Pricing algorithms out of the box: a study of the repricing industry *

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Abstract

Businesses, including sellers on online marketplaces, are increasingly adopting repricing algorithms, which autonomously set prices. Despite concerns about potential consequences such as inflated prices in online marketplaces, there is a notable lack of research focusing on the supply-side dynamics of the repricing industry. In this study, we address this gap by systematically documenting and classifying repricers, ranging from basic fixed-rule algorithms to sophisticated self-learning AI algorithms. Drawing on suppliers' descriptions, we analyze product features, fees, and associated services. Although the analysis is descriptive, we offer a first, broad overview of this new industry, potentially affecting millions of consumers in online marketplaces. Our focus is on describing the technical feature claims of these products where they are relevant for economic analysis in academic research and policy.

Keywords: Pricing algorithms, Artificial Intelligence, repricer, marketplaces, online commerce
JEL: D21, D43, D83, L12, L13

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1 Introduction

While shopping online, buyers increasingly encounter prices determined by software algorithms known as "repricing algorithms" or "dynamic pricing algorithms." These algorithms automate pricing for sellers in online marketplaces, leveraging vast amounts of data to adjust prices rapidly based on various factors such as competitors' pricing, stock levels, and customer reactions. In promising to optimize sellers' profits across diverse product offerings, repricing algorithms have become accessible even to small-scale online sellers, potentially reshaping market dynamics.

However, the widespread adoption of repricing algorithms also raises concerns about potential market abuse. For instance, regulatory bodies like the UK Competition and Markets Authority (CMA) and the US Department of Justice have intervened in cases where repricing software was exploited to fix prices on online marketplaces. These instances underscore the need for scrutiny and regulation to ensure fair competition in digital markets.[1] In another case, travel agents used algorithms to fix prices on an online booking platform. In particular, the online booking system informed travel agents that the pricing algorithm was capping price discount at 3% maximum and fined the platform and the agents.[2] In 2018, both the European Commission and the CMA found that repricing algorithms could be used to enforce the (forbidden) resale price maintenance, as algorithms allow to promptly and automatically detect deviation from agreed prices.[3]

A nascent economic literature has addressed these developments with theoretical and empirical research and studies the novel impact of repricing algorithms on competition in digital marketplaces. Calvano et al. (2020), Klein (2018) and Johnson, Rhodes, and Wildenbeest (2023) have utilized simulations to demonstrate how self-learning algorithms could lead to collusive pricing outcomes. Empirical research, such as that conducted in the German retail gasoline market by Assad et al. (2020), and on online marketplaces by Hanspach, Sapi, and Wieting (2024), has shown varying impacts of pricing algorithms on price-cost margins depending on market structure. With a theoretical analysis, Brown and MacKay (2021) show that simple pricing algorithms that react quickly to a rival's price change can increase price levels and price dispersion.

Despite these initial insights, research on repricing algorithms is hindered by limited understanding of their functionality and deployment. Repricing companies often shield their algorithms' details to protect intellectual property, and the rapidly evolving repricing industry remains largely unexplored. For example, we do not know how many options sellers have, e.g., for repricing mass-market products and in terms of reaction speed. Nor do we know how competitive the repricing market is and which

[1] See the decision of the CMA, Online sales posters and frames, Case 50223, 12 August 2016 and United States of America v David Topkins, Plea Agreement, Department of Justice, Antitrust Division, No. CR 15-00201 WHO. Another early case in the airline industry was United States v Airline Tariff Publ'g Co., 836 F. Supp. 9 (D.D.C. 1993).

[2] Case C-74/14 Eturas' UAB and Others v Lietuvos Respublikos konkurencijos taryba EU:C:2016:42, Judgment of the Court, 21 Jan 2016.

[3] European Commission cases AT.40465 (Asus), AT.40469 (Denon and Marantz), AT.40181 (Philips) and AT.40182 (Pioneer), decisions of 24 July 2018; decision of the CMA, Digital piano, and digital keyboard sector: anti-competitive practices 50565-2, 8 October 2019.

contractual agreements it uses to attract clients. This paper aims to address this gap by providing a systematic overview of repricing algorithms' supply, fees, and market positioning.

For these reasons, early research on repricing algorithms has relied so far on indirect assessments of the properties of repricing software. For example, early discussions conjectured features of such software (Schwalbe, 2018), or relied on certain classes of practical algorithms in simulated environment (Calvano et al., 2020). The empirical research identified the use of algorithms for pricing, but with no information on their characteristics (Assad et al., 2020 for the gasoline market, Chen, Mislove, and Wilson, 2016 on Amazon, Hanspach, Sapi, and Wieting, 2024 on the marketplace Bol.com, Brown and MacKay, 2021 for pharmaceutical markets), although the latter two papers show that characteristic algorithmic pricing patterns can be generated by simple pricing rules. However, the lack of information about the characteristics of the available algorithms, and the range of offers, is problematic. The details of algorithms turn out to be essential for their implications and also for policy assessment.

This paper contributes to the debate about repricing algorithms with a systematic overview of these algorithms' supply, fees, market positioning, and claimed features. Underlying this paper is a descriptive study of 185 repricing algorithms by 130 firms, spanning different countries and use cases. While we do not have the opportunity to investigate the actual underlying software of these proprietary algorithms, we study claimed features and pricing schemes. The analysis allows identifying new and valuable information that could help understand this market and its segments and characterize the capabilities of today's software. Our focus is on describing the technical feature claims of these products where they are relevant for economic analysis in academic research and policy.

Our analysis focuses on third-party repricing algorithms available for purchase online, aiming to understand their claimed features and pricing schemes. While we lack access to proprietary algorithms' underlying software, we analyze available data to characterize the capabilities and market landscape of repricing algorithms. These products vary in how they are deployed, arrive at their price recommendations, and how expensive and sophisticated they are. All repricing algorithms that we study have in common that they are readily available for purchase and allow instant or at least swift repricing (typically with no more than a claimed few minutes delay) of hundreds, if not thousands of products without human intervention. However, there is a wide range of (claimed and actual) characteristics. When and why a repricing algorithm decides to adjust prices can be different from case to case. While many off-the-shelf products offer to reprice products only based on fixed, predetermined rules, other products claim to run independent "A/B-tests" (i.e., testing consumers' and rivals' reactions to variants of selling policies) or to learn about competitive parameters such as own-price elasticity, rivals' strategies, and demand.

While the current interest in big data analytics and artificial intelligence (AI) makes the latter cases the focus of much conjecture about algorithmic collusion, even less sophisticated products can impact competition. Ezrachi and Stucke (2017), for example, discuss the justification strategies used by cartelists and assert that even an unsophisticated computer program increases the mental distance to any wrongdoing, making collusion easier.

While our analysis is a snapshot of a rapidly evolving industry and is necessarily limited by what information firms share, we have already found a deep market for online stores. Sellers have a choice of hundreds of repricing algorithms that can be as cheap as a few dozen Euros per month. This is irrespective of whether sellers rely on marketplaces such as Amazon and eBay or own shops built on shop software such as Shopify or Magenta. As a result, we expect that algorithmic repricing might already be commonplace, especially in markets where the Internet is an important sales channel. At the same time, even firms without specific technical expertise can purchase high-end repricing algorithms that claim to make use of self-learning AI and features such as A/B-testing or demand elasticity estimation.

Researchers and authorities should therefore take note of algorithmic repricers as an important market feature especially for products for which the Internet is the main distribution channel. It is highly likely that many of these products are already priced by algorithms.[4] Where they aren't, adoption can potentially happen quickly due to the wide availability of affordable repricers. Nonetheless, there are price differences between the more and less sophisticated repricers that might put the most powerful repricing technology out of reach for small sellers, placing them at a disadvantage on marketplaces. To our knowledge, the literature has so far ignored differences in the fees and sophistication of algorithms that different sellers may use. This difference could be weighed against the possibility of free riding: smaller sellers might use simple rules-based algorithms to piggyback on demand-driven price changes implemented by a rival's sophisticated algorithm.

We suggest that algorithms are not just of interest because of the risk of high prices. They also give an insight into the objectives of the firm, due to the availability of strategies other than profit maximization. Finally, researchers and authorities might even be able to leverage the ability of repricers to identify competing products for their own purposes. By shedding light on this evolving industry, we hope to inform academic research and policy discussions surrounding algorithmic pricing and its implications for market competition and consumer welfare.

The paper is organized as follows. Section 2 provides an introduction to the class of algorithms that we call "repricer" and are the subject of this paper. Section 3 contains a general description of algorithms and repricers, an explanation of the methodology under which the data was collected. We present summary statistics in Section 4. Section 5 contains a discussion of categorizations and insights on algorithmic repricers based on our data. Section 6 concludes.

[4] In a study of 2015, Chen et al. (2016) show that roughly 30% of prices in US Amazon Marketplace were most likely set by repricers, a figure that we expect to have considerably increased since then.

2 Introduction to algorithms and repricing

In its broadest definition, an algorithm refers to a computational procedure designed to solve a mathematical problem in a finite number of steps. In the context of digital markets, algorithms play an increasingly pivotal role in everyday products and services, facilitating tasks such as optimizing search engine results and curating content platforms.

A repricer, as a specialized type of algorithm, is employed by businesses, particularly sellers on online marketplaces, to recommend and sometimes implement price adjustments for products. For instance, an electronics seller on platforms like Amazon may utilize a repricer to dynamically update prices and manage inventory. These repricers possess the capability to swiftly modify a large number of prices while considering various data points, surpassing the monitoring and analytical capabilities of a human decision-maker. For example, a repricing algorithm may observe a large number of rival products simultaneously and increase the prices of products for which competitors have run out of stock while decreasing the price for goods for which competitors are also reducing the price. A repricer might identify additional data helpful to predict demand and suggest prices according to its objectives.

A fundamental distinction exists between "fixed-rule" repricing algorithms and "self-learning" ones. Fixed-rule repricers adhere to predetermined rules set by users, such as undercutting competitors or adjusting prices based on predefined thresholds. Alternatively, they could adjust the price when it deviates too far from the median of a comparison group. Despite their seemingly simple, deterministic nature, these algorithms can include large amounts of data and complex decision rules that can condition the behavior of the repricing on multiple and sophisticated dimensions. Fixed-rules algorithms have been used for repricing for several decades, for example, in the hotel and airline industries. Although these fixed-rule repricing can be relatively sophisticated, it should be understood that their behavior is entirely pre-designed and built into the algorithm.

For example, a rules-based repricer might automatically identify relevant competitor products based on matching images and product descriptions. The user might then manually modify the selection of competitors, e.g., to tell the algorithm to ignore a particular competitor that charges very low prices. Other standard inputs for such an algorithm may include maximum and minimum prices or price-cost margins. Different rules-based algorithms are designed to continuously undercut rivals by some predetermined tick, and at regular intervals, they automatically "reset" the price to a high level. With these fixed rules in place, the algorithm monitors changes in the input data that may trigger a repricing event depending on the pre-specified rules. For example, a drop in a competitor's price may trigger a price decrease. An example is provided in Figure 1 in the Appendix. This screenshot from the repricing algorithm Prisync allows users to chain simple conditions into rules such as "I would like to be 5.00 EUR higher than the cheapest of all my competitors as long as I respect min margin/markup as Cost+5.00 EUR."

Conversely, self-learning algorithms adapt and evolve based on market conditions, enabling them to autonomously respond to dynamic pricing environments. They learn from past interactions, experiment with pricing strategies, and adjust their behavior accordingly. Self-learning algorithms are equipped with fewer rules and are designed to learn how to respond to market conditions autonomously. The ability to learn from market conditions allows these algorithms to adapt and change their actual behavior that may thus be different from its behavior under the same conditions observed at other points in time. Simplifying, the programmer of these algorithms indicates the possible goals, such as sales/stock turnover maximization or profit maximization, between which the seller can choose and change, depending on business strategy and current position in the marketplace. An example is provided in Figure 2 in the Appendix for the company Bqool, which allows users the choice between repricing strategies that vary between turnover maximization and per-unit profit maximization.

The learning method that transforms what the algorithm monitors at any point in time into some pricing decision is also specified, taking into account the goal set by the seller. Finally, these algorithms can be designed to actively experiment, sometimes using certain price levels just to determine how consumers and rivals react. These algorithms are considered more modern with respect to fixed-rules algorithms and are an application of AI and machine learning in particular.

When it comes to self-learning algorithms, they primarily vary along three dimensions. Firstly, they differ in their capacity to learn, such as whether they account for intertemporal trade-offs, like considering profits over an extended period. Secondly, the extent to which they engage in experimentation while learning varies. Lastly, they diverge in whether they are model-free, abstracting entirely from the market environment, or if they incorporate pre-coded conditions and information. For instance, they may include insights like the tendency for demand to increase when prices decrease, which could be updated through learning. Additionally, they may be limited to considering specific price levels.

Certain repricing companies claim to use these types of more modern algorithms that learn from market conditions and continuously improve over time.[5] Others instead focus on more mundane fixed-rule repricers. Clearly, these two types of algorithms have pros and cons. In particular, fixed-rule repricers lack the flexibility to adapt to unforeseen changes in market conditions. On the other hand, the flexibility with self-learning repricers may back-fire as learning and experimentation while the algorithm operates in the markets can be expensive for sellers.[6]

Despite these nuances, repricers play a crucial role in enhancing economic efficiency by promptly adjusting to market dynamics and potentially fostering competition. They can also feed information into the pricing of products more systematically and comprehensively than human decision-makers.

[5] One example is the algorithmic repricer by BQool that claims to have these features in contrast to a rules-based repricer. We will discuss this further in the next sections.

[6] In fact, often these types of algorithms are at least in part pre-trained offline, that is, in virtual environments that emulate the markets.

As shown in the introduction, there are also potential risks for consumers in spreading repricing algorithms. The most salient risk is the fear that repricing algorithms might directly or indirectly help sellers coordinate to raise prices, resulting in less competitive online marketplaces.

3 Data and methodology

This section outlines our approach to data collection, the method used to identify relevant repricers, and the variables collected, followed by the presentation of descriptive statistics. To begin, we initiated a comprehensive search to identify potential repricing tools for online markets. This involved employing conventional online search techniques using keywords such as "repricing" and "dynamic pricing" tools. Additionally, we supplemented our search by consulting market overviews of "Pricing Optimization Software" provided by Capterra, a firm that compares business software. We follow the industry's convention for naming these products. We expand our search through comparisons of pricing software by market research firms G2[7] and Gartner.[8]

While our approach captured a wide array of mass-market third-party repricing software available for purchase, we do not observe pricing software developed by companies in-house or fully bespoke software (although we do observe some firms offering customized products). We take this approach because our focus is on the actual offer rather than the precise effects of algorithmic pricing software, especially for off-the-rack use in the mass market of online retail. To this end, we analyze pricing algorithms advertised for marketplaces rather than their behavior.

In a subsequent step, we refined our sample to include repricing tools capable of autonomously adjusting sellers' prices. This involved excluding software focused solely on monitoring competitors' prices or providing price suggestions without the ability to actively modify prices. Through this process, we identified 185 distinct pricing tools offered by 130 different firms.

In the final step, we collected publicly available information from repricing companies' websites and trial accounts, where feasible. For each firm in our sample, we analyzed their range of repricing software and created one observation for each feature-distinct software product. We classified products as feature-distinct if they offered a unique set of features, such as additional variables considered or a significantly higher repricing frequency. However, variations in scale, such as the ability to connect to more marketplaces or reprice a greater number of stock-keeping units (SKU), were not considered feature-distinct.[9] This decision is motivated by our focus on studying the capabilities and varieties of repricing algorithms in the market. To account for tiered software that is not feature-distinct, we do, however, note the pricing structure (e.g., tiered by number of SKU, by revenue) and compute fees,

[7]https://research.g2.com/

[8]Gartner, "Market Guide for Retail Unified Price, Promotion and Markdown Optimization Applications", Robert Hetu, 6 January 2021. https://www.gartner.com/en/documents/3995226/market-guide-for-retail-unified-price-promotion-and-mark

[9]SKU are code numbers that identify single inventory items at the lowest level of granularity for inventory control, for example selling or purchasing.

where possible, for hypothetical sellers of different sizes.[10]

Finally, we analyze each website according to qualitative and quantitative criteria, which we define from the terminology and features we find in common between several sellers. We record the features that we consider most helpful and interesting in classifying and distinguishing websites. Our criteria reflect that repricing algorithms are heterogeneous in terms of their sophistication, transparency, pricing, features, scope, and breadth, ranging from industry-specific expert systems to all-purpose pricing software.

Apart from basic information about the firm selling the repricing software, such as the URL of their website and country, we collect information on the marketplaces where this software can be used, with additional information on which national Amazon marketplaces are mentioned, if any. We also identify if a firm offers pricing-related consulting (possibly with a more strategic rather than operational focus) with human experts as an add-on to their repricing service. We collect information on whether a firm makes certain specific claims about its product: whether it learns demand, uses AI, is based on game theory, is based on economics, is self-learning, uses dynamic pricing, and whether it uses price discrimination (or segmentation). We also note if the product is advertised only to B2C channels, for example, retailers with webshops, or B2B channels, helping manufacturers or wholesalers selling to retailers. We look for evidence of facilitating switching from rival services.

For the fees of the different tariffs of the repricers, we consider the following: the components of the overall service fee (e.g., setup fee, revenue thresholds, per number of SKU), the currency, the costs of contracting for one month for hypothetical small, medium, or large shops and whether a free trial exists. For this purpose, we define representative small, medium, and large shops, which we explain in detail further below. Practically all products in our sample are subscription services, often as a "Software as a Service" (SAAS) model, where customers purchase the use of the repricing algorithm for a specific period. Therefore, we also check for discounts for long-term contracts and, if such a discount exists, the shortest and most extended periods for which a buyer can contract and the implied discount.

We also analyze the following features of repricing algorithms: the declared number of price changes per hour, the maximum number of products that an algorithm can handle, whether the algorithm can focus on or exclude specific competitors, which pricing rules are used, whether an algorithm specifically targets or claims to win the Amazon Buy Box or similar (where applicable), and whether it keeps track of rivals' stocks.[11] Finally, we record if the product comes with analytics and, if so, which form they take.

[10] To avoid confusion, we indicate with the fee the payment charged by the software firm for the repricing services and the price that the algorithm automatically determines for the seller.

[11] The Amazon Buy Box is the clickable white or yellow box, generally located at the top right part of the web page, that buyers may click to initiate their purchase of a particular product. It is estimated that more than 80% of Amazon transactions refer to products associated with the Buy Box. For this reason, competing sellers of the same product try to win it. Although the precise rule used by Amazon to temporarily allocate the Buy Box to a seller is not precisely known, a low price and high-ranked reviews are among the most relevant elements, although certainly not the only ones.

We also collect geographical information. To this end, we first look for information on the website about the company's home country. If we do not find any further information, we assign a country based on office location. When several offices are listed, we assign a country based on the location of the first office listed.[12]

It's important to note that our dataset reflects advertised product features rather than verified functionalities. Additionally, firms' claims may sometimes be exaggerated or misleading. Some product features, while significant, may not be explicitly listed, while others may be mentioned despite their limitations. Table 6 in the Appendix lists and describes all the variables that form our analysis.

4 Descriptive analysis of repricers

The first interesting observation is the geographical distribution of locations for the 130 repricing firms. Approximately one-third of the 185 repricing algorithms in our sample are affiliated with companies based in the United States (32.4%), followed by the United Kingdom (11.9%), France (7.6%), and Germany (7.6%) the next most common locations. Notably, only a small portion of repricing algorithms (16, or 8.6%) originate from the Asia-Pacific region, with entries from Australia, India, New Zealand, Singapore, and Taiwan and 2 (1%) from South America. However, our overview reveals some notable gaps, particularly the absence of representation from China, which we would expect to have a domestic industry. It's essential to acknowledge that our English-language search might overlook firms that do not offer websites in English, potentially skewing our results.[13] Consequently, we anticipate our findings to be most relevant to Europe and North America. The full Table 7 of pricing algorithms' "homes" is in the Appendix.

Nevertheless, it's crucial to note that the location of a repricing firm does not necessarily limit its ability to offer services globally. While there may be factors unrelated to the market, such as international sanctions, influencing a firm's reach, the absence of statements indicating geoblocking or other geographical restrictions suggests global accessibility. However, the accessibility of online marketplaces, particularly the different national Amazon platforms (e.g., www.amazon.it, www.amazon.de), may pose significant constraints. Nonetheless, the ability of repricers to operate across various marketplaces, as observed in our data, raises potential concerns related to collusion through multi-market contact. It would be interesting to see if algorithms learn from different marketplaces simultaneously. For example, in an across-platforms coordination scheme, repricing algorithms may react to price cuts by a competitor on one platform with price cuts across several platforms to inflict harsher punishments on competitors that deviate from high prices.

A geographic overview of repricers clearly does not allow us to conclude any market definition in

[12]Typically, nothing precludes that a software company based in one country deals with customers in other countries. Our use of search terms in English allows us to identify companies that operate in many countries.

[13]Some websites we covered are not available in English or only translate a limited part of their website to English, for example, https://by.prexus.co/

a competition law sense, which would necessarily be case-specific. Neither the fact that the websites of these repricers can be accessed globally nor the tailoring of repricers to specific applications (see Section 5.1) alone is sufficient to argue the case for a wide or narrow market definition. It does seem plausible that due to different languages, functionalities, and target audiences, only a subset of repricers will constitute substitutes for any given seller. It seems very unlikely for most imaginable cases that all of these repricers covered in this paper could be part of a single relevant market in the competition policy sense.

Without further information on the sales of repricing companies, it is also not possible to make any statements about the size or market share of the firms we study. The focus of our paper is on the capabilities and availability of repricing algorithms for sellers in online marketplaces, more than on the market structure in the algorithmic repricing market, although we do collect some information, notably on product differentiation and target industries, that is also relevant to the latter.

Of 185 repricing algorithms, 69 (37%) list specific marketplaces, such as Amazon and eBay, for which they are suitable. The remainder either make no explicit statement on the marketplaces they integrate with or offer connection via API to existing webshops. We list those as "platform-independent". Of those 69 repricing algorithms that name compatible marketplaces, 41 (59% of 69) list more than one marketplace. The ability of repricers to operate in several marketplaces raises possible concerns related to theories of strengthening collusion through multi-market contact, which in this case could take place on different platforms and thus be more challenging to identify.

In addition to the observation that most repricing algorithms are geared towards sellers on Amazon, it is worth mentioning that Amazon offers a free repricing service as well.[14] Amazon claims that its tool can "adjust your prices quickly and automatically against your competition" to increase sellers' chances of winning the Buy Box, which Amazon also calls the "Featured Offer", the first offer that is shown on an Amazon product site. The main listed features of Amazon's repricing algorithm are the options to select a "pre-configured 'competitive price rule' or customize your strategy, choosing whether to compete based on feedback rating, fulfillment channel, and other options". Amazon's repricer is based upon simple, fixed rules that allow sellers to start and stop repricing for designated products and to set price limits.

Algorithmic repricers also advertise being compatible with common enterprise software packages, including marketplace software, and customer relationship management (CRM)[15] software, or enterprise resource planning (ERP)[16] software. Some repricers advertise compatibility with industry-specific revenue management software solutions, such as Marketron (media), Wideorbit (premium ads), or Sqills (transportation). This compatibility underscores the versatility of repricing algorithms

[14]https://sell.amazon.com/tools/automate-pricing

[15]CRM encompasses a firm's practices in dealing with its clients, including prediction and analysis of customer trends, sales, after-sales, and support.

[16]Companies use ERP to integrate functions such as inventory planning, sales, marketing, human resources, and finance into a unified and comprehensive system.

in various business contexts. In total, 43 of 185 repricing algorithms mention integration with such tools (23%). The most commonly named ones are tools that allow sellers to create their online shops, such as Shopify (13 mentions, 30% of 43) and Magento (6, 14%). 35 other software packages are mentioned 5 times or less, with some examples including Tableau (data visualization), LS Retail (retail point-of-sale software), or Microsoft Dynamics (a business software suite), each of which is mentioned once. The complete list is reported in Table 8 in the Appendix.

5 Analysis

In this section, which forms the backbone of the paper, we examine our sample of repricing algorithms. We systematically explore different aspects, starting with an analysis of the various companies involved in algorithmic repricing in Section 5.1, followed by an examination of the different types of algorithmic repricing in the marketplace in Section 5.2 and concluding with an investigation into the relevant implications for economists in Section 5.3.

5.1 Analysis of algorithmic repricing companies

In the ongoing discussion regarding competition's impact on AI applications, scholars differentiate between entry conditions across various points of the value chain. With the evolving role of AI in the economy and growing concerns about concentration within the AI value chain, understanding the vibrancy of entry for AI applications, including certain forms of algorithmic repricing, becomes crucial.[17] Although not every algorithmic repricer fits the definition of an AI application, much attention has been directed towards these repricers in the field. Entry into AI applications faces fewer barriers compared to upstream markets supplying inputs for AI development, such as cloud computing or foundation models (Carugati, 2023; Schrepel and Pentland, 2023). Therefore, exploring the self-description and history of companies that opted to develop repricing tools provides valuable insights into the gateways into this specific AI application.

Repricing software is offered by various companies, categorized based on the breadth of their product portfolio. We propose four typical characterizations of repricing companies: a) startups exclusively offering repricing algorithms, b) pricing consultants expanding their services with algorithmic repricers, c) price management and observation firms providing algorithmic pricing software as an extension of existing software or standalone products, and d) corporate software vendors including repricers as part of their product portfolio.

Some repricing software companies specialize in targeting specific industries. Contrary to the common perception of repricing algorithms, these are not limited to online marketplaces, hotels, or plane tickets. This industry specialization is particularly prevalent among firms extending pricing

[17] For example, expressed in an OECD conference on regulation of AI, https://www.oecd.org/economy/reform/regulation-ai/.

expertise to sectors like Heating, Ventilation, Air Conditioning (HVAC), government procurement, transport, and energy contracts, leveraging their sector-specific knowledge into repricing software (type b, above). In contrast, especially type-a) but also type-c) firms emphasize the universality of their algorithms, generating prices based on competitors' prices and stocks across various industries. Other notable variations on repricing offers include i) promotional planning (pricing discounts) and ii) analysis of "price-image", i.e., influencing customer perception about the general price level of a seller.

Beyond technical expertise tailored to specific industries, several repricers are offered alongside additional pricing consulting services. Approximately 26 % of repricing algorithms (46) are promoted jointly with pricing consulting services, often purchased as optional add-ons. These consulting services range from strategy training or workshops with customer sales teams to personalized algorithms, provided either by the repricing software seller or in collaboration with a third-party consultant.

Regarding sellers' sectors, we identified ten different specializations among companies offering repricing algorithms for specific industries, including i) pricing tickets for the entertainment industry, ii) pricing for the hospitality industry (hotels, short-term rentals), iii) power purchasing agreements (and energy markets in general), iv) transport and logistics, v) HVAC, electric and plumbing, vi) tyre manufacturers, vii) travel ("capacity constrained industries"), viii) revenue management for airlines, ix) corporate banking, x) telecommunications. Notably, some industries, like airline revenue management, were unexpected findings, as such capabilities are typically in-house with large airlines. This admittedly ad-hoc list is not exhaustive but merely serves as an illustration of the repricers that we find.

While not categorized as repricing software, it's worth mentioning adjacent pricing products specialized in generating quotes or supporting sales teams, particularly geared towards B2B offerings or firms involved in government contracts. These products cater to specific B2B needs, such as compliance paperwork for procurement contracts, managing complex rebate and discount schemes, and electronic management of extensive pricing catalogues, such as those found in automotive companies with complex product specifications and pricing structures across multiple currencies.

5.2 Analysis of repricing algorithms

Repricing algorithms can be categorized based on their use case or functionality. Use cases typically fall into two main categories: repricers for third-party marketplaces and those tailored for sellers' shops. The former category tends to be more standardized, offering comprehensive information about prices and product features for platforms like Amazon, eBay, and Walmart. In contrast, solutions designed for sellers' websites are often more customized, featuring individualized and non-public pricing structures, with sales typically conducted through personal demonstrations.

5.2.1 Repricing fees

We observe that rather than being sold as one-time purchases (similar to video games or office software on CDs in the early 2000s), repricing algorithms are typically marketed through subscription and licensing models. Customers purchase access to pricing software via monthly or annual subscriptions. Interestingly, only half of all repricers display fixed prices upfront, with the other half requiring customers to contact the seller for individual quotes. It's reasonable to expect that sellers of algorithmic repricing software utilize sophisticated algorithms or data-driven approaches themselves to determine their service fees. In Table 1, we outline the main fee models we've identified. In 93 cases (50%), no information about the fees is publicly posted. Another 64 (35%) repricing algorithms are offered at a fixed fee, often with limitations on functionality such as a maximum number of SKU or marketplaces. The remaining options feature flexible fees that scale with factors like the number of items, revenue, or a combination thereof, sometimes incorporating separate setup fees and resulting in a two-part tariff pricing structure.

Table 1: Frequency of repricing fee rules

Main determinant of repricing fee	Number of repricers	% of total
Individual quotes	93	50
Fixed fee	64	35
Number of items	12	6
Mixed rule	6	3
Other	6	3
Total revenue	3	3
Total revenue plus fixed fee	1	1

Percentage relative to total of 185 repricers, difference to 100% from rounding.

Based on the information we collected from the websites, we have computed the fees for three hypothetical shops based on the following characteristics[18]:

1. Small shop: 10 items, 100 sales, 10,000 € monthly turnover, 1 national Amazon marketplace or sales platform
2. Medium-sized shop: 500 items, 5,000 sales, 500,000 € monthly turnover, 7 national Amazon marketplaces or sales platforms
3. Large shop: 15,000 items, 150,000 sales, 5 mio. € monthly turnover, 10 national Amazon marketplaces or sales platforms

We assess the fee for a one-month subscription, inclusive of one-time setup costs, presented separately by currency.

Table 2 presents the distribution of fees for these three hypothetical shops. We distinguish between offers in USD and Euros. There are only three products with fees in other currencies (two in GBP,

[18]These numbers were also informed by personal communication with actual sellers.

and one in BRL). We observe 50 repricers that list fees in "EUR" and 31 in "USD" (the websites were accessed from Eurozone countries). So, only 44% of repricers (84) come with a publicly posted fee. The range of fees is broad, ranging from under a hundred Euros or US dollars for small shops to several times more expensive for higher-tier offers. It would be insightful to determine whether this fee disparity is due to variations in value or uncertainties regarding the value delivered by repricers. The wide range of fees, coupled with the availability of trial versions and live demonstrations, underscores the significant challenge in persuading customers of the value-added by a repricer.

Nevertheless, an important insight from the analysis of the general price level is that algorithmic repricing is quite affordable. Sellers of various sizes have access to low-cost options for pricing their online stores with repricing algorithms. Consequently, we can anticipate that many sellers, including relatively small ones, will quickly adopt pricing algorithms if they haven't already. Indeed, Table 4 in Hanspach, Sapi, and Wieting (2024) suggests that more than half of sellers on Bol.com, the largest online marketplace in the Netherlands and Belgium, might be using algorithmic pricing.

Table 2: Repricing algorithm costs

	Currency	Min.	1st Quartile	Median	Mean	3rd Quartile	Max.
Small shop	EUR	20.00	81.50	197.00	402.92	449.00	2490.00
	USD	0.00	20.50	75.00	755.09	124.50	14000.00
Medium shop	EUR	25.00	121.25	274.00	501.76	649.00	2490.00
	USD	4.00	28.21	99.00	911.00	186.50	14000.00
Large shop	EUR	59.00	144.50	304.00	627.57	860.00	2490.00
	USD	8.00	97.50	149.00	1478.61	772.50	14000.00

The minimum of 0 is due to one firm, Priceva, which offers a permanent free tier for their repricer that is limited to 20 products.

When assessing the average costs of repricers, it's essential to consider not only the headline subscription fees but also long-term discounts. Thus far, to standardize fees, we have compared prices for the shortest available subscription period, typically one month. Similar to other subscription-based products like newspapers or gym memberships, many repricers provide discounts for longer subscription durations. We find 38 repricers (21 %) that offer long-term discounts, as opposed to 65 that don't (35%) and 82 (44%) for which no information is available. More detailed information about the availability of long-term discounts is shown in Figure 3 and Table 9 of the Appendix. These discounts suggest that the final fee may average 5-10% lower (up to 40% lower in one case). Additionally, it's worth noting that many repricers offer individually negotiated fees for larger customers.

5.2.2 Learning and AI

Given the diverse approaches observed, it's helpful to make a useful distinction between fixed-rule and self-learning repricers, reflecting the spectrum of more and less sophisticated repricing tools. In one case, a company mentions that they "develop mathematical and computational methodologies based on statistics, physics and mechanics, as well as time series analysis and operational research to understand and predict events and behaviors."[19] Another company offered "14 different time series methods, including recurrent neural networks, deep learning, probabilistic, ARIMA and other models to choose from."[20] While verifying these features wasn't entirely feasible, the detailed descriptions suggest authenticity.

Many tools offer repricing without claiming to use AI. Instead, they typically allow users to set rules, like minimum and maximum prices for products or desired positions relative to other products or sellers. While most repricers emphasize maximizing profit, some are also advertised for other goals, such as maximizing revenue or achieving inventory management targets. This flexibility hints at repricers being utilized in complex organizational settings, possibly with delegated management and managers incentivized to maximize revenue or meet targets besides profit.

We're particularly interested in the technical features of repricing algorithms, especially how many claim to include AI or are self-learning. As we rely on self-reported data, the overview might skew towards feature-rich algorithms, as sellers might find it more marketable to report the presence of a feature rather than its absence. For this reason, we also mention which share of repricing algorithms even come with a specific claim attached. Out of 185 repricing algorithms, 101 (55%) explicitly claim to use AI, but only half as many indicate in some sense that their algorithms are self-learning (50 mentions, 27%), that is AI that trains itself and determines the pricing strategy autonomously, using unlabeled data. However, it's unclear whether marketers who advertise their algorithms as "self-learning" apply this definition, and some claims may be exaggerated. We find it most useful to distinguish between more and less sophisticated repricers. We classify all algorithms claiming to use AI or to be self-learning as more sophisticated and the rest as less sophisticated, keeping in mind the limitations mentioned earlier. Just over half (106, or 57%) of repricers are more sophisticated by this definition.

The number of algorithms claiming to learn demand or demand elasticities falls in between those claiming to use AI and those claiming to be self-learning, at 74 (40%). Only 10 repricing algorithms (5%) are claimed to be built using game theory and 15 (8%) explicitly reference economics. 127 repricing algorithms (69%) are described as pricing dynamically and 158 (85%) offer additional analytics. About half of all algorithms (92, 50%) can target specific competitors (i.e., condition pricing rules on their prices or exclude specific firms), but only 58 (31%) actively track rivals' stocks (for example, to increase prices when rivals run out of stock).[21]

We also look at the subset of the most expensive repricers. This analysis is limited by a large number of missing values for the fee structure of repricers because most firms do not report their fee structure but instead rely on individual offers. We tabulate the technical features separately for those 34 repricers with above-median prices for the hypothetical large shop. The frequency of different

[19] https://premoneo.com/en/solutions/
[20] https://www.remi.ai/demandforecasting
[21] See below for an analysis of correlations between these features.

technical claims for the full sample as well as the 34 most expensive repricers is shown in Table 3.

Looking at the subset of the most expensive repricers, we observe no clear pattern. While one might expect technically sophisticated features like self-learning and AI to be more prevalent, they're either less frequent or only slightly more prevalent (27% of all repricers claim to be self-learning, but even among the most expensive ones only 32% do). Due to the low sample size and many missing values for fees, we refrain from interpreting too much (or conducting regression analysis) as the results would likely be misleading.

Instead of comparing the features of the most and least expensive repricers, we can compare repricer fees by category. Using our proposed classification of self-learning and AI-based repricers versus "simpler" fixed-rule repricers, we find that the latter tend to be much cheaper. For example, the hypothetical large shop would face a monthly mean price of 1967.6 Euros for a "self-learning" repricer versus 338.68 Euros for one of the remaining repricers (median: 617.9 Euros and 195 Euros, respectively). Sophisticated repricers end up costing circa six times more than the simple ones. Similar figures emerge for medium-sized and small shops, with self-learning and AI-powered repricers costing circa four to five times more than other repricers.

While these prices might seem small relative to the turnover of large sellers, the difference in fees between the most and least sophisticated algorithms may hinder smaller sellers from adopting the most sophisticated technology. This can put smaller sellers at a disadvantage on marketplaces where they compete with larger sellers for which even a sophisticated repricer is but a small expense. However, this disadvantage must be weighed against the possibility of free-riding, where smaller sellers might use simple algorithms to piggyback on demand-driven price changes implemented by a rival's sophisticated and expensive algorithm. This could limit the attractiveness of investing in a sophisticated repricing algorithm in the first place.

A more sobering explanation for the widely different prices and features of repricers is the difficulty in evaluating the value added by such tools. Perceptions of the substitutability of rival products and value-added are crucial but may be aspirational. Investors putting a premium on firms using AI may also contribute to an unclear relationship between the price and usefulness of pricing algorithms. All these factors might lead to the seemingly weak relationship between price and product features.

Regarding the use of AI to choose prices, repricers vary drastically. Most companies that claim to use AI or algorithms for pricing do not provide detailed information about how their models are trained, what kind of model is used, or what data is used to train the repricers. When information about the algorithm's training is provided, it typically falls into one of two categories: either the repricing company uses historical sales data of the seller to train its algorithm, or it conducts its own A/B tests. In both cases, the repricing companies often claim to learn demand elasticities to inform their models.

Other firms claim to "estimate demand models". It is questionable whether the use of these expressions in the self-marketing of these products is equivalent to the use of these terms in the economics literature (e.g., in empirical industrial organization), if for no other reason than the lack of detailed explanation such as the kinds of demand model considered by the algorithm and how the applicable demand model is chosen. Other approaches to learning demand are mentioned as well. These include conjoint analysis[22] and the use of historical data. For instance, one repricing company advertises the size of its proprietary dataset rather than emphasizing the use of client data.

Examining the correlation between these different features in Table 4, we find that claims of demand-learning, AI, and self-learning often appear together. Similarly, claims to track rivals' stock and to target specific rivals often appear together, unsurprisingly. Interestingly, a few features have a (small) negative correlation, suggesting that they appear together less frequently. For example, game theory/dynamic pricing and economics/analytics are two such pairs, as are demand/target competitors and AI/analytics. Self-learning is negatively correlated with tracking rivals' stock and targeting competitors, as are analytics and tracking rivals' stock.

These correlations help us identify those pairs of features or terms that often appear together, allowing us to classify products. We can then identify some products for which both of these terms appear and understand why they do so, thereby guiding an essentially qualitative examination of the sample. Understanding *when* these terms related to the theoretical and technical sophistication of the algorithm appear together is often simple, understanding *why* is harder. Most commonly, these terms appear together in white papers, blogs, or additional resources. We suggest that some repricing firms differentiate themselves by discussing the technical background of their repricing algorithms as a way to signal quality.

These correlations and a more qualitative assessment of the studied websites allow a rough distinction between two broad categories for repricers. We find a cluster of AI-first, technology-driven repricing algorithms that, in the very extreme, are very narrow products that seek to integrate with existing revenue-management software. These products may sometimes forego more basic features such as data analytics, as the requirement of input data implies that a customer must have revenue management and analytics already in place. In terms of our analysis, these products are advertised as using "self-learning" and "artificial intelligence", sometimes powered by "game theory" or "economics".

A different group of products includes broader price management systems that sometimes offer repricing as an add-on on top of a range of more basic analytics or competitor monitoring features. This includes the family of rules-based repricing algorithms that do not claim to learn competitors' behavior. They instead focus on identifying relevant competitors and then allow the implementation of mechanical rules (e.g., always undercut the lowest rival offer, always track the median price of a

[22]In conjoint analysis, a group of respondents is shown a sequence of product pairs with different characteristics. Respondents have to communicate a preference between the two shown products. By repeating this procedure and systematically varying the product characteristics, conjoint analysis helps to identify hedonic preferences, i.e., preferences over product features.

comparison group, subject to a specific price corridor, minimum margins etc.)

Table 3: Frequency table of technical features of repricing algorithms

	All repricers		Most expensive repricers	
Feature	Yes (%)	No (%)	Yes (%)	No (%)
Learns demand	111 (60%)	74 (40%)	9 (26%)	25 (74%)
Uses AI	103 (56%)	82 (44%)	15 (44%)	19 (56%)
Uses game theory	10 (5%)	175 (95%)	1 (3%)	33 (97%)
Uses economics	15 (8%)	170 (92%)	1 (3%)	33 (97%)
Is self-learning	50 (27%)	135 (73%)	11 (32%)	23 (68%)
Uses dynamic pricing	127 (69%)	58 (31%)	27 (79%)	7 (21%)
Offers analytics	158 (85%)	27 (15%)	31 (91%)	3 (9%)
Targets specific competitors	92 (50%)	93 (50%)	22 (65%)	12 (35%)
Tracks rivals' stock	15 (44%)	19 (56%)	15 (44%)	19 (56%)

Based on repricing firms' claims, e.g., 50 out of 185 repricers are claimed to be "self-learning", 135 make no such claim. "Most expensive" repricers selected as 34 repricers with above median fee for the large hypothetical shops when the fee was available.

Table 4: Correlation matrix between technical features

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Learns demand [1]	1.00	0.68	0.24	0.12	0.45	0.10	0.03	-0.06	0.04
Uses AI [2]	0.68	1.00	0.17	0.19	0.47	0.10	-0.03	0.15	0.06
Uses game theory [3]	0.24	0.17	1.00	0.28	0.07	-0.10	0.10	0.19	0.25
Uses economics [4]	0.12	0.19	0.28	1.00	0.09	0.12	-0.10	0.10	0.18
Is self-learning [5]	0.45	0.47	0.07	0.09	1.00	0.15	0.11	0.00	-0.02
Uses dynamic pricing [6]	0.10	0.10	-0.10	0.12	0.15	1.00	0.12	0.11	0.13
Offers analytics [7]	0.03	-0.03	0.10	-0.10	0.11	0.12	1.00	0.07	-0.02
Targets specific competitors [8]	-0.06	0.15	0.19	0.10	0.00	0.11	0.07	1.00	0.59
Tracks rivals' stock [9]	0.04	0.06	0.25	0.18	-0.02	0.13	-0.02	0.59	1.00

Column headers replaced by index numbers to save space.

Overall, it is remarkable and surprising how few algorithmic repricers are really AI-based, despite the common association of algorithmic repricing with artificial intelligence in the literature Calvano et al., 2020; Johnson, Rhodes, and Wildenbeest, 2023. This finding can be attributed to a sort of "goldrush-mentality" around AI and the fact that simple repricing tools are likely much easier to bring on the market than self-learning algorithms. Additionally, sellers in online marketplaces may prefer transparent algorithms.

5.2.3 Repricing speed

One of the primary attractions of repricers is their ability to change prices across a large inventory faster and more frequently than humans can. A total of 50 repricers made some statement about repricing speed. Interpreting a rather vague but common claim of "instant repricing" as up to 3600 repricing events per hour (one per second), we find a range between 0.042 (once per day) and 3600 (once per second). Table 5 reports some summary statistics on these claims. Almost half of the 50 repricers (21, or 42%) that give any information about repricing speed claim "instant repricing," and only three repricers (6%) reprice only once a day.[23]

Table 5: Summary statistics for repricing frequency

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.04	1.00	30.00	1553.55	3600.00	3600.00

Sample refers to 50 repricers out of the full sample which report information about repricing speed. Repricing speed measured as frequency of repricing per hour.

Repricers targeting Amazon often emphasize the significance of winning the Buy Box, noting that 80-90% of sales happen there. They may hint at the opacity of the BuyBox algorithm to induce urgency for the reader. They will also emphasize (more than other repricers) the speed at which they reprice, some of them claiming that Amazon limits 3rd-party tools to up to 30 repricing events per hour, while others claim not to suffer from any of these constraints. From the authors' experience with Amazon, Amazon limits the frequency of price changes, so even if a repricer claims to adjust prices frequently, a marketplace may still set binding and relevant constraints on the frequency of price changes, which some sellers may not know.

5.3 General implications

The use of AI extends beyond learning and applying pricing strategies; it often involves discovering related and competitively relevant products. However, it remains unclear whether this refers solely to recognizing similar product names, descriptions, and images, or if it includes using AI to find products with high price correlations or other economic features, finding products that pose a competitive constraint. In the latter case, this could be an interesting and novel case of AI-driven market definition. This use of pricing algorithms could be potentially interesting for antitrust authorities. However, the way this feature is typically described, the former seems more likely. Product discovery and market observation are closely linked to algorithmic repricing because competitors' prices are typically a necessary input variable to the suggested price. Consequently, many repricing software options come equipped with analytics and business intelligence tools, particularly those offered by firms specializing in price management and observation (type c).

For repricing software targeted at "brands", "manufacturers" or any other kind of B2B business, repricing is commonly bundled with tools for monitoring compliance with retail price maintenance, such as detecting "MAP violations" (MAP = minimum advertised price). However, the legality of this practice and compliance in regions where retail price maintenance is banned remain open questions.

The price monitoring feature for discovering competitively relevant products holds practical relevance for research economists and practitioners, including competition authorities. AI-based identification of competitively relevant products, especially when incorporating a complete demand system

[23] Those three algorithms are related to only two firms, one of which focuses on e-commerce, and one on hotel room pricing.

of cross-price elasticities, could offer a more accurate and systematic approach to product market definition. This might require that sellers draw upon additional data, for example on sales and market shares. This data is typically available from market research companies. Conceptually, product market definition in competition economics relies on identifying all products that provide a competitive constraint to each other and are jointly worth monopolising. Practically, the need to limit quantitative investigations of product market definition (for example, to respect the resource constraints of an agency) requires a selection of "plausible" candidate products that could form part of a relevant market. AI-powered product market definition could also impact empirical research in industrial organisation.

Interestingly, few algorithmic repricers mention the economic underpinnings of their algorithms, with game theory being occasionally referenced. Economic theory is rarely mentioned in the description of repricers, game theory is sometimes mentioned. To the extent that game theory is discussed as a consideration in the design of the repricer, this often refers to the avoidance of price wars, comparing pricing to either a prisoner's dilemma or some variation on the Cournot or Bertrand game. However, economic theory informs some of the strategies implemented by repricing algorithms or the reasons for their adoption. Similarly to how the Bertrand pricing game in the managerial/MBA education is framed in terms of "escaping the Bertrand trap", some repricers mention how they help avoid the "Bertrand trap".

Other strategies and pricing rules involve cyclical prices, defined by undercutting other sellers to capture the Buy Box and resetting to a higher price once a predefined minimum price is reached. One repricing firm calls this an "oscillation" or "oscillate" strategy.[24] Another way to think of such a strategy is "tit-for-tat" with forgiveness from the prisoner's dilemma literature. Under this interpretation, the seller using the repricer retaliates against price cuts with own price cuts but "forgives" by resetting to high prices to avoid permanent price wars.

Finally, the data sheds some light on the potential for price discrimination in the form of "personalized pricing". While theoretically well understood by economists, personalized pricing has been rarely observed in practice. With the advent of data-driven, real-time pricing, however, there have been increasing predictions that personalized pricing will become more common (Goldfarb and Tucker, 2019). In our data, 59 repricers (32%) claim to offer either personalized or segmented pricing. However, it is clear that repricing companies try to disassociate themselves from the negatively charged term "price discrimination".[25] In our survey of real user interfaces, we did not find any obvious examples of price discrimination or segmentation such as "charge 5% extra for users on an iOS device". Further research

[24]Bqool mentions this strategy on a website, `https://www.bqool.com/products/rule-based-repricing-central/`, and provides a brief characterization in a video, last retrieved from YouTube on 27.05.2022, `https://www.youtube.com/watch?v=zuyBGieuj_E`.

[25]For example, this article discusses price discrimination alongside a wider scope for personalized dynamic pricing which includes price matching in response to consumers discovering cheaper competitors, https://competera.net/resources/articles/dynamic-pricing-personalization.

is needed to document and describe personalized pricing in practice.

6 Conclusion

This paper provides an overview of the burgeoning repricing industry, which offers software algorithms for automating pricing decisions in online markets. We categorize the players in this industry and classify repricing algorithms, distinguishing between self-learning algorithms and those using fixed rules. While our approach doesn't allow for precise verification of these repricers' capabilities, it offers a unique glimpse into this industry.

It's crucial for regulators, researchers, and consumers to recognize that affordable pricing algorithms are readily available online. In markets where the Internet is a major distribution channel, many sellers are likely already using algorithmic repricing or have the potential to adopt this technology soon. Moreover, our findings highlight the increasing availability of sophisticated AI capabilities for sale. This underscores the urgency with which economists have been advancing the literature on algorithmic pricing. However, significant differentiation in the fees and sophistication of repricers suggests that the level of sophistication and effectiveness of pricing strategies that small and large sellers can afford may vary, impacting the structure of online retail markets and consumers' surplus.

Additionally, economists may find it noteworthy that pricing algorithms are not solely advertised for profit maximization but also to optimize other objectives, such as revenue or inventory turnover speed. This observation suggests potential future research avenues on algorithmic pricing in delegated management scenarios and institutional setups where managers pursue goals beyond profit maximization.

Competition authorities should take note of repricers' potential use to maintain vertical restraints, such as minimum advertised prices. Moreover, certain capabilities of repricers, such as identifying relevant competitor products, could aid in market definition and point towards a more sophisticated method of market definition in competition policy. Tools that identify pricing constraints, substitutes, and complements from a potentially large universe of products could enhance the implementation of existing approaches to market definition. Future research can focus on the analysis of the practical capabilities of the algorithms on offer.

A Tables

Variable name	Description
Company name	Name of the company offering the repricer
Product name	Name of the repricer product
URL	Website of the company
Marketplaces	Online marketplaces that are compatible with the repricer
Country	Home country of the firm
Full Amazon integration	Repricer integrates with Amazon
Amazon marketplaces	List of compatible Amazon marketplaces
Tariff learns demand	Repricer learns demand or price elasticities
Uses AI	Repricer is advertised to use AI
Uses GT	Repricer is advertised to be designed using game theory
Uses econ	Repricer is advertised to be designed using economics
Uses self-learning	Repricer is advertised to be self-learning
Uses dynamic pricing	Repricer is advertised to use dynamic pricing
Uses price discrimination	Repricer is advertised to use price discrimination
B2B	Repricer is advertised for business-to-business/wholesale use
B2C	Repricer is advertised for business-to-customer/retail use
Facilitates switching	Firm advertises easy switching
Tariff name	Name of the repricing tariff
Tariff pricing	Mode of tariff pricing
Tariff loyalty	Tariff offers discounts for longer contract durations
Tariff shortest	Minimum contract duration
Tariff longest	Maximum listed contract duration for discounts
Tariff discount	Long-term discount relative to one month contract (or closest equivalent)
Tariff minimum	Is there a minimum cost to renting this tariff
Tariff minimum amount	What is the minimum amount of renting this tariff
Currency	Currency of prices
Tariff cost example small	Cost of hypothetical small vendor
Tariff cost example medium	Cost of hypothetical medium-sized vendor
Tariff cost example large	Cost of hypothetical large vendor
Tariff trial available	Free trial or test version of the repricer available
Tariff repricing per hour	Number of repricing events per hour
Tariff max products	Maximum number of repriced SKU
Tariff analytics yes or no	Repricer includes additional analytics
Tariff analytics notes	Self-description of analytics
Pricing consulting service	Cost of hypothetical small vendor
Tariff specific competitors	Tariff can target specific competitors
Tariff pricing rules	List of pricing rules that the repricer offers. Full list below.
Tariff buy box	Does the tariff target the Amazon Buy Box?
Tariff tracks rivals stock	Does the tariff keep track of rivals' stock and running out of stock?
Notes	Miscellaneous notes and quotes
Trial accessible	Free trial accessible without credit card information or existing online shop?

All data as of collection in October 2021. Pricing rules include optimizing for the Amazon BuyBox, competitors' prices, other suppliers' prices and stocks, combination of rules, demand factors, own stock, self-learning, time of day, price elasticity, decision tree, resetting to a maximum price, seasonality, weather, historical data, or unreported.

Table 6: Fields of the data set

Table 10 contains the full list of marketplaces and price-comparison websites that were mentioned

Table 7: Number of repricing firms by country of origin

Country	Frequency	Country	Frequency
United States	37	Bulgaria	1
United Kingdom	15	Canada	1
France	12	Colombia	1
Germany	12	Czech Republic	1
Netherlands	8	Denmark	1
Spain	7	Finland	1
Poland	5	Luxembourg	1
India	4	New Zealand	1
Israel	4	Portugal	1
Italy	4	Russia	1
Australia	3	Serbia	1
Switzerland	2	Singapore	1
Turkey	2	Sweden	1
Brazil	1	Taiwan	1
		Total	130

Table 8: Number of compatible repricing algorithms for different business software

Software	Count of repricing algorithms	Software	Count of repricing algorithms
Shopify	13	Microsoftdynamics	1
Magento	6	Advarics	1
Woocommerce	5	Prohandel	1
SAP	4	Roqqio	1
Bigcommerce	3	Höltl Retail Solutions	1
Prestashop	3	Intelligix	1
Salesforce	3	LS Retail	1
Shopware	2	Intersys	1
Skucloud	1	Hiltes Software GmbH	1
Lengow	1	3D Cart	1
Shoppingfeed	1	Wideorbit	1
Plentymarkets	1	Hudson MX	1
JTL	1	Marketron	1
Microtech	1	Rars2	1
Vario	1	Sqills	1
MS Dynamics AX	1	Tableau	1
MS Navision	1	NRS	1
Oxid	1	PriceFX	1
Oracle	1		

by different repricers. The most commonly mentioned marketplace is Amazon (57 mentions, 83% of 69), followed by eBay (29, 42%), and Walmart (9, 13%). Some repricers mention price comparison websites, such as Google Shopping (6, 9%). 16 other marketplaces were mentioned five times or less. Some of these less frequently mentioned marketplaces are likely specific to the main region or country where the repricing firm is active, such as Mercado Libre (South America), Fnac Darty (France), Kaufland.de (Germany).

Table 9: Summary statistics of long-term discounts

Min.	1st Quartile	Median	Mean	3rd Quartile	Max.
0%	0%	0%	6%	10%	40%

Table 10: Number of compatible repricing algorithms for different marketplaces

Marketplace	Count of repricing algorithms	Marketplace	Count of repricing algorithms
Amazon	57	Etsy	2
Ebay	29	Bonanza	2
Walmart	9	Wish	2
Google Shopping	6	Mercadolibre	2
Cdiscount	5	Facebook	2
Cdiscount	5	Instagram	2
Fnac	4	Tesco	1
Darty	3	Rakuten	1
Manomano	3	Kaufland.de	1
Rueducommerce	3	Idealo	1

B Figures

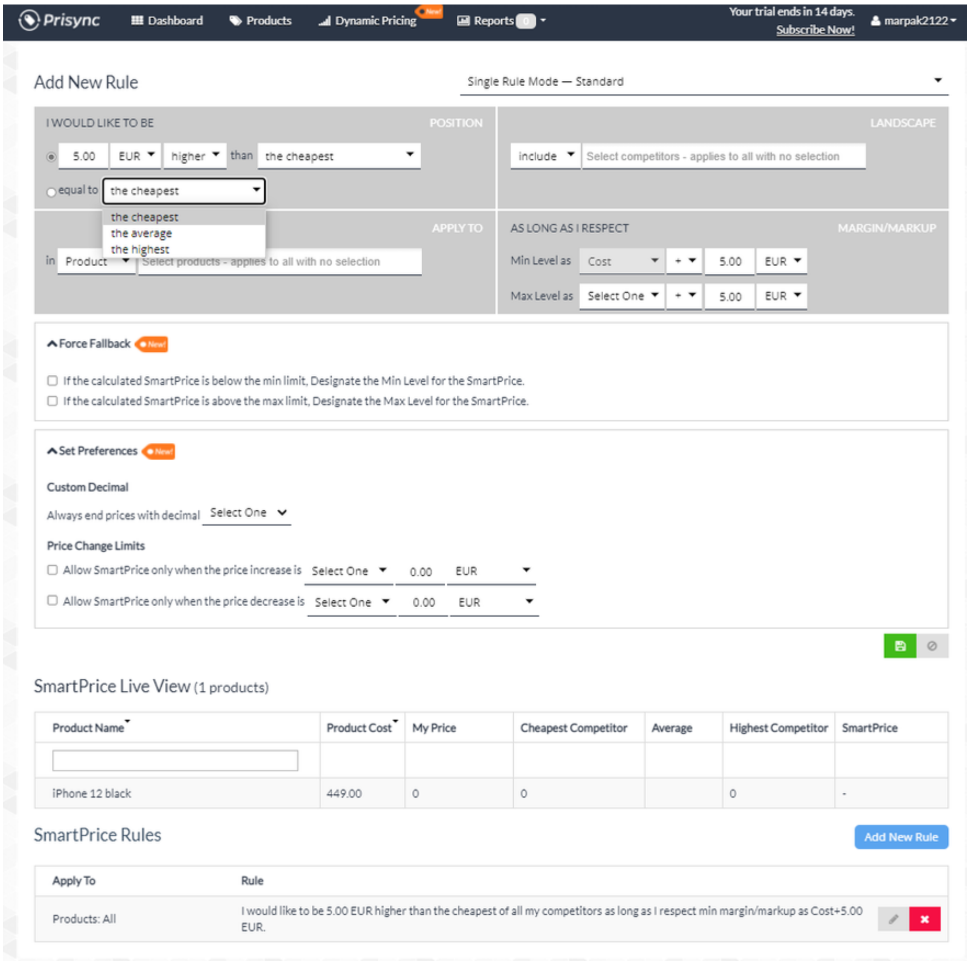

Figure 1: Prisync pricing rules, taken from https://prisync.com/

In Figure 3 we present a boxplot of long-term discounts. We find 38 repricers (21 %) that offer long-term discounts, as opposed to 65 that don't (35%) and 82 (44%) for which no information is

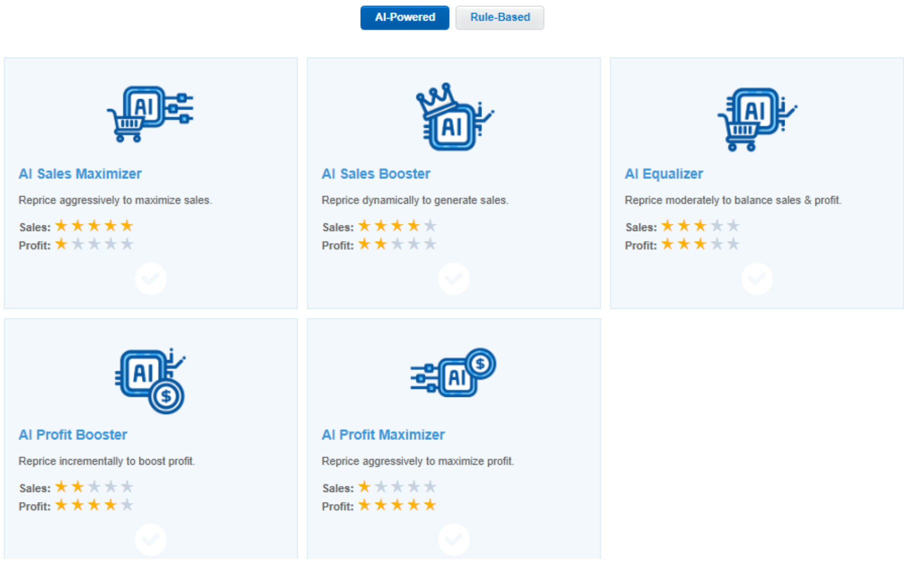

Figure 2: BQool pricing rules, taken from https://support.bqool.com

available. We report the distribution for the 103 entries that are not missing to give readers a clearer idea of the average fees for repricers that sellers would pay in a regular market environment where discounts play some role. The discount is for an annual subscription relative to a one-month contract, with few exceptions. The descriptive statistics are in Table 9. Long-term discounts are offered by a sizeable minority of repricers (and possibly some of those for which information on fees is missing) and lowers the final fee to sellers by typically between 5 and 10% (up to 40% in one case).

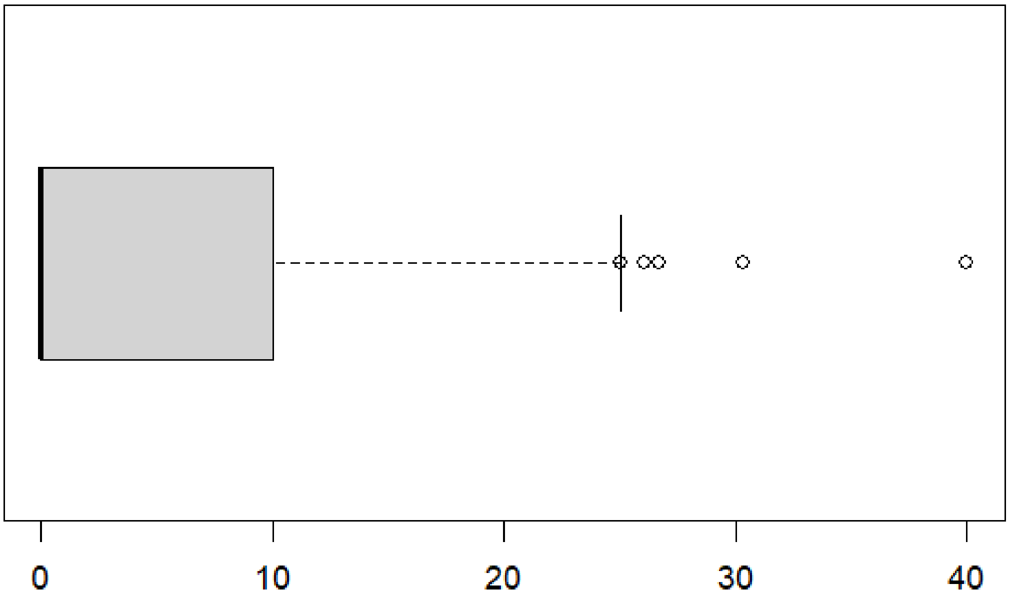

Figure 3: Distribution of long-term discounts in percent

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