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Detecting resale price maintenance for competition law purposes: Proof-of-concept study using web scraped data

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ABSTRACT

Computational antitrust tools can support competition authorities in the detection of antitrust infringements. However, these tools require the availability of suitable data sets in order to produce reliable results. The present proof-of-concept study focuses on the understudied area of resale price maintenance, that is, the fixing of retail prices between manufacturers and retailers. By applying web scraping to price data for washing machines in Austria from a publicly accessible price comparison website, we compiled a comprehensive data set for a period of nearly three months. Visualised with the help of interactive dashboards, this data was then analysed using various benchmarks in order to determine whether individual washing machine manufacturers and their retailers may be engaging in resale price maintenance. We conclude that the availability of data is a strong driver for research into and the application of computational antitrust tools. If market data were publicly accessible and provided in a more structured format, researchers and competition enforcers could develop ever more refined computational antitrust applications and screens that would, ultimately, help safeguard competition in markets.

1. Introduction

An increasing number of data-driven applications can support competition authorities in the detection of antitrust infringements.³ These methods can be summarised under the heading of *computational antitrust*. A successful application of these methods requires the availability of suitable data sets. For this reason, the data-driven detection of bid rigging – for which publicly accessible data is available in many parts of Europe – is particularly well studied. Further kinds of antitrust infringements, such as price fixing, are also being increasingly studied using data-driven methods.⁴ For other types of infringements, however, empirical studies are so far lacking as data is not readily available.

Our contribution adds to the literature on the data-driven detection of resale price maintenance (RPM), i.e., the anti-competitive fixing of retail prices by manufacturers and retailers. We carry out a proof-of-concept study using web scraping to generate a large-scale data set that enables us to apply computational antitrust methods to RPM. More specifically, we used price data available on a publicly accessible price comparison website to compile a comprehensive data set of prices from 1247,003 offers for a period of nearly three months for a specific product group, namely washing machines. The data was then analysed using various benchmarks to determine whether individual washing machine manufacturers and their retailers may be engaging in RPM. Visualised with the help of interactive dashboards, we find that this price data can

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¹ At the time of writing, Jan Amthauer was employed at the University of Graz.

² This contribution forms part of the project “DataComp – Data-Driven Detection of Competition Law Infringements: Setting Out the Legal Framework”, funded by the Field of Excellence Smart Regulation at the University of Graz.

³ For an overview, see OECD, ‘Data Screening Tools for Competition Investigations’ DAF/COMP/WP3(2022)5 (2022); Jan Amthauer, Jürgen Fleiß, Franziska Guggi and Viktoria HSE Robertson, ‘Ready or not? A systematic review of case studies using data-driven approaches to detect real-world antitrust violations’ (2023) 49 Computer Law & Security Review.

⁴ See the overview in Amthauer, Fleiß, Guggi and Robertson (n 3).

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indeed allow for insights into potential RPM practices that can be useful for competition authorities in their daily enforcement work. At same time, however, the approach we apply is unable to account for other potential explanations for the observed patterns. We also conclude that the availability of data is a strong driver for research into and the application of computational antitrust tools. If market data were publicly accessible and provided in a structured format, researchers and competition enforcers could develop ever more refined computational antitrust applications that would ultimately safeguard competition in markets.

In the following, the legal background for RPM under EU competition law and some practical insights are discussed (section 2). Then, we set out our approach to generating a data set for detecting RPM in the Austrian washing machine market (section 3). Subsequently, we present our results (section 4) and discuss their implications (section 5).

1.1. Resale price maintenance and competition law

1.1.1. The legal framework for resale price maintenance in Europe

In Europe, price fixing is regarded as a particularly reprehensible antitrust offence. While price fixing often occurs between competitors offering the same goods or services (horizontal price fixing), it can also be realised at a vertical level, for instance between a manufacturer and its retailers. This vertical type of price fixing is called resale price maintenance or RPM. It can take the form of a ‘recommended’ retail price that turns out to be the effective retail price at which the retailer must price the contract goods or services, or it can be a minimum price below which the retailer is not allowed to sell. While US antitrust law is generally not suspicious of RPM under § 1 Sherman Act,⁵ competition law in the European Union and its Member States regards RPM as a particularly anti-competitive practice that public enforcement needs to curtail.

In the following, the legal framework for RPM under EU and Austrian competition law is broadly set out to provide a background to the data-driven analysis of RPM that is carried out in subsequent parts of this study.

1.1.2. EU competition law on resale price maintenance

Article 101(1)(a) TFEU⁶ prohibits companies to ‘directly or indirectly fix purchase or selling prices’. This prohibition covers both horizontal and vertical conduct.⁷ Although vertical restraints of competition are often regarded as less of a potential threat than horizontal agreements,⁸ EU competition law takes a rather strict stance on vertical price fixing and regards both minimum and fixed resale prices that a manufacturer and its retailers agree on as restrictions of competition by object.⁹ Whenever a restriction of competition comes within the ‘object category’, the competition authority does not need to show that the agreement entails negative effects on the market.¹⁰ In its *Asus* decision, the European Commission emphasised that RPM ‘may be considered so likely to have negative effects, in particular on the price, choice,

⁵ See Sherman Antitrust Act (1890), 15 USC § § 1–7, as amended; *Leegin Creative Leather Products, Inc v PKSK*, 551 US 877 (2007).

⁶ Consolidated Version of the Treaty on the Functioning of the European Union (TFEU) [2016] OJ C202/47. The Austrian equivalent of this prohibition on price fixing can be found in § 1(2)(a) Austrian Cartel Act (Kartellgesetz 2005), Austrian Federal Law Gazette I 2005/61 as amended.

⁷ Ioannis Lianos, Valentine Korah and Paolo Siciliani, *Competition Law – Analysis, Cases & Materials* (OUP 2019) 1289.

⁸ Case C-211/22 *Super Bock* ECLI:EU:C:2023:529, para 33; Guidelines on vertical restraints [2022] OJ C248/1, para 10.

⁹ Andrei Gurin and Luc Peepkorn, ‘Vertical Agreements’, in Jonathan Faull and Ali Nikpay (eds), *The EC Law of Competition* (3rd edn, OUP 2014) para 9.94.

¹⁰ European Commission, Guidelines on the application of Article 81(3) of the Treaty [2003] OJ C101/97, paras 21 and 23.

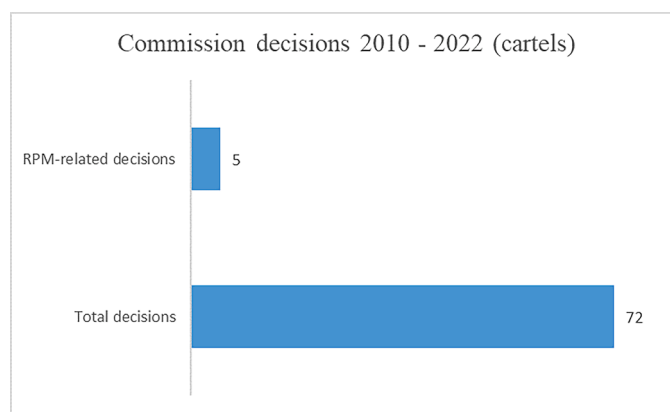


Fig. 1. Commission decisions and fines (2010 - 2022).

quantity or quality of the goods and services, that it may be considered redundant [...] to prove that they have actual effects on the market’.¹¹ This is also the reason why RPM is black-listed under the European Commission’s Vertical Agreements Block Exemption Regulation of 2022, meaning that distribution agreements containing RPM may not benefit from the safe harbour of block exemption.¹² An individual exemption for RPM is also very unlikely.¹³ In its recent preliminary ruling in *Super Bock*, the Court of Justice of the European Union emphasised, however, that RPM should not automatically be presumed anti-competitive without assessing such an agreement’s harm to competition.¹⁴

RPM can be realized directly or indirectly.¹⁵ For instance, a distribution agreement may directly impose a pre-determined minimum price on the distributor, or it might indirectly achieve the same result by contractually setting the distribution margin or the maximum level of discounts that may be granted, or by displaying the recommended resale price on the product itself.¹⁶ Subsequently, the supplier can increase the effectiveness of these RPM measures by relying on price monitoring software.¹⁷

A number of competitive harms are associated with RPM, such as higher prices, facilitating collusion between suppliers,¹⁸ eliminating intra-brand competition,¹⁹ softening competition between manufacturers and retailers,²⁰ lowering pressure on the manufacturer’s margin,²¹ and reducing dynamism and innovation at the distribution

¹¹ *Asus* (Case AT.40465) Commission Decision 338/08 [2018] OJ C338/13, paras 105-107.

¹² 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 (TFEU) to categories of vertical agreements and concerted practices (VABER) [2022] OJ L134/4, art 4(a).

¹³ Guidelines on vertical restraints 2022, paras 181 and 197.

¹⁴ Case C-211/22 *Super Bock* ECLI:EU:C:2023:529, para 43.

¹⁵ VABER, art 4(a).

¹⁶ Eg, see Austrian Supreme Cartel Court 1.12.2009, 16 Ok 10/09 – *Press-grosso II*; Guidelines on vertical restraints [2010] OJ C130/1, para 48.

¹⁷ Price monitoring in itself, however, is not considered to constitute RPM; Guidelines on vertical restraints 2022, paras 190 and 191.

¹⁸ Luc Peepkorn, ‘Resale Price Maintenance and its Alleged Efficiencies’ (2008) 4 *European Competition Journal* 201, 206.

¹⁹ Christian Ewald, ‘The Economics of Resale Price Maintenance – Why Europe is Right not to Follow the USA on the Slippery Slope of Leegin’ (2012) 3 *Journal of European Competition Law & Practice* 300, 301.

²⁰ Johan W. Van de Gronden and Catalin S. Rusu, *Competition Law in the EU – Principles, Substance, Enforcement* (Edward Elgar 2021) 81.

²¹ Vanessa Turner, Agustín Reyna and Nicolas Fafchamps, ‘Vertical restraints in the online world – the consumer perspective’ (2022) 7 *Competition Law & Policy Debate* 30, 32.

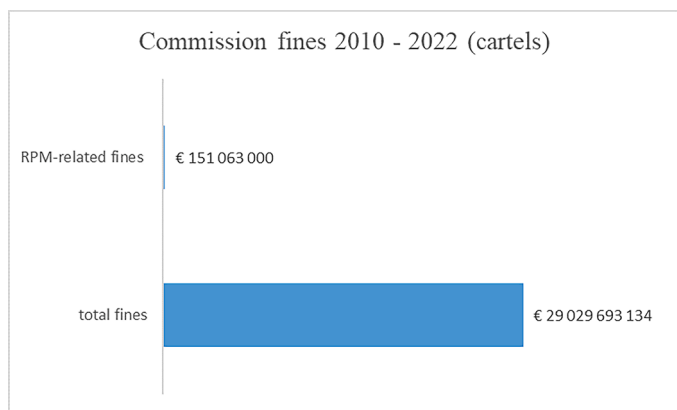


Fig. 2. Commission decisions and fines (2010 - 2022).

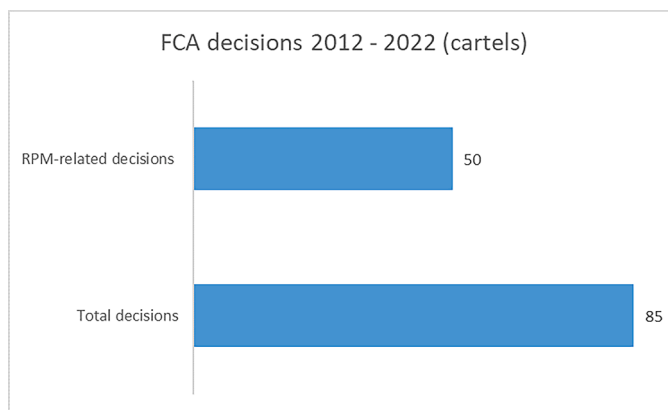


Fig. 3. FCA decisions and fines (2012 - 2022).

level.²² At the same time, RPM is also capable of realising efficiencies that benefit consumers. When a new product is introduced by a manufacturer, RPM may help to make the launch of the product a success. The extra margin provided by the use of RPM may also allow retailers to provide pre-sales services.²³ Such efficiencies may justify an individual exemption for certain RPM practices under Article 101(3) TFEU.

Maximum and recommended resale prices are generally not seen as restrictions by object unless they are combined with certain incentives to observe them.²⁴

1.1.3. Case law on resale price maintenance in Europe

As shown in Figs. 1 and 2, the European Commission issued 72 decisions on anti-competitive agreements with fines totalling € 29 billion between 2010 and 2022. Only five of these decisions concerned RPM, with overall fines of € 151 million.²⁵

Regarding recent cases at the EU level, in 2018, the European Commission imposed fines totalling € 111 million on four different manufacturers active in the electronics sector, mainly for RPM.²⁶ In *Asus*, the well-known electronics manufacturer used a monitoring tool to track its online retailers' resale prices, for example on price comparison websites, to ensure that they were selling at the level of the recommended retail price (RRP). It further made use of internal software monitoring tools helping to identify those online retailers selling below the RRP. *Asus* reacted to low-pricing retailers by asking them to increase their prices. Moreover, it established a bonus programme with the aim of rewarding online retailers for following the RRP. *Asus* also threatened online retailers that it would prohibit their use of the *Asus* Online Logo if they did not align with *Asus*'s pricing policy.²⁷ In *Pioneer*, RPM was ensured through serial number tracking to identify retailers with lower prices.²⁸

Austria has a long history of antitrust enforcement in the area of

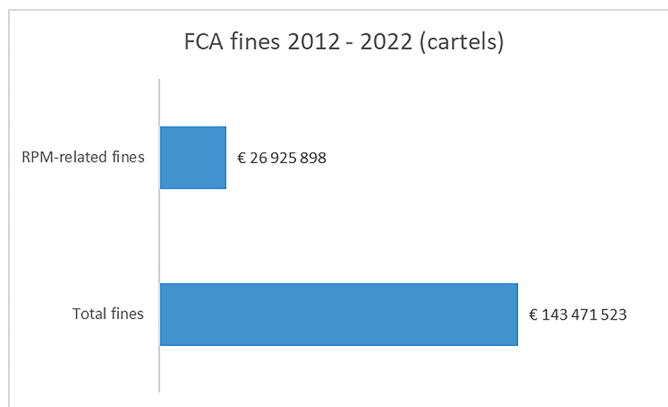


Fig. 4. FCA decisions and fines (2012 - 2022).

RPM. In 2017, the Austrian Federal Competition Authority (FCA) published its 'Standpoint on Resale Price Maintenance'²⁹ containing a code of conduct with examples of prohibited RPM practices. The Standpoint also lists behaviour that strongly indicates the existence of RPM, such as the involvement of traders in the monitoring of retail prices by suppliers and vice versa.³⁰ In Austria, the FCA cannot adopt infringement or fining decisions. Instead, it must request such decisions from the Cartel Court, which is a designated 'judicial competition authority' as foreseen in the ECN+ Directive.³¹

As shown in Figs. 3 and 4, the Austrian Cartel Court issued 85

²² Guidelines on vertical restraints 2022, para 196; Lianos, Korah and Siciliani (n 7) 1378.

²³ Guidelines on vertical restraints 2022, para 197; Gurin and Peeperkorn (n 9) paras 9.105 ff.

²⁴ Guidelines on vertical restraints 2022, para 188.

²⁵ European Commission, 'Search competition cases (all policy areas)' <https://ec.europa.eu/competition/elojade/isef/index.cfm?fuseaction=dsp_result&policy_area_id=1> accessed 29 May 2023.

²⁶ *Asus* (Case AT.40465) Commission Decision 338/08 [2018] OJ C338/13; *Denon & Marantz* (Case AT.40469) Commission Decision 335/04 [2018] OJ C335/5; *Philips* (Case AT.40181) Commission Decision 340/07 [2018] OJ C340/10; *Pioneer* (Case AT.40182) Commission Decision 338/11 [2018] OJ C338/19.

²⁷ *Asus* (Case AT.40465) Commission Decision 338/08 [2018] OJ C338/13.

²⁸ *Pioneer* (Case AT.40182) Commission Decision 338/11 [2018] OJ C338/19.

²⁹ Federal Competition Authority, 'Standpoint on Resale Price Maintenance' (July 2014) <https://www.bwb.gv.at/fileadmin/user_upload/PDFs/PDFs3/BWB_Standpoint_on_Resale_Price_Maintenance_english.pdf>.

³⁰ Federal Competition Authority, 'Standpoint on Resale Price Maintenance', 12-13.

³¹ Directive (EU) 2019/1 to empower the competition authorities of the Member States to be more effective enforcers and to ensure the proper functioning of the internal market (ECN+ Directive) [2019] OJ L11/3, art 1(3).

decisions³² on anti-competitive agreements³³ with fines totalling € 143.5 million between 2010 and 2022. Astonishingly, 50 of these cases dealt with RPM, leading to overall fines of nearly € 27 million.

Regarding recent Austrian cases, in 2021 the Cartel Court imposed a fine of € 3.4 million on the company Fond of, the manufacturer of the popular ‘Ergobag’ and ‘Satch’ school bags.³⁴ Three retailers were also sanctioned.³⁵ In this case, retailers were given supposedly non-binding retail prices by the manufacturer, which they subsequently mostly adhered to. Fond of also partially restricted the possibility of online sales by retailers.

In *Bose*, the Cartel Court granted the FCA’s request for a fine of € 665,000 to be imposed on the electronics producer Bose for vertical agreements on resale prices over a period of nearly 4 years.³⁶ Distributors were asked, both orally and in writing, to implement Bose’s ‘recommended’ retail prices or to increase their online sales prices.

2. Computational antitrust

Computational antitrust adds to the competition authorities’ enforcement tools by applying computer-based methods that make use of the large troves of publicly available or privately held data in order to detect possible antitrust infringements. These tools can aim at automating the detection of antitrust infringements in the form of screens³⁷ as well as at assisting human case handlers.

Computational antitrust law can be described as ‘that branch of legal informatics concerned with the mechanization of [antitrust] legal analysis.’³⁸ Going a step further, in automated law enforcement a computer-based method algorithmically determines that a crime has been committed and takes a responsive action.³⁹

Computational antitrust is steadily increasing its applications,

³² Total number including proceedings that have been brought together for the purpose of joint proceedings and decision-making: 104. Republik Österreich Ediktsdatei, ‘Entscheidungen des Kartellgerichts’ < [accessed 29 May 2023.](https://edikte.justiz.gv.at/edikte/ek/ekedi17.nsf/suchedi?SearchView&subf=e&SearchOrder=4&SearchMax=4949&retfields=vertikal%20Preis*&ftquery=vertikal%20Preis*&query=%28vertikal%20Preis%29%20AND%20%28%5BDATBM%5D%3E%3D01.10.2012%29>” accessed 29 May 2023; Rechtsinformationssystem des Bundes, ‘Judikatur – Justiz’ <<a href=)

³³ These decisions related to the infringement of Article 101 TFEU or its national equivalent, § 1 Austrian Cartel Act.

³⁴ Austrian Cartel Court 15.7.2021, 24 Kt 5/21d – Fond of. The fine was reduced due to leniency.

³⁵ Austrian Cartel Court 12.5.2022, 24 Kt 1/22k – Kastner & Öhler; Austrian Cartel Court 1.7.2022, 25 Kt 4/22h – Thalia; Austrian Cartel Court 5.12.2022, 25 Kt 8/22x – Georg Hausmann KG.

³⁶ Austrian Cartel Court 14.6.2019, 24 Kt 7/19p – Bose.

³⁷ Thibault Schrepele, ‘Computational Antitrust: An Introduction and Research Agenda’ [2021] Stanford Computational Antitrust 1.

³⁸ Michael Genesereth, ‘Computational law: the cop in the backseat’ [2015] CodeX – The Stanford Center for Legal Informatics 2.

³⁹ Lisa A Shay et al, ‘Confronting Law Enforcement’ in Ryan Calo, A Michael Froomkin and Ian Kerr (eds), *Robot Law* (Edward Elgar 2016) 239.

although most competition authority projects are still in the development phase.⁴⁰ In Spain, the Catalan Competition Authority (ACCO) developed an artificial intelligence tool named ERICCA that, inter alia, identifies public tenders where participating operators are more likely to have entered into collusive arrangements before submitting their bids. The system uses an unsupervised machine learning approach based on non-Euclidean distances. As ACCO has to face some challenges, all of which ultimately relate to the underlying data, ERICCA is not yet applied to real cases.⁴¹ The Brazilian Competition Authority (CADE) developed a tool named Cérebro to detect bid rigging with the help of data mining and statistical tests. Cérebro was first used in 2018 to initiate investigations purely on the basis of its findings.⁴²

Despite the improvements that computational antitrust can undoubtedly bring to antitrust enforcement, there are still several concerns that need to be addressed in future research, especially where unsupervised machine learning and AI are involved. These mainly revolve around algorithmic bias, due process, and a possible lack of transparency.⁴³

Using web scraping to generate data for screening for resale price maintenance in the Austrian washing machine market

3. Background

To apply computational antitrust tools to RPM, our first step was to select a product category that met several criteria. The product should have different models that are all clearly identifiable. Smartphones, for example, can be problematic because they have different memory sizes and can be indistinguishable based solely on the product name. Furthermore, the product category should have a variety of manufacturers, with different models and a sufficiently large number of vendors; otherwise, the results may depend too much on individual vendors or products. The last requirement was that manufacturers could, in principle, impose RPM for the product. Based on our initial research, these criteria were met by the washing machine market, a market in which multiple manufacturers and retailers are active and where models are clearly distinguishable. From anecdotal evidence, RPM also represented a possibility in this sector.⁴⁴

It should be pointed out right at the start that, while our proof-of-concept study focuses on the Austrian washing machine market, it can be replicated for any product group for which prices can be web scraped.

3.1. Collecting online price data through web scraping

Data-driven investigations of RPM rely on the availability of price data. Traditionally, approaches to collecting price data aiming to

⁴⁰ For a comprehensive overview see OECD (n 3); Thibault Schrepele and Theodora Groza, ‘The Adoption of Computational Antitrust by Agencies: 2021 Report’ [2022] Stanford Computational Antitrust 78.

⁴¹ Thibault Schrepele and Theodora Groza, ‘The Adoption of Computational Antitrust by Agencies: 2021 Report’ [2022] Stanford Computational Antitrust 111-112.

⁴² OECD (n 3) 11 Box 1.

⁴³ See Cary Coglianese and Alicia Lai, ‘Antitrust by Algorithm’ [2021] Stanford Computational Antitrust 18; Daryl Lim, ‘Can Computational Antitrust Succeed’ [2021] Stanford Computational Antitrust 47-48; Andreas von Bonin and Sharon Malhi, ‘The Use of Artificial Intelligence in the Future of Competition Law Enforcement’ (2020) 11 Journal of European Competition Law & Practice 468.

⁴⁴ For example, in an Austrian online forum discussion about discounts for appliances, a participant stated that ‘especially for Miele appliances, we were always told that Miele is setting the prices and the maximum discounts...’; <[4](https://www.energiesparhaus.at/forum-miele-rabatt-aktuelle-bora-preise/47742” accessed on 4 July 2023 (own translation).</p>
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Typ: Mini (2) Toplader (78) Frontlader (827)

Energieeffizienzklasse (A bis G): bis A (418) bis B (563) bis C (719) bis D (831) bis E (864) bis F (875) unbekannt (30)

Energieeffizienzklasse alt (A+++ bis D): bis A+++ (122) bis A++ (125) bis A+ (128) unbekannt (777)

Fassungsvermögen ab: ab 3kg (867) ab 5kg (862) ab 6kg (856) ab 7kg (801) ab 8kg (618) ab 9kg (380) ab 10kg (97) ab 11kg (21) ab 12kg (8) ab 13kg (4) ab 15kg (3) ab 17kg (2) unbekannt (38)

Fassungsvermögen alt ab: unter 3kg (1) ab 3kg (295) ab 5kg (292) ab 6kg (291) ab 7kg (272) ab 8kg (195) ab 9kg (100) ab 10kg (20) ab 12kg (3) ab 15kg (2) ab 17kg (1) unbekannt (609)

Besonderheiten: Touch-Control-Bedienung (6) Programmablaufanzeige (441) Restlaufzeitanzeige (807) Lichtprojektion (7) Restzeitprojektion (7) Zeitvorwahl (851) Dosierautomatik (109) Nachfüllklappe (32) AquaStop (740) Überlaufschutz (66) Kindersicherung (853) Unwuchtkontrolle (436) Stabilisierungstechnik (279) Beladungserkennung (127) Schaumerkennung (427) Mengenautomatik (674) Selbstreinigungsschublade (96) Trommelbeleuchtung (145) optionaler Warmwasseranschluss (3)

Ansicht: inkl. Versand Sortieren nach: Beliebtheit (Zugriffe) Blättern: 30 ...

Bild	905 Produkte	Bewertung (Anzahl)	Testberichte	Angebote	LZ	Preis*	Händler mit Bestpreis
	Gorenje WNHEI74SAPS/AT Frontlader (20010928) Bauart: Standgerät • Energieeffizienzklasse: A (A bis G) • Farbe: weiß • Schleuderdrehzahl max.: 1400/min • Fassungsvermögen: 7.00kg • Programmanzahl: 15 • Programme: Allergie, BabyCare, Baumwolle, Daunen, Eco 20°C, Eco 40-60°C, Feinwäsche, Kurz, ...	(zu wenige)		17	<input type="checkbox"/>	ab € 349,00 € 379,00 -8%	Servicehansa und 2 weitere Händler
	Samsung WW90T4543AE Frontlader Bauart: Standgerät • Energieeffizienzklasse: D (A bis G) • Farbe: weiß • Schleuderdrehzahl max.: 1400/min • Fassungsvermögen: 9.00kg • Programme: Baumwolle, Buntwäsche, Eco 40-60°C, Hygiene Steam, Mix, Pflegeleicht, Schleudern/Abpumpen, Schnell ...	★★★★★ 7 Bewertungen		12	<input type="checkbox"/>	ab € 444,00 € 474,00 -6%	Köck und 1 weiterer Händler
	Siemens IQ300 WM14NK23 Frontlader Bauart: Standgerät • Energieeffizienzklasse: A (A bis G) • Farbe: weiß, grau • Schleuderdrehzahl max.: 1400/min • Fassungsvermögen: 8.00kg • Programme: Baumwolle, Hamden/Business, Hundene, Outdoor, Pflegenleicht ...	(zu wenige)		14	<input type="checkbox"/>	ab € 541,00	Alternate.at

Fig. 5. Price comparison website www.geizhals.at – overview page for washing machines
Source: <https://geizhals.at/?cat=hwaschf> (4 July 2023).

calculate inflation, for instance, rely on manually collecting prices. However, the use of online prices has become more common and is also used by, e.g., Statistics Austria for calculating the consumer price index.⁴⁵ Online prices are generally seen as less rigid compared to in-store prices.⁴⁶ However, a study of 56 multichannel retailers in 10 countries found that, on average, online and offline prices of the surveyed products were identical for around 72 % of all products sampled.⁴⁷ Thus, online prices are a viable alternative to offline prices, which are more difficult to access. In addition, online prices might be even more suited for studying RPM, as those prices are more easily monitored by manufacturers employing RPM, as was done, e.g., by Asus for their online retailers.⁴⁸

With the help of web scraping, online prices can be collected more easily than their offline counterparts. Web scraping can be defined as an automated process of retrieving specified information from web pages

and storing it in a structured form.⁴⁹ While generally agnostic to the type of information that is collected, it has been used to gather or monitor information relevant to RPM like, e.g., product or contact information, price changes, or product reviews.⁵⁰ Generally, the use of web scraping greatly reduces the time and effort necessary to collect in-store price data or to manually collect online price data.

To collect the price data for different products, a programme accesses web pages in a similar way as a human would. All products on predetermined pages are visited one after the other and the selected information is extracted, reformatted, and saved in a structured way.⁵¹ Web scrapers can be written in various programming languages, including languages commonly used for statistics and data science, such as Python or R. This requires a certain amount of competency in those languages, but it allows to control all parameters as well as the data

⁴⁵ Statistik Austria, 'Standard-Dokumentation Metainformationen (Definitionen, Erläuterungen, Methoden, Qualität)' (4 November 2022) <https://www.statistik.at/fileadmin/shared/QM/Standarddokumentationen/VW/std_v_vpi_hvpi.pdf>.

⁴⁶ Judith Hillen, 'Web scraping for food price research' (2019) 121 British Food Journal 3350.

⁴⁷ Alberto Cavallo, 'Are Online and Offline Prices Similar? Evidence from Large Multi-Channel Retailers' (2017) 107 American Economic Review 283.

⁴⁸ Asus (Case AT.40465) Commission Decision 338/08 [2018] OJ C338/13.

⁴⁹ Hillen (n 46).

⁵⁰ Bo Zhao, 'Web Scraping' in Encyclopedia of Big Data (Springer 2017) 1; Statistik Austria (n 45).

⁵¹ Daniel Glez-Peña et al., 'Web scraping technologies in an API world' (2014) 15 Briefings in Bioinformatics 788; Zhao (n 50). Note that not all sites allow web scraping. Information can be found in the robots.txt specifications or the terms of service; see James Snell and Nicola Menaldo, 'Web scraping in an era of big data 2.0' (2016) Bloomberg Law News <<https://www.perkinscoie.com/images/content/1/5/v2/156775/snell-web-scraping-bnai.pdf>>.

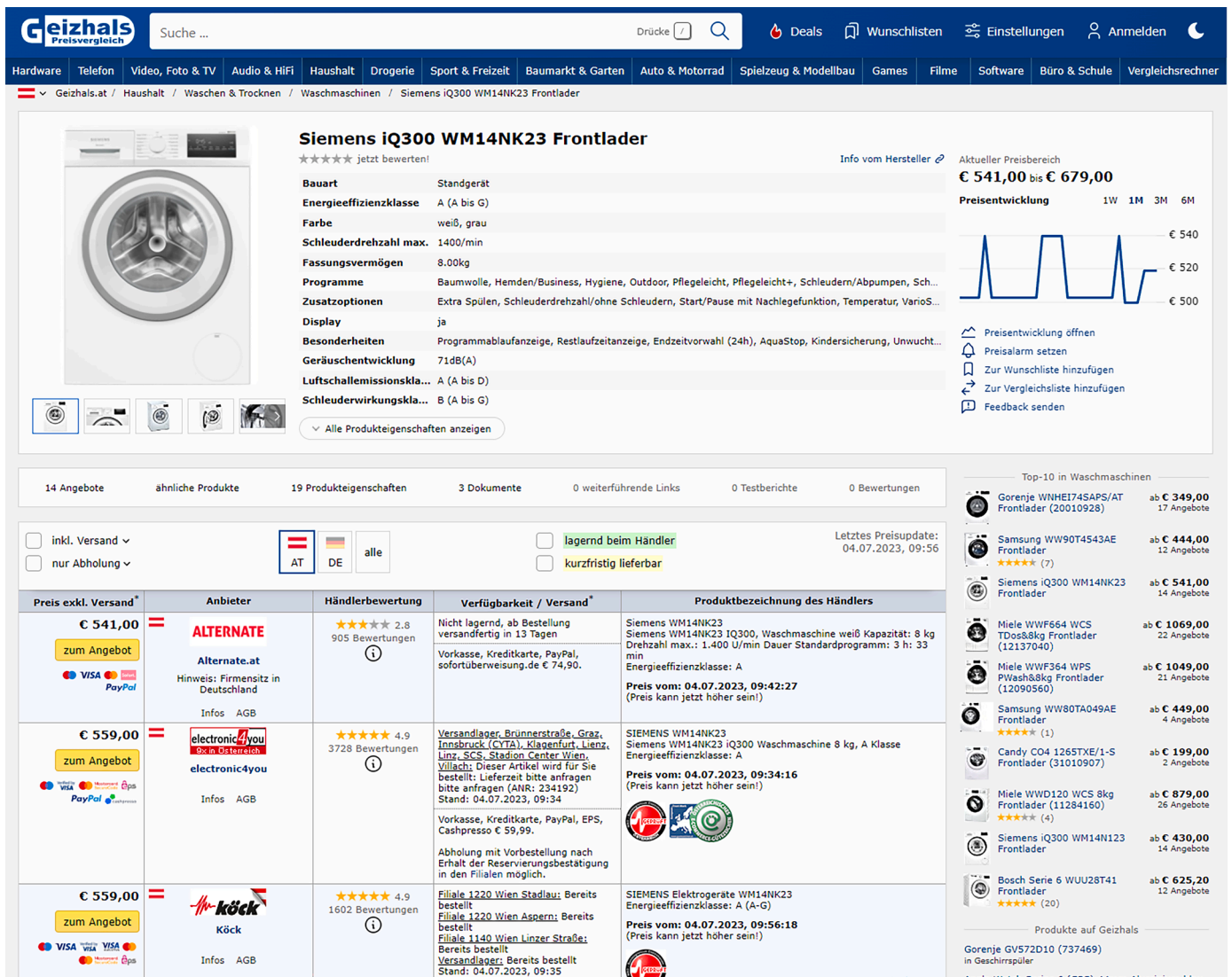


Fig. 6. Price comparison website www.geizhals.at – detail page for a washing machine model by manufacturer Siemens
 Source: https://geizhals.at/siemens-iq300-wm14nk23-frontlader-a2876217.html?hloc=at (4 July 2023).

preparation. Low-code or no-code solutions are also available, with the latter typically being commercial, but providing a point-and-click interface, allowing for the selection of the data to be scraped inside the web browser.

Web scraping is generally a cost-efficient technology for collecting extensive real-time information compared to manual information collection.⁵² However, it is unable to access data that is no longer available online at the time of collection.⁵³ Therefore, data must be collected repeatedly to obtain a sufficiently large time series data set. Such continuous data collection also increases the effort that is required, as changes to the websites and other issues that may arise require continuous monitoring and correction.

3.2. Data collection for the Austrian washing machine market

In this section, we describe our own data collection via web scraping to generate a data set that can be used to detect possible RPM in the

⁵² Alberto Cavallo and Roberto Rigobon, ‘The Billion Prices Project: Using Online Prices for Measurement and Research’ (2016) 30 Journal of Economic Perspectives 151.
⁵³ Hillen (n 46).

Austrian washing machine market. The goal was to generate a data set containing all offers and prices for each washing machine model at a given time, observed over multiple months. We collect our data from the Austrian shopping comparison website www.geizhals.at, a highly popular provider. This site offers the advantage that it does not prohibit access by web scrapers, is relatively well-structured, and at the time the data collection started, it listed a significantly larger number of washing machine types and vendors compared to other price comparison websites, such as www.idealoo.at or www.preisvergleich.at.

We then identified all relevant information to be collected (on this see the description below). The web scraping script was written in the programming language R.⁵⁴ It was executed on a server based at the University of Graz, where it ran continuously from 7 November 2022 to 31 January 2023.

The script first looks up the number of pages containing the different washing machine models and then visits all overview pages and collects all links leading to the washing machine types. Fig. 5 shows the first overview page, which contains the first set of washing machine models,

⁵⁴ Alex Bradley and Richard J E James, ‘Web Scraping Using R’ (2019) 2 Advances in Methods and Practices in Psychological Science 264.

as well as the information on the total number of overview pages to be accessed.

The script then visits all individual washing machine model pages (see Fig. 6 for an example) and collects the product name and number, as well as, for each offer of the product, the price with and without shipping costs, the retailer, the last price update of the product, the retailer rating and the link to the product. If a value cannot be determined, such as the shipping cost, which is not listed by all vendors, it is set to NA (not available).

After all the data of a washing machine model has been saved, a short pause is included so that the scraper is not misrecognized as a DDOS attack due to too many requests being made in a short time and to ensure that no stress is placed on the web server.⁵⁵ The duration of the pause is randomly selected to last between 8 and 12 s. After the pages of all washing machine models have been accessed, the data is saved both locally in a separate file and as appended to the complete data set. The separate file is also sent by email each time a scraping run is completed, both to save it as an additional backup and to check that the file has been sent and the programme is running without error.

Before starting the data collection, a testing and revision phase took place to ensure an error-free data collection. This included, for example, accounting for changes in the total number of washing machine types that occurred by recalculating the total number with each run of the script. However, several weeks after the start of our data collection, the website was modified, which led to errors that were then corrected after the unsuccessful runs.

While we focused on washing machine data, the script for the web scraper can easily be rewritten for other product groups listed on www.geizhals.at and can be replicated for other shopping comparison websites with properties similar to the Austrian one. This allows for many more applications of this computational tool. The script also has further optimization potential, such as automatically reporting when an error occurs. Currently, the email sent after each pass has to be checked manually.

The resulting final raw data set consists of a total of 1,247,003 offers for 1044 washing machine models sold by a total of 94 vendors, generated by collecting data of all offers for washing machines four times a day from 7 November 2022, 06:00 to 31 January 2023, 18:00. For 25,421 of the 1,247,003 offers, no price without shipping cost was available and we thus drop those observations from our data set. This leaves us with a total of 1,221,582 offers by 91 vendors for 1039 machine types from 36 manufacturers. This constitutes the cleaned data set that is used for the dashboards and the descriptive results presented in the next section. Note that in the dashboards, additional options for reducing the data set, like the minimum number of vendors offering a model, are available and are outlined and applied in the analyses presented in the next section.

4. Results

Descriptive statistics and two interactive dashboards are used for data exploration and analysis.⁵⁶ These were created using R and the R package ‘Shiny’.⁵⁷ In our analysis, we follow Imhof⁵⁸ in using simple

⁵⁵ Rizwan Ur Rahman and Deepak Singh Tomar, ‘Threats of price scraping on e-commerce websites: attack model and its detection using neural network’ (2021) 17 J Comput Virol Hack Tech 75.

⁵⁶ The interactive dashboards can be accessed at <https://bandas.uni-graz.at/rconnect/pricerpm/> and <https://bandas.uni-graz.at/rconnect/variationrpm/>

⁵⁷ Winston Chang, Joe Cheng, JJ Allaire, Carson Sievert, Barret Schloerke, Yihui Xie, Jeff Allen, Jonathan McPherson, Alan Dipert and Barbara Borges, ‘shiny: Web Application Framework for R. R package version 1.7.4.1,’ (2023) <<https://shiny.posit.co/>>.

⁵⁸ David Imhof, ‘Simple Statistical Screens to Detect Bid Rigging’ Working Paper Series (Université de Fribourg 2017).

statistical measures as those have been shown to often be sufficient in detecting anomalies indicative of antitrust violations, as in the case of variance screens. Specifically, we rely on the coefficient of variation of prices excluding shipping costs.

The coefficient of variation is a relative measure of dispersion, calculated as the standard deviation σ of prices divided by the mean price λ . It has been used in computational antitrust analyses in the past⁵⁹ and allows for comparing products in different price ranges as the standard deviation is expressed relative to the mean value. A low coefficient of variation, especially in comparison with other regions, time periods or manufacturers, can indicate a lack of competition and may be an indication of a competition law violation or, in our specific case, RPM.⁶⁰ We calculate the coefficient of variation CV for each model m on offer separately for each single point in time t (i.e., a single one of the four daily runs of our web scraper over all machines and offers). This result in one coefficient of variation calculated for a given model for every point in time that vendors offered the model on the price comparison website.

$$CV_{t,m} = \frac{\sigma_{t,m}}{\lambda_{t,m}}$$

The coefficient of variation values reported for manufacturers at a given point in time are then calculated as the mean value of the coefficients of variation for every model offered at this point in time by this manufacturer. We only include a model at one point in time if at this time it was offered by at least 5 vendors, to ensure that variation is generally possible. This reduces the number of offers in our data set to 763,942. After removing machines that are not offered on at least 75 % of the timepoints, our data set reduces to 753,277 offers. We then exclude manufacturers that have fewer than 3 models that are offered at any given point in time. This does not apply to any of the remaining observations. From this data set, we calculate the coefficients of variation and then remove outliers above and below 1.5 times the interquartile range, following Tukey’s rule.⁶¹ This leaves us with a total of 752,991 offers. This corresponds to the default settings in the dashboards discussed below (see Table 2).

4.1. Screening for RPM

We begin our analysis by presenting an overview of the complete data set of manufacturer Miele and of one of Miele’s washing machine models. We zoom in on Miele for two reasons: first of all, Miele is the most popular brand on the Austrian washing machine market with an estimated 15 % market share.⁶² This is also reflected on www.geizhals.at, as Miele manufactures the 20 washing machine models with the highest number of offers. Secondly, Miele is the manufacturer of the ‘Miele WWD120 WCS 8 kg front loader’, the washing machine model for which most data points could be gathered from www.geizhals.at. This model is further examined in section.⁶³

Table 1 shows that Miele is, on average, more expensive in terms of prices without shipping (1490.69€ mean price without shipping costs) than the average manufacturer of the complete data set (967.78€ mean price without shipping costs). However, the coefficient of variation is

⁵⁹ For an overview, see Amthauer, Fleiß, Guggi and Robertson (n 3).

⁶⁰ Rosa M Abrantes-Metz, Luke M Froeb, John Geweke and Christopher T Taylor, ‘A variance screen for collusion’ (2006) 24 International Journal of Industrial Organization 467; David Imhof, ‘Detecting bid-rigging cartels with descriptive statistics’ (2019) 15 Journal of Competition Law & Economics 427.

⁶¹ John W Tukey, *Exploratory Data Analysis* (vol 2, Addison-Wesley 1977).

⁶² Statista, ‘Waschmaschinen-Marken in Österreich 2022’ (18 January 2023) <<https://de.statista.com/prognosen/1000274/oesterreich-beliebteste-waschmaschinen-marken>>.

⁶³ Geizhals.at, Miele WWD120 WCS 8kg Frontlader | Preisvergleich Geizhals Österreich (15 January 2023) <<https://geizhals.at/miele-wwd120-wcs-8kg-frontlader-11284160-a2175950.html>>.

Table 1

Descriptive statistics of prices and coefficients of variation for the statistical distribution of the complete data set, for manufacturer Miele (both on manufacturer level) and for the model Miele WWD120 WCS (machine level).

		Min	Q1	Median	Mean	Q3	Max
Full data set (n = 752,991)	Price incl. shipping	269.00	630.00	856.99	967.78	1168.90	2845.90
	Price excl. shipping	269.00	587.35	799.00	925.27	1149.00	2841.00
	Shipping cost	0.00	30.00	35.00	42.51	59.99	150.00
	Coefficient of Variation	0.00	0.018	0.113	0.108	0.177	0.414
Miele (n = 210,878)	Price incl. shipping	779.00	1158.90	1364.00	1490.69	1689.00	2845.90
	Price excl. shipping	779.00	1099.00	1329.00	1456.29	1619.00	2841.00
	Shipping cost	0.00	35.00	35.00	34.40	35.00	150.00
	Coefficient of variation	0.000	0.000	0.000	0.008	0.016	0.107
WWD120 WCS (n = 8591)	Price incl. shipping	879.00	949.00	984.00	974.44	984.00	1099.00
	Price excl. shipping	879.00	949.00	949.00	936.02	949.00	1004.00
	Shipping cost	0.00	35.00	35.00	39.42	38.00	150.00
	Coefficient of variation	0.000	0.000	0.020	0.015	0.021	0.039

Source: Own table.

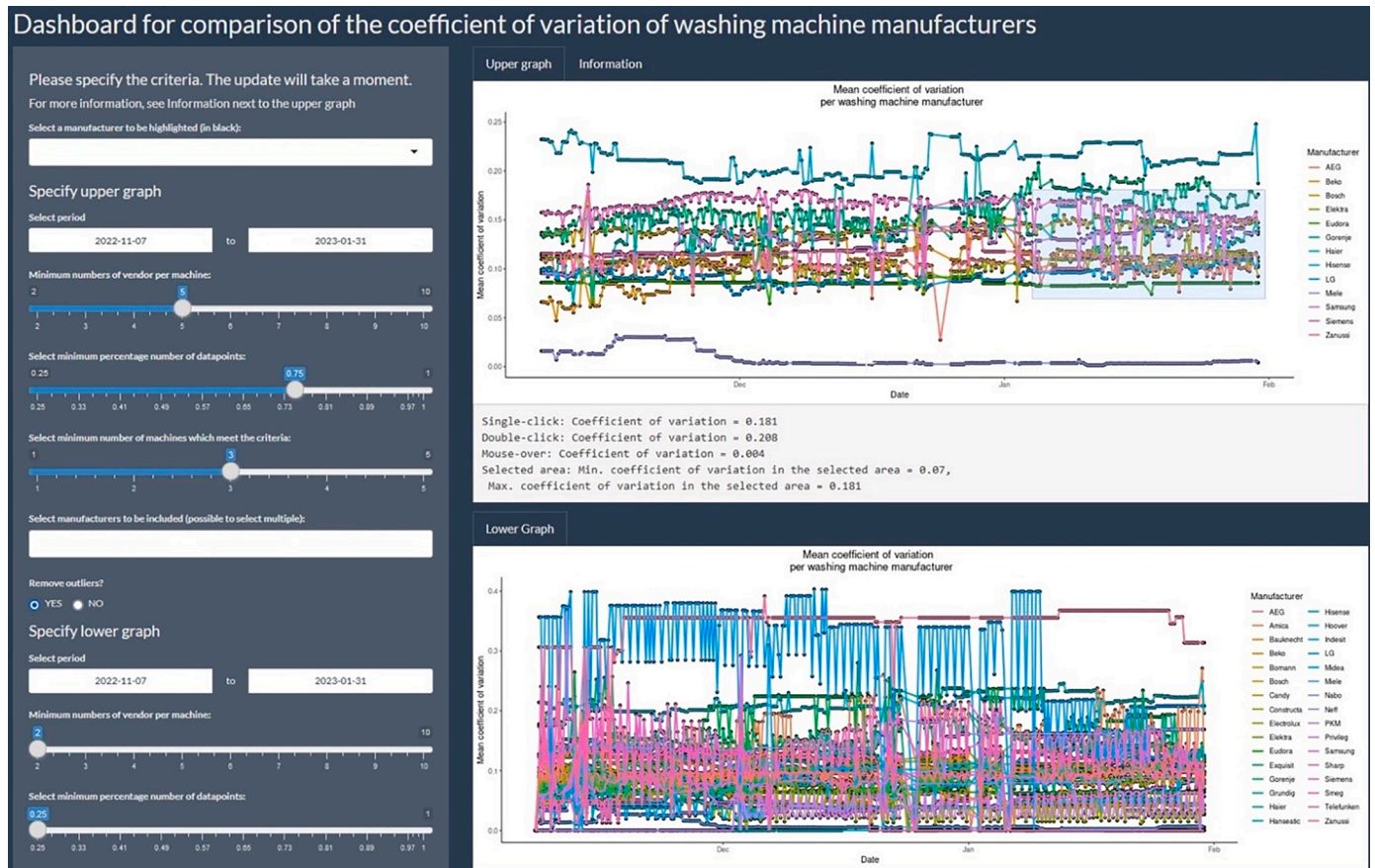


Fig. 7. Dashboard 1 - Coefficient of variation of washing machine manufacturers over time.

lower, with an average of 0.008 and a maximum value of 0.107 compared to an average of 0.108 and a maximum of 0.414 for the complete data set containing all manufacturers. The coefficient of variation in the first quartile in the complete data set equals 0, mainly because this quartile predominantly consists of Miele appliances. Miele accounts for 28 % of the total offers and is particularly present in the first quartile of the coefficient of variation. The selected model, Miele WWD120 WCS, is priced below the Miele average with a mean price of 936.02€. It accounts for 4.1 % of all Miele machines. It is noticeable that for this model, the mean coefficient of variation is at 0.015 and thus higher compared to other Miele machines, but it is still considerably lower than in the complete data set.

To detect deviating patterns in price variation indicative of RPM, we developed two interactive dashboard prototypes to facilitate

comparisons of various subsets of the data based on, e.g., manufacturer. The first dashboard (Fig. 7) shows a line chart of the mean coefficient of variation for manufacturers at each point in time, allowing to compare the coefficient of variation over time for each manufacturer separately and between manufacturers. In addition, there are the options of clicking, double-clicking, selecting a range and mouse-over to display the corresponding coefficient of variation.

The default settings of the upper graph apply several filters that mainly eliminate manufacturers with only very few models, models that are offered by a small number of vendors and models only offered at few points in time. Those settings prevent manufacturers with too few machines or too little data over the time period from distorting the results, as they may have an extremely low or high coefficient of variation due to the small number of offers at any given point in time. Importantly,

Table 2
Filter options for dashboard 1.

Filter options (default setting)	Function
Period of time (complete)	The available period of time is 07.11.2022 to 31.01.2023
Minimum number of vendors per machine (5)	To avoid low coefficient of variation levels due to a low number of vendors
Minimum number of data points per machine (75 %)	To ensure that a machine has enough data points and not only a few dispersed ones
Machines per manufacturer that meet the criteria (3)	To exclude manufacturers with too few machines
Manufacturer inclusion (all)	Only selected manufacturers can be shown in order to compare them specifically
Manufacturer highlighting (none)	If necessary, one manufacturer can be highlighted in black
Outliers (removed)	Some manufacturers have strong outliers. Removes products based on the 1.5 IQR method (Tukey 1977), applied to the coefficient of variation

outliers – i.e., ‘observations that do not follow the statistical distribution of the bulk of the data, and consequently may lead to erroneous results with respect to statistical analysis’⁶⁴ – are removed by default. Concretely, observations with variation coefficients lower than 1.5 times the interquartile range below the first quartile and higher than 1.5 times above the third quartile are identified as outliers. This, for example, removes one particularly pronounced outlier for the manufacturer Gorenje, where a single vendor increased the price of a model without shipping to 16,904.76€ with the second highest price offered at 483.90€, raising the average price for models of this manufacturer to 5927.16€. All filter options, as well as their respective default options, are outlined in Table 2.

Dashboard 2 (Fig. 8) allows for the analysis of price trends and fluctuations at the manufacturer or machine level for two manufacturers as well as for the comparison of two different models. In the two line graphs, the prices over a certain period of time by two manufacturers, as well as two models made by those two manufacturers, can be compared. The graphs display mean prices for the selected manufacturers over time highlighted in bold and add the individual prices with low transparency. Point thickness increases with the number of times the value is observed. Thus, if only few, particularly thick points are present, the model is offered by multiple vendors at exactly the same price.

For the two manufacturers selected as default in our dashboard 2, the upper graph shows that the average prices of Miele hardly change, although this is calculated for a wide range of machines of the manufacturer. With the manufacturer Bosch, the prices fluctuate more, which is illustrated by the many data points located around the average with a relatively balanced degree of thickness. In the lower graph, you can compare two respective machines of the specified manufacturers with each other to verify the results. The graph below shows that there are many different data points of the model of the manufacturer Bosch (in red), which greatly differ among themselves. For the model from Miele (in blue), there are only a few data points, which are particularly thick. Below the graphs, the data is located as a table which is used for the calculation at the machine level. This allows us to manually investigate changes in the price or the coefficient of variation over time.

5. Manufacturer comparison

As can be seen in the upper panel of dashboard 1 in Fig. 7, using the default filters that the results from the previous section are also based on, the coefficients of variation of the different manufacturers vary both over time within manufacturers as well as between manufacturers. For

the manufacturer Miele, we observe a lower coefficient of variation compared to others and this difference is stable over time. Miele’s average coefficient of variation ranges between 0.001 and 0.033 for the average of all Miele models at a specific point in time. Table 3 provides a comparison of Miele with the manufacturers Bosch, Samsung and Siemens, which are comparable to Miele because they offer some machines in the same price segment and have a high number of retailers and products. However, Miele’s average prices and the average number of retailers are far higher than those of all other manufacturers. Overall, these four manufacturers have a 65 % share of offers of the total data set. However, for Bosch, Siemens and Samsung, the mean values for the coefficient of variation range between 0.135 and 0.183 as compared to 0.008 for Miele.

We look at the comparison of the distribution of coefficient of variation values for Miele models with all other manufacturers in Fig. 9, which displays a histogram of all coefficients of variation, highlighting offers of models manufactured by Miele. The coefficients of variation for Miele models represent a clear cluster of outliers at the lower end of the distribution. Revisiting the underlying pattern of prices, again with the model ‘Miele WWD120 WCS 8 kg front loader’ that was already used as an example in the previous section of the analysis, on 18 October 2022, all 28 vendors on www.geizhals.at,⁶⁵ as well as all seven vendors on www.idealo.at⁶⁶ showed an identical price (excluding shipping). Price differences only exist when shipping costs are taken into account, with these being independent of the brand and applying to the product category.^{67,68}

6. Discussion and implications

Our proof-of-concept study demonstrates how computational tools can be implemented to generate a data set that allows to identify suspicious pricing patterns that are consistent with resale price maintenance. This is reproducible for other types of product categories, and on other shopping comparison websites with similar characteristics as the Austrian portal www.geizhals.at. We draw two main conclusions from our study, one on a metalevel and a further on a microlevel.

6.1. Implications of our findings for the deployment of computational antitrust tools

On a metalevel, we must return to our initial observation that the availability of suitable data sets is the *conditio sine qua non* for data-driven computational tools in antitrust (and beyond). As was pointed out above, the availability of bidding data from public bids is what drove the study of computational tools to detect bid rigging. It is safe to say that a suitable enabling digital environment is required to apply data-driven methods such as statistical analysis or machine learning.⁶⁹

⁶⁵ Geizhals.at, ‘Miele WWD120 WCS 8kg Frontlader’ (15 January 2023) <<https://geizhals.at/miele-wwd120-wcs-8kg-frontlader-11284160-a2175950.html>>.

⁶⁶ www.idealo.at, ‘Miele WWD120WCS ab € 949,00’ (15 January 2023) <https://www.idealo.at/preisvergleich/OffersOfProduct/6779527_-wwd120wcs-miele.html>.

⁶⁷ Elektro-Shop Köck, ‘Transport- bzw. Versandkosten Übersicht’ (15 January 2023) <<https://www.elektroshopkoeck.com/webshop/common/shipmentinfo.aspx>>; Expert, ‘Lieferung & Versand’ (15 January 2023) <<https://www.expert.at/lieferungundversand>>; MediaMarkt Österreich, ‘Lieferung und Montageservice im Onlineshop’ (15 January 2023) <<https://red.mediamarkt.at/lieferung-und-montage-im-onlineshop.html>>.

⁶⁸ It would be interesting to compare price distributions to the recommended resale price of manufacturers as a benchmark. However, as of their November 2022 marketing material available online, the manufacturer Miele does not publish recommended resale prices anymore (https://media.miele.com/ex/at/pdfs/202211_PUE_Waeschepflege_22-0993.pdf, 20 September 2023).

⁶⁹ OECD (n 3).

⁶⁴ Hancong Liu, Sirish Shah and Wei Jiang, ‘On-line outlier detection and data cleaning’ (2004) 28 Computers & Chemical Engineering 1635, 1635.

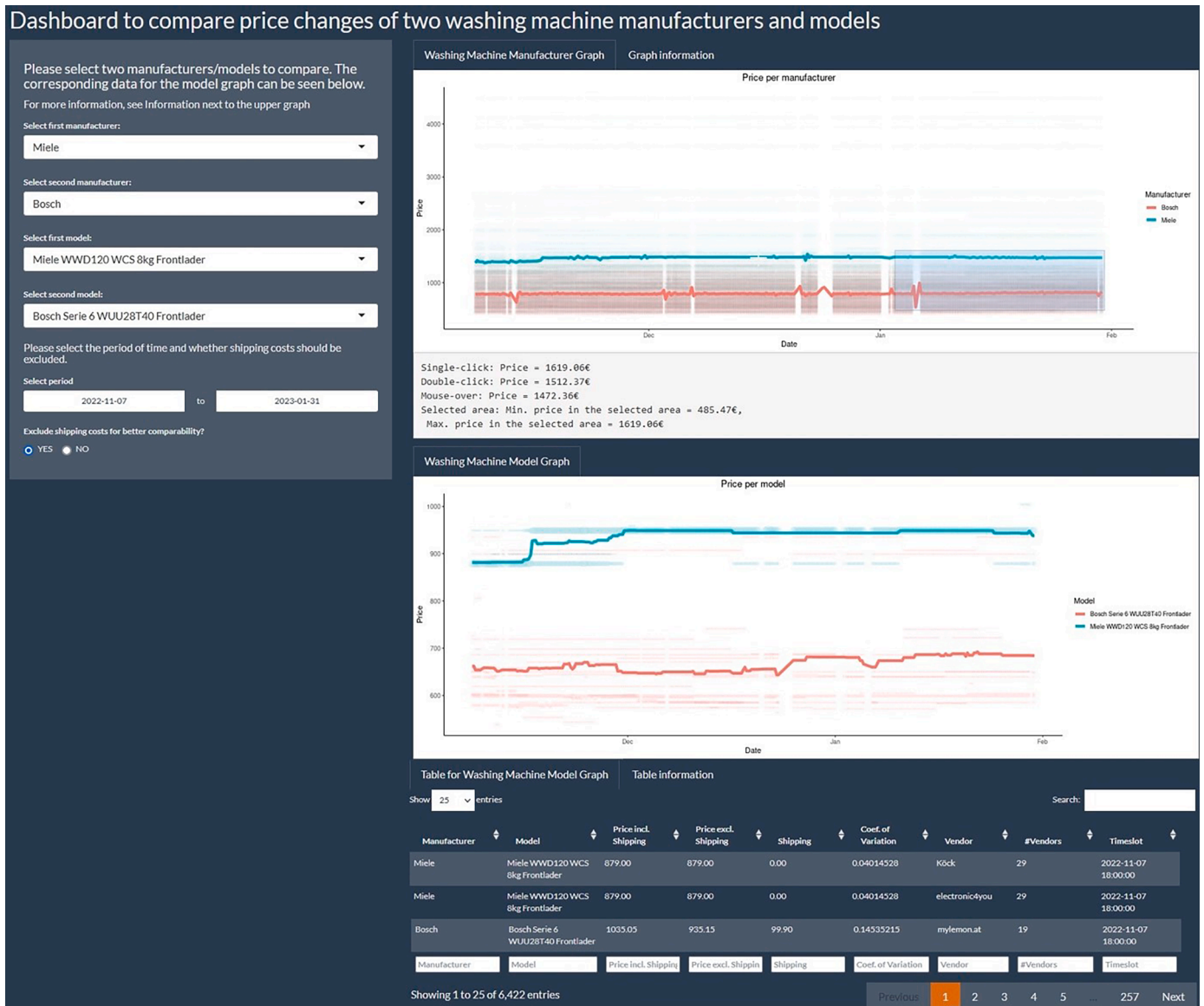


Fig. 8. Dashboard 2 - Comparison of price changes for two manufacturers/models over time with data table below corresponding to the model graph.

Table 3
Comparison of manufacturers Miele, Bosch, Samsung, Siemens, and complete data set.

	Miele	Bosch	Samsung	Siemens	All
#Models	41	116	40	93	549
Mean vendor per model	22.81	10.41	11.03	14.06	14.88
Mean price excl. shipping	1456.29	746.15	746.73	791.51	925.27
Mean price incl. shipping	1490.69	795.24	789.96	835.23	967.78
Mean coefficient of variation	0.008	0.150	0.135	0.183	0.108
Share of offers	28.0 %	16.6 %	4.0 %	18.4 %	100 %
N	145,949	124,607	30,285	210,878	752,991

From our study, we experienced that an enabling digital environment for computational antitrust tools rests on two determining factors, as visualized in Fig. 10: The degree to which the data is structured, and how readily the data is available. The X axis in Fig. 10 represents the degree to which the data set is structured. In general, structured data sets, such

as spreadsheets, are more usable than unstructured data, such as prices distributed over multiple vendor websites. The Y axis represents the ease of availability of the data source, i.e., whether the data is publicly or only privately available. Publicly available data is more accessible, which also makes its use for data-driven methods more feasible. Depending on the data source and the degree to which the data is structured, different methods can be used. To enable automated anti-trust screens, publicly available structured data or readily accessible structured data from public sources is required. The other types of data only allow for targeted case studies with varying degrees of effort needed to access and prepare the data.

Horizontal antitrust violations, such as bid rigging or price fixing, are relatively well-researched in the computational antitrust literature.⁷⁰ This research was enabled by structured data sets from public procurement auctions that is more readily available than other data sets. To enable studies for other types of antitrust violations, an enabling digital environment should make structured data sets publicly available, thus moving data availability to the upper right quadrant of Fig. 10. The web

⁷⁰ See the overview in Amthauer, Fleiß, Guggi and Robertson (n 3).

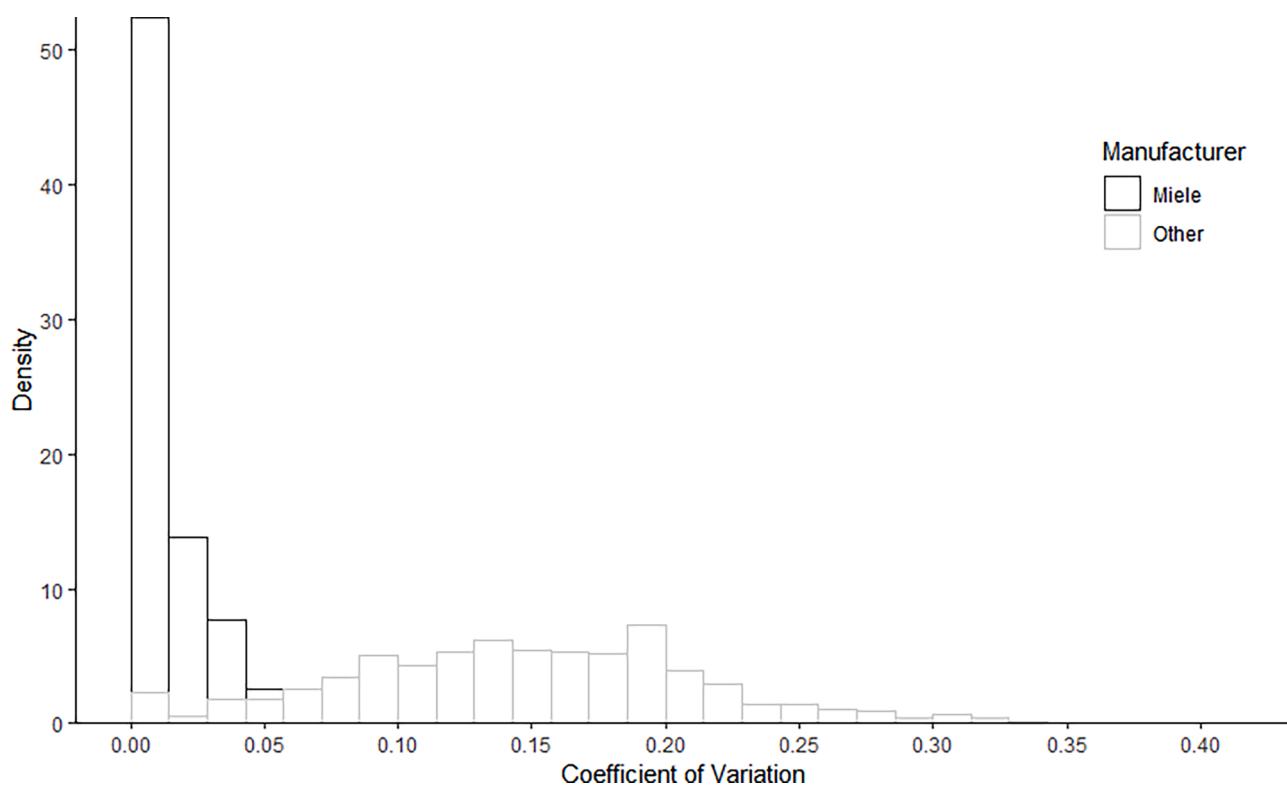


Fig. 9. Stacked histogram of coefficients of variation for Miele and all other manufacturers.

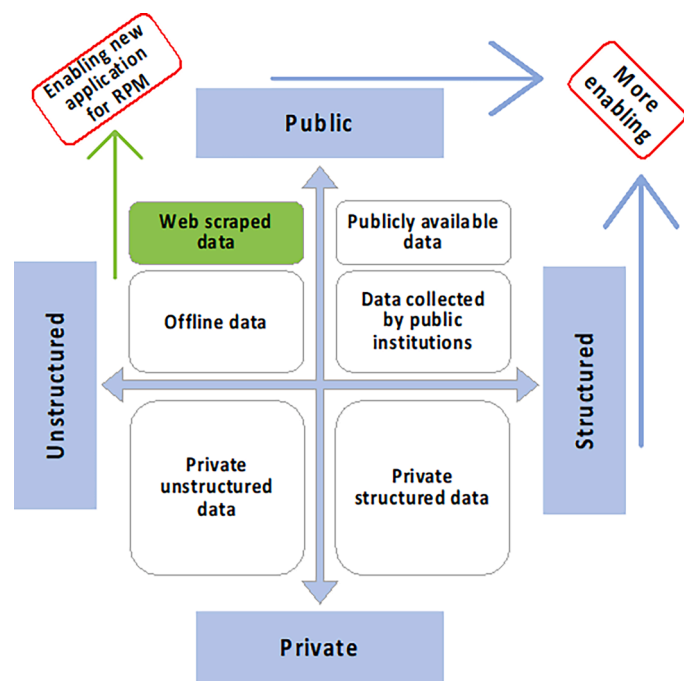


Fig. 10. Digital environment enabling data-driven methods for detecting antitrust infringements
Source: Own figure.

scraping approach applied in this study enables the collection and structuring of data that is originally not structured from websites. New data sources enable new methods and areas of application; in our case: the investigation of RPM. As further applications are developed, an important challenge will lie in obtaining time series data, as antitrust

violations usually occur over a longer period of time and can therefore be better identified with time series data.⁷⁰

6.2. Implications of our findings for RPM detection and antitrust enforcement

On a microlevel, our proof-of-concept study zoomed in on possible RPM in the Austrian washing machine market. Our analysis established that the manufacturer Miele represents a clear outlier with lower price variation compared to the other manufacturers. The type of analysis we present can be best seen as an example application for a simple variance screen that is able to identify anomalies consistent with RPM, provided that the required data is available in a suitable format. If this is the case, such a screen is “uncomplicated, reliable, and therefore, suitable for competition agencies to use”⁷² and can easily be applied to different products and markets.

While the results are consistent with the presence of RPM, other underlying causes might also create such a pattern and simple screens based on descriptive statistics are unable to account for these.⁷³ It is thus possible that other underlying differences between Miele and other manufacturers can produce the observed pattern. Simple variance screens do not account for such alternative explanations and must thus be distinguished from more elaborate econometric methods that attempt to do so. Such additional analyses could include, for example, the use of the recommended resale price of the manufacturer (if available) or firm characteristics.

Therefore, caution is necessary, as further evidence would be

⁷¹ Ioannis Lianos, ‘Computational Competition Law and Economics’ (24 May 2021) <<https://www.epant.gr/en/enimerosi/publications/research-publications/item/1414-computational-competition-law-and-economics-inception-report.html>>.

⁷² Imhof (n 60).

⁷³ Anthauer, Fleiß, Guggi and Robertson (n 3).

required to establish whether an agreement or concerted practice between a manufacturer and its retailers underlies the observed pattern, as this is what competition law requires under Article 101(1) TFEU and its national equivalents. Also, alternative explanations for the observed pattern need to be kept in mind, such as mere parallel behaviour that is not illegal under the antitrust laws.

The legal implications of the computational tool developed in this study are manifold. Our proof-of-concept study shows how rich data sources – especially where they are publicly available and structured – can lead to the identification of possibly anti-competitive behaviour, thereby complementing traditional antitrust enforcement. At a time when leniency applications are in decline, competition authorities may want to turn to computational tools in order to detect market anomalies that can point to possible anti-competitive behaviour. In many jurisdictions, such competition screenings can provide an important impetus for a competition authority to further look into a suspected infringement. A screening such as the RPM screening carried out in this study may also constitute sufficient evidence to warrant the dawn raid of a business or a request for information.⁷⁴ However, the evidentiary standard that needs to be applied to the finding of an antitrust infringement is necessarily higher than the one applied to requests for a search warrant. When it comes to proving an antitrust infringement, additional findings on an anti-competitive agreement between manufacturer and retailer would therefore need to be added to the findings from the

dashboards in order to rule out alternative explanations for the suspicious patterns that were identified.

For antitrust enforcement, computational antitrust can represent a powerful tool that authorities should make use of to complement their enforcement strategies. Using these tools, however, requires certain capabilities that need to be further developed in an interdisciplinary manner. It is foreseeable that computational tools will increasingly be relied on for public antitrust enforcement at all stages of the antitrust inquiry: the raising of an initial suspicion, the request for a search order and the substantive analysis of market conduct. In this respect, it will be vital to ensure that the analysis carried out with the help of – or even by – computational tools remains explainable and reproducible so as to ensure that the relevant standard of proof can be satisfied and companies' rights of defence are safeguarded.⁷⁵

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

⁷⁴ On the legal implications of evidence produced by computational tools from an Austrian perspective, see also Franziska Guggi and Viktoria HSE Robertson, 'Kartellaufdeckung 2.0' (2023) *ecolex* (forthcoming). On the limits of data requests in competition proceedings before the European Commission, see Michael J Frese, 'Big Data Requests: The Commission's Powers to Collect Documents in Investigations Under Articles 101 and 102 TFEU' (2023) 46 *World Competition* 273.

⁷⁵ For a more in-depth discussion, see Guggi and Robertson (n 74).