



INSTITUTE OF RETAIL ECONOMICS

A HEURISTIC FOR IDENTIFYING ALGORITHMIC PRICING IN LOW- RESOLUTION PRICE DATA

CHARLIE LINDGREN, ROSS MAY, NIKLAS RUDHOLM &
KENNETH CARLING

HFI WORKING PAPER No 43

A Heuristic for Identifying Algorithmic Pricing in Low-Resolution Price Data

Charlie Lindgren*, Ross May*, Niklas Rudholm[‡], and Kenneth Carling*

^{*}Dalarna University, Falun, Sweden.

^{*}Corresponding author. niklas.rudholm@hfi.se. +46706254627. Institute of Retail Economics, Stockholm, Sweden.

Abstract: This study introduces a heuristic for detecting retailers utilizing algorithmic pricing in low-resolution price data. By using metrics that account for both the frequency of price adjustments and the degree of retailer market presence, we improve upon existing methods for detecting algorithmic pricing retailers. Our results show that there are algorithmic pricers active in all 16 product categories under study in the UK, while only seven out of the 16 categories have at least one algorithmic pricer in Denmark. As for categories, algorithmic pricers are more common in the consumer electronics categories than in household appliances. They are least common in the Cookers category, where only the UK has at least one algorithmic pricer in the market. On the other hand, for the Headphones, Mobile phones, PC-games, Portable speakers, Tablets and Xbox games categories, algorithmic pricers are present in all seven national markets under study. As such, algorithmic pricing is nowadays common in many national and product markets.

Keywords: Algorithmic pricing, retail competition, heuristic detection, pricing dynamics, market presence.

JEL classifications: C81, D40, L12, L13, L81.

1. Introduction

Increasingly, companies are adopting algorithms for pricing decisions. According to Chen et al. (2016), one-third of the top 1600 bestsellers on Amazon’s US platform utilise algorithmic pricing. For the European market, the European Commission (2017) reports that most retailers use software to monitor competitors’ prices, and two-thirds of the retailers who monitor competitors’ prices also use automated pricing based on competitors’ prices in some form. Evidence from the Nordic region points in the same direction: the Norwegian Competition Authority (2021) found that 55% of the surveyed companies used monitoring algorithms, while 20% used some form of algorithmic pricing. Notably, some retailers had already begun experimenting with self-learning algorithms—tools capable of adapting their strategies over time to achieve goals such as profit maximization. The spread of algorithmic pricing has also been facilitated by the growing number of commercial providers offering off-the-shelf pricing algorithms.

The increased use of algorithmic pricing, coupled with the introduction of self-learning algorithms, has sparked a lively debate among competition authorities worldwide. A central concern is that these algorithms may increase the likelihood of price coordination. Equally troubling is that such coordination may not be illegal, or at least extremely difficult to prosecute, under existing competition law. The challenge lies in distinguishing between algorithms that merely “fail to learn to compete” and those that actively “learn to collude,” a distinction that is crucial for antitrust enforcement (Assad et al., 2024; Calvano, Calzolari, Denicolò, Harrington, et al., 2020; Harrington, 2018; Swedish Competition Authority, 2021a).

The research literature on how algorithmic pricing affects competition primarily consists of theoretical and experimental studies (Klein, 2021). Based on theoretical contributions regarding factors that facilitate price coordination in traditional markets, it is likely that algorithmic pricing facilitates price collaborations, primarily because of the high

frequency of interactions between firms, a feature common to both e-commerce markets and algorithmic pricing (Ezrachi & Stucke, 2017; Mehra, 2015)

The experimental contributions to the literature have instead focused on demonstrating that algorithms can be induced to create price coordination under various conditions (Calvano, Calzolari, Denicolò, & Pastorello, 2020; Calvano, Calzolari, Denicolò, Harrington, et al., 2020; Klein, 2021). The results from these studies show that algorithms can collaborate in ways that raise prices beyond what would apply in a competitive market. However, such cooperation typically requires hundreds of iterations, meaning that in practice several months may pass before price coordination emerges. Researchers who conducted these studies have questioned whether algorithmic price coordination is a problem with today's technology. In an as-yet-unpublished study, Hettich (2021) created algorithms that achieve coordination much faster and involve more companies than in previous studies. He concludes that price collaborations can already occur in an environment with pricing algorithms.

Empirical studies examining the occurrence of price coordination through algorithmic pricing are rare. Chen et al. (2016) develop a methodology for detecting algorithmic pricing and then use it to ascertain the extent to which it is used on the Amazon Marketplace as well as the strategies employed by such algorithms. They observe that sellers identified as algorithmic pricers tend to win the Buy Box status (the recommended product on the marketplace) more regularly, thereby increasing the company's chance of greater profits, as such status invariably leads to more sales. Assad et al. (2024) analyse data from German gas stations, where some employ algorithmic pricing while others do not. They find that in situations where a local duopoly exists and both parties use algorithmic pricing, the trading margin increases by a substantial 28% compared to markets where no algorithmic pricing is used. Musolff (2022) investigates how algorithmic pricing affects prices on Amazon's US marketplace. In the short term, it leads to lower prices, but over time, companies often transition to pricing strategies that create

Edgeworth cycles—starting with a high initial price that gradually decreases until a company raises it back to the initial high level. Additionally, Hanspach et al. (2024) examine how algorithmic pricing impacts prices on the Dutch marketplace Bol.com. Their results show that retailers using algorithmic pricing more frequently achieve Buy Box status and do so at higher prices than companies reaching the same status without algorithmic pricing.

As an initial step towards answering whether tacit collusion is occurring among pricing algorithms, we need to identify which retailers are using such technology. Such information is not readily available as retailers rarely disclose the use of pricing algorithms. To address this challenge, prior studies seeking to identify algorithmic pricing with publicly available data have relied on statistical markers that are consistent with specific characteristics of price-setting algorithms. One common marker appearing in several recent empirical studies (Assad et al., 2024; Chen et al., 2016) concerns counting the number of price changes over a given sampling period. Then, based on a chosen threshold, retailers exceeding this are classified as using pricing algorithms. This method works well for high-frequency data, that is, data collected on the order of minutes. However, for data of a much lower resolution, for example, a single data point per retailer-product pair collected daily, refinements of already existing methods are required.

In this paper, we contribute two innovations to the literature for identifying pricing algorithms using price data. First, we adapt the most common marker used in earlier studies working with high-resolution price data. Instead of simply counting price changes, we compute the *average rate of price change (ARPC)* for each retailer across its full product portfolio. This helps in identifying retailers who consistently change prices across large parts of their product portfolio, as an ARPC equal to one implies that the retailer has changed the price of all its products during all days the data was collected.

Note, however, that if a retailer only sells one or very few products in a product market with few competitors and for a short period of time, and for this one retailer-product we

observe an ARPC tending to 1, then the likelihood of us misclassifying this retailer as implementing algorithmic pricing is greatly increased since frequent repricing of just a few products over a short period could plausibly be managed by experienced staff without automation. To address this potential issue and reduce the risk of misclassifications, we propose a complementary marker: *Market presence*.

Market presence is a measure of the share of all possible product-day combinations that a retailer markets the products within their product portfolio on the PriceSpy website. As such, a market presence measure of one would mean that the retailer in question is omnipresent in the market, while a retailer with a market presence equal to zero would be non-existent. Using the market presence as a marker will mitigate extreme cases where a retailer appears fleetingly in the market with a few products but with many price changes, something that, given the nature of our data, could well be a human price setter.

Our results show that algorithmic pricers are present in several categories in all seven national markets and have their highest share for the Tablets category in Norway, where 14.3% of prices are being set by algorithms. Comparing the prevalence of algorithmic pricing over national markets, there are algorithmic pricers active in all 16 categories in the UK, while only seven out of the 16 categories have at least one algorithmic pricer in Denmark. As for categories, algorithmic pricers are least common in the Cookers category, where only the UK has any algorithmic pricer in the market. On the other hand, for the Headphones, Mobile phones, PC-games, Portable speakers, Tablets and Xbox games categories, algorithmic pricers are present in all seven national markets.

The rest of this paper is organised as follows. Section two presents the data used for exploring the heuristic. Section three elaborates on the proposed heuristic for identifying algorithmic pricing retailers. Section four gives empirical results on classified algorithmic retailers for our seven national markets and 16 product categories. Finally, section five summarises the results, provides a discussion, and some suggestions for future work with regard to using our novel heuristic.

2. Data

2.1 Data collection

This study is based on price quote data from 7 countries: Denmark, Finland, Norway, Sweden, the United Kingdom, France and New Zealand, for 16 product categories (11 consumer electronics categories and 5 household appliances categories) collected from the price comparison website PriceSpy.¹ Data collection was launched in September 2020 with an initial goal to gather at least one year of data. The initial data collection period (September–December 2020) was ambitious in scope, and for a subset of products, data was collected at 15-minute intervals. This frequency was chosen since PriceSpy updates its prices several times a day, and we did not know how common within-day price changes were. However, since the data showed that within-day price changes were almost non-existent, the decision was made to reduce the frequency of recordings to daily. After this initial review of the data and the scraping process, data collection commenced again in June 2021 and was sustained until March 2022, when significant changes to the PriceSpy website caused a break in data collection. After a revision of the scraping script, data collection resumed in May 2022 until December 2022.

The first step in the data collection consisted of running R scripts to gather ID variables for the product categories. This was done by using readily available lists of products on

¹ PriceSpy was founded in Sweden in 2002. They listed approximately 5,000 firms in the Swedish market in 2020 (Lindgren et al., 2022), and at that time there were approximately 60,000 retailers in total in Sweden (Confederation of Swedish Retailers, 2021). However, all major Swedish home electronics and household appliances chains are listed on the Swedish PriceSpy website, and coverage in terms of market share is thus likely to be high (above 80%). For the other countries in our dataset, we have no comparable information regarding market coverage.

the UK PriceSpy website, where products are ordered by popularity. On the day the product list was constructed, we gathered all product IDs for the selected categories. Following this, multiple R sessions were run simultaneously using a script coded to collect information about prices. Each iteration in the script gathers information from all countries simultaneously for one unique product ID using regular expressions based on the HTML code, saves the information in a .rds (R data serialised) file as lists, and then enters a sleep timer until the next iteration. Once collected, the .rds files were then looped over to construct the dataset as .csv files for each product category. Once all products (i.e., product ID variables) had been gathered for one day, the script would then stop collecting product ID until the next day (at midnight). To avoid bias from repeatedly scraping the same products at the same time of day (e.g., morning, evening, night), the product list was randomised after each full cycle.

Products in the dataset can be uniquely identified across all countries through universal ID variables assigned by PriceSpy. These identifiers function similarly to manufacturing numbers but are specific to the PriceSpy platform. For example, the product-ID 5405328 consistently refers to the PlayStation 4 game Marvel's Spider-Man: Miles Morales in every country covered. By contrast, retailer identifiers are country-specific and cannot be transferred across markets. A retailer operating in both Sweden and Norway, for instance, will be assigned different IDs in each country's PriceSpy database. While the data collection procedure described ensures comprehensive coverage of the selected product categories on PriceSpy, it does not extend to all categories available on the platform (e.g., clothing, apparel, or watches). Thus, the dataset can be considered exhaustive for the sectors under study, but it does not capture the entire range of retail activity on the platform.

3. A Heuristic for Classifying Algorithmic Pricing

The number of price changes has been employed as an indicator of algorithmic pricing in several settings. Chen et al. (2016) analysed price dynamics on the Amazon marketplace using a dataset of intra-daily prices for over one thousand products collected over two distinct crawl periods: between September 15, 2014, and December 8, 2014; then again between August 11, 2015, and September 21, 2015. Assad et al. (2024) examined algorithmic behavior in the German retail gasoline market with station-level intra-daily prices spanning 2014–2019. Hanspach et al. (2024) studied the Bol.com marketplace using transaction-level and intra-daily price data covering two different crawl periods: December 26, 2018, to January 25, 2019; then again between February 18, 2020, to April 20, 2020. All the preceding studies referenced above used high-frequency data² to identify algorithmic pricers, whereas we use daily data. We do so as the retailers within our sample do not change prices more than, at most, once a day. As such, we have a single data point collected each day over the data collection period for each retailer and their respective products. To account for the lower resolution of our data, we have adapted a common marker from the earlier studies (Assad et al., 2024; Chen et al., 2016; Hanspach et al., 2024) to also work when using low-resolution data. Additionally, we have defined one additional marker not used in previous studies. The adaptation of the previous marker, as well as a precise definition of the new marker, are described in subsection 3.1.

3.1. Markers

A common marker seen in different forms in the (Assad et al., 2024; Chen et al., 2016; Hanspach et al., 2024), is the total number of price changes. This marker is applied in isolation to each product, assessing whether that product alone appears to be priced

² Data that was collected on the order of minutes.

algorithmically. Since the retailers in our sample do not change prices more than once a day, the resolution of our data is low compared to these former works. We do, however, have access to data for all products marketed through the price comparison website, i.e., we, in most cases, have access to data for a large number of retailer-product combinations within each product category and national market.

Thus, we instead consider the *Average Rate of Price Changes (ARPC)* over all products for each retailer as a marker for algorithmic pricing. The rationale is that a single product's daily price change provides little guidance as to whether the adjustment was made algorithmically. However, by collecting the number of changes for each retailer-product combination and then averaging them over all products, the higher this average is, the more likely it is that the retailer is automating the setting of these prices. The intuition is straightforward: simultaneously repricing many products becomes increasingly difficult for a limited number of employees as the size of the product portfolio grows. Indeed, to carry out such a feat, the employees would have to monitor the competitors in the market for all retailer-product combinations at each moment in time for that specific product category and national market. This act becomes increasingly harder as the number of products and competitors grows, especially so, as this number increases beyond the number of human beings tasked with the job of monitoring and repricing.

To compute ARPC, we first define the following indicator function,

$$\mathbb{I}_{\mathbb{R}^+}(|p_t - p_{t+1}|) = \begin{cases} 1 & \text{if } |p_t - p_{t+1}| \in \mathbb{R}^+ \\ 0 & \text{if } |p_t - p_{t+1}| \notin \mathbb{R}^+ \end{cases},$$

where p_t , and p_{t+1} denote, respectively, the prices at day t and $t + 1$, and $\mathbb{R}^+$ is the set of positive real numbers.³ In words, if there is a price change during a specific day for a retailer-product combination i, j , the indicator function takes the value one, otherwise zero. With this definition in hand, the retailer i 's rate of price change for the product j is computed as,

$$q_{i,j} \stackrel{\text{def}}{=} \frac{\sum_{t=k}^{T_j^i} \mathbb{I}_{\mathbb{R}^+}(|p_t - p_{t+1}|)}{T_j^i},$$

where T_j^i is defined as the total number of days in the market for the product j of retailer i , that is, the number of days the retailer i is posting prices on PriceSpy for the product j over the data collection period. We treat the collected prices over time as an indexed sequence of prices.⁴ This simplifies the computation of $q_{i,j}$ and also handles cases in which a retailer i exits the market and then re-enters again. Thus, $q_{i,j}$ simply measures the total number of price changes observed over the data collection period ($\sum_{t=k}^{T_j^i} \mathbb{I}_{\mathbb{R}^+}(|p_t - p_{t+1}|)$) divided by the total possible number of price changes (i.e., data collection days, T_j^i) for retailer-product combination i, j . Thus, $q_{i,j} = 1$ indicates that retailer i changes the price of product j each day.

The ARPC for retailer i over all products j is then the arithmetic mean,

$$\overline{q}_i = \frac{\sum_{j=1}^n q_{i,j}}{n}.$$

³ This is understood as not including the number zero.

⁴ In other words, we consider $\{p_i\}_{i=1}^n$.

As such, $\overline{q}_i = 1$ implies that retailer i has changed the price of all its products during all the days the data has been collected for.

Note, however, that if a retailer only sells one or very few products in a product market with few competitors and for a short period of time, and for this one retailer-product we observe an ARPC tending to 1, then the likelihood of misclassifying this retailer as using algorithmic pricing increases, since frequent repricing of a small number of products over a short period could still be managed by skilled staff. To address this potential issue and reduce the risk of misclassifications, we propose a complementary marker: *Market presence*.

To compute the market presence of a retailer in the market, we first consider the overall length of time a product j has been in existence in the market. To do this, let the set $\mathcal{T}$ represent all recorded time points for the product j over all retailers i . Then, we define

$$T_j = \max(\mathcal{T}) - \min(\mathcal{T})$$

to be the overall number of days product j has been marketed through the PriceSpy website by any retailer. Note that this T_j we define above is not to be confused with that which we defined when describing ARPC. Based on the above, we then define the *market presence denominator* to be,

$$\tau_j \stackrel{\text{def}}{=} \sum_{j=1}^N T_j.$$

where N is the total number of distinct products listed on the PriceSpy website for any retailer. Thus, τ_j represents the aggregate exposure of all products over time, providing a benchmark against which the presence of individual retailers can be assessed.

We further define $T_{j|i}$ to be the overall number of days that the product j was marketed through the PriceSpy website by the retailer i . The *market presence numerator* for the

retailer i , $\tau_{j|i}$, is then the sum of days in the market across all products sold by the retailer i , that is,

$$\tau_{j|i} \stackrel{\text{def}}{=} \sum_{j=1}^N T_{j|i}.$$

The share of the total market presence of the retailer i over all products j measured in days is then defined as

$$\Pi_i \stackrel{\text{def}}{=} \frac{\tau_{j|i}}{\tau_j}.$$

Observe that both $\overline{q}_i, \Pi_i \in [0,1]$ for all i . One can think of $\overline{q}_i$ as a measure of activity where $\overline{q}_i = 1$ would mean retailer i is always changing prices and $\overline{q}_i = 0$ would mean it is never changing prices. Similarly, $\Pi_i = 1$ would mean that retailer i is omnipresent in the market. Conversely, $\Pi_i = 0$ would mean retailer i is non-existent. In practice, these extreme values are never attained. The purpose of Π_i is to mitigate extreme cases where a retailer can appear fleetingly with a few products but with many price changes, which, given the nature of our data, could well be a human price setter.

Finally, since the distributions of both $\overline{q}_i$ and Π_i can be skewed, we standardise these measures by subtracting the median and dividing by the interquartile range (IQR) of each. This type of standardisation is robust against outliers and particularly well-suited to skewed distributions. To reduce the chance of misclassifying a retailer as applying algorithmic pricing, we set the following heuristic: *if both the standardised values $\overline{q}_i^*, \Pi_i^*$ are bigger than 2 IQRs away from the median for each respective marker then we classify this retailer as using algorithmic pricing.*

4. Results

Figure 1 illustrates the heuristic where each quadrant indicates whether a retailer is identified as algorithmically pricing. For instance, a retailer with a low market presence ratio (measured by IQR) and a high frequency of price changes (also measured by IQR) would be classified as a non-algorithmic, since frequent price changes for only a few products over limited periods are feasible for humans to manage. The threshold to determine high or low is set by exceeding 2 IQRs in either measurement. A retailer is categorised as algorithmically pricing only if both IQR measures exceed 2 IQRs.

To illustrate the classification according to the proposed heuristic, Figure 2 presents threshold plots of standardised markers for retailers in the Swedish Xbox One Games market. Each point in the scatterplot represents an individual retailer. Retailers falling within the upper-right quadrant are classified as using algorithmic pricing, indicated by standardised values exceeding 2 IQRs from the median. A substantial share of retailers falls between extremes, neither consistently changing prices nor maintaining fixed ones. Conversely, another notable group either adjusts prices frequently or keeps them largely stable. Upon closer examination, retailers identified by the proposed heuristic as employing algorithmic pricing, marked by a red circle, notably include the Amazon marketplace, consistent with the findings from Chen et al. (2016).

Table 1 provides the equivalent share of retailers exceeding this threshold by country and category. For instance, the share of algorithmic pricing retailers for the Xbox One Games market in Sweden is equal to 4.3%, corresponding to the four retailers flagged as algorithmic pricers in Figure 2. Table 1 shows that algorithmic pricers appear in several categories across all seven markets, with the highest share in Norway's Tablets category, where 14.3% of retailers are setting prices algorithmically. Comparing the prevalence of algorithmic pricing over national markets, there are algorithmic pricers active in all 16 categories in the UK, while only seven out of the 16 categories have at least one algorithmic

pricer in Denmark. As for categories, algorithmic pricers are least common in the Cookers category, where only the UK has an algorithmic pricer in the market. On the other hand, for the Headphones, Mobile phones, PC-games, Portable speakers, Tablets and Xbox games categories, algorithmic pricers are present in all seven national markets.

In relation to the Norwegian market, the average prevalence of algorithmic pricers stands at 6.4%. According to a 2021 report by the Norwegian Competition Authority, 20% of the retailers in their sample openly admitted to employing algorithmic pricing. However, their methodology involved sampling primarily the largest 3-5 retailers based on annual turnover, or in some cases, the top 5 most visited retailers. This approach inevitably skewed the results towards a higher proportion of retailers flagged for algorithmic pricing as this is more common in larger firms. To ensure a more equitable comparison, a filtering mechanism was implemented. Specifically, only data with market presence IQR (Interquartile Range) exceeding 2 was utilized for analysis. This adjustment allows for a comparison between retailers with high and low pricing frequency, focusing on significant market players similar to those in the Norwegian study. The filtering criteria are depicted in Figure 3, where the selection of retailers is highlighted by a red rectangle, based on a market presence ratio IQR exceeding 2, specifically for Xbox One games in Sweden. Through this adjustment, the proportion shifts from 4.3% to 23.5%, aligning closely with the findings from the Norwegian report. Table 2 presents proportions across all considered countries and categories, consistently revealing a notably higher percentage of retailers identified as employing algorithmic pricing when focusing on larger retailers, echoing the observations of the Norwegian Competition Authority (2021).

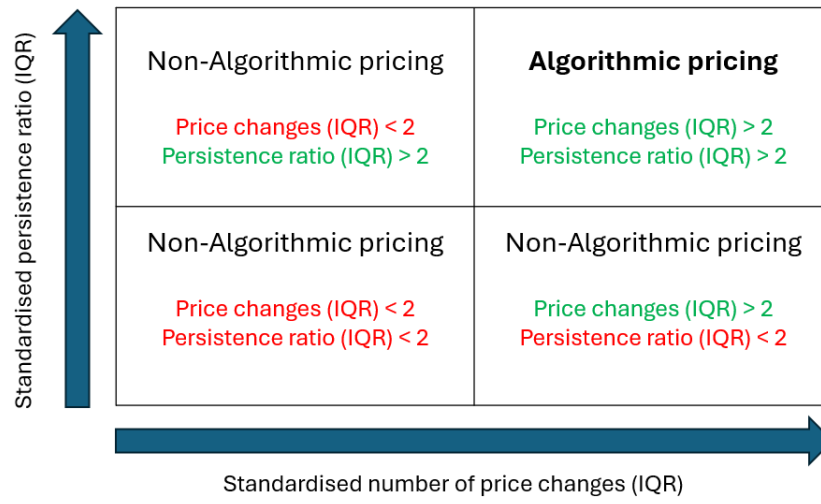


Figure 1. Visualisation of the principles of the heuristic.

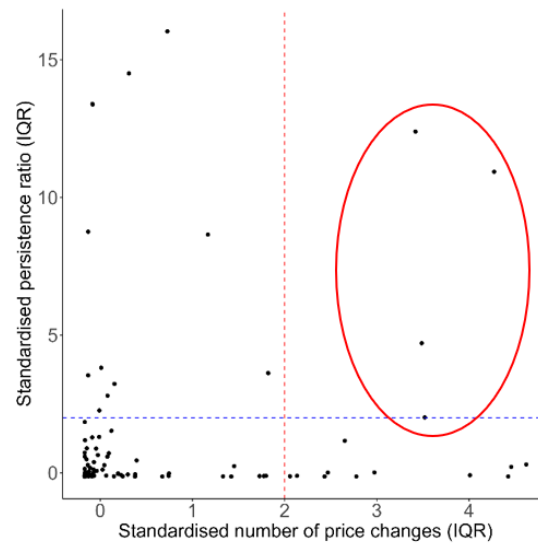


Figure 2. Threshold plots of standardised markers for retailers in the Swedish Xbox One Games market. Algorithmic pricing retailers circled.

Table 1. Percentage of retailers, categorised by country and product category, whose Interquartile Range (IQR) thresholds exceed 2 for both markers.

Category	Denmark	Finland	France	UK	Norway	New Zeeland	Sweden
Cookers	0.0	0.0	0.0	7.6	0.0	0.0	0.0
Dishwashers	0.0	7.7	1.7	5.2	9.1	0.0	3.3
Freezers	0.0	0.0	0.0	5.9	4.8	0.0	6.2
Fridges	0.0	0.0	0.0	5.5	10.9	0.0	2.9
Game Consoles	0.0	1.9	0.0	3.4	3.8	0.0	1.6
Headphones	6.3	4.1	6.4	4.4	9.2	4.9	5.7
Mobile Phones	3.1	6.1	1.8	4.4	11.4	6.2	6.6
Nintendo Switch Games	0.0	2.1	3.6	3.1	3.9	5.0	3.7
PC Games	3.8	3.6	2.9	6.5	4.1	11.8	6.1
Portable Speakers	5.2	5.1	5.9	3.8	6.4	4.7	4.2
PS4 Games	0.0	2.0	8.3	3.7	2.2	3.8	5.1
Tablets	3.8	5.1	5.2	5.5	14.3	1.9	9.0
Tumble Dryers	0.0	0.0	0.0	5.2	9.1	0.0	0.0
TVs	0.0	7.0	1.1	1.0	0.0	0.0	4.4
Washing Machines	3.2	0.0	0.0	4.4	10.0	0.0	2.3
Xbox One Games	2.2	5.9	7.4	4.9	2.6	4.0	4.3

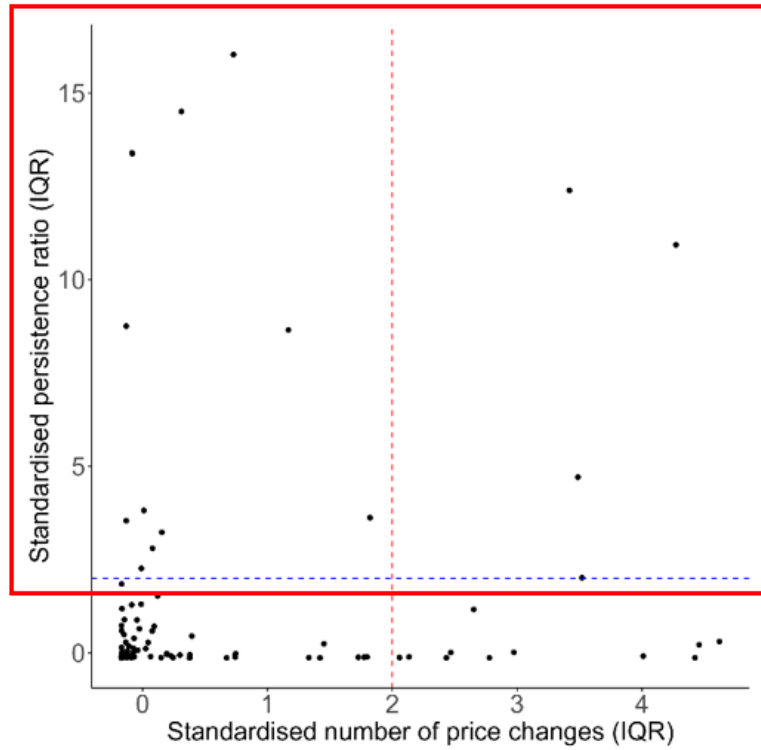


Figure 3. Filter of retailers with standardised market presence IQR above 2 (i.e., large retailers).

Table 2: Percentage of retailers with interquartile range (IQR) of price frequency exceeding 2, categorised by country and product type, specifically for market presence ratio IQR exceeding 2 across all product categories.

Category	Denmark	Finland	France	UK	Norway	New Zealand	Sweden
Cookers	0	0	0	45	0	0	0
Dishwashers	0	100	25	50	100	0	33
Freezers	0	0	0	47	100	0	50
Fridges	0	0	0	50	46	0	17
Game Consoles	0	17	0	29	40	0	18
Headphones	36	30	35	29	52	40	38
Mobile Phones	27	62	20	37	67	44	49
Nintendo Switch Games	0	14	20	20	25	33	28
PC Games	18	20	12	33	17	67	38
Portable Speakers	32	38	37	26	48	36	27
PS4 Games	0	11	43	21	17	25	27
Tablets	43	75	50	50	82	25	61
Tumble Dryers	0	0	0	78	67	0	0
TVs	0	44	11	10	0	0	33
Washing Machines	100	0	0	60	100	0	33
Xbox One Games	12	30	31	30	17	25	24

5. Discussion

Companies are increasingly adopting algorithmic pricing, and according to Chen et al. (2016), one-third of the bestsellers on Amazon’s US platform utilise algorithmic pricing. Moreover, the European Commission (2017) found that most retailers in Europe use software to monitor competitors’ prices, and many also use automated pricing in some form. The Norwegian Competition Authority (2021) likewise found that 55% of surveyed companies used monitoring algorithms, and 20% employed some form of algorithmic pricing.

In this research, we have introduced a heuristic method designed to detect algorithmic pricing patterns using low-resolution price data. Our heuristic uses two standardised indicators to uncover the prevalence of algorithmic pricing in retail in seven national markets and for 16 product categories. By integrating market presence alongside average pricing frequency, our heuristic can detect algorithmic pricers also in low-resolution (daily) price data.

We observe that algorithmic pricing is widespread in the markets we have examined. There are algorithmic pricers active in all 16 product categories in the UK, and for the Headphones, Mobile phones, PC-games, Portable speakers, Tablets and Xbox games categories, algorithmic pricers are present in all seven national markets under study. We also find that our heuristic accurately identifies known algorithmic pricing retailers, such as Amazon, and that the resulting shares of algorithmic pricers align closely with those reported in the Norwegian Competition Authority’s survey when similar samples are considered. The Norwegian Competition Authority (2021) study inherently favoured larger retailers, likely leading to an overestimation of algorithmic pricers, since such practices are more common among firms with the resources to implement them. Our proposed heuristic addresses this bias as well, and our results are thus also likely to be a more accurate estimate of the share of retailers engaged in algorithmic pricing than in previous studies.

A reliable method for identifying retailers that use pricing algorithms is important for several reasons, not least for safeguarding competition in markets where algorithmic pricing is prevalent. Many competition authorities worldwide believe that the growing use of algorithmic pricing could increase the likelihood of price coordination. Moreover, such coordination would likely not be illegal, or at least extremely difficult to prosecute, under current competition law (Assad et al., 2024; Calvano, Calzolari, Denicolò, & Pastorello, 2020; Harrington, 2018; Swedish Competition Authority, 2021a).

Despite the potential importance for consumer welfare, the research literature on how algorithmic pricing affects competition primarily consists of theoretical and experimental studies, while empirical studies are rare (Klein, 2021). One reason for this is a lack of knowledge of which retailers use pricing algorithms, and another is that there is also a lack of methods for identifying price patterns that are the likely outcome of tacit- or outright collusive pricing based on online market price data. An important avenue for future research is to develop methods for detecting collusion in low-resolution price data, and to examine whether collusive pricing is more common in markets where algorithms set prices.

Acknowledgments

This work was supported by the Hakon Swenson Foundation (grant number 2022/011), as well as the Swedish Competition Authority (grant number 443/2022). The Hakon Swenson Foundation or the Swedish Competition Authority was not involved in the study design, data collection, data analysis, or the decision to submit the paper for publication. The authors have no financial or personal relationship that could cause a conflict of interest regarding this article. The authors are grateful to the participants of the EURO 2024 conference in Copenhagen, Denmark, June 29th to July 3rd, 2024; the NRW 2024 conference in Helsingborg, Sweden, November 5th to November 7th, 2024; the RARCS 2025 conference in Zagreb, Croatia, July 7th to July 10th, as well as to the participants at a

seminar at Dalarna University on March 26th, 2025, for valuable comments and suggestions.

References

- Assad, S., Clark, R., Ershov, D., & Xu, L. (2024). Algorithmic Pricing and Competition: Empirical Evidence from the German Retail Gasoline Market. *Https://Doi.Org/10.1086/726906*, 132(3), 723–771. <https://doi.org/10.1086/726906>
- Calvano, E., Calzolari, G., Denicolò, V., Harrington, J. E., & Pastorello, S. (2020). Protecting consumers from collusive prices due to AI. *Science*, 370(6520), 1040–1042. <https://doi.org/10.1126/SCIENCE.ABE3796>
- Calvano, E., Calzolari, G., Denicolò, V., & Pastorello, S. (2020). Artificial Intelligence, Algorithmic Pricing, and Collusion. *American Economic Review*, 110(10), 3267–3297. <https://doi.org/10.1257/AER.20190623>
- Chen, L., Mislove, A., & Wilson, C. (2016). An empirical analysis of algorithmic pricing on amazon marketplace. *Proceedings of the 25th International Conference on World Wide Web*, 1339–1349. <https://doi.org/10.1145/2872427.2883089>
- Competition and Markets Authority. (2017). *Digital comparison tools market study: Final report*.
- Confederation of Swedish Retailers. (20221) Läget i handeln, 2021. <https://www.svenskhandel.se/api/documents/rapporter/laget-i-handeln-2021.pdf>
- European Commission. (2017). *Preliminary Report on the E-commerce Sector Inquiry*.
- Ezrachi, A., & Stucke, M. E. (2017). Artificial Intelligence & Collusion: When Computers Inhibit Competition. *University of Illinois Law Review*, 2017.

<https://heinonline.org/HOL/Page?handle=hein.journals/unilllr2017&id=1816&div=&collection=>

Hanspach, P., Sapi, G., & Wieting, M. (2024). Algorithms in the marketplace: An empirical analysis of automated pricing in e-commerce. *Information Economics and Policy*, 69, 101111. <https://doi.org/10.1016/J.INFOECOPOL.2024.101111>

Harrington, J. E. (2018). Developing Competition Law for Collusion by Autonomous Artificial Agents. *Journal of Competition Law & Economics*, 14(3), 331–363. <https://doi.org/10.1093/JOCLEC/NHY016>

Hettich, M. (2021). Algorithmic Collusion: Insights from Deep Learning. *SSRN Electronic Journal*. <https://doi.org/10.2139/SSRN.3785966>

Klein, T. (2021). Autonomous algorithmic collusion: Q-learning under sequential pricing. *The RAND Journal of Economics*, 52(3), 538–558. <https://doi.org/10.1111/1756-2171.12383>

Lindgren, C., Li, Y., & Rudholm, N. (2022). Why Do Firms Compete on Price Comparison Websites? The Impact on Productivity, Profits, and Wages. *The International Review of Retail, Distribution and Consumer Research*, 00(14), 1–40. <https://doi.org/10.1080/09593969.2022.2070773>

Mehra, S. K. (2015). Antitrust and the Robo-Seller: Competition in the Time of Algorithms. *Minnesota Law Review*, 100. <https://heinonline.org/HOL/Page?handle=hein.journals/mnlr100&id=1363&div=&collection=>

Musolf, L. (2022). Algorithmic Pricing Facilitates Tacit Collusion. *EC '22: Proceedings of the 23rd ACM Conference on Economics and Computation*, 32–33. <https://doi.org/10.1145/3490486.3538239>

Norwegian Competition Authority. (2021). *Hvilken effekt kan algoritmer ha på konkurransen? Konkurransetilsynets markedsundersøkelse om overvåknings- og prisingsalgoritmer.*

Swedish Competition Authority. (2021a). Collusion in algorithmic pricing. *Konkurrensverket Uppdragsforskning 2021:3.*

Swedish Competition Authority. (2021b). Konkurrens och tillväxt inom e-handeln. *Rapportserie, 3.*