_{i=1}^{n}\left(\frac{x_i-\bar{x}}{s}\right)^4 - \frac{3(n-1)^2}{(n-2)(n-3)}$$

where *n* is the number of observations, x_i represents each element in the dataset, *s* and x^{-} is the sample standard deviation and mean.

The CV is the most prevalent screen in capturing collusive pricing processes; nevertheless, additional screens utilized in the literature as price screens include spreads, relative distance, normalized relative distance, Kolmogorov-Smirnov Statistics (Huber and Imhof 2019, p.283-284; Wallimann et al. 2023, p.1679-1682; Silveira et al. 2022, p.13-15). However, in this study, we will examine moment screens, which have been extensively employed by both competition authorities and academics due to their applicability and convenience of use in various price series, including both continuous and discrete types.

(b) Quantity markers: Firms involved in a collusion scheme agree to maintain steady market shares, which align with long-term strategies and expectations. Short-term deviations are frequently addressed by sanctions from other members of the conspiracy, resulting in a long-term equilibrium in market shares. Harrington (2006) provides some quantity markers as "Market shares are highly stable over time", "There is a subset of firms for which each firm's share of total supply for that subset of firms is highly stable over time", and "A firm's market share is negatively correlated over time".

Structural breaks and anomalies are other types of behavioral screens (Harrington and Imhof 2022, p.140-144; Mårtensson 2021, p.9-11). A structural break refers to rapid changes in time series data. Although an intelligent cartel may manage its transition from competitive to collusive pricing, making the cartel's formation less obvious to external observers, this tactic can only partially lower the detection mechanism's efficacy. (Harrington and Imhof 2022, p.140). Collusion necessitates modifying the price-generation process in order to achieve profitability and supra-competitive returns. In contrast, an anomaly is a data pattern that deviates from or contradicts expectations under competitive conditions (Harrington and Imhof 2022, p.142). For instance, consider a scenario where historically the price of a particular product is roughly 1.5 times its production cost. A rapid increase in the product's price, raising this ratio to 2.5, could be identified as an anomaly. However, the discovery of an anomaly in the data needs an explanation, which may warrant a further investigation (Harrington and Imhof 2022, p.142).

3.3. ML-Based Screening Methods

Machine Learning Algorithms (MLA) are a collection of algorithms divided into three categories: supervised, unsupervised, and reinforcement learning. Supervised learning approaches include linear and polynomial regression, support vector machines, decision trees, random forests, and XGBoost regression. This category also includes regularization techniques, specifically L1 and L2 regularization. Classification problems can also be tackled using methodologies such as decision trees, random forests, k-nearest neighbors, and support vector machine classification. This category allows for the creation of an economic or business model, as well as the labeling of data based on the objective function. On the other hand, unsupervised learning focuses on hidden links. The idea is to extract information from data without labeling. Clustering and dimensionality reduction techniques can be applied to this goal.

The principal objective of these algorithms is to learn from data and then make predictions or judgments based on that information. A ML approach consists of four main components: a dataset, a cost or loss function, an optimization procedure, and a model. Normally, the dataset is divided into non-overlapping portions for training, validation, and testing purposes. The model's performance is evaluated using cost or loss functions, which help to optimize its accuracy and efficiency (Li 2017, p.10-11).

ML applications have gained popularity in recent years, particularly in the last decade, as both an empirical tool in academia and an instrument for discovering cartels among competition authorities. As previously stated, regulatory organizations in several countries have developed data analysis teams that specialize in big data and machine learning applications. Academics have also shown a strong interest in applying machine learning techniques into traditional screening procedures, either by combining them with current methodologies or improving them. Huber and Imhof (2019) combine ML approaches with statistical screens derived from the distribution of bids in Swiss construction tenders. The authors employed statistical screens as predictors and achieved an 84% correct classification ratio of the whole bidding processes when determining whether tenders were collusive or not. Huber et al. (2022) also used screens as predictors and built a ML classification model for the Okinawa bid-rigging cartel using data from April 2003 to March 2007. The correct classification rates varied from 88% to 97% depending on the ML model. A similar study conducted by Silveira et al. (2022) investigated gasoline price distribution in Brazil. The authors achieved a high correct classification ratio of 99.2% in the Belo Horizonte database while using supervised ML algorithms to specify cartel and non-cartel periods. Another application of ML techniques in screening, conducted by Wallimann and Sticher (2023), involved detecting potential collusion in the tender processes of the Swiss Federal Railways.

From previous research, it is evident that bid-rigging and public tenders have been central concerns for legal authorities and academia. This focus may be attributed to the accessibility of data in the procurement sector and the availability of historical data categorized as competitive or collusive, which serves as training data for ML applications. Conversely, a significant number of cartels have formed in retail markets, where data from continuous price series are not readily accessible and are often considered strict business secrets.

In 2024, a study by Yalçın and Öztürk demonstrated the potential of ML techniques for both gathering market data and screening algorithmic pricing in online marketplaces. In the following section, we will provide a brief overview of the findings from this study and compare them with the results from traditional moment screens.

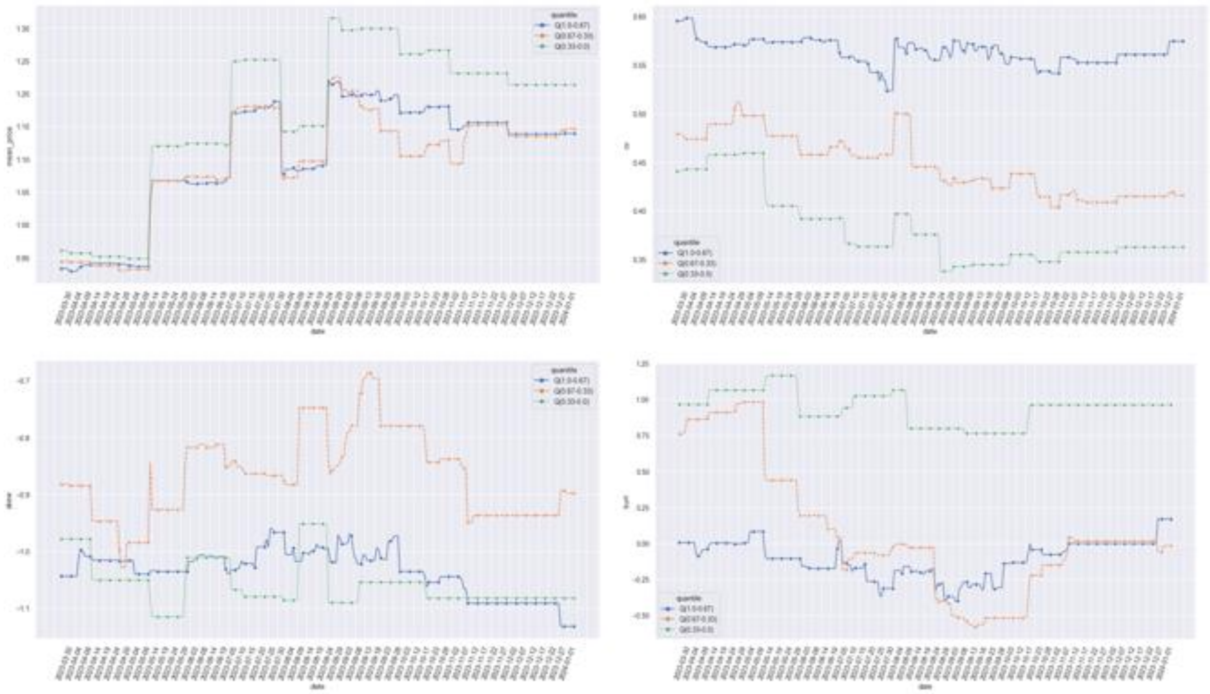
4. Comparing the Performance of Traditional Moment Screening Methods with the ML-Based Screening Technique Used by Yalçın and Öztürk (2024)

The study by Yalçın and Öztürk (2024) explores the intricate relationship between algorithmic pricing strategies and current market dynamics. Utilizing machine learning techniques and data collected via web-scraping tools from the Trendyol website from March 2023 to January 2024, the research analyzes two specific breakfast products: "milk" (Panel A) and "cereal" (Panel B). The findings from Panel A were particularly robust and consistent, indicating a systematic and positive correlation between algorithmic pricing and competitive dynamics. This relationship highlights the potential impacts of automated pricing systems on market competition.

Panel A of the study divides the dataset into two categories: Dataset 1, which includes the unique merchant feature, and Dataset 2, which includes the unique brand feature. Pricing data from both datasets in Panel A were used in the research, allowing for a thorough examination of the effects of various behavioral factors on pricing strategies. In this study, we also used pricing data in both datasets under Panel A.

The pricing data in this study was adjusted using the dairy producer's index prices to mitigate potential inflationary effects, ensuring that the analysis focuses purely on price dynamics unaffected by general inflation. The analysis incorporated traditional moment screens -mean price, coefficient of variation (CV), skewness, and kurtosis- commonly employed to detect signs of collusive behavior. Echoing the innovative approach of Yalçın and Öztürk (2024), a significant aspect of the current study is the use of quantiles based on price changes, leveraging one of the most noticeable effects of algorithmic pricing: its capability to respond swiftly to market conditions. By categorizing daily prices into quantiles (high, middle, low), the study could delineate the differences between algorithmic and non-algorithmic pricing and their respective impacts on market competitiveness. For Panel A: Dataset 1, which includes the unique merchant feature, the daily moment screens are presented as follows:

Figure 1: Daily Moment Screens (mean prices, variation, skewness, and kurtosis) for Panel A: Dataset 1

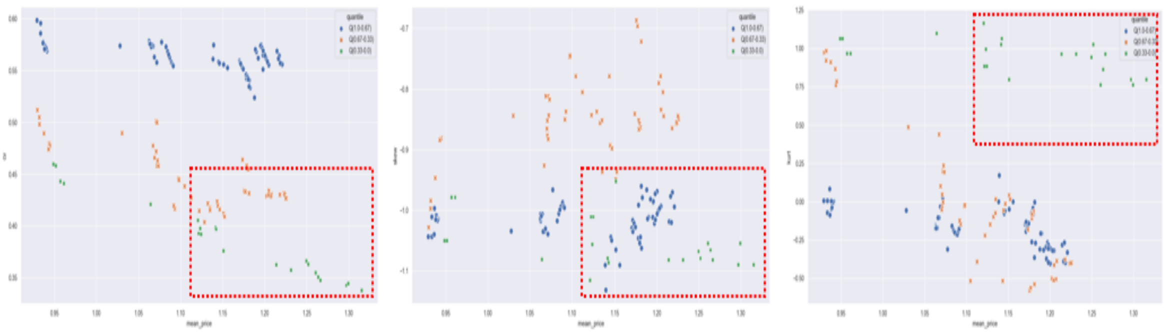


The studies on behavioral screens show that during a collusive period standard deviation, and coefficient of variation tends to be lower (Abrantes-Metz et al. 2006; Esposito and Ferrero 2006; Abrantes-Metz and Pereira 2007; Bolotova et al. 2008; Muthusamy et al. 2008; Abrantes-Metz et al. 2012; Jiménez and Perdiguero 2012; Byrne and De Roos 2019), while mean prices (Abrantes-Metz and Pereira 2007; Byrne and De Roos 2019), skewness, and kurtosis values (Wallimann et al. 2023, p.1680-1681) tend to be higher.

Figure 1 of the study depicts four different screens used to discover algorithmic pricing habits. The investigation of mean milk prices in the "high quantile", which indicates algorithmic pricing, reveals significant jumps. However, these jumps do not indicate a distinct price pattern when compared to other quantiles linked with non-algorithmic pricing. This finding is supported by the CV screen, which demonstrates that algorithmic pricers face a significant level of price variance. Furthermore, the study detects modest skewness and low kurtosis in the pricing data. Essentially, the presence of algorithmic pricing does not inevitably result in higher or supra-competitive profits than non-algorithmic alternatives.

Furthermore, we examined the dual relationships of moment screens with mean prices in Figure 2:

Figure 2: Dual Relationships of Mean Prices with CV, skewness, and kurtosis for Panel A: Dataset 1



When assessing potential instances of collusion, using multiple indicators increases the likelihood of discovering true instances of collusive behavior. As a result, investigating dual relationships can improve the effectiveness of the screening process. Figure 2 of the study shows pair plots of mean prices together with their coefficient of variation (CV), skewness, and kurtosis. The red rectangle indicates probable collusion areas with low CV and high mean price values, skewness, and kurtosis.

For the pairings of mean price with CV and mean price with kurtosis, the patterns suggest that algorithmic pricing does not exhibit collusive behavior. However, the skewness screen considers both positive and negative skewness values. Skewness values ranging from -1 to +1 are considered slightly or lowly skewed, indicating a close alignment with a normal price distribution. Deviations from this range may suggest an unusual distribution.

The red rectangle in the mean price-skewness pair plot shows entries from both the “high quantile” and “low quantile”. At this point, values around -1 are not typically concerning for collusion, but significant departures from this level may warrant further investigation to ensure they do not indicate collusive behavior. The overall examination of the pair plots in both Figure 1 and Figure 2 does not align with an algorithmic collusion scheme among sellers in Dataset 1, implying that pricing behavior is not collusive.

Panel A: Dataset 2 includes distinct brand-specific attributes, allowing for an investigation of competitive dynamics within the brand landscape. Producers (explicit or tacit collusion) and/or intermediaries (hub-and-spoke cartels) may engage in collusion in this scenario. Daily moment screens are shown below:

Figure 3: Daily Moment Screens (mean prices, variation, skewness, and kurtosis) for Panel A: Dataset 2

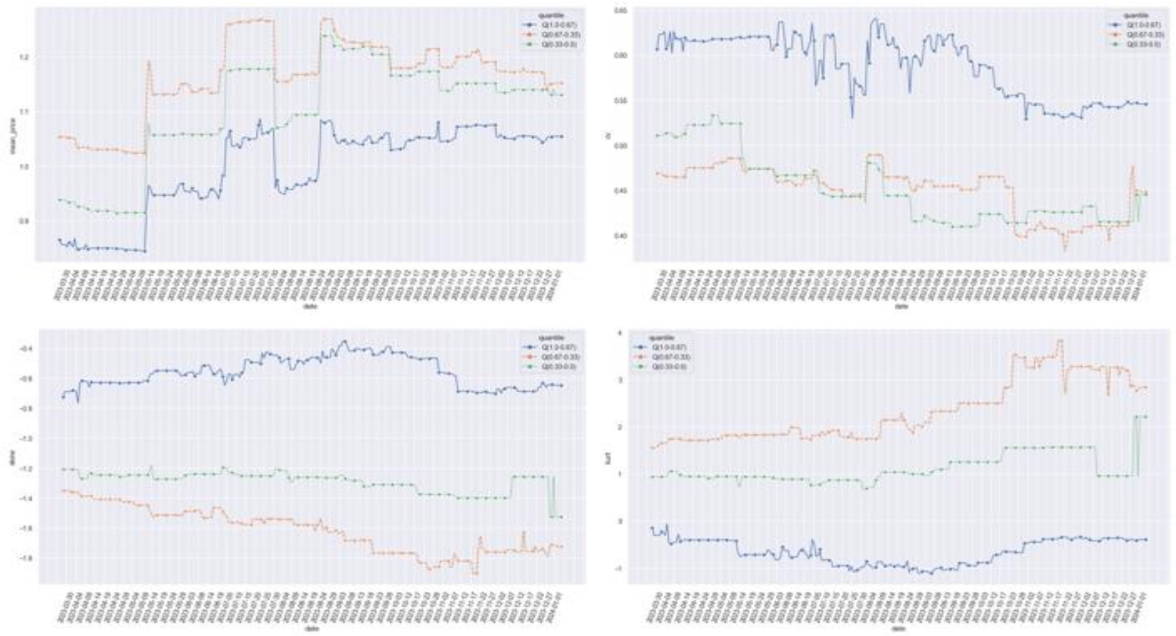


Figure 3 shows that the average price in the "high quantile" group, which represents algorithmic pricing, is lower than in other categories. The coefficient of variation (CV) is significantly higher in this group, with skewness around 0 and lower kurtosis. Additionally, Figure 4 provides further evidence supporting the competitive nature of algorithmic pricing in Dataset 2.

Figure 4: Dual Relationships of Mean Prices with CV, skewness, and kurtosis for Panel A: Dataset 2

Pair plots, like preceding data, demonstrate non-collusive algorithmic pricing outcomes. They consistently display lower average price levels, with skewness and kurtosis that resemble a normal distribution. Consequently, our findings suggest that algorithmic collusion is unlikely among producers, and there is no statistical evidence to support the notion of a hub-and-spoke cartel.

5. Discussion and Conclusion

Over the past decade, the electronics sector, especially computer hardware, has seen remarkable progress, significantly enhancing computational and storage capabilities. This advancement has facilitated the development of new tools for data storage, management, and analysis across various sectors. While terms like "big data" and "collusion" have become widely recognized, the concept of "algorithmic collusion" is gaining traction, particularly with the rise of autonomous devices and programs. Global manufacturing processes are increasingly automated and dynamic, with algorithms playing a crucial role in enhancing efficiency and decision-making. However, these advancements pose challenges to traditional collusion detection methods, which were developed before the rapid evolution of autonomous decision-making. The paper outlines a discussion on collusion theory, introduces algorithmic collusion, and categorizes classical and modern collusion detection techniques. It also proposes a novel machine learning-based approach to analyzing algorithmic pricing in online marketplaces, aiming to compare outcomes with traditional methods. This study anticipates shedding light on the implications of algorithm-driven environments on market theories and applications.

Based on the current screening results, we can conclude that the probable use of algorithmic pricing does not result in an anti-competitive consequence for the dataset under consideration. This finding aligns with Yalçın and Öztürk's (2024) ML-based approach. A limitation and advantage of this study is that we do not know the exact nature of the algorithms utilized by sellers in digital markets. In general, competition authorities employ screens as signal generators and/or supplementary evidence to back up their legal findings in an investigation. Because authorities cannot know the operating principles or rules of an algorithmic pricing system before conducting an investigation, we believe that the methodologies provided in this paper have the ability to provide convenient preliminary checks on market dynamics.

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Author Contributions: author contributions are below;

Introduction: 1. Author and 2. author

Literature: 1. author

Methodology: 1. author

Conclusion: 1. Author and 2. author

1st author's contribution rate:70 %, 2nd author's contribution rate: 30%.