# DETECTING RESALE PRICE MAINTENANCE WITH UNSUPERVISED MACHINE LEARNING

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**ABSTRACT**

Computational antitrust, the data-driven investigation of potential antitrust violations, has found more and more applications in recent years, including through the use of machine learning. However, the availability of labelled data to train algorithms proves to be an obstacle. In this paper, we explore the use of unsupervised machine learning to detect Resale Price Maintenance (RPM) in price data. We develop assumptions that RPM prices exhibit increased similarity, a right-skewed distribution including a cut-off point, and fewer price changes over time compared to non-RPM prices. Based on these assumptions, we extract features based on simple statistical coefficients and perform clustering to detect products with price characteristics consistent with RPM. Subsequently, this can serve as a sufficient basis to conduct more in-depth antitrust investigations. We test our approach on five real-world product datasets scraped from a price comparison website. We show that our screen successfully clusters products with price patterns indicative of RPM.

**JEL:** C63, K21, K42, L42, L68

## I. INTRODUCTION

Antitrust violations result in considerable costs for the public, other companies, and consumers.[1] Traditionally, the detection of antitrust violations heavily relies on leniency applications. Leniency programmes allow companies participating in a price-fixing cartel, for instance, to inform a competition authority of the infringement and cooperate in uncovering it, in return for being spared from paying any antitrust fines. However, leniency applications are in decline,[2] calling into question the future effectiveness of this enforcement tool. Fortunately, at the same time, we observe the maturing of a new tool in the competition authorities' toolkit: computational antitrust.

Computational antitrust uses computational methods to detect potential antitrust violations.[3] These methods become possible thanks to the increasing availability of data, which in turn results from the continued digitalisation of markets.[4] The methods used by computational antitrust include both simple statistical tests and indicators, such as variance screens,[5] as well as various methods pertaining to (un-)supervised machine learning. While the use of computational antitrust tools in general and the use of machine learning in particular have risen in recent years, the availability of data generally drives the types of antitrust screens that can be applied.[6] For instance, the application of computational antitrust to resale price maintenance (RPM) remains scarce because it requires high resolution

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1 Christian Beyer, Elke Kottmann, and Korbinian von Blanckenburg, *The Welfare Implications of the European Trucks Cartel*, 55 INTERECONOMICS, 120 (2020).

2 OECD, *OECD Competition Trends 2024* (2024).

3 Thibault Schrepel, *Computational Antitrust: An Introduction and Research Agenda*, 1 STANF. COMPUT. ANTIT. 1 (2021).

4 Jan Amthauer, Jürgen Fleiß, Franziska Guggi, and Viktoria H.S.E. Robertson, *Detecting Resale Price Maintenance for Competition Law Purposes: Proof-of-concept Study Using Web Scraped Data*, 51 COMPUT. L. SECUR. REV. (2023).

5 David Imhof, *Detecting Bid-Rigging Cartels With Descriptive Statistics*, 15 J. COMPET. L. & ECON. 427 (2019).

6 Jan Amthauer, Jürgen Fleiß, Franziska Guggi, and Viktoria H.S.E. Robertson, *Ready or Not? A Systematic Review of Case Studies Using Data-driven Approaches to Detect Real-world Antitrust Violations*, 49 COMPUT. L. SECUR. REV. (2023).

price data, ideally collected over time.[7] This is especially pronounced when supervised machine learning is relied upon for an antitrust screen, the training of which requires bidding or market data where the correct classification of whether an antitrust violation occurred is known (i.e. accurately labelled training data). Only then can an algorithm learn to reliably detect the presence of antitrust violations in novel data. Such training data is generally hard to come by. With the availability of data on public tenders,[8] it became possible to analyse the antitrust violation of bid-rigging with computational antitrust screens.[9] As a reaction to the scarcity of labelled data, competition authorities have begun to explore the use of unsupervised machine learning that does not require labelled training data.[10]

In the present contribution, we focus on the applicability of computational antitrust for detecting patterns consistent with RPM in price data. This requires fine-grained data in the form of all the prices from different vendors for products in a market at a given time. To the best of our knowledge, no such data is currently available, nor can it be constructed after the fact, for periods where a manufacturer was proven to have engaged in RPM. In the present contribution, we therefore exclusively explore the suitability of unsupervised machine learning methods for the detection of antitrust violations, using the example of RPM. As data input, we use web scraped product price data from Amthauer et al.,[11] supplemented by our own data for additional products. We then calculate several indicators from antitrust screening approaches, such as the coefficient of variation, as features for unsupervised machine learning algorithms to cluster products. We find that for our data, the clustering algorithms successfully create clusters of similar products with price characteristics consistent with RPM, if such pricing patterns are present. They also successfully replicate the manual analysis of a variance screen performed by Amthauer et al.,[12] showing that unsupervised machine learning is a promising tool to further automate traditional screening methods that rely on human judgement. This promises to considerably facilitate antitrust enforcement by competition authorities, especially as the methods applied cannot be easily circumvented by companies.

The remainder of the article is structured as follows: In Section II, we discuss the application of competition law and computational antitrust to resale price maintenance. We also lay out our expectations on how RPM in a given market will change prices, their distribution, and therefore the indicators based on these expectations. Section III describes our data and its collection, as well as the pre-processing. The features that serve as the basis for our unsupervised machine learning approach and the results are presented in Section IV. Finally, Section V discusses the findings and their implications.

## II. RESALE PRICE MAINTENANCE AND COMPETITION LAW

Resale price maintenance (RPM) is the practice of a manufacturer requiring a retailer to price the contract goods or services at a certain resale price, thereby preventing the price to be freely set by the retailer based on factors such as supply, demand, competition or a short-term promotional sale. RPM is also referred to as vertical price-fixing, as it occurs between companies that are active at different levels of the supply chain. It can take the form of a minimum price below which the contract products are not allowed to be sold, or it can be masked as a 'recommended resale price' (RRP) that retailers are then coerced into observing. This coercion can take various forms, such as an (implicit) threat not to be sold the contract products in case of deviating prices, the knowledge that certain sought-after contract products will be delivered to the retailer last, or digital monitoring of the observance of the 'RRP' and reminder emails in case of non-observance.[13]

### A. The legal framework for resale price maintenance in Europe

In Europe, the pricing practice of RPM is frequently regarded as problematic under competition law. The cartel prohibition of the European Union forbids both horizontal and vertical price-fixing, such as RPM.[14] Under EU competition law, RPM is traditionally regarded as a type of agreement that constitutes a restriction of competition

7 Jan Amthauer, Jürgen Fleiß, Franziska Guggi, and Viktoria H.S.E. Robertson, *Detecting Resale Price Maintenance for Competition Law Purposes: Proof-of-concept Study Using Web Scraped Data*, 51 COMPUT. L. SECUR. REV. (2023).

8 Martin Huber and David Imhof, *Machine learning with screens for detecting bid-rigging cartels*, 65 INT. J. IND. ORGAN. 277 (2019).

9 Jan Amthauer, Jürgen Fleiß, Franziska Guggi, and Viktoria H.S.E. Robertson, *Detecting Resale Price Maintenance for Competition Law Purposes: Proof-of-concept Study Using Web Scraped Data*, 51 COMPUT. L. SECUR. REV. (2023).

10 Thibault Schrepel and Teodora Groza, *Computational Antitrust Within Agencies: 3rd Annual Report*, 4 STANF. COMP. ANTIT. 53 (2024).

11 Jan Amthauer, Jürgen Fleiß, Franziska Guggi, and Viktoria H.S.E. Robertson, *Detecting Resale Price Maintenance for Competition Law Purposes: Proof-of-concept Study Using Web Scraped Data*, 51 COMPUT. L. SECUR. REV. (2023).

12 Id.

13 *Asus* (Case AT.40465) Commission Decision, (2018) OJ C338/13.

14 Consolidated Version of the Treaty on the Functioning of the European Union (TFEU), (2016) OJ C202/47.

'by object'. This entails that the agreement's anti-competitive effects do not need to be shown by the competition authority in order to apply fines to the companies involved.[15] Under the 'by object' approach, it suffices for the competition authority to demonstrate that RPM took place, upon which it can impose hefty antitrust fines amounting to up to 10% of the company's turnover in the previous year.[16] Both the imposition of fixed and minimum sales prices prevents a distribution agreement from benefiting from block exemption under the European Commission's Vertical Block Exemption Regulation.[17] The practice of imposing maximum prices or of recommending prices, on the other hand, is not as such considered as constituting a restriction of competition if this practice does not – directly or indirectly – amount to imposing a fixed or minimum sales price.[18]

The recent *Super Bock* judgement by the Court of Justice of the European Union clarified that RPM may not automatically be considered a restriction of competition by object,[19] contrary to long-standing practice.[20] *Super Bock* concerned a system of RPM imposed by Super Bock Bebidas, a manufacturer of beverages, on all its exclusive distributors with the 'aim of ensuring a stable and consistent minimum price level throughout the market' (para 13), which covered nearly all of Portugal. Super Bock had put in place a tight monitoring system to ensure compliance with its RPM. The Court, when faced with whether this type of RPM could automatically be considered a restriction of competition by object, rejected this interpretation. Instead, it held that for an RPM agreement to be considered a restriction of competition by object, one had to assess whether 'that agreement presents a sufficient degree of harm to competition, taking into account the nature of its terms, the objectives that it seeks to attain and all the factors that characterise the economic and legal context of which it forms part' (para 43).

Following *Super Bock*, not every RPM agreement will therefore be assessed under the 'by object' approach – although for many RPM practices, this will continue to be the case.[21] Where one concludes that the distribution agreement in question did not have the object of restricting competition, one needs to consider the agreement's effects on competition. This changes the burden of proof that a competition authority needs to satisfy, and may move the European approach just a little closer to the one prevailing in the US, where RPM has been assessed under the rule of reason (rather than under the per se approach) since the US Supreme Court's ruling in *Leegin*.[22] However, as pointed out above, in many instances RPM will still be seen as a restriction of competition by object based on the circumstances of a case.

The intensity with which RPM is pursued in some jurisdictions within the EU is remarkable. While at the European level, 7% of Commission decisions on anti-competitive agreements between 2010 and 2022 concerned RPM, in some Member States, the focus on RPM is much more pronounced. This is true for Austria, where nearly 60% of all Cartel Court decisions on anti-competitive agreements between 2012 and 2022 related to RPM.[23]

### B. Computational antitrust in RPM

Competition authorities need to employ ever more sophisticated methods to uncover anti-competitive agreements between companies, not least because, as mentioned above, one of their main tools to detect cartels – leniency applications – is in world-wide decline.[24] One such new tool is computational antitrust. As a branch of legal informatics,[25] computational antitrust applies computational methods to identify anti-competitive patterns in data. To do so, it relies on the analysis of publicly or privately available data through descriptive statistics or machine learning.[26] Most studies using real-world data to detect anti-competitive conduct zoom in on bid-rigging, as data

15 *Asus* (Case AT.40465) Commission Decision, (2018) OJ C338/13.

16 Council Regulation (EC) No 1/2003 of 16 December 2002 on the implementation of the rules on competition laid down in Articles 81 and 82 of the Treaty, (2003) OJ L1/1

17 Article 4(a) of Commission Regulation (EU) 2022/720 of 10 May 2022 on the application of Article 101(3) of the Treaty on the Functioning of the European Union to categories of vertical agreements and concerted practices, (2022) OJ L134/4.

18 European Commission, Guidelines on Vertical Restraints, (2022) OJ C248/1, paras 185ff.

19 Super Bock Bebidas SA and Others v. Autoridade da Concorrência, (2023) C-211/22, ECLI:EU:C:2023:529

20 Frank Wijckmans and Filip Tuytschaever, *Vertical agreements in EU competition law: Third edition* (2018).

21 Pablo I. Colomo, *Resale Price Maintenance in EU Competition Law: Understanding the Significance of Super Bock*, 47 WORLD COMPET. 407 (2024).

22 *Leegin Creative Leather Products Inc. v. PKSK Inc.*, 551 U.S. 877 (2007).

23 Jan Amthauer, Jürgen Fleiß, Franziska Guggi, and Viktoria H.S.E. Robertson, *Detecting Resale Price Maintenance for Competition Law Purposes: Proof-of-concept Study Using Web Scraped Data*, 51 COMPUT. L. SECUR. REV. (2023).

24 OECD, *OECD Competition Trends 2024* (2024).

25 Michael Genesereth, *Computational law: The Cop in the Backseat* (2015).

26 Viktoria H.S.E. Robertson and Jürgen Fleiß, *Computational Antitrust and the Future of Competition Law Enforcement*, 73 GRUR INT. 915 (2024).

from public tenders is often publicly available.[27] RPM, on the other hand, has only been studied three times so far.[28] This is not surprising, for its analysis requires access to extensive price datasets that – even if sometimes publicly available – are usually not available in a structured format that would make the analysis straightforward. In the case of RPM, the computational antitrust screen needs to look for pricing patterns that indicate that a manufacturer may have imposed RPM, such as identical prices, price changes occurring at the same time, etc.

A computational antitrust screen built to identify RPM must take into account the recent clarification in *Super Bock*, which places considerable emphasis on the circumstances of a distribution agreement to assess whether it constitutes a restriction of competition by object, or whether further evidence needs to prove its anti-competitive effect. Competition authorities must therefore be prepared to provide this additional evidence in addition to proving the RPM itself. Evidence provided by a computational antitrust screen may support a competition authority's request to carry out an on-site inspection,[29] to verify (i) whether the RPM was part of an agreement between the companies involved, and possibly also (ii) its anti-competitive effects.

### C. Assumptions about price characteristics under RPM

The use of unsupervised machine learning to detect RPM requires the construction of features on which the clustering will then be based. Those features capture our assumption of how prices influenced by RPM will display characteristics different from non-RPM products, similar to the use of different statistical indicators in behavioural screens. Specifically, we assume that under RPM, as compared to non-RPM products, prices are (a) more similar, (b) have a more right-skewed distribution including a cut-off point, and (c) show fewer price changes over time due to less price competition.

**Assumption 1: RPM leads to more similar prices.** RPM restricts the freedom of retailers to set the price of a product.[30] It can be assumed that the manufacturer sets a minimum price higher than retailers might price the product if this minimum price were not enforced. If a manufacturer instead set a minimum price below the resale price that the retailer charges, the manufacturer would gain little, be it in terms of maintaining a premium brand image, preventing free-rider problems related to advertising, or other benefits associated with RPM.[31] It can therefore be assumed that the price floor set by the manufacturer is substantially higher than the price the retailers would choose without RPM. As a result, retailers who would have set their price below the price floor will set their price exactly at or slightly above the price floor, to avoid losing customers to lower-priced competitors.[32] Subsequently, prices that would otherwise be dispersed below the price floor will increase, and cluster at or slightly above the price floor, thereby lowering the variance in prices compared to a scenario in which RPM is absent. This argument follows the one for variance screens on bid-rigging, where otherwise lower bids move up to the agreed minimum bid in bid-rigging cartels, also resulting in comparatively low variance. This can be used as an indicator for detecting bid-rigging cartels.[33]

The assumption that RPM leads to the increase of otherwise lower prices to or slightly above the price floor is also supported by the fact that manufacturers employing RPM have been shown to closely monitor the prices of retailers who sell the manufacturer's product and apply pressure on retailers pricing below the manufacturer's price floor.[34] This includes the threat and use of sanctions, such as terminating the business relationship with non-compliant retailers.[35]

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27 Jan Amthauer, Jürgen Fleiß, Franziska Guggi, and Viktoria H.S.E. Robertson, *Ready or Not? A Systematic Review of Case Studies Using Data-driven Approaches to Detect Real-world Antitrust Violations*, 49 COMPUT. L. SECUR. REV. (2023).

28 Tongil "TI" Kim, *When Franchisee Service Affects Demand: An Application to the Car Radiator Market and Resale Price Maintenance*, 40 MKTG. SCI. 101 (2021); Rob Nicholls, *Regtech as an Antitrust Enforcement Tool*, 9 J. ANTITR. ENF'T, 135 (2021); Jan Amthauer, Jürgen Fleiß, Franziska Guggi, and Viktoria H.S.E. Robertson, *Detecting Resale Price Maintenance for Competition Law Purposes: Proof-of-concept Study Using Web Scraped Data*, 51 COMPUT. L. SECUR. REV. (2023).

29 Franziska Guggi and Viktoria H.S.E. Robertson, *Kartellaufdeckung 2.0*, 11 ECOLEX, 962 (2023).

30 Gregory T. Gundlach and Riley T. Krotz, *Resale Price Maintenance: Implications of Marketing Trends for the Colgate Doctrine and the Leegin Factors*, 39 J. PUB. POL'Y & MKTG. 48 (2020).

31 *Leegin Creative Leather Products Inc. v. PKSK Inc.*, 551 U.S. 877 (2007).

32 Frank G. Mathewson and Ralph A. Winter, *The Incentives for Resale Price Maintenance under Imperfect Information*, 21 ECON. INQ. 337 (1983); Rob Nicholls, *Regtech as an Antitrust Enforcement Tool*, 9 J. ANTITR. ENF'T, 135 (2021); Jan Amthauer, Jürgen Fleiß, Franziska Guggi, and Viktoria H.S.E. Robertson, *Detecting Resale Price Maintenance for Competition Law Purposes: Proof-of-concept Study Using Web Scraped Data*, 51 COMPUT. L. SECUR. REV. (2023).

33 David Imhof, *Detecting Bid-Rigging Cartels With Descriptive Statistics*, 15 J. COMPET. L. & ECON. 427 (2019).

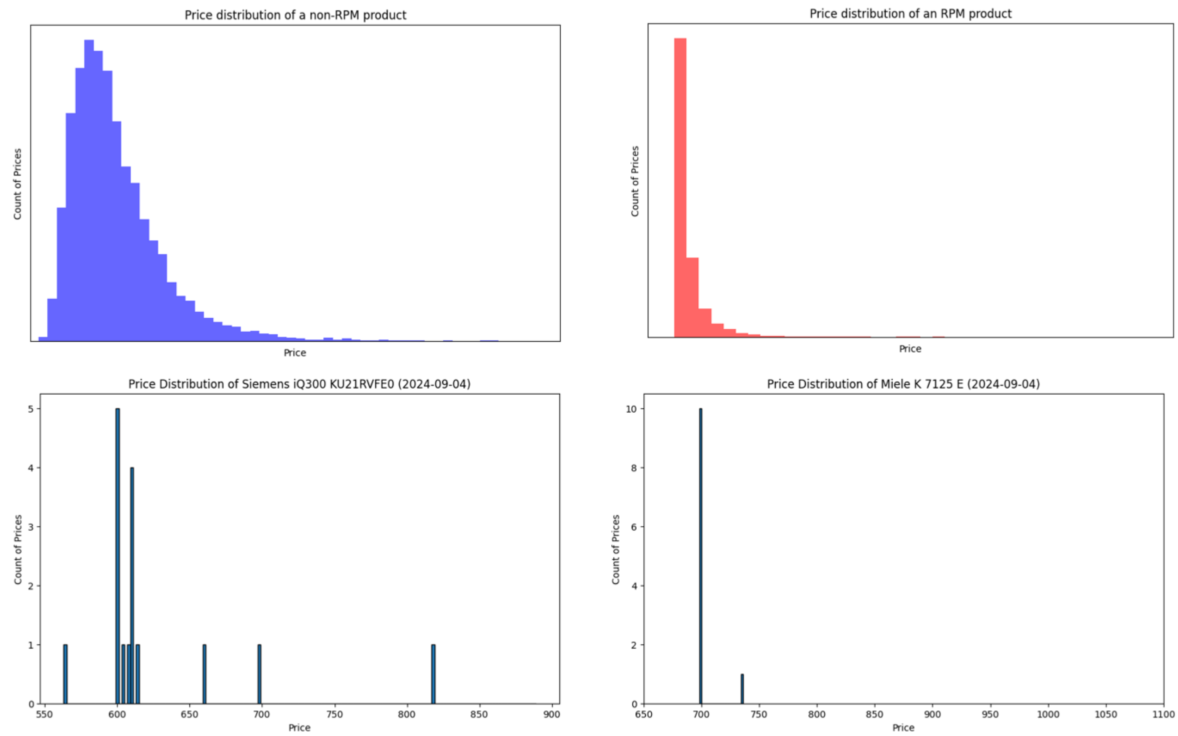
34 *Asus* (Case AT.40465) Commission Decision, (2018) OJ C338/13; *Pioneer* (Case AT.40182) Commission Decision, (2018) OJ C338/19.

35 Kenneth G. Elzinga and David E. Mills, *The Economics of Resale Price Maintenance*, 3 ISS. COMPETITION LAW AND POLICY (2008).

**Assumption 2: RPM leads to a more right-skewed price distribution with a cut-off point.** Since under RPM, retailers are allowed to freely set their prices above the price floor set by the manufacturer, but not below it, the price distribution for a product under RPM tends to be right-skewed, i.e. prices cluster at or closely above the price floor.[36] Although asymmetric price distributions have also been observed with non-RPM products,[37] we assume, according to the arguments made in support of assumption 1, that the presence of RPM makes this skewness more pronounced compared to the price distribution for comparable products by other manufacturers. Additionally, we expect there to be a noticeable cut-off on the lower end at the manufacturer's price floor. Based on the assumption that under RPM most retailers will charge exactly the 'RRP', the lowest price will also be the modal price (after rounding to account for minimal differences). Without RPM, it is unlikely that the modal price would also be the lowest, as such a situation would create a strong incentive for retailers to slightly undercut the modal price, intending to gain a substantial share of the market.[38]

In Figure 1, the two histograms at the top show idealised price distributions for non-RPM and RPM products, illustrated using synthetic data. The top-left histogram represents the expected distribution for a non-RPM product, while the plot directly below shows the actual price distribution of a non-infringing product from the refrigerators dataset. Similarly, the top-right histogram illustrates the expected distribution for a product under RPM, with the actual price distribution of a product flagged as possibly infringing in the refrigerators dataset shown directly below.

Figure 1: Typical price distribution for a non-RPM product and an RPM-product




**Assumption 3: RPM reduces price changes.** When a retailer already charges a price at the price floor of an RPM product, the only RPM-compliant option for a price adjustment is an increase. However, raising the price would likely result in a loss of market share for the retailer, as its price would then be higher than most of its competitors'. Therefore, we assume that retailers selling at the price floor tend to only change their price in reaction to the manufacturer changing the price floor. In comparison, prices for non-RPM products would be adjusted more frequently due to promotional sales or in response to competitor prices.[39] Under RPM, only those retailers that sell above the price floor are allowed to offer discounts, provided the new price is not lower than the price floor.[40]

[36] Rob Nicholls, *Regtech as an Antitrust Enforcement Tool*, 9 J. ANTITR. ENF'T, 135 (2021).

[37] Alex Coad, *On the Distribution of Product Price and Quality*, 19 J. EVOL. ECON. 589 (2009).

[38] Judith Chevalier and Austan Goolsbee, *Measuring Prices and Price Competition Online: Amazon.com and BarnesandNoble.com*, 1 QUANT. MKTG. & ECON. 20 (2003).

[39] Etienne Gagnon and David López-Salido, *Small Price Responses to Large Demand Shocks*, 18 J. EUROP. ECON. ASS'N, 792 (2019).

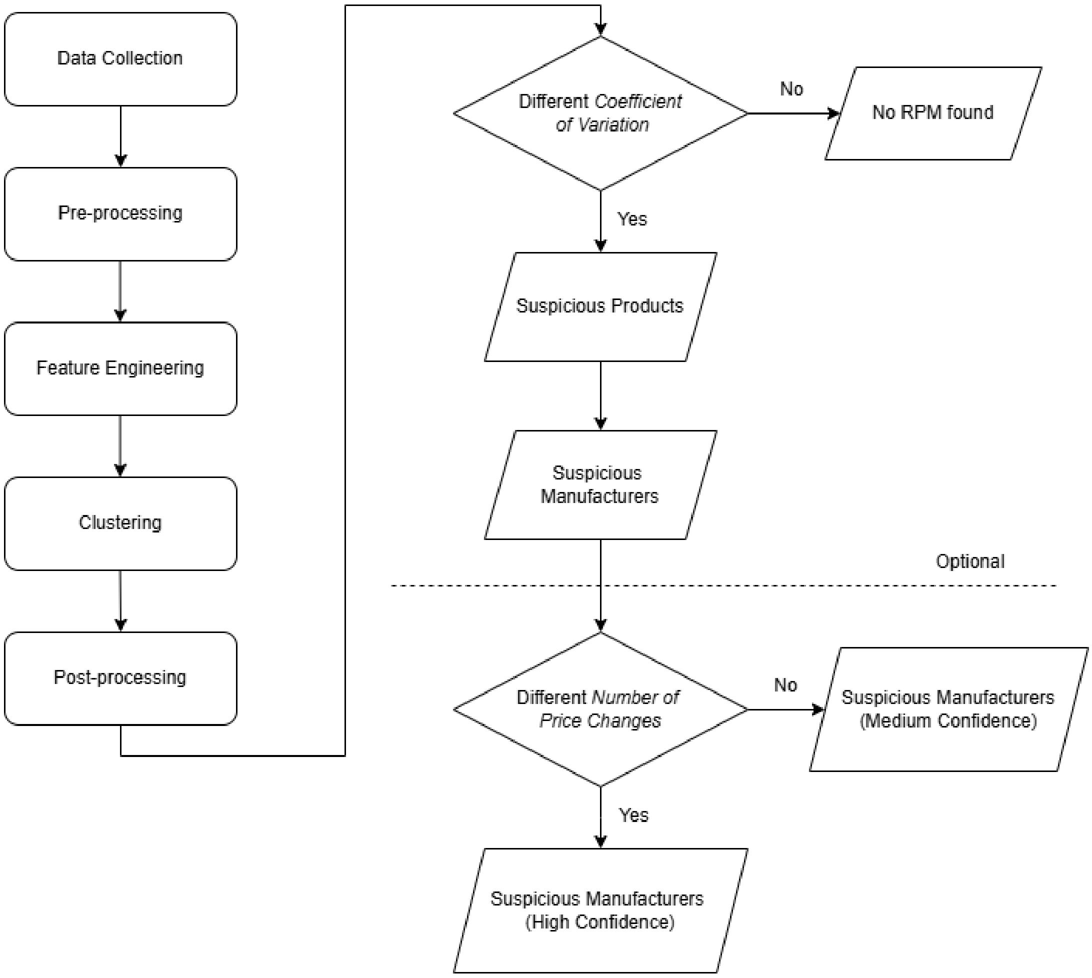
[40] Gregory T. Gundlach and Riley T. Krotz, *Resale Price Maintenance after Leegin: The Curious Case of Contact Lenses* (2015).

Therefore, we assume that the prices of RPM products vary less over time compared to the prices of non-RPM products.

## III. METHOD

In this section, we describe our data collection and pre-processing. The whole pipeline is outlined in Figure 2.

Figure 2: Method overview




The various steps of the analysis are explained in more detail in the following sections.

### A. Data collection

We test the applicability of unsupervised machine learning for detecting RPM on a total of five different datasets concerning washing machines, refrigerators, freezers, dishwashers and loudspeakers. The washing machine dataset was collected by Amthauer et al.[41] via web scraping from the Austrian price comparison site Geizhals.at[42] and is the most extensive dataset, with prices for all offerings on the site scraped four times a day from November 2022 to January 2023. We scraped the price datasets for the other products from the same website between June 2024 and September 2024, once per month. All products meet the criteria outlined by Amthauer et al.,[43] with

[41] Jan Amthauer, Jürgen Fleiß, Franziska Guggi, and Viktoria H.S.E. Robertson, *Detecting Resale Price Maintenance for Competition Law Purposes: Proof-of-concept Study Using Web Scraped Data*, 51 COMPUT. L. SECUR. REV. (2023).

[42] https://geizhals.at, accessed on 02.01.2025.

[43] Jan Amthauer, Jürgen Fleiß, Franziska Guggi, and Viktoria H.S.E. Robertson, *Detecting Resale Price Maintenance for Competition Law Purposes: Proof-of-concept Study Using Web Scraped Data*, 51 COMPUT. L. SECUR. REV. (2023).

different products being clearly identifiable, there being a variety in both manufacturers and retailers, and RPM being possible.

An overview of the datasets is presented in Table 2. The number of products refers to the number of different products after pre-processing. All datasets are publicly available.[44]

| **Product Category** | **Geizhals.at Link** | **Timespan** | **Frequency of Scraping** | **Number of Products** |
|---|---|---|---|---|
| Washing Machines | https://geizhals.at/?cat=hwaschf | 07.11.2022 - 31.01.2023 | Four times a day | 205 |
| Refrigerators | https://geizhals.at/?cat=hkuehlsch | 04.06.2024 - 04.09.2024 | Once a month | 509 |
| Freezers | https://geizhals.at/?cat=hgefr | 26.06.2024 - 26.08.2024 | Once a month | 234 |
| Dishwashers | https://geizhals.at/?cat=hgeschirr60 | 26.06.2024 - 26.08.2024 | Once a month | 606 |
| Loudspeakers | https://geizhals.at/?cat=hifibox | 12.07.2024 - 12.09.2024 | Once a month | 143 |

Table 1: Datasets Overview

The columns presented in Table 2 are used in the analysis and are therefore present in every dataset.

| **Column** | **Example Value** |
|---|---|
| Product | Siemens iQ500 KI21RADD1 |
| Price [EUR] | 574.78 |
| Retailer | Amazon.at |
| Timepoint | 2024-06-04 18:00 |

Table 2: Datasets Overview

For our analysis, we use the prices without shipping cost, as differences in shipping costs can obscure the similarity of product prices. As the product names on Geizhals.at always include the manufacturer at the beginning of the product name, a separate column 'Manufacturer' is created by extracting the first word of the product name.

### B. Data pre-processing

Table 3 shows the pre-processing steps as well as the number of rows after each step was performed.

[44] https://doi.org/10.5281/zenodo.14476278

| Pre-Processing Step | Washing Machines | Refrigerators | Freezers | Dishwashers | Loudspeakers |
|---|---|---|---|---|---|
| Initial Rows | 1,457,413 | 25,420 | 9,897 | 26,581 | 5,838 |
| Drop NA | 1,269,436 | 25,420 | 9,897 | 26,581 | 5,838 |
| Offers by Manufacturers | 1,122,113 | 22,595 | 8,600 | 21,536 | 5,838 |
| Drop Duplicates | 1,078,744 | 21,999 | 8,438 | 20,987 | 4,735 |
| Drop Variants | 1,060,715 | 21,756 | 8,317 | 20,737 | 4,261 |
| Drop Outliers | 1,042,862 | 21,077 | 8,087 | 19,699 | 4,141 |
| Minimum 5 Retailers | 653,419 | 17,847 | 7,242 | 17,556 | 3,308 |
| 75% Time Points | 566,404 | 17,067 | 6,683 | 16,503 | 2,827 |

Table 3: Processing Steps Overview

First, any rows with missing values in relevant columns (see Table 2) are discarded. Then, offers where the manufacturer name is contained in the retailer name are excluded. This is to ensure that the price data focuses on independent retailers, instead of stores operated by the manufacturers themselves. The data may contain duplicates, as Geizhals.at sometimes lists multiple offerings by the same retailer for a product. These duplicates were removed.

In some cases, the same retailer sells the same product at different prices at the same time. This can happen when a retailer offers different variants of the product, e.g. different colours. Since it is not possible to distinguish between these product variants in the data, only the row with the lowest price is retained.

For each product, outlier prices were identified and removed. Offers with prices 50% higher or lower than the median price of the product were considered outliers. Although alternative methods, such as the interquartile range (IQR) approach,[45] are commonly used to detect outliers, they were deemed unsuitable for this analysis, given the effect we hypothesise RPM to have on prices. To illustrate, consider a product offered by five retailers, four of which charge the same lowest price and one charging a higher price. In this scenario, the IQR would be zero, leading to the fifth price being flagged as an outlier, even if its deviation from the other prices is minimal.

Next, products that are not offered by at least five retailers at a specific point in time are removed for that time point. Furthermore, a product must be offered during at least 75% of all time points in the data. These last two steps are also part of the default settings used by Amthauer et al. for their dashboard.[46]

For the sake of reproducibility[47], our source code and dataset can be found on GitHub: `https://github.com/ValentinForster/RPM-Detection`.

## IV. RESULTS

We calculate five metrics, four of which are used as features for clustering, and the last being used to validate the clustering results (see Table 4). Each metric is calculated per product. Except for *number of price changes*, all metrics are calculated for each product at each time point and then averaged over all time points.

[45] H.P. Vinutha, B. Poornima, and B.M. Sagar, *Detection of Outliers Using Interquartile Range Technique from Intrusion Dataset,* 701 ADV. INTEL. SYST. COMPUT. 511 (2018).

[46] Jan Amthauer, Jürgen Fleiß, Franziska Guggi, and Viktoria H.S.E. Robertson, *Detecting Resale Price Maintenance for Competition Law Purposes: Proof-of-concept Study Using Web Scraped Data*, 51 COMPUT. L. SECUR. REV. (2023).

[47] Harald Semmelrock, Tony Ross-Hellauer, Simone Kopeinik, Dieter Theiler, Armin Haberl, Stefan Thalmann, and Dominik Kowald, *Reproducibility in machine-learning-based research: Overview, barriers, and drivers*, 46 AI MAGAZINE, e70002 (2025).

| Metric | Used for | Based on Rounded Prices | Direction Indicating RPM |
|---|---|---|---|
| Coefficient of Variation | Clustering | No | Low |
| Entropy | Clustering | Yes | Low |
| Percentage of Identical Prices | Clustering | Yes | High |
| Percentage of Lowest Price | Clustering | Yes | High |
| Number of Price Changes | Validating | No | Low |

Table 4: Metrics Overview

A crucial step in calculating certain metrics is rounding. As three of the metrics are influenced by the number of distinct prices that are charged for the product, small differences in prices should be ignored. For example, 799.00 € and 799.99 € should not be treated as two distinct prices. While rounding to the nearest integer could be sufficient for lower price values, for higher price values, such as those in the thousands, rounding to the nearest ten is more suitable. The degree of precision in rounding should thus be adjusted based on the magnitude of the prices in the dataset. We opted to round the prices according to one percent of the median price of the product. This means that two prices for the same product are only counted as two separate prices if they differ by more than one hundredth of the median price of the product.

**Coefficient of variation.** The coefficient of variation measures the relative dispersion of the prices of a product. Thus, it pertains to our first assumption. It has been shown to be an important metric for detecting antitrust violations in bid-rigging.[48] The coefficient was also the primary metric by which Amthauer et al. analysed price data for the presence of RPM.[49] For our analysis, we calculate the coefficient of variation by dividing the price variance by the mean price of each product at each time point, thus expressing the variance as a percentage of the mean price of products. This division allows us to compare the variation in the prices of products in different price ranges. A low coefficient of variation for a particular product means that the prices charged by the retailers of a product are very similar, which, according to our first assumption, indicates RPM. Note that this measure is only relevant in comparison between manufacturers, and less for its absolute value. Contrary to Amthauer et al.,[50] we did not include variance over time (i.e. price adjustments by retailers) for the calculation of the coefficient of variation, since variance over time is measured separately via the metric *number of price changes*. Thus, for the coefficient of variation, the price variance was calculated for each product at each time point where data was collected, and then the mean value of those was calculated for each product.

The coefficient of variation $CV_{p,t}$ for a given product $p$ and time point $t$ is calculated as follows:

$$CV_{p,t} = \frac{\sigma^2_{p,t}}{\mu_{p,t}}$$

where $\sigma^2_{p,t}$ is the variance of the prices of the product at that time point and $\mu_{p,t}$ is the arithmetic mean of the prices of the product at that time point.

A limitation of using the coefficient of variation is that it is influenced not only by the number of prices that

48 David Imhof, *Detecting Bid-Rigging Cartels With Descriptive Statistics*, 15 J. COMPET. L. & ECON. 427 (2019).

49 Jan Amthauer, Jürgen Fleiß, Franziska Guggi, and Viktoria H.S.E. Robertson, *Detecting Resale Price Maintenance for Competition Law Purposes: Proof-of-concept Study Using Web Scraped Data*, 51 COMPUT. L. SECUR. REV. (2023).

50 Id.

deviate from the mean but also by the magnitude of the deviations, with larger deviations having a stronger influence. Thus, it is not robust to the presence of outlier prices. For example, suppose that four out of five retailers price the product at 500 €, with one retailer charging 550 €. If this one retailer priced the product at 600 € instead, the coefficient of variation would increase. However, RPM is equally likely in both cases, as the retailer stays above the price floor in both instances. Note that the other proposed metrics are not influenced by the magnitude of price deviations, thus compensating for this limitation of the coefficient of variation.

**Entropy.** In information theory, entropy is a measure of the uncertainty or unpredictability of a system.[51] This metric again concerns our first assumption. In our case, the higher the entropy of the prices of a product, the harder it is to predict a random price from the price distribution of the product. Conversely, low entropy can be interpreted as non-random prices, which would be more likely in the case of RPM compared to when RPM is absent and each retailer individually sets its price for a given product.

The entropy $H_{p,t}$ for a product $p$ at a given time point $t$ is calculated as follows:

$$H_{p,t} = -\sum_{i=1}^{n} p_{i,p,t} \log_2(p_{i,p,t})$$

where:

$$p_{i,p,t} = \frac{\text{count of prices in bin } i}{\text{total number of prices}}$$

for the product $p$ at the time point $t$, and:

$$n = \text{number of bins (equal to the number of unique prices)}$$

Unlike the coefficient of variation, entropy is not affected by how much prices deviate from the mean. However, it is strongly influenced by the number of different prices in the distribution, which is undesirable for detecting RPM. To illustrate, consider a scenario where three out of five retailers charge 500 €, one charges 550 €, and another charges 600 €. If the retailer charging 550 € changes its price to 600 €, the overall entropy decreases. However, this change does not necessarily make RPM more likely.

**Percentage of identical prices.** Compensating for the limitations of the first two metrics, this metric focuses only on identical prices, calculated as the proportion of the most common price after rounding to one percent of the median price. Again, this metric is based on our first assumption. It is calculated by first determining the modal price, i.e. the price most frequently charged for the product. Then the percentage of all prices for the product that are the modal price is calculated. The higher the share of retailers selling the product at the same price, the more consistent the price distribution is with RPM.

The calculation for product $p$ and time point $t$ can be expressed as:

$$Percent_{\text{identical}(p,t)} = \frac{\text{count}(P_{Mo(p,t)})}{\text{count}(P_{p,t})} \times 100$$

where count($P_{Mo(p,t)}$) is the number of offers at the modal price for product $p$ at time point $t$, and count($P_{p,t}$) is the total number of offers for that product at that time point.

**Percentage of lowest price.** Like the previous metric, this metric counts identical prices after rounding. The count is then normalised by dividing it by the total number of prices for the product. However, unlike the previous metric, the focus here is on the proportion of the lowest price rather than the modal price. The aim is to quantify the extent to which the price distribution exhibits a sharp cut-off at its lower end, as described in our second assumption. A high percentage of offers with the lowest price indicates an abrupt cut-off in the price distribution, which is consistent with RPM. One potential limitation of this metric is its sensitivity to retailers who, intentionally or unintentionally, price below the assumed price floor. However, according to our assumptions discussed above, this would be rare.

[51] Chun-Wang Ma and Yu-Gang Ma, *Shannon Information Entropy in Heavy-ion Collisions*, 99 PROGR. PART. NUCL. PHYS. 120 (2018); Claude Elwood Shannon, *A Mathematical Theory of Communication*, 27 BELL SYS. TECH. J., 379 (1948).

The *percentage of lowest price* was calculated as:

$$Percent_{\text{lowest}(p,t)} = \frac{\text{count}(P_{min(p,t)})}{\text{count}(P_{p,t})} \times 100$$

where count($P_{min(p,t)}$) is the number of offers at the lowest price for product $p$ at time point $t$ and count($P_{p,t}$) is the total number of offers for $p$ at that same time point $t$.

All four features introduced until here, based on assumptions 1 and 2, are used as features in the clustering and are correlated (see the correlation matrix in the appendix). As laid out above, every feature has limitations, which, by itself, would potentially make them unreliable for detecting RPM under certain conditions. However, by clustering on multiple features, the individual limitations can be offset.

Since the different features are not on the same scale, the feature values are standardised in order for the data to have a mean of zero and a standard deviation of one. This normalisation ensures that all features equally contribute to the clustering result.[52]

**Number of price changes.** Based on our third assumption, this metric measures how frequently retailers adjusted the price of the product over the duration of the dataset. First, for each retailer of a given product $p$, the number of distinct prices in the dataset is calculated. To measure the number of price changes that occurred, 1 is subtracted. This number is then averaged across all retailers of the product.

$$N_{changes(p)} = \text{unique}(P_{v,p}) - 1$$

where unique($P_{v,p}$) is the number of distinct prices a given retailer charges for product $p$ throughout the dataset. The *number of price changes* is calculated for every retailer and product and then averaged per product.

It is not used as a feature in clustering for two reasons. First, while products under RPM typically exhibit few price changes, the inverse is not necessarily true. Not all products with stable prices are products under RPM. Price stability can result from various factors, and RPM is just one possible explanation. As a result, the metric has high specificity for identifying RPM but lacks sensitivity. Second, the method described in this paper is designed to work with datasets spanning short periods of time. If the manufacturer adjusted the RRP within this limited time frame, the metric could yield a high value, skewing the results. Therefore, we use this metric only to validate the results.

### A. Comparison between clustering methods

Different clustering algorithms excel in different domains.[53] To find the best performing algorithm for our method, three different and commonly used clustering algorithms were tested: k-means,[54] hierarchical clustering (agglomerative clustering)[55] and DBSCAN.[56] For evaluation, the silhouette coefficient was calculated for each clustering result. The silhouette coefficient is a widely used metric for evaluating clustering quality.[57] It quantifies how well a data point fits within its assigned cluster, compared to its similarity with data points in other clusters.[58]

Table 5 shows the silhouette coefficient for each algorithm and dataset. Hierarchical clustering and DBSCAN produced the highest scores, with only a marginal difference between their scores. Since DBSCAN had a smaller standard deviation than hierarchical clustering, it was chosen as the algorithm for the analysis.

52 Yuanyao Zuo, *Investigation on the Impact of Preprocessing Methods and Parameter Selection in Acoustic Scene Classification Based on K-means Clustering Algorithm,* ICIAAI 2023, 300 (2023).

53 Rui Xu and Donald Wunsch, *Survey of Clustering Algorithms*, 16 IEEE TRANSA. NEUR. NETW. 645 (2005).

54 Tapas Kanungo, David M. Mount, Nathan S. Netanyahu, Christine Piatko, Ruth Silverman, and Angela Y. Wu, *The Analysis of a Simple k-Means Clustering Algorithm*, 123 PROC. 16TH ANN. SYMP. COMPUT. GEOM. 1 (2000).

55 Marcel R. Ackermann, Johannes Blömer, Daniel Kuntze, and Christian Sohler, *Analysis of agglomerative clustering*, 69 ALGORITHMICA, 184 (2014).

56 Erich Schubert, Jörg Sander, Martin Ester, Hans Peter Kriegel, and Xiaowei Xu, *DBSCAN Revisited, Revisited: Why and How You Should (Still) Use DBSCAN*, 42 ACM TRANS. DATABASE SYST. 1 (2017).

57 Ketan R. Shahapure and Charles K. Nicholas, *Cluster Quality Analysis Using Silhouette Score,* 2020 IEEE 7TH CONF. DSAA, 747 (2020); Ylber Januzaj, Edmond Beqiri, and Artan Luma, *Determining the Optimal Number of Clusters using Silhouette Score as a Data Mining Technique*, 19 IJOE, 174 (2023).

58 Peter J. Rousseeuw, *Silhouettes: a graphical aid to the interpretation and validation of cluster analysis*, 20 J. COMP. APPL. MATH. 53 (1987).

| Dataset | K-Means | DBSCAN | Hierarchical Clustering |
|---|---|---|---|
| Washing Machines | 0.673 | 0.673 | 0.673 |
| Refrigerators | 0.562 | 0.573 | 0.552 |
| Freezers | 0.564 | 0.586 | 0.583 |
| Dishwashers | 0.597 | 0.585 | 0.600 |
| Loudspeakers | 0.444 | 0.585 | 0.595 |
| Mean | 0.568 | 0.600 | 0.601 |
| Standard Deviation | 0.074 | 0.037 | 0.040 |

Table 5: Clustering Results Overview

The parameters *epsilon* and *minimum number of samples* were optimised using the silhouette score. A similar approach was employed for k-means clustering, as demonstrated by Januzaj et al.[59] and Shahapure & Nicholas[60].

## B. Clustering

Figure 3 presents visualisations of the clustering results for each dataset after clustering but before post-processing, which is discussed in the next section. To allow for easier visualisation, Principal Component Analysis (PCA) was applied to reduce the dimensionality of the data.[61] PCA was only applied to create the visualisations; the clustering was based on all four features. It should be noted that variability in how the PCA components are computed can cause the RPM cluster to appear on different sides of the plot.

Clustering revealed two distinct clusters in all datasets except for the loudspeaker dataset, where four clusters were revealed. Since we assume that products under RPM exhibit a specific feature profile, low *coefficient of variation* and *entropy* in combination with a high *percentage of identical* and *lowest prices*, we expect these products to be grouped into their own cluster.

To identify the RPM cluster, the *coefficient of variation* at the first quartile of each cluster is compared. The cluster with the lowest value is most likely to contain products that exhibit characteristics consistent with RPM and is thus selected for further analysis. The reason why the first quartile is chosen instead of the median or mean is that DBSCAN also identifies noise and outliers in the data, which are grouped into their own cluster.[62] Thus, it may happen that products under RPM are classified as outliers and put in the 'noise cluster' together with other types of outliers, e.g. products with particularly high price variance. By taking the first quartile, we ensure that the cluster containing the products under RPM is identified even if the majority of data points in the cluster are high-variance outliers. To account for high price variance outliers in the RPM cluster, post-processing is necessary.

The plot for the dishwasher dataset, in the second row and second column of Figure 3, shows the importance of removing outliers of high price variation from the RPM cluster in post-processing. There are six products (located at the top right of the plot) that were part of the cluster indicating possible RPM, yet they are detached from the rest of the suspicious cluster. In this case, the products under RPM were classified as noise, leading to the RPM cluster containing both high price variation outliers and RPM-products (low price variation products). These six products are high price variation outliers and are thus removed from the cluster in post-processing.

[59] Ylber Januzaj, Edmond Beqiri, and Artan Luma, *Determining the Optimal Number of Clusters using Silhouette Score as a Data Mining Technique*, 19 IJOE, 174 (2023).

[60] Ketan R. Shahapure and Charles K. Nicholas, *Cluster Quality Analysis Using Silhouette Score,* 2020 IEEE 7TH CONF. DSAA, 747 (2020).

[61] Sidharth P. Mishra, Uttam Sarkar, Subhash Taraphder, Sanjay Datta, Devi Swain, Reshma Saikhom, Sasmita Panda, and Menalsh Laishram, *Multivariate Statistical Data Analysis - Principal Component Analysis (PCA)*, 7 INT. J. LIVEST. RSCH. 60 (2017).

[62] Erich Schubert, Jörg Sander, Martin Ester, Hans Peter Kriegel, and Xiaowei Xu, *DBSCAN Revisited, Revisited: Why and How You Should (Still) Use DBSCAN*, 42 ACM TRANS. DATABASE SYST. 1 (2017).

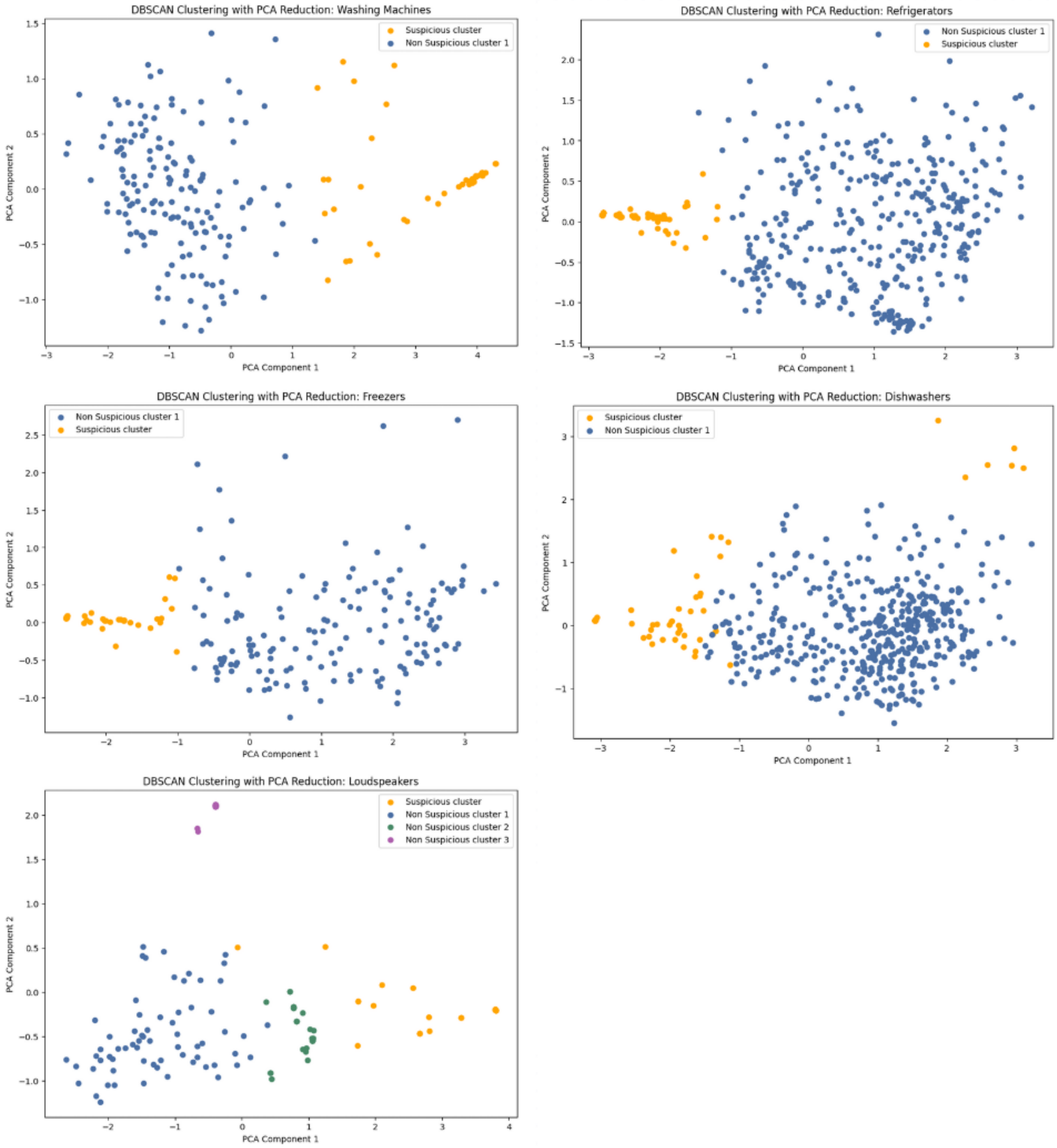



Figure 3: Scatter plots after clustering

### C. Post-processing and automated evaluation

Several post-processing steps are used to reduce false positives, as two-cluster solutions may also result from other data characteristics.

To separate outliers with high price variation from potential RPM products, a minimum *percentage of identical prices* of 65% can be enforced. Thus, products where less than 65% of the retailers charge the same price are considered false positives and are removed from the RPM cluster. False positives were identified using the method proposed in Arve et al. as one of the main problems when screening for collusive behaviour.[63] This fixed threshold also serves as a safeguard to ensure that RPM is not misidentified based only on clustering results. The threshold was set at 65%, as we believe that such products are not indicative enough of RPM. In addition, it was chosen to ensure that the six remote data points in the dishwasher dataset were excluded from the cluster indicating possible RPM. Note, however, that, other thresholds are possible, subject to the preferences regarding false positives of the competition authority employing such a screen.

Post-processing based on our criteria leads to the removal of three products in the washing machine dataset, six in the dishwasher dataset, one in the loudspeaker dataset, and none in the remaining datasets.

Similarly, we can also use a fixed threshold to account for false negatives, that is, products that were not assigned to the RPM cluster but should have been. Any product with a feature value of more than 85% in *percentage of lowest prices* was considered a false negative and added to the RPM cluster in post-processing. Again, the cut-off was set at 85% because such a product would likely be deemed indicative of RPM. This step only affected one product in the refrigerators dataset and one product in the freezers dataset. As with false negatives, the threshold can be varied to account for the preferences of a competition authority or the specific requirements of the legal framework that the competition authority operates within.

As a next step to automate the task of a human case handler, we verify that the RPM cluster is sufficiently different from the other cluster(s) with respect to the RPM indicators by using a one-tailed Mann-Whitney u-test on both the *coefficient of variation* and the *number of price changes*. For the test, the values of the products of the RPM cluster are compared to the values from the products of the cluster with the second lowest first quartile *coefficient of variation*.

If the *coefficients of variation* of the products in the RPM cluster are not significantly lower than the *coefficients of variation* of the products in the other cluster, the products in the RPM cluster are not different enough to be able to claim the presence of RPM. In this case, the analysis stops here, as RPM could not be detected. With our datasets, the RPM cluster always had a significantly different *coefficient of variation*. Therefore, products that are consistent with the presence of RPM were identified in each of our datasets.

To corroborate these results, a second Mann-Whitney u-test is performed, this time on the metric *number of price changes*. If there can be shown to be significantly fewer price changes in products in the RPM cluster than for the products in the other cluster, the results are validated. In that case, the products in the RPM cluster exhibit characteristics consistent with RPM. This was the case with every single one of our datasets. The number and percentage of products that indicate RPM are shown for every dataset in Table 6.

Finally, for every manufacturer in the dataset, the percentage of products assigned to the RPM cluster is calculated. At this point, the final decision on whether to classify manufacturers as possibly applying RPM has to be left up to human judgement. For Table 7, we only included manufacturers that had 40% or more of their products flagged as consistent with RPM, with a minimum of five flagged models. Again, such thresholds can be adapted to the preferences of the competition authority investigating the possible infringement. In each dataset, the manufacturers flagged as employing price strategies consistent with RPM represented nearly all products consistent with RPM. Although there were some products consistent with RPM from mainly non-consistent manufacturers, most of the products consistent with RPM were concentrated on one or two manufacturers. In the loudspeaker dataset, the manufacturer with the highest percentage of RPM-consistent products only reached 26.19%, which is not enough to satisfy our threshold of 40%. The full results (all manufacturers and their percentage of products consistent with RPM) for all five datasets can be found in the Appendix.

Since all results were able to be validated by the *number of price changes*, the products within the RPM group fit very well into our expected profile for RPM. The validity of the results is further confirmed by the fact that the same two manufacturers are identified as having products which display characteristics consistent with the presence of RPM. In the case of Miele, this is consistent with the findings of Amthauer et al., who also found that

[63] Malin Arve, Armando J. Garcia Pires, Ronny Gjendemsjø, Ignacio Herrera Anchustegui, and Frode Skjeret, *The Value of Screening Tools in Cartel Cases,* EUROP. COMPET. J., 1 (2024).

| Dataset | Number of Products Displaying Characteristics of RPM | Products Displaying Characteristics of RPM as % of All Products |
|---|---|---|
| Washing Machines | 43 | 20.98% |
| Refrigerators | 143 | 28.09% |
| Freezers | 79 | 33.76% |
| Dishwashers | 153 | 25.25% |
| Loudspeakers | 23 | 16.08% |

Table 6: Suspicious products overview

Miele washing machines had a particularly low variance in prices compared to other manufacturers.[64] However, while these characteristics would be expected to appear when RPM is present, it is important to note that this initial suspicion does not conclusively prove that the observed characteristics stem from RPM. The initial suspicion would need to be further substantiated, especially since RPM requires an agreement between the retailer(s) and the manufacturer.

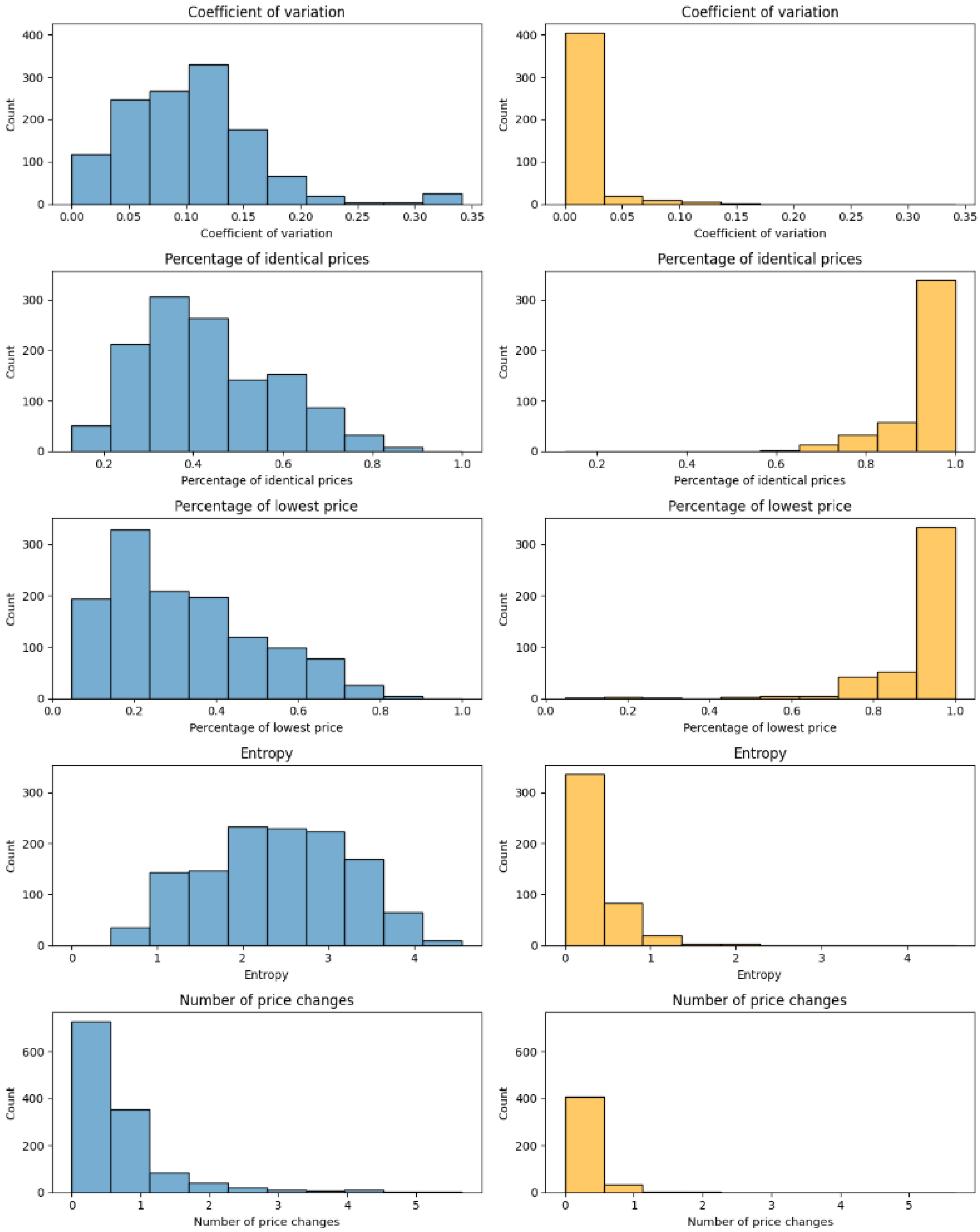
Figure 4 shows the value distributions for each metric of all products exhibiting characteristics consistent with RPM for all datasets (after post-processing) in the right column. For comparison, the distributions for non-consistent products are shown in the left column of Figure4. The distributions for the non-consistent products appear more symmetrical and roughly follow the shape of a normal distribution, with the exception of the *number of price changes*. Here, most of the retailers' offerings remained at the same price throughout the dataset, since the datasets only span a few months. Still, products marked as consistent with RPM experienced noticeably fewer price changes on average (0.10) than non-consistent products (0.63), which shows that this metric can be useful for validating the results.

As a final robustness check, we replicate the clustering results with data from the first point in time only. The results from these limited datasets can be found in the Appendix. Note that more manufacturers are present in the results of those single point in time datasets compared to the full datasets, as some pre-processing steps can only be applied on datasets spanning multiple time points (see chapter III, section B).

We find only minor differences between the single-time point to the full dataset results, indicating the robustness of the clustering approach with regard to the data required.

64 Jan Amthauer, Jürgen Fleiß, Franziska Guggi, and Viktoria H.S.E. Robertson, *Detecting Resale Price Maintenance for Competition Law Purposes: Proof-of-concept Study Using Web Scraped Data*, 51 COMPUT. L. SECUR. REV. (2023).

Figure 4: Feature distributions for non-RPM products and possible RPM products




**Non-RPM Products** **Products flagged for RPM**

| Dataset | Manufacturer | % of Products Displaying Characteristics of RPM in All Products of Manufacturer | % of Manufacturer Products of All Products in RPM Cluster |
|---|---|---|---|
| Washing Machines | Miele | 100.00% | 67.44% |
| Refrigerators | Miele | 92.31% | 16.67% |
| | Liebherr | 70.21% | 69.44% |
| Freezers | Liebherr | 83.33% | 70.00% |
| | Miele | 62.50% | 18.75% |
| Dishwashers | Miele | 94.50% | 67.32% |
| Loudspeakers | None | - | - |

Table 7: Overview of manufacturers possibly applying RPM, and their respective product shares

## V. DISCUSSION AND IMPLICATIONS

While there are various applications of computational antitrust to detect antitrust violations, it has only rarely been applied to detect RPM.[65] We present a novel approach to detect potential RPM using unsupervised machine learning based solely on single snapshots of unlabelled price data available from public price comparison websites.

This approach has multiple advantages over previous applications of both supervised machine learning solutions and screens based on simple statistical measures. In comparison to the former, our approach eliminates the need for labelled training data that is often difficult to obtain, where the ground truth in the form of the presence of an antitrust violation has to be known beforehand. Compared to the latter, and in particular to calculating the coefficient of variation, our approach considerably reduces the need for human judgement and instead provides competition authorities with a more automated tool for finding patterns in price data consistent with antitrust infringements.

An antitrust investigation will rely on a range of evidence in order to reach a conclusion on a possible antitrust infringement such as RPM. Such evidence can emanate from requests of information, interviews and dawn raids that the competition authority conducts,[66] as well as from public data or from whistleblowers and leniency applicants. Computational antitrust is one way of making sense of the information that is available to a competition authority at a given time and will typically be complemented by a range of other tools. A computational tool flagging a possible incidence of RPM can, for instance, serve as an incentive to conduct a dawn raid at a particular company in addition to serving as evidence when proving an infringement.[67] While some competition authorities need to apply for the authorisation to conduct such a dawn raid with a court and thus require evidence to support their application,[68] others can directly rely on a computational antitrust screen to justify their own decision to take an investigatory step such as a dawn raid.[69] This decision may later be subject to judicial review.

The increase in automation that our computational antitrust screen provides means that this tool can be more widely used by competition authorities, given the widespread availability of suitable data. Thereby, competition

65 Rob Nicholls, *Regtech as an Antitrust Enforcement Tool*, 9 J. ANTITR. ENF'T, 135 (2021); Jan Amthauer, Jürgen Fleiß, Franziska Guggi, and Viktoria H.S.E. Robertson, *Ready or Not? A Systematic Review of Case Studies Using Data-driven Approaches to Detect Real-world Antitrust Violations*, 49 COMPUT. L. SECUR. REV. (2023); Jan Amthauer, Jürgen Fleiß, Franziska Guggi, and Viktoria H.S.E. Robertson, *Detecting Resale Price Maintenance for Competition Law Purposes: Proof-of-concept Study Using Web Scraped Data*, 51 COMPUT. L. SECUR. REV. (2023).

66 Articles 18, 19 and 20 of Council Regulation (EC) No 1/2003 of 16 December 2002 on the implementation of the rules on competition laid down in Articles 81 and 82 of the Treaty, (2003) OJ L1/1.

67 Franziska Guggi and Viktoria H.S.E. Robertson, *Kartellaufdeckung 2.0*, 11 ECOLEX, 962 (2023).

68 For Austria, see Federal Competition Act, as amended effective 10 September 2021, § 12(1).

69 Articles 20 and 21 of Council Regulation (EC) No 1/2003 of 16 December 2002 on the implementation of the rules on competition laid down in Articles 81 and 82 of the Treaty, (2003) OJ L1/1.

authorities can become less dependent on leniency applicants and whistleblowers. This allows them to shift from a reactive to a more proactive role, to potentially identify RPM earlier and to reduce the damage that the public, competitors and customers incur.

A particular advantage of our screen is that none of the features used for clustering are dependent on time-series data. Instead, we demonstrate that price data from only one point in time can be effective to find preliminary evidence of RPM. This considerably reduces the data collection efforts compared to previous approaches based on long time-series data.[70] Note, however, that we do rely on time-series data for the *number of price changes* metric used for validation of the findings.

Despite the considerable advantages of our computational tool, it cannot overcome one particular difficulty: the application of web scraping, even for obtaining cross-sectional data, requires considerable effort and knowledge. Standardised APIs for price comparison websites that deliver structured price data would significantly lower the barriers for competition authorities to deploy screens such as the one developed in this paper. Another limitation is the necessity to make assumptions about the effects of RPM on prices in a market to develop features indicative of the presence of RPM, which then are used for clustering. While we took care to ground our assumptions in the literature, alternative economic theories may lead to different assumptions and thus features. As it stands, however, our approach reflects not only economic literature but also the European legal paradigm on RPM. In addition, we do not have a ground truth in the sense that manufacturers in our datasets were proven to have engaged in RPM during the periods for which data was collected. That said, RPM in domestic appliances appears to be a pervasive legal issue, as recent cases in a number of European jurisdictions have shown. In 2024, for instance, the Greek competition authority settled a case with Miele in which the manufacturer was said to have engaged in RPM, thereby infringing Greek competition law as well as Article 101 TFEU. Miele agreed to pay a fine of € 46,160.[71] That same year, the French competition authority imposed fines totalling € 611 million on a number of manufacturers of household appliances, including Miele, Whirlpool and LG, for RPM.[72] Two distributors were also fined. Further cases in which the manufacturers of household appliances were fined for RPM included Miele in Bulgaria[73] and, outside of the European Union, Miele, SEB and others in Turkey.[74] While this does not validate our findings in a statistically significant way, it does show that a multitude of competition authorities have found manufacturers of household appliances, such as the ones we study, to have engaged in anti-competitive RPM.

Initially in our research, we considered using simple thresholds for each metric instead of clustering, where any value above or below that threshold would label the product as consistent with RPM in that metric. If a product was consistent with RPM in three or all four metrics, it would be considered consistent with RPM. However, we decided against such an approach and chose to use clustering instead for two main reasons. First, how high should the threshold for each metric be specified? As can be seen in the scatter plots, there is no clear gap between the RPM cluster and the non-RPM cluster. Second, it is not reasonable to assume that the same fixed threshold would be appropriate for different data of different types of products. Clustering algorithms solve both problems by finding the optimal 'separation line' based on all four dimensions and dynamically identifying dissimilar data points based on the current dataset.

## VI. CONCLUSION AND FUTURE RESEARCH

One common concern in computational antitrust is that computational screens to detect antitrust violations are only effective as long as bad actors remain unaware of how the detection system works. Once bad actors understand what they need to be aware of, they can adapt and continue their anti-competitive behaviour undetected.[75] We do not believe this type of circumvention to be feasible with our method. To avoid detection, retailers would need to charge prices that are significantly different from each other, which in itself undermines the very purpose of the

[70] Jan Amthauer, Jürgen Fleiß, Franziska Guggi, and Viktoria H.S.E. Robertson, *Detecting Resale Price Maintenance for Competition Law Purposes: Proof-of-concept Study Using Web Scraped Data*, 51 COMPUT. L. SECUR. REV. (2023).

[71] Hellenic Competition Authority, The Hellenic Competition Authority imposes a fine against a domestic electric appliances manufacturer following the decision adopted under the settlement procedure (Miele Hellas), 20 June 2024, e-Competitions June 2024, Art. N° 119267

[72] Autorité de la concurrence, BSH, Candy Hoover, Eberhardt, Electrolux, Whirlpool, LG, Miele, SEB, Smeg, Boulanger & Darty, Decision 24-D-11 (19 December 2024)

[73] Bulgarian Competition Authority, The Bulgarian Competition Authority imposes a pecuniary sanction on a household electrical appliances wholesaler for participating in a resale price maintenance agreement with retailers (Miele Bulgaria EOOD), 3 July 2023, e-Competitions July 2023, Art. N° 113575

[74] Mustafa Ayna, Özlem Başıböyük Coşkun, Arda Deniz Diler, The Turkish Competition Authority accepts proposed commitments to conclude an investigation against a leading household appliances company (BSH), 8 September 2022, e-Competitions September 2022, Art. N° 112242

[75] OECD, *Data Screening Tools for Competition Investigations*, 284 OECD ROUNDT. COMPET. POL'Y PAP. (2022).

manufacturer's RPM. Either the manufacturer lowers the price floor, allowing price competition among retailers (again defeating the purpose of RPM), or the price floor remains high, causing many retailers to charge the same price, which would make it possible to detect this pricing behaviour. Thus, detecting the presence of RPM with computational screens such as the one presented would essentially result in behaviour that is not anti-competitive in the first place.

As discussed above, in its preliminary ruling in *Super Bock*, the Court of Justice of the European Union cautioned that RPM warranted a nuanced assessment and could not automatically be assumed to constitute a restriction of competition by object.[76] Going forward, competition authorities may therefore need to take a two-step approach: they first need to demonstrate that RPM took place for a specific product or category of products. A computational antitrust screen that identifies RPM, such as the one we developed, may be sufficient evidence to apply for or decide on a dawn raid. In the course of the investigation, this evidence for the existence of RPM would then need to be supplemented by evidence that there was an agreement between the companies involved, rather than the observed pricing patterns being independent pricing decisions.[77] Where the circumstances of the case allow for that conclusion, a restriction by object may be found. Otherwise, and proceeding to the second step, competition authorities need to show that the RPM in question did (actual or potential) harm to competition. For both steps, a computational antitrust screen powered by unsupervised machine learning can support the competition authority's work. During the first step, the antitrust screen can flag pricing patterns that give rise to a suspicion of RPM. During the second step, the data collected by the antitrust screen can be used to compare the pricing patterns over time observed in 'suspicious' product categories with those in non-suspicious product categories. This comparison of differences, however, needs to bear the phenomenon of umbrella pricing in mind: manufacturers and retailers not engaging in RPM may take a known or observed practice of RPM by other manufacturers and retailers into account when setting their own (higher) prices.[78]

Future research could extend our method by incorporating additional aspects of RPM into the analysis. During our work on this paper, we identified two additional aspects of product prices that would improve the accuracy of such an RPM detection tool further, but which we were not able to analyse based on our data: The RRP and synchronous price changes. In addition, should fine-grained price datasets become available for periods where manufacturers were proven to have engaged in RPM, the results presented in this paper could be verified by comparing it to the results of supervised machine learning approaches.

Provided the RRP constitutes the price floor, meaning the manufacturer does not have an official RRP and a separate figure relating to the minimum price, including the RRP in the analysis would make detecting RPM much easier. When no RPM is used, most retailers will charge prices below the RRP.[79] With RPM however, retailers must set their prices at or above the RRP. This contrast would make RPM easily detectable even with simple statistical means. The price comparison website we scraped our data from did not provide data about the RRP of the product, meaning that this information would need to be obtained elsewhere.

As previously discussed, most retailers are incentivised to only change the price of RPM products when the manufacturer provides a new RRP for the product. When a new RRP is released, this could lead many retailers to change their prices simultaneously. If such a synchronous price change is observed for a product, which otherwise experienced very little price changes by retailers, this would be a strong indication of RPM. However, to be able to implement this into the analysis, price data would need to be continuously observed.

Finally, given the limited availability of labelled data, our approach diverges from traditional computational antitrust methods by leveraging unsupervised machine learning to identify latent structures that correspond to RPM and non-RPM behaviour. This enables scalable analysis and offers a data-driven alternative to manual labelling, thereby advancing methodological tools for RPM detection.

## DECLARATION OF COMPETING INTEREST

The authors declare no conflict of interests pertaining to this paper.


## ACKNOWLEDGEMENTS

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76 Case C-211/22, *Super Bock Bebidas SA and Others v. Autoridade da Concorrência*, ECLI:EU:C:2023:529.

77 Id.

78 Case C-557/12, *Kone AG and Others v. ÖBB-Infrastruktur AG*, ECLI:EU:C:2014:1317, para 30.

79 Rob Nicholls, *Regtech as an Antitrust Enforcement Tool*, 9 J. ANTITR. ENF'T, 135 (2021); Simona Fabrizi, Steffen Lippert, Clemens Puppe, and Stephanie Rosenkranz, *Manufacturer suggested retail prices, loss aversion and competition*, 53 J. ECON. PSYCH. 141 (2016).

## APPENDIX

Figure 5: Spearman correlation matrix (based on all datasets)

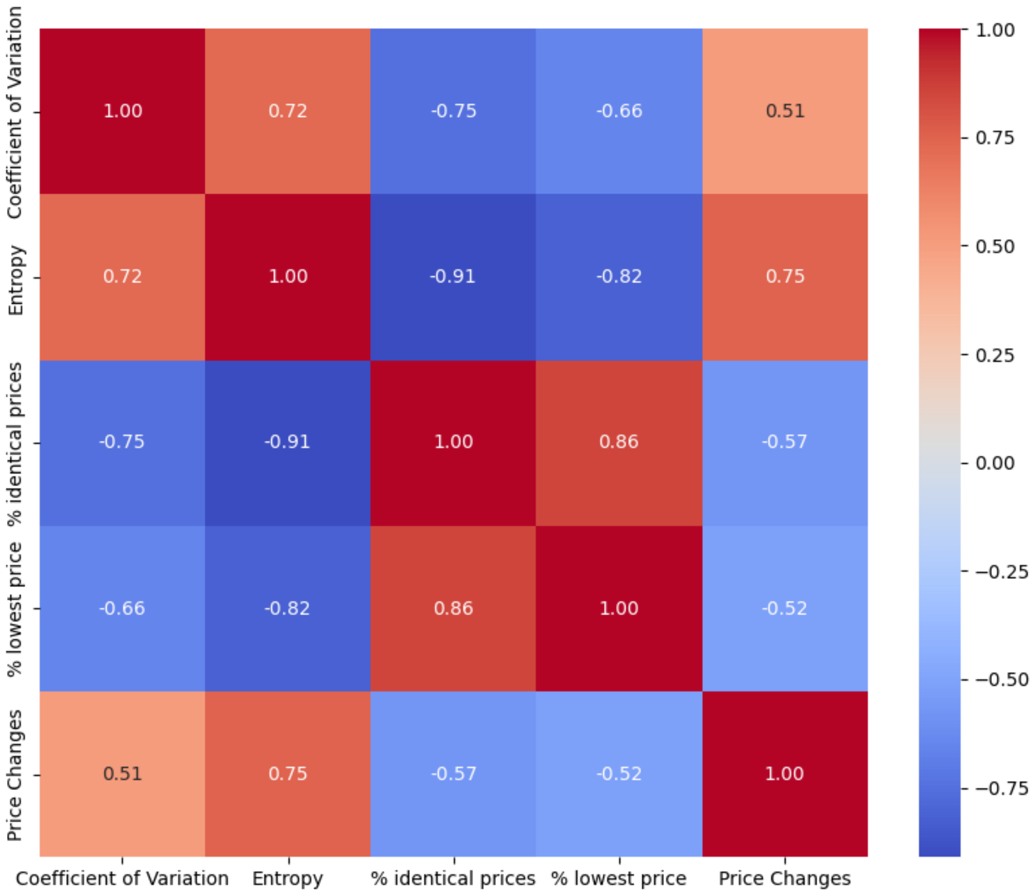

Figure 6: Washing machine dataset full results

| | Manufacturer | total_products | suspicious_products | %_suspicious_products | %_of_suspicious_cluster |
|---|---|---|---|---|---|
| 2 | Miele | 29 | 29 | 100.00 | 67.44 |
| 19 | Candy | 1 | 1 | 100.00 | 2.33 |
| 10 | Zanussi | 5 | 1 | 20.00 | 2.33 |
| 8 | Elektra | 7 | 1 | 14.29 | 2.33 |
| 7 | Beko | 8 | 1 | 12.50 | 2.33 |
| 5 | Samsung | 9 | 1 | 11.11 | 2.33 |
| 6 | Gorenje | 9 | 1 | 11.11 | 2.33 |
| 0 | Bosch | 44 | 4 | 9.09 | 9.30 |
| 1 | Siemens | 37 | 3 | 8.11 | 6.98 |
| 3 | AEG | 24 | 1 | 4.17 | 2.33 |
| 4 | LG | 11 | 0 | 0.00 | 0.00 |
| 9 | Hisense | 5 | 0 | 0.00 | 0.00 |
| 11 | Eudora | 3 | 0 | 0.00 | 0.00 |
| 12 | Haier | 3 | 0 | 0.00 | 0.00 |
| 13 | Amica | 2 | 0 | 0.00 | 0.00 |
| 14 | Nabo | 2 | 0 | 0.00 | 0.00 |
| 15 | Neff | 2 | 0 | 0.00 | 0.00 |
| 16 | Bauknecht | 2 | 0 | 0.00 | 0.00 |
| 17 | Electrolux | 1 | 0 | 0.00 | 0.00 |
| 18 | Privileg | 1 | 0 | 0.00 | 0.00 |

Figure 7: Washing machine dataset results, after clustering with coefficient of variation only

| | Manufacturer | total_products | suspicious_products | diff_suspicious_products | %_suspicious_products | diff_%_suspicious_products | %_of_suspicious_cluster |
|---|---|---|---|---|---|---|---|
| 0 | Miele | 29 | 29 | 0 | 100.00 | 0 | 85.29 |
| 1 | Samsung | 9 | 1 | 0 | 11.11 | 0 | 2.94 |
| 2 | Bosch | 44 | 2 | -2 | 4.55 | -4.54 | 5.88 |
| 3 | AEG | 24 | 1 | 0 | 4.17 | 0 | 2.94 |
| 4 | Siemens | 37 | 1 | -2 | 2.70 | -5.41 | 2.94 |
| 5 | LG | 11 | 0 | 0 | 0.00 | 0 | 0.00 |
| 6 | Gorenje | 9 | 0 | -1 | 0.00 | -11.11 | 0.00 |
| 7 | Beko | 8 | 0 | -1 | 0.00 | -12.50 | 0.00 |
| 8 | Elektra | 7 | 0 | -1 | 0.00 | -14.29 | 0.00 |
| 9 | Hisense | 5 | 0 | 0 | 0.00 | 0 | 0.00 |
| 10 | Zanussi | 5 | 0 | -1 | 0.00 | -20 | 0.00 |
| 11 | Eudora | 3 | 0 | 0 | 0.00 | 0 | 0.00 |
| 12 | Haier | 3 | 0 | 0 | 0.00 | 0 | 0.00 |
| 13 | Amica | 2 | 0 | 0 | 0.00 | 0 | 0.00 |
| 14 | Nabo | 2 | 0 | 0 | 0.00 | 0 | 0.00 |
| 15 | Neff | 2 | 0 | 0 | 0.00 | 0 | 0.00 |
| 16 | Bauknecht | 2 | 0 | 0 | 0.00 | 0 | 0.00 |
| 17 | Electrolux | 1 | 0 | 0 | 0.00 | 0 | 0.00 |
| 18 | Privileg | 1 | 0 | 0 | 0.00 | 0 | 0.00 |
| 19 | Candy | 1 | 0 | -1 | 0.00 | -100 | 0.00 |

Figure 8: Washing machine dataset results, earliest time point only

| | Manufacturer | total_products | suspicious_products | %_suspicious_products | %_of_suspicious_cluster |
|---|---|---|---|---|---|
| 3 | Miele | 29 | 29 | 100.00 | 60.42 |
| 19 | Constructa | 1 | 1 | 100.00 | 2.08 |
| 11 | Amica | 4 | 2 | 50.00 | 4.17 |
| 13 | Candy | 4 | 2 | 50.00 | 4.17 |
| 1 | Bosch | 42 | 5 | 11.90 | 10.42 |
| 6 | Elektra | 10 | 1 | 10.00 | 2.08 |
| 7 | Gorenje | 10 | 1 | 10.00 | 2.08 |
| 5 | Samsung | 12 | 1 | 8.33 | 2.08 |
| 4 | LG | 13 | 1 | 7.69 | 2.08 |
| 0 | Siemens | 45 | 3 | 6.67 | 6.25 |
| 2 | AEG | 34 | 2 | 5.88 | 4.17 |
| 8 | Beko | 8 | 0 | 0.00 | 0.00 |
| 9 | Hisense | 5 | 0 | 0.00 | 0.00 |
| 10 | Zanussi | 5 | 0 | 0.00 | 0.00 |
| 12 | Haier | 4 | 0 | 0.00 | 0.00 |
| 14 | Eudora | 3 | 0 | 0.00 | 0.00 |
| 15 | Hoover | 3 | 0 | 0.00 | 0.00 |
| 16 | Exquisit | 2 | 0 | 0.00 | 0.00 |
| 17 | Bauknecht | 2 | 0 | 0.00 | 0.00 |
| 18 | Electrolux | 1 | 0 | 0.00 | 0.00 |
| 20 | Nabo | 1 | 0 | 0.00 | 0.00 |
| 21 | Neff | 1 | 0 | 0.00 | 0.00 |

Figure 9: Refrigerator dataset full results

| | Manufacturer | total_products | suspicious_products | %_suspicious_products | %_of_suspicious_cluster |
|---|---|---|---|---|---|
| 8 | Miele | 26 | 24 | 92.31 | 16.67 |
| 0 | Liebherr | 141 | 100 | 70.92 | 69.44 |
| 10 | Nabo | 11 | 2 | 18.18 | 1.39 |
| 5 | AEG | 32 | 4 | 12.50 | 2.78 |
| 2 | Exquisit | 55 | 6 | 10.91 | 4.17 |
| 1 | Bosch | 55 | 4 | 7.27 | 2.78 |
| 3 | Smeg | 54 | 2 | 3.70 | 1.39 |
| 6 | Gorenje | 28 | 1 | 3.57 | 0.69 |
| 4 | Siemens | 48 | 1 | 2.08 | 0.69 |
| 7 | Neff | 26 | 0 | 0.00 | 0.00 |
| 9 | Beko | 13 | 0 | 0.00 | 0.00 |
| 11 | Elektra | 6 | 0 | 0.00 | 0.00 |
| 12 | Zanussi | 5 | 0 | 0.00 | 0.00 |
| 13 | Respekta | 4 | 0 | 0.00 | 0.00 |
| 14 | Silva | 3 | 0 | 0.00 | 0.00 |
| 15 | Mobicool | 1 | 0 | 0.00 | 0.00 |
| 16 | Hisense | 1 | 0 | 0.00 | 0.00 |

Figure 10: Refrigerator dataset results, after clustering with coefficient of variation only

| | Manufacturer | total_products | suspicious_products | diff_suspicious_products | %_suspicious_products | diff_%_suspicious_products | %_of_suspicious_cluster |
|---|---|---|---|---|---|---|---|
| 0 | Miele | 26 | 25 | +1 | 96.15 | +3.84 | 15.24 |
| 1 | Liebherr | 141 | 105 | +5 | 74.47 | +3.55 | 64.02 |
| 2 | Nabo | 11 | 4 | +2 | 36.36 | +18.18 | 2.44 |
| 3 | Exquisit | 55 | 12 | +6 | 21.82 | +10.91 | 7.32 |
| 4 | AEG | 32 | 6 | +2 | 18.75 | +6.25 | 3.66 |
| 5 | Bosch | 55 | 5 | +1 | 9.09 | +1.82 | 3.05 |
| 6 | Neff | 26 | 2 | +2 | 7.69 | +7.69 | 1.22 |
| 7 | Siemens | 48 | 2 | +1 | 4.17 | +2.09 | 1.22 |
| 8 | Smeg | 54 | 2 | 0 | 3.70 | 0 | 1.22 |
| 9 | Gorenje | 28 | 1 | 0 | 3.57 | 0 | 0.61 |
| 10 | Beko | 13 | 0 | 0 | 0.00 | 0 | 0.00 |
| 11 | Elektra | 6 | 0 | 0 | 0.00 | 0 | 0.00 |
| 12 | Zanussi | 5 | 0 | 0 | 0.00 | 0 | 0.00 |
| 13 | Respekta | 4 | 0 | 0 | 0.00 | 0 | 0.00 |
| 14 | Silva | 3 | 0 | 0 | 0.00 | 0 | 0.00 |
| 15 | Mobicool | 1 | 0 | 0 | 0.00 | 0 | 0.00 |
| 16 | Hisense | 1 | 0 | 0 | 0.00 | 0 | 0.00 |

Figure 11: Refrigerator dataset results, earliest time point only

| | Manufacturer | total_products | suspicious_products | %_suspicious_products | %_of_suspicious_cluster |
|---|---|---|---|---|---|
| 7 | Miele | 31 | 28 | 90.32 | 15.82 |
| 0 | Liebherr | 147 | 99 | 67.35 | 55.93 |
| 11 | Zanussi | 8 | 3 | 37.50 | 1.69 |
| 1 | Exquisit | 66 | 24 | 36.36 | 13.56 |
| 14 | Silva | 3 | 1 | 33.33 | 0.56 |
| 5 | AEG | 36 | 7 | 19.44 | 3.95 |
| 10 | Nabo | 12 | 2 | 16.67 | 1.13 |
| 6 | Gorenje | 32 | 3 | 9.38 | 1.69 |
| 8 | Neff | 26 | 2 | 7.69 | 1.13 |
| 3 | Bosch | 55 | 4 | 7.27 | 2.26 |
| 4 | Siemens | 47 | 3 | 6.38 | 1.69 |
| 2 | Smeg | 58 | 1 | 1.72 | 0.56 |
| 9 | Beko | 12 | 0 | 0.00 | 0.00 |
| 12 | Elektra | 6 | 0 | 0.00 | 0.00 |
| 13 | Respekta | 5 | 0 | 0.00 | 0.00 |
| 15 | Bomann | 2 | 0 | 0.00 | 0.00 |
| 16 | Hisense | 1 | 0 | 0.00 | 0.00 |
| 17 | Mobicool | 1 | 0 | 0.00 | 0.00 |

Figure 12: Freezer dataset full results

| | Manufacturer | total_products | suspicious_products | %_suspicious_products | %_of_suspicious_cluster |
|---|---|---|---|---|---|
| 0 | Liebherr | 66 | 56 | 84.85 | 70.00 |
| 10 | Elektra | 3 | 2 | 66.67 | 2.50 |
| 4 | Miele | 24 | 15 | 62.50 | 18.75 |
| 5 | AEG | 10 | 2 | 20.00 | 2.50 |
| 8 | Nabo | 5 | 1 | 20.00 | 1.25 |
| 1 | Exquisit | 35 | 3 | 8.57 | 3.75 |
| 2 | Bosch | 31 | 1 | 3.23 | 1.25 |
| 3 | Siemens | 30 | 0 | 0.00 | 0.00 |
| 6 | Gorenje | 8 | 0 | 0.00 | 0.00 |
| 7 | Beko | 8 | 0 | 0.00 | 0.00 |
| 9 | Neff | 5 | 0 | 0.00 | 0.00 |
| 11 | Silva | 3 | 0 | 0.00 | 0.00 |
| 12 | Haier | 1 | 0 | 0.00 | 0.00 |
| 13 | Hisense | 1 | 0 | 0.00 | 0.00 |
| 14 | Bauknecht | 1 | 0 | 0.00 | 0.00 |
| 15 | Privileg | 1 | 0 | 0.00 | 0.00 |
| 16 | Smeg | 1 | 0 | 0.00 | 0.00 |
| 17 | Zanussi | 1 | 0 | 0.00 | 0.00 |

Figure 13: Freezer dataset results, after clustering with coefficient of variation only

| | Manufacturer | total_products | suspicious_products | diff_suspicious_products | %_suspicious_products | diff_%_suspicious_products | %_of_suspicious_cluster |
|---|---|---|---|---|---|---|---|
| 0 | Liebherr | 66 | 58 | +2 | 87.88 | +3.03 | 58.59 |
| 1 | Miele | 24 | 16 | +1 | 66.67 | +4.17 | 16.16 |
| 2 | Elektra | 3 | 2 | 0 | 66.67 | 0 | 2.02 |
| 3 | Beko | 8 | 5 | +5 | 62.50 | +62.50 | 5.05 |
| 4 | Nabo | 5 | 3 | +2 | 60.00 | +40 | 3.03 |
| 5 | AEG | 10 | 3 | +1 | 30.00 | +10 | 3.03 |
| 6 | Exquisit | 35 | 10 | +7 | 28.57 | +20 | 10.10 |
| 7 | Bosch | 31 | 2 | +1 | 6.45 | +3.22 | 2.02 |
| 8 | Siemens | 30 | 0 | 0 | 0.00 | 0 | 0.00 |
| 9 | Gorenje | 8 | 0 | 0 | 0.00 | 0 | 0.00 |
| 10 | Neff | 5 | 0 | 0 | 0.00 | 0 | 0.00 |
| 11 | Silva | 3 | 0 | 0 | 0.00 | 0 | 0.00 |
| 12 | Haier | 1 | 0 | 0 | 0.00 | 0 | 0.00 |
| 13 | Hisense | 1 | 0 | 0 | 0.00 | 0 | 0.00 |
| 14 | Bauknecht | 1 | 0 | 0 | 0.00 | 0 | 0.00 |
| 15 | Privileg | 1 | 0 | 0 | 0.00 | 0 | 0.00 |
| 16 | Smeg | 1 | 0 | 0 | 0.00 | 0 | 0.00 |
| 17 | Zanussi | 1 | 0 | 0 | 0.00 | 0 | 0.00 |

Figure 14: Freezer dataset results, earliest time point only

| | Manufacturer | total_products | suspicious_products | %_suspicious_products | %_of_suspicious_cluster |
|---|---|---|---|---|---|
| 17 | Constructa | 1 | 1 | 100.00 | 1.03 |
| 0 | Liebherr | 76 | 58 | 76.32 | 59.79 |
| 4 | Miele | 26 | 16 | 61.54 | 16.49 |
| 14 | Bomann | 2 | 1 | 50.00 | 1.03 |
| 9 | Elektra | 5 | 2 | 40.00 | 2.06 |
| 8 | Nabo | 8 | 3 | 37.50 | 3.09 |
| 5 | AEG | 11 | 4 | 36.36 | 4.12 |
| 1 | Exquisit | 47 | 10 | 21.28 | 10.31 |
| 6 | Beko | 10 | 1 | 10.00 | 1.03 |
| 2 | Bosch | 34 | 1 | 2.94 | 1.03 |
| 3 | Siemens | 32 | 0 | 0.00 | 0.00 |
| 7 | Gorenje | 9 | 0 | 0.00 | 0.00 |
| 10 | Neff | 5 | 0 | 0.00 | 0.00 |
| 11 | Silva | 3 | 0 | 0.00 | 0.00 |
| 12 | Hisense | 3 | 0 | 0.00 | 0.00 |
| 13 | Haier | 3 | 0 | 0.00 | 0.00 |
| 15 | Bauknecht | 1 | 0 | 0.00 | 0.00 |
| 16 | Privileg | 1 | 0 | 0.00 | 0.00 |
| 18 | Smeg | 1 | 0 | 0.00 | 0.00 |
| 19 | Zanussi | 1 | 0 | 0.00 | 0.00 |

Figure 15: Dishwasher dataset full results

| | Manufacturer | total_products | suspicious_products | %_suspicious_products | %_of_suspicious_cluster |
|---|---|---|---|---|---|
| 2 | Miele | 109 | 103 | 94.50 | 67.32 |
| 4 | AEG | 48 | 11 | 22.92 | 7.19 |
| 8 | Beko | 11 | 2 | 18.18 | 1.31 |
| 11 | Zanussi | 6 | 1 | 16.67 | 0.65 |
| 1 | Siemens | 109 | 13 | 11.93 | 8.50 |
| 5 | Exquisit | 34 | 4 | 11.76 | 2.61 |
| 0 | Bosch | 140 | 15 | 10.71 | 9.80 |
| 3 | Neff | 65 | 3 | 4.62 | 1.96 |
| 6 | Gorenje | 26 | 1 | 3.85 | 0.65 |
| 7 | Smeg | 21 | 0 | 0.00 | 0.00 |
| 9 | Elektra | 10 | 0 | 0.00 | 0.00 |
| 10 | Respekta | 6 | 0 | 0.00 | 0.00 |
| 12 | Nabo | 6 | 0 | 0.00 | 0.00 |
| 13 | Sharp | 4 | 0 | 0.00 | 0.00 |
| 14 | Bauknecht | 4 | 0 | 0.00 | 0.00 |
| 15 | Samsung | 3 | 0 | 0.00 | 0.00 |
| 16 | Hisense | 2 | 0 | 0.00 | 0.00 |
| 17 | Amica | 1 | 0 | 0.00 | 0.00 |
| 18 | Bomann | 1 | 0 | 0.00 | 0.00 |

Figure 16: Dishwasher dataset results, after clustering with coefficient of variation only

| | Manufacturer | total_products | suspicious_products | diff_suspicious_products | %_suspicious_products | diff_%_suspicious_products | %_of_suspicious_cluster |
|---|---|---|---|---|---|---|---|
| 0 | Miele | 109 | 106 | +3 | 97.25 | +2.75 | 51.71 |
| 1 | Exquisit | 34 | 16 | +12 | 47.06 | +35.30 | 7.80 |
| 2 | AEG | 48 | 21 | +10 | 43.75 | +20.83 | 10.24 |
| 3 | Zanussi | 6 | 2 | +1 | 33.33 | +16.66 | 0.98 |
| 4 | Samsung | 3 | 1 | +1 | 33.33 | +33.33 | 0.49 |
| 5 | Elektra | 10 | 3 | +3 | 30.00 | +30 | 1.46 |
| 6 | Beko | 11 | 3 | +1 | 27.27 | +9.09 | 1.46 |
| 7 | Siemens | 109 | 24 | +11 | 22.02 | +10.09 | 11.71 |
| 8 | Bosch | 140 | 21 | +6 | 15.00 | +4.29 | 10.24 |
| 9 | Neff | 65 | 6 | +3 | 9.23 | +4.61 | 2.93 |
| 10 | Gorenje | 26 | 2 | +1 | 7.69 | +3.84 | 0.98 |
| 11 | Smeg | 21 | 0 | 0 | 0.00 | 0 | 0.00 |
| 12 | Respekta | 6 | 0 | 0 | 0.00 | 0 | 0.00 |
| 13 | Nabo | 6 | 0 | 0 | 0.00 | 0 | 0.00 |
| 14 | Sharp | 4 | 0 | 0 | 0.00 | 0 | 0.00 |
| 15 | Bauknecht | 4 | 0 | 0 | 0.00 | 0 | 0.00 |
| 16 | Hisense | 2 | 0 | 0 | 0.00 | 0 | 0.00 |
| 17 | Amica | 1 | 0 | 0 | 0.00 | 0 | 0.00 |
| 18 | Bomann | 1 | 0 | 0 | 0.00 | 0 | 0.00 |

Figure 17: Dishwasher dataset results, earliest time point only

| | Manufacturer | total_products | suspicious_products | %_suspicious_products | %_of_suspicious_cluster |
|---|---|---|---|---|---|
| 2 | Miele | 113 | 104 | 92.04 | 62.65 |
| 19 | Constructa | 2 | 1 | 50.00 | 0.60 |
| 5 | Exquisit | 41 | 9 | 21.95 | 5.42 |
| 4 | AEG | 49 | 10 | 20.41 | 6.02 |
| 13 | Zanussi | 6 | 1 | 16.67 | 0.60 |
| 1 | Siemens | 124 | 17 | 13.71 | 10.24 |
| 0 | Bosch | 166 | 19 | 11.45 | 11.45 |
| 8 | Beko | 14 | 1 | 7.14 | 0.60 |
| 3 | Neff | 74 | 3 | 4.05 | 1.81 |
| 6 | Gorenje | 32 | 1 | 3.12 | 0.60 |
| 7 | Smeg | 21 | 0 | 0.00 | 0.00 |
| 9 | Elektra | 11 | 0 | 0.00 | 0.00 |
| 10 | Nabo | 7 | 0 | 0.00 | 0.00 |
| 11 | Bauknecht | 7 | 0 | 0.00 | 0.00 |
| 12 | Respekta | 7 | 0 | 0.00 | 0.00 |
| 14 | Sharp | 4 | 0 | 0.00 | 0.00 |
| 15 | Samsung | 3 | 0 | 0.00 | 0.00 |
| 16 | Amica | 2 | 0 | 0.00 | 0.00 |
| 17 | Privileg | 2 | 0 | 0.00 | 0.00 |
| 18 | Hisense | 2 | 0 | 0.00 | 0.00 |
| 20 | Bomann | 1 | 0 | 0.00 | 0.00 |
| 21 | Hoover | 1 | 0 | 0.00 | 0.00 |

Figure 18: Loudspeaker dataset full results

| | Manufacturer | total_products | suspicious_products | %_suspicious_products | %_of_suspicious_cluster |
|---|---|---|---|---|---|
| 12 | Bowers | 1 | 1 | 100.00 | 4.35 |
| 14 | Sonus | 1 | 1 | 100.00 | 4.35 |
| 7 | Triangle | 3 | 2 | 66.67 | 8.70 |
| 0 | DALI | 42 | 11 | 26.19 | 47.83 |
| 6 | Elac | 5 | 1 | 20.00 | 4.35 |
| 1 | Monitor | 36 | 7 | 19.44 | 30.43 |
| 2 | Klipsch | 18 | 0 | 0.00 | 0.00 |
| 3 | Edifier | 15 | 0 | 0.00 | 0.00 |
| 4 | Polk | 5 | 0 | 0.00 | 0.00 |
| 5 | Wavemaster | 5 | 0 | 0.00 | 0.00 |
| 8 | Vision | 3 | 0 | 0.00 | 0.00 |
| 9 | LG | 2 | 0 | 0.00 | 0.00 |
| 10 | Canton | 2 | 0 | 0.00 | 0.00 |
| 11 | Sharp | 2 | 0 | 0.00 | 0.00 |
| 13 | Samsung | 1 | 0 | 0.00 | 0.00 |
| 15 | Sony | 1 | 0 | 0.00 | 0.00 |
| 16 | Bose | 1 | 0 | 0.00 | 0.00 |

Figure 19: Loudspeaker dataset results, after clustering with coefficient of variation only

| | Manufacturer | total_products | suspicious_products | diff_suspicious_products | %_suspicious_products | diff_%_suspicious_products | %_of_suspicious_cluster |
|---|---|---|---|---|---|---|---|
| 0 | Triangle | 3 | 3 | +1 | 100.00 | +33.33 | 7.69 |
| 1 | Bowers | 1 | 1 | 0 | 100.00 | 0 | 2.56 |
| 2 | Sonus | 1 | 1 | 0 | 100.00 | 0 | 2.56 |
| 3 | DALI | 42 | 21 | +10 | 50.00 | +23.81 | 53.85 |
| 4 | Monitor | 36 | 12 | +5 | 33.33 | +13.89 | 30.77 |
| 5 | Elac | 5 | 1 | 0 | 20.00 | 0 | 2.56 |
| 6 | Klipsch | 18 | 0 | 0 | 0.00 | 0 | 0.00 |
| 7 | Edifier | 15 | 0 | 0 | 0.00 | 0 | 0.00 |
| 8 | Polk | 5 | 0 | 0 | 0.00 | 0 | 0.00 |
| 9 | Wavemaster | 5 | 0 | 0 | 0.00 | 0 | 0.00 |
| 10 | Vision | 3 | 0 | 0 | 0.00 | 0 | 0.00 |
| 11 | LG | 2 | 0 | 0 | 0.00 | 0 | 0.00 |
| 12 | Canton | 2 | 0 | 0 | 0.00 | 0 | 0.00 |
| 13 | Sharp | 2 | 0 | 0 | 0.00 | 0 | 0.00 |
| 14 | Samsung | 1 | 0 | 0 | 0.00 | 0 | 0.00 |
| 15 | Sony | 1 | 0 | 0 | 0.00 | 0 | 0.00 |
| 16 | Bose | 1 | 0 | 0 | 0.00 | 0 | 0.00 |

Figure 20: Loudspeaker dataset results, earliest time point only

| | Manufacturer | total_products | suspicious_products | %_suspicious_products | %_of_suspicious_cluster |
|---|---|---|---|---|---|
| 16 | Sonus | 1 | 1 | 100.00 | 7.14 |
| 10 | Pro-Ject | 2 | 1 | 50.00 | 7.14 |
| 9 | Triangle | 3 | 1 | 33.33 | 7.14 |
| 1 | Monitor | 36 | 7 | 19.44 | 50.00 |
| 0 | DALI | 52 | 4 | 7.69 | 28.57 |
| 2 | Klipsch | 21 | 0 | 0.00 | 0.00 |
| 3 | Edifier | 19 | 0 | 0.00 | 0.00 |
| 4 | Polk | 8 | 0 | 0.00 | 0.00 |
| 5 | Wavemaster | 7 | 0 | 0.00 | 0.00 |
| 6 | Elac | 5 | 0 | 0.00 | 0.00 |
| 7 | Vision | 3 | 0 | 0.00 | 0.00 |
| 8 | LG | 3 | 0 | 0.00 | 0.00 |
| 11 | Sharp | 2 | 0 | 0.00 | 0.00 |
| 12 | Yamaha | 2 | 0 | 0.00 | 0.00 |
| 13 | Canton | 2 | 0 | 0.00 | 0.00 |
| 14 | Samsung | 1 | 0 | 0.00 | 0.00 |
| 15 | Bowers | 1 | 0 | 0.00 | 0.00 |
| 17 | Sony | 1 | 0 | 0.00 | 0.00 |
| 18 | Magnat | 1 | 0 | 0.00 | 0.00 |
| 19 | Celexon | 1 | 0 | 0.00 | 0.00 |
| 20 | Bose | 1 | 0 | 0.00 | 0.00 |