Algorithms in the Marketplace: An Empirical Analysis of Automated Pricing in E-Commerce

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Preliminary: Current version here (comments welcome).

Abstract

We analyze algorithmic pricing on the largest online marketplace in the Netherlands and Belgium. Based on two months of pricing data for around 2800 products, we find an *inverted-U* shaped relationship between the price of the Buy Box (the most prominently displayed offer for a product) and algorithmic competition. The presence of algorithmic sellers in monopoly markets goes hand-in-hand with lower prices. We explain this by the inability of traditional product managers to manually adjust prices product-by-product for a large number of items, which automated agents may correct. Consistently with collusion, prices are particularly high in duopolies where two algorithms bid against each other. With a sufficient number of competitors, algorithmic sellers reduce the Buy Box price and compete fiercely. We also identify several algorithmic pricing patterns that are consistent with collusion. Overall, our findings call for careful policy with respect to pricing algorithms.

JEL-Classification: D42, D82, L42

Keywords: Algorithmic pricing, Artificial intelligence, Collusion, Forensic economics

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1 Introduction

The advance of digitization, big data processing and analysis triggered new applications of *algorithmic pricing*, whereby sellers automate price-setting using sophisticated software tools. The increased prominence of algorithmic pricing in consumer-facing markets such as retail gasoline and e-commerce has recently attracted the attention of academics, practitioners and policy advocates. The main concern is that ever more intelligent algorithms may learn to (tacitly) collude, refrain from competing aggressively and keep prices high.

Despite the policy debate around algorithmic pricing, empirical research on the ability of algorithms to collude and sustain high prices is surprisingly scarce. We aim to fill this gap and investigate algorithmic pricing on *Bol.com*, the largest online marketplace in Belgium and the Netherlands. Based on two months of high-frequency pricing data for more than 2,800 popular products, we explore the potential of algorithmic retailers to successfully increase prices. To our knowledge, our article is the first to empirically explore whether the presence of algorithmic pricing coincides with higher prices.

Our analysis of the Dutch market leader e-commerce platform *Bol.com* is likely to be relevant for other marketplaces as well. *Bol.com* is very similar to Amazon in format, functions, products and the availability of third-party re-pricer software. These marketplaces are particularly interesting environments to explore the effects of algorithmic pricing: They are consumer-facing, very supportive for dynamic pricing and are surrounded by a wide and active ecosystem of algorithmic pricing software providers, who often make little effort to hide their intent to raise prices and avoid competition (Section 2.1).

We find that algorithmic pricing is associated with higher average Buy Box prices, in particular when the number of sellers is limited and algorithmic agents price against each other.

We also qualitatively explore our dataset and structure the price data into several re-occurring patterns. Some of these patterns are consistent with algorithmic sellers tacitly colluding. Our graphical analysis aims at providing practical forensic economic tools to competition policy makers interested in screening high-frequency price data for traces of collusion. Our aim is not to *prove* collusion. Instead, we aim to distill price patterns and products that can serve as simple first screens for competition authorities, firms and researchers scanning the horizon for potentially anti-competitive practices. A significant practical advantage of our screen is that it relies purely on publicly accessible data.

Interestingly, we document a large price *reduction* due to algorithmic agents in monopoly products, compared to similar products sold by traditional sellers. This is a novel phenomenon that we explain by the improved ability of pricing algorithms to experiment and adjust prices separately for thousands of products, a task that is prohibitive for humans.

The paper is structured as follows. In Section 2, we present the online shopping platform *Bol.com* and the features of re-pricing software. Section 3 reviews the related literature on algorithmic pricing and collusion in off- and online markets. In Section 4 we describe the dataset and the underlying cloud scraping procedure. Section 5 provides descriptive statistics as well as a graphical analysis of the main algorithmic pricing patterns. In Section 6 we conduct econometric analysis of algorithmic pricing. Section 7 discusses the policy implications of our findings.

2 Background

We start with an introduction of the marketplace platform *Bol.com*, its Buy Box (in Dutch, the *koopblok*), the sellers active on the platform and algorithmic re-pricer services.

2.1 Bol.com and Third-Party Sellers

Bol.com is the largest online store in the Netherlands offering products in categories such as books, music, computers, toys, baby, cosmetics, clothing, and DIY (Bol.com, 2021b).[1] Bol's revenues in the Netherlands exceeded 1.6 billion Euro in 2018, amounting to about five times the revenue Amazon achieved in the country (Statista, 2019). Since 2011, *Bol.com* admits third-party sellers and is itself acting both as seller as well as platform operator. In 2018

[1] *Bol.com* is also popular in the Dutch-speaking part of Belgium. We focus on the *Bol.com* platform as accessed from the Netherlands.

Bol.com hosted more than 20,000 third-party retailers who accounted for about 40% of the company's sales (EcommerceNews, 2018).[2]

The platform *Bol.com* charges third-party sellers a fixed fee per article sold as well as a percentage commission of the sales price. *Bol.com* is surprisingly opaque about the precise amounts, which seem to vary by product type and sellers must upload the article list to find out the exact fees payable per item (Bol.com, 2021c).

2.2 The Buy Box

Similarly to other online market places including Amazon, the product page on *Bol.com* contains a *Buy Box*: the promoted seller chosen automatically by the marketplace operator. The *Buy Box* seller is displayed very prominently filling the bulk of the product page (Figure 2). For a seller on a marketplace platform such as Bol or Amazon, winning the *Buy Box* is an important achievement, as it typically generates around $80-90\%$ of sales (RepricerExpress, 2021).

This is very interesting from a competition perspective. One may think about the Buy Box as a "*winner-takes-it-all*"-feature which assigns all demand to whoever offers the lowest price. As the price is likely the key factor in the assignment algorithm to the Buy Box and revenue streams are largely dependent on owning the Buy Box, competition for the Buy Box mostly reduces to price competition (Musolff, 2021). This sets the stage for further analysis, in which we try to assess whether the presence of reprice engines is associated with higher prices.

While the ultimate algorithm to determine the Buy Box winner is secret, Bol lists some factors it takes into account for its choice (Bol.com, 2021d). These include primarily the product and shipping prices, delivery time, availability of the item in stock and the *seller performance score*. The latter is a mix of seller rating and other key performance indicators, such as on-time delivery, telephone accessibility, completeness of product description, track-and-trace information and seller cancellations (ChannelEngine, 2018).

[2] Own sales constitute the bulk of the remaining 60%.

2.3 Re-Pricer Software

The term *algorithmic pricing* is used interchangeably in different contexts. The literature distinguishes several types of pricing algorithms.[3] The simplest range from pure *pricing rules* that allow retailers to set different prices depending on various conditions. Software solutions are available to monitor these market conditions and turn them into inputs that the pricing algorithm can comprehend.

More complex algorithms may offer a higher level of autonomy to the re-pricer engine in setting prices: *adaptive learning* algorithms calculate the optimal price based on a set of input variables such as costs, inventories or rivals' prices. These algorithms are *adaptive* because they autonomously experiment with prices, learn and adapt to find the optimal values. Algorithms may offer *static* optimization, that does not consider long-term consequences of actions, such as often associated with retaliatory, collusive outcomes. *Dynamic optimization algorithms* provide the largest degree of autonomy, and take into account longer-term consequences of actions, such as retaliating and maintaining collusive outcomes.

On *Bol.com*, third-party sellers can programmatically manage their inventory and adjust the parameters of their offer (sales price, shipping fee, delivery time, availability) via Bol's APIs. Sellers on *Bol* can manually manage their prices, but it seems fair to say that *Bol.com* is designed to facilitate dynamic pricing. As manual pricing becomes complex with a larger inventory, sellers are often aided by external repricing software that combines inventory management with algorithmic pricing features.

Re-pricer services such as ChannelEngine, EffectConnect, Channable, Vleks, Price-search.io and RepricerXL integrate with the *Bol.com* retailer API and automate the pricing process. They are able to update the price of a large number of items in near real-time and allow the seller to provide more or less guidance on setting these prices.[4] For example, repricer.nl explains that the seller can set minimum and target prices, choose which competitors to follow or ignore, but she can also leave the re-pricer freedom to adjust the prices

[3] Klein (2021b) provides a detailed discussion of this topic.

[4] It seems that most re-pricer services - on Bol and Amazon likewise - update the prices every 20 minutes. See for example Chen et al. (2016) for Amazon and EffectConnect (2021) for Bol.

(RepricerExpress, 2021).

ChannelEngine (2021) offers a detailed look under the hood of a re-pricer software.[5] It permits pricing rules based on among many others minimum, maximum, cost-plus and rival-plus type pricing. The seller can define scenarios and various triggers of new price rules. It also allows choosing the reference competitors, such as merchants using fulfilment services, Buy Box winners, sellers with a certain rating or manually picked rivals.

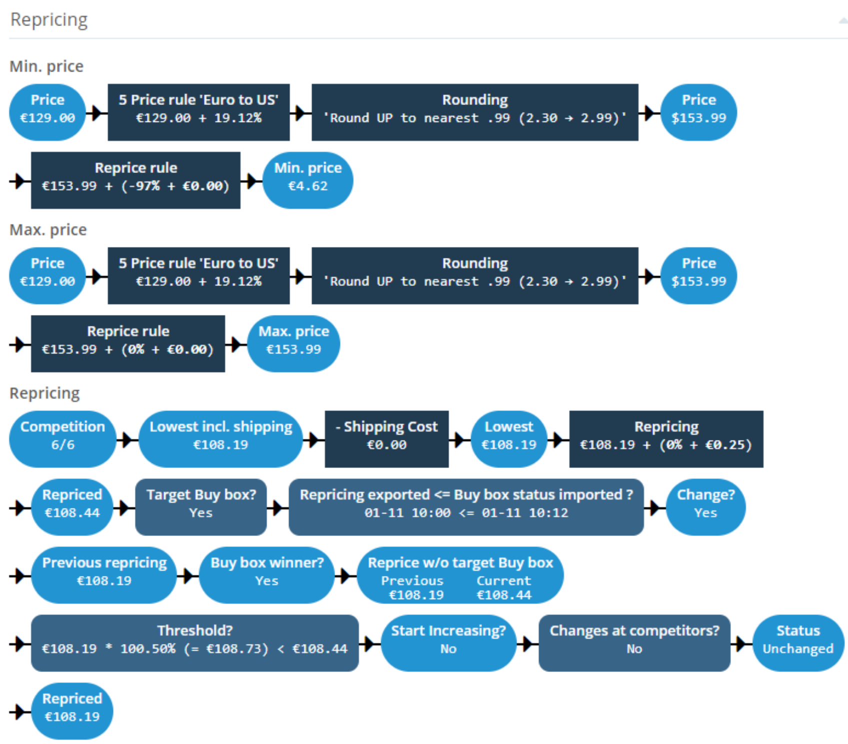


Figure 1: ChannelEngine repricing rule illustration. Reproduced from `https://help.channelengine.com/article/47-repricer`, retrieved on the 17th of September 2021.

In this paper we find that algorithmic pricing in a competitive environment is associated with higher prices vis-à-vis consumers. This is in line with the statements made by re-pricer software vendors, who explicitly advertise their ability to raise prices and avoid competition, even using economic textbook language of collusion.

For example, SellerSnap - an Amazon re-pricer - warns its clients: *"Don't Be a Prisoner in Amazon Price Wars"*, explaining that *"your goal should be to get the Buy Box share you are entitled to while keeping the price high instead of racing to the bottom"* (IndustryNews

[5]ChannelEngine integrates with, among other e-commerce platforms, *Bol.com*.

(2018)). EffectConnect, a leading re-pricer for *Bol.com* recognizes its goal to raise prices: *"when your competitor increases the price, your price will go up along with that of your competitor"* (EffectConnect (2021)). Other re-price engines provide features to engage in price re-setting once a chosen minimum price has been reached in order to break a downward price correction spell (Musolff (2021)). Channable, another leading *Bol.com* re-pricer offers an entire menu block for *"Do not compete with"*, where the seller can configure the re-pricer to avoid price competition with rivals selected based on various criteria (Channable (2019)).

Despite the high level of automation these re-pricer algorithms allow, there are humans behind them. Autoridade da Concorrência (2019) reports exchanges in marketplace forums, where sellers using re-pricer software discuss competition, and make statements such as: " *The race to the bottom is a race that EVERYONE loses. STOP REPRICING YOUR STUFF INTO OBLIVION*," "*MATCH the lowest person's price rather than attempting to undercut them. Undercutting is a win for no one other than the buyer*," *"I see u have a repricer on that undercuts the lowest FBA offer.[...] The result is loss of profitability for everyone. Now your price is your choice and this message is in no way an attempt to fix pricing. You set your price to whatever you like but I just wanted to send you a message on what I observed on the listings you are on and share my thoughts with you."*[6]

Finally, the marketplace operator *Bol.com* openly declares its doubts about the lawfulness of some of its own policies. In particular, it notes about its price-transparency policy that *"providing this information might lead to price increases, possibly interfering with Dutch and Belgian competition law"* (Bol.com (2021a)): it is to be expected that such information is most valuable to algorithmic sellers, who frequently revise prices.[7] Overall, we believe Bol is an exciting environment to study pricing algorithms, with re-pricer software vendors openly advertising their ability to raise prices and the platform operator venturing into what it *itself* considers as the grey zone of the law.

[6]To be clear: we do not suggest or claim any of these slogans prove collusion. But they certainly do a good job catching the attention of a very diverse audience interested in algorithmic pricing, including sellers, researchers and policy makers.

[7]We suspect Bol may be concerned that its announced maximum prices may serve as focal points for collusion (Knittel and Stango (2003)).

3 Related Literature

Our paper is closely related to the literature on the intersection between algorithmic pricing and collusion. Legal scholars and policy makers recently expressed significant concerns about the potential of algorithmic pricing to facilitate collusive behavior. Capobianco and Gonzaga (2020), Ezrachi and Stucke (2016a,b, 2017), Mehra (2015) and Harrington (2018) discuss the competition policy implications of the question.[8]

In general, economic theory predicts three main avenues by which algorithms may facilitate collusion. First, by increased transparency: automated, large-scale monitoring of rivals' actions may enable the quick detection of deviations from a collusive agreement. Transparency may therefore help sustain (tacit) collusion (Albæk et al. (1997), Albano et al. (2006)).

Second, dynamic pricing increases the frequency of interaction: quick reaction to a deviation from collusive prices reduces the deviating firm's profit and therefore stabilizes collusion (Bigoni et al. (2019), Kühn and Tadelis (2017), Brown and MacKay (2020)).

Third, by rival firms delegating business decisions to common agencies, such as advertising bureaus or pricing software vendors, who act as the *hub* to facilitate coordination among the *spokes* in a *hub-and-spoke* scheme (Bernheim and Whinston (1985), Decarolis and Rovigatti (2019)).

The theoretical literature linking pricing algorithms to collusion remains ambiguous about the ability of programmatic agents to collude. Calvano et al. (2020), Klein (2021a) and Johnson et al. (2020) show based on simulations in a repeated game framework that under certain conditions Q-Learning algorithms are able to converge to the collusive outcome, sustain supra-competitive prices and punish deviations. Other authors emphasize that the improved ability of algorithms to better predict demand and react to stochastic shocks destabilizes collusion as deviation becomes more profitable (Miklós-Thal and Tucker (2019),

[8] Despite the attention from competition authorities (Konkurransetilsynet.no (2021), Autoridade da Concorrência (2019), GOV.UK (2021)), to our knowledge so far no agency led a case involving autonomous algorithmic collusion. See Ritter (2017) for a list of antitrust cases where algorithms played a significant role in some form.

O'Connor and Wilson (2020)).

A handful of papers investigate how human and algorithmic agents interact in markets. Leisten (2021) develops a model of competition in which managers may override an automated pricing rule after the rule is chosen. Prices remain higher than a competitive benchmark, but collusion breaks down when managers must respond to a common demand or cost shock. Under such conditions, both the prediction-enhancing as well as the commitment-enhancing features of algorithms may serve to sustain supra-competitive prices. In the same strand, Normann et al. (2021) compare tacit collusion incentives in a laboratory setting when only humans interact to the case of one firm in the market delegating its decisions to an algorithm. The authors find that in three-firm markets the presence of one algorithmic player makes collusion more likely, but this effect wears off with four firms competing. Somewhat surprisingly, the algorithmic player earns lower profits than the rivals. Werner (2021) provides experimental evidence in a setting of human sellers relying on algorithms. Oligopoly markets seem to be especially prone to collusion for three-firm markets given most firms rely on algorithms.

While most commentators appear to be wary of algorithms eventually facilitating collusion, there are also critical views in policy circles, arguing that the idea of algorithms forming cartels may be speculative: the argument is that mindless algorithms can never achieve a "*meeting of minds*," which is the legal standard for collusion (Colombo (2018)). In a similar vein, some economists emphasize the inability of algorithms to sustain collusion without explicit communication. Referring mainly to experimental economics literature, Kühn and Tadelis (2017) and Schwalbe (2018) argue that, much like humans, self-learning algorithms would do poorly in coordinating actions to achieve a desirable collusive outcome, at least in absence of explicit communication.

Empirical literature analyzing algorithmic pricing in real markets is scarce and we aim to contribute in this strand. In a recent paper, Assad et al. (2020) study Germany's retail gasoline market where algorithmic-pricing software became widely available around mid-2017. The authors find that the adoption of algorithmic pricing software increases margins significantly, especially in duopoly markets where both rivals move to algorithmic pricing.

The magnitude of price increase is consistent with other recent papers studying collusion in retail gasoline markets (Clark and Houde, 2013, 2014; Byrne and De Roos, 2019).

Our article is closely related to research on algorithmic pricing and competitive strategies in electronic marketplaces. Chen et al. (2016) studies the behavior of algorithmic sellers on Amazon. The authors develop a methodology for identifying algorithmic sellers and find that compared to non-algorithmic competitors, these win the Buy Box more often, are active in the marketplace for significantly longer, (surprisingly) tend to specialize on *fewer* products and acquire a larger number of positive feedback, suggesting that they also sell more. We draw inspiration from Chen et al. (2016) to identify algorithmic sellers and extend this research by focusing on collusion and sustaining higher prices.

Zhu and Liu (2018) analyze the patterns of Amazon's entries into its third-party sellers' product spaces. The authors find that Amazon is more likely to enter as seller in more popular products with higher seller ratings. Jiang et al. (2011) provide descriptive evidence for Amazon specializing on high-demand products and leaving the sale of long-tail of products for third-parties.

Musolff (2021) provides causal evidence on the effect of algorithmic sellers on price competition exploiting data directly from re-pricers and Amazon. He finds that the presence of algorithmic sellers initially decreases prices but introduces re-setting strategies similar to Maskin-Tirole's Edgeworth cycles which aim at *avoiding* fierce price competition à la Bertrand.

Brown and MacKay (2020) show how asymmetries in pricing technology may translate into asymmetries in prices. This contrasts with the common assumption in this literature that firms set prices based on symmetric price setting technology. Indeed, firms with more frequent price changes are associated with lower prices. If price setting frequency can be chosen, between-seller asymmetry in price setting frequency is the supra-competitive equilibrium associated with overall higher profits. Most notably, even price strategies that *do not* appear collusive at face-value (unlike reward-punishment schemes) but are merely commitments on linear functions of rivals' prices may lead to such supra-competitive outcomes.

To our knowledge our paper is the first to empirically investigate the propensity of algorithms to raise prices on a popular *European* B2C e-commerce platform. Earlier research on pricing algorithms focused predominantly on petrol markets as well as on Amazon. We are first to consider how dynamic pricing may facilitate collusion and allow sustaining elevated prices on a local giant, European online marketplace.

4 Data

The data used in this article was obtained by scraping the *Bol.com* website in two rounds. The first crawl was conducted between the 26th of December 2018 and the 25th of January 2019. The second crawl took place between the 18th of February 2020 and the 20th of April 2020 and covered the same list of products as the first crawl.[9]

In late December 2018, we scraped the top 500 pages of bestselling products on *Bol.com*. Each page contains 24 products, yielding a total list of 12,000 products. From this list we eliminated products that were not available for sale (*out of stock*) between the 28th and 30th of December 2018. The final sample covers 2,846 products that were available for sale in a stable manner in the course of three consecutive days. For each of these products we scraped the *product* page (Figure 2) and the *compare all sellers* page (Figure 3).

The *product* page prominently shows the Buy Box price and featured seller next to an image of the product. In this example, the Buy Box price is 22.99 and Bol.com is the featured seller ("*verkoop door bol.com*"). It is further indicated that the same product is also offered by six other sellers.

The *compare all sellers* page can be reached by clicking on a link from the *product page*. It is a paginated list of all sellers offering the product at a given time. We focus on the first page of the list with the top-ten sellers of new items and exclude second hand offers. We extract the seller rating (0-10), all prices, shipping costs and expected delivery times.

Our dataset contains the following variables:

[9]The second crawl skipped the first week of April 2020 due to a subscription issue with our cloud-based scraping service provider.

Figure 2: The *product* page.

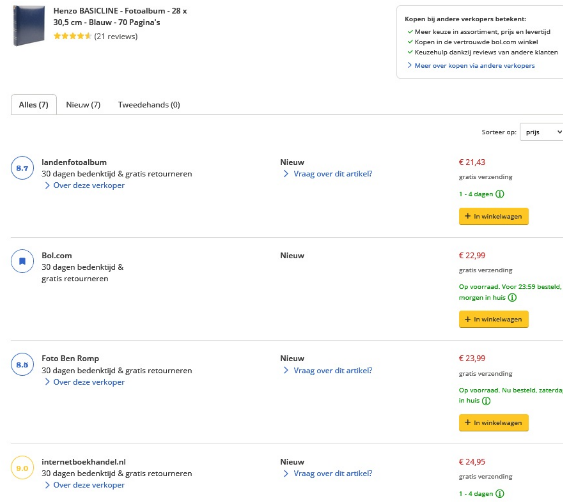


Figure 3: The *compare all sellers* page.

1. **Timestamp**: The timestamp of the crawl (in seconds).
2. **Seller**: The ID and name of the seller of the product.
3. **Seller rating**: The rating of the seller (0-10).
4. **Seller delivery time**: The delivery time of the seller for the product (in days).
5. **Seller shipping fee**: Shipping fee of the seller for the product (in Euro).
6. **Buy Box seller**: The ID and name of the Buy Box seller.
7. **Buy Box price**: The price of the Buy Box product (in Euro).

We used a cloud-based web-scraping service to conduct the crawls, and increased the computing resources during the second crawl. The urls scraped are identical between the two crawls with the exemption of products that disappeared from the platform by the second crawl.

Seller rating is the only variable where some data interpolation was necessary. The reason is that sellers new to the market at the time of our crawl may not have yet had the time to obtain ratings. In particular, for unrated sellers we use the average seller rating in the detailed (3rd level) product category.[10] We decided for this approach by asking ourselves

[10] In case there are insufficient ratings in a sub-category, we take the average rating of the higher level category.

what a buyer would most likely assume about the *quality* of a seller with no rating. We believe assuming an average quality is realistic, and this quality may differ by product category such as Health or Toys.[11]

In our remaining analysis we will assess competitive conditions by product, and ignore potential substitution from other products. This is a practical, empirical necessity that we cannot circumvent and that is inherent in the kind of data we have. Our products are therefore not necessarily *relevant markets* in the antitrust sense.

5 Descriptive Analysis

5.1 General Statistics

Table 1 presents summary statistics for the underlying dataset with respect to both waves of the data. The second crawl comprises substantially more observations than the first crawl due to the higher crawl frequency.

We present the main results using data from Crawl 1 and provide most corresponding results for Crawl 2 as robustness check in the Appendix. Crawl 1 is particularly interesting for a number of reasons. First, it has more products than Crawl 2, as shown in Table 1. The number of products is reduced by around 900 in the second crawl. This is because we kept the same list of URLs for both crawls, which consisted of top selling products in early 2019. By the time of Crawl 2, in spring 2020, a large number of these products, such as music, computer equipment and fashion items, became outdated and disappeared from the marketplace platform.

Second, for the remaining products the number of sellers increased rapidly, with the consequence that the number of monopoly products reduced significantly in Crawl 2 (Figure 4). As in Assad et al. (2020), monopoly products constitute an interesting benchmark in our analysis, and are better captured in Crawl 1. Finally, part of Crawl 2 coincides with

[11] An alternative would be assuming a rating of zero. This however appears unrealistically harsh towards new sellers, since seller ratings are typically rather close to the upper end of the range. It appears unlikely that consumers would regard new, not-yet-rated sellers so negatively.

the first lockdowns during the COVID-19 pandemic. During these days many sellers had to swiftly expand their online presence due to store closures. This may imply potential confounding factors in Crawl 2 that may deserve a dedicated analysis. Importantly, our main qualitative results do not differ significantly between the two crawls. This lends credence to the robustness of our results over time.

Table 1 provides the main summary statistics for both crawls. It shows that the average Buy Box price is lower than the average price per product. This is not surprising, since Bol takes into account prices when awarding the Buy Box to a particular seller (see Section 2.2). Both, the seller prices as well as the Buy Box price are highly left-skewed. Prices and the number of products reduced on average between the two crawls. This is consistent with the view of a subset of products churning over time as they become outdated.

Figure 4 shows the distribution of products by the number of sellers. Products offered by ten or more sellers are grouped in the last bin of *ten sellers*. Two things are noteworthy in Figure 4. First, the typical product tends to see three to four sellers. Second, as explained above, the number of monopoly products reduced significantly in Crawl 2. This is because the products that were best-selling in Crawl 1 likely became less novel in more than a year of time by Crawl 2, as more sellers had time to stock up.

Figure 5 shows the average Buy Box price over product categories. The Buy Box price tends to be highest in electronic products, men's fashion and bike accessories. Health care, books and music are the lowest-price categories. Average Buy Box prices are very close in both crawls, but there was a large reductions in Crawl 2 in the top categories. This is consistent with the view that many products in computer, men's fashion and bike/accessories became outdated till Crawl 2: these are the most innovative product categories where we would expect some churn to take place.

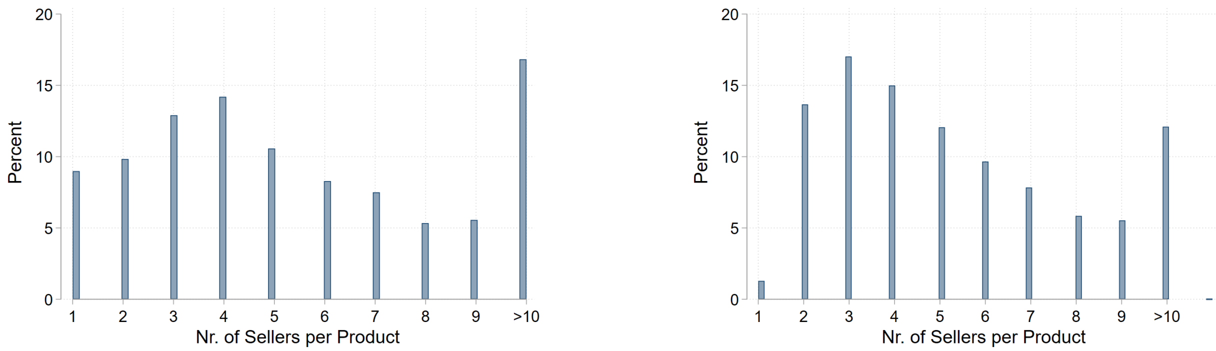


Figure 4: Number of sellers per product. Left: Crawl 1, Right: Crawl 2.

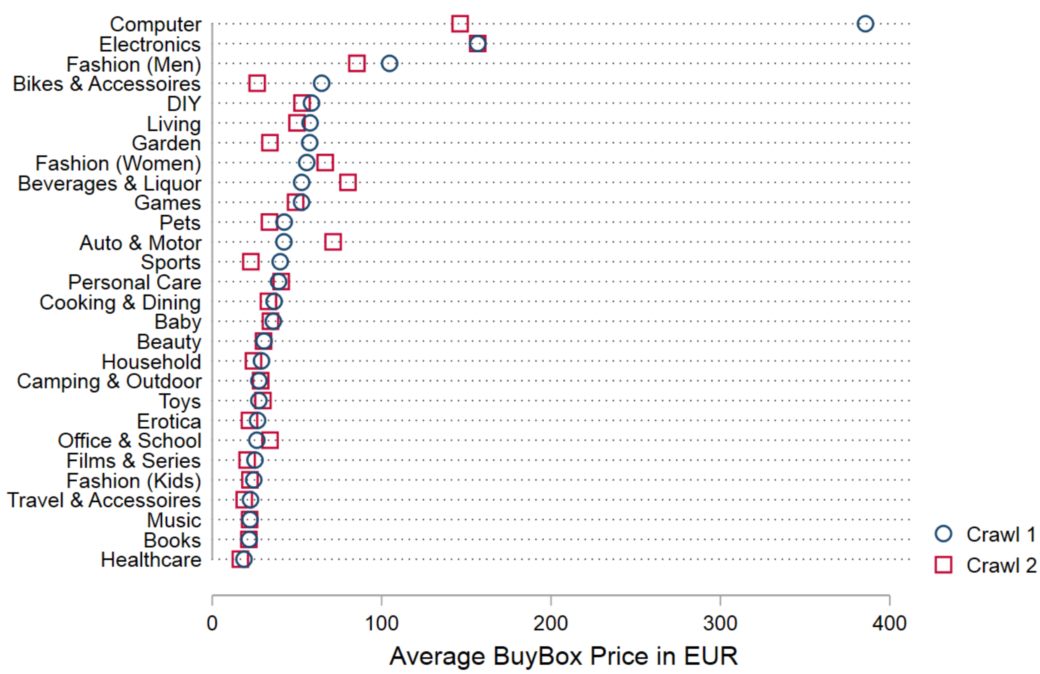


Figure 5: Average Buy Box price by category

	Crawl 1 Mean (sd)	Crawl 2 Mean (sd)
BuyBox Price in EUR	45.04 (87.29)	39.34 (88.55)
Price in EUR	50.03 (87.40)	43.04 (89.59)
Seller Rating (1-10)	8.78 (.44)	8.75 (.58)
Delivery Time in Days	2.99 (2.92)	3.77 (2.47)
Nr. of Sellers per Product	6.05 (2.74)	5.51 (2.65)
Shipping Fees in EUR	.03 (.27)	.03 (.31)
Crawl Frequency in Min.	122.85 (453.82)	32.89 (439.67)
N	2437557	17066561
Products	2846	1949
Sellers	1871	2190
Period	Dec 18 - Jan 19	Feb - Mar 20

Table 1: Summary Statistics

5.2 Identifying Algorithmic Sellers

We do not directly observe which sellers rely on automatic pricing tools.[12] We therefore apply *heuristics* that allows us to identify algorithmic sellers with a high probability based on their observed behavior. To do so, we draw inspiration from Chen et al. (2016) to define sellers as algorithmic. Our thinking was guided by the following observations for choosing criteria to label sellers as algorithmic:

- *Algorithmic sellers change their prices often*: we can define a seller as algorithmic if it performed a certain number of price changes within a given time period (e.g. a crawl,

[12]This is a practical problem a competition authority would typically face in the horizon-scanning phase for potentially anti-competitive conduct. In that stage, public data is particularly valuable as sending information requests and organizing unannounced inspections are often premature.

a week or a month).

- *Algorithmic sellers' prices correlate with other benchmarks* (e.g. lowest price, second lowest price, *Bol.com*'s price, any competitor's price): we can define a seller as algorithmic if its prices show sufficiently strong correlation with one or more of such benchmarks.

We conducted extensive analysis with different individual criteria and combinations of criteria to identify algorithmic sellers. We concluded that the *number of total price changes* over a crawl is the most reliable approach to select algorithmic sellers, and is superior to other criteria for the following reasons:

A high number of price changes by a seller for a product is a reasonable indicator of the seller using pricing algorithms. Since our data very likely covers only a small sample of seller's product range, a high number of price changes for a product likely implies orders of magnitude more price changes in the seller's full product portfolio, for which automated pricing tools are very likely needed. For example, for some products we observe sellers with hundreds of price changes. We are confident that this seller uses an automated pricing engine, since, as we discuss below in more detail, she could not manually set such prices on possibly hundreds of her products outside our crawl.

Looking at the time elapsed between price changes could in theory be an indicator used to identify algorithmic sellers, but in practice this measure is also inevitably affected by the crawl frequency: the latter is by nature somewhat uneven over the period of data collection, due to latency and the varying availability of cloud computing resources by time.

Correlations with other price series is another potential marker, and it was also the chosen approach in Chen et al. (2016). For our purposes, this heuristic has the drawback that we may fail to spot algorithmic sellers who do not adopt a price-correlation strategy. The potential error by such *false negatives* is rather large in our view: For example, as we will explain in SubSection 5.3, some sellers seem to randomly experiment with prices, that do not show any obvious correlation with other series. These sellers are clearly algorithmic, but the price correlation criterion would not label them as such. A further drawback is that for one-seller products this measure cannot be defined. Monopoly markets constitute an interesting benchmark and deserve attention on their own, and we report novel findings for one-seller products.[13]

The single criterion with the total number of price changes is our most preferred screen to identify algorithmic sellers, for multiple reasons. First, this criterion strikes a reasonable balance between type-1 and 2 errors: Visually inspecting the prices of those product-seller pairs that are deemed algorithmic by this criterion confirms that the classification is correct, hence there is little risk of flagging sellers as algorithmic that should not be regarded as such.

Second, the number-of-price-changes criterion is the most general with respect to the pricing strategies algorithmic sellers may employ, since it does not require a particular correlation with other prices. It is also available for monopoly products (unlike price-correlations), a benchmark we wish to exploit in our analysis.

We explain below the detailed implications of various definitions of algorithmic sellers and provide robustness checks using criteria that take the number of changes as baseline and combine these with various price correlations in Section 6.2.

Total Number of Price Changes

We first filter algorithmic seller accounts by looking at the distribution of the total number of price changes across the crawl period, separately in the two crawls for every product-seller pair. The left panel in Figure 6 presents the CDF over the total number of price changes. It indicates that most product-seller pairs experience few price changes, if at all. For a small share of product-seller pairs we observe hundreds of price changes in the long tail of the distribution. Frequent price changes are very likely the result of algorithmic price engines at work. As the characteristics of a certain product may drive its frequency of price changes, we further normalize the distribution of price changes per product and consider algorithmic pricing if it exceeds the mean by 2 (3) standard deviations in the

[13] We do observe sellers that operate alone and clearly set prices automatically.

overall normalized distribution shown in the right panel of Figure 6.[14].

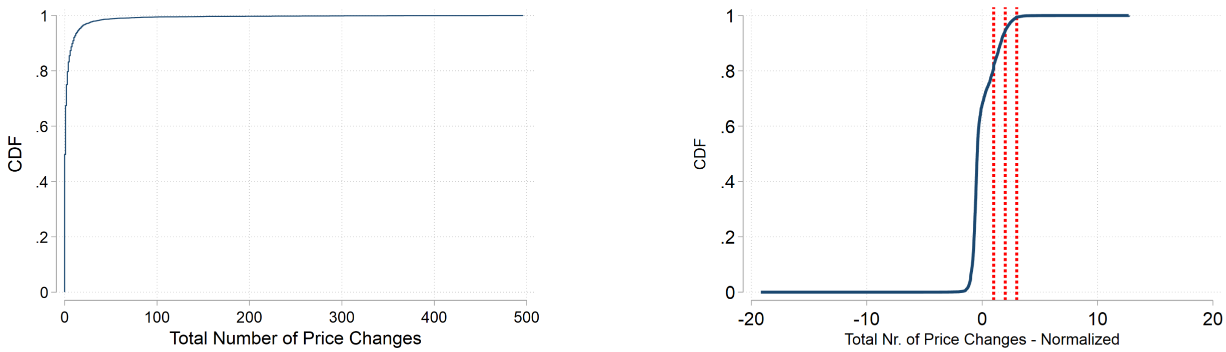


Figure 6: CDF of the number of total price changes (left) and normalized on product-level (right, 1-3 standard deviations indicated in red).

In our main analysis we also treat a seller with a product where it displays an algorithmic pricing as algorithmic on all of her products[15] In Section 6.2 we relax the *"once algo always algo"* assumption and only consider sellers as algorithmic on products where we observe such patterns.

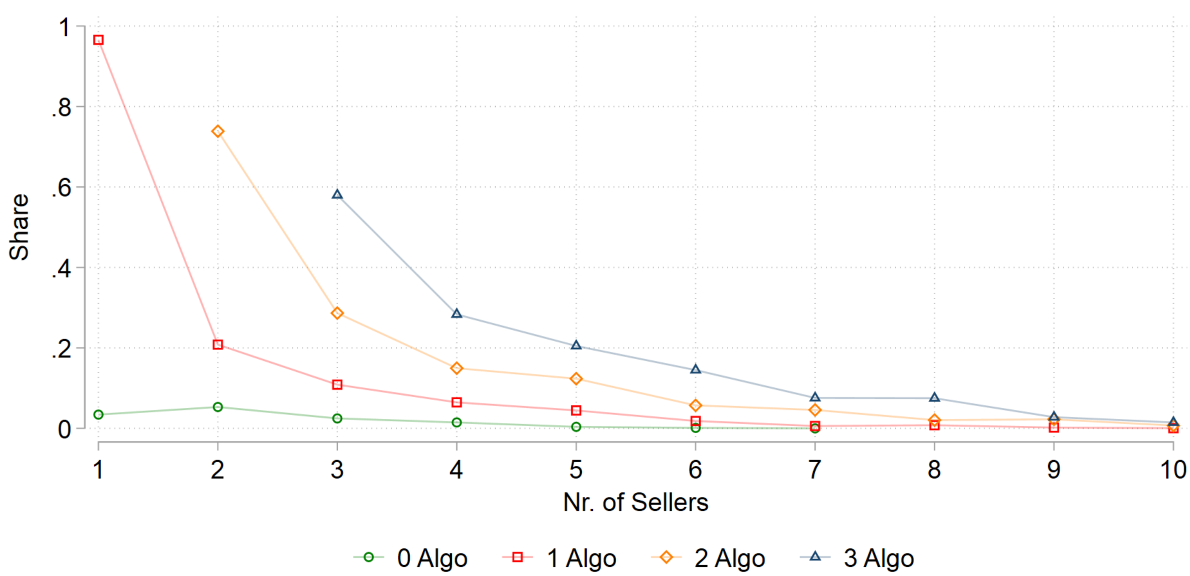


Figure 7: Share of algorithmic sellers on all sellers

Figure 7 shows the distribution of algorithmic and non-algorithmic sellers over the num-

[14]The number of affected sellers by applied criterion can be found in Table 6 in Section 6.2

[15]If a seller is able to perform algorithmic pricing on one product, it likely has access to a re-pricer software that is capable of automating prices on a large number of products.

ber of sellers.[16] We observe a downward sloping curve with the bulk of algorithmic sellers on products with few sellers. For instance, for duopolies, in about 20% of the observations one seller is algorithmic. In about 70% of the observations both sellers are algorithmic.

Price correlations

Sellers using automated re-pricers may set prices relative to others on the platform. As explained in Section 2.3, re-pricer tools offer the functionality to peg prices to rivals, the Buy Box price and other references. Following Chen et al. (2016) we use the price of any competitor $k \neq j$ on the same product i. We calculate Spearman's rank correlation coefficients for all sellers $j \neq k$ for product i, ρ_{jik}.

For each seller-product pair we use the maximum entry jk of the correlation matrix as our measure of algorithmic pricing. We refine our criterion on the normalized total number of price changes with a cut-off of .7 in terms of the price correlation with a competitor on the same product.[17]

In the remainder of this article, we present the main results obtained by flagging sellers as algorithmic using the number of total price changes heuristic.[18] In Section 6.2 we provide robustness checks combining with other heuristics to identify algorithmic sellers.

	Algo=0		Algo=1		Difference
	mean	sd	mean	sd	p
BuyBox Price	0.03	4.86	-0.01	8.39	(0.00)***
Price	0.23	7.49	-0.07	7.77	(0.00)***
BuyBox share	0.12	0.32	0.34	0.47	(0.00)***
Rating	8.74	0.62	8.79	0.34	(0.00)***
Nr. of price changes per product-seller	1.75	8.71	5.07	22.71	(0.00)***
Nr. of Products per Seller	11.17	14.63	509.91	752.64	(0.00)***
Price change in % (stdd.)	-0.03	0.81	0.01	1.25	(0.01)**

(Buy Box) Price and Price changes are residualized by Product Fixed Effects.

Table 2: Buy Box Price by Subsamples (Crawl 1)

[16] For this figure we rely on the number of price changes as underlying criterion on algorithmic pricing.
[17] In Section 6.2 we perform robustness checks varying this cut-off.
[18] Precisely, two standard deviations above the normalized distribution of price changes - assuming that algorithmic selling occurs on all products of a seller.

Table 2 provides summary statistics on the relevant indicators for non-algorithmic and algorithmic sellers. In order to make a comparison more informative, prices are residualized against product fixed effects. Algorithmic sellers set slightly lower prices and Buy Box prices. Furthermore, algorithmic sellers *win* the Buy Box more often than traditional sellers. Lastly, we see that algorithmic sellers manage substantially more products than non-algorithmic sellers.

5.3 Algorithmic Pricing Patterns

Which price patterns emerge in markets with algorithmic sellers? The question is relevant for researchers and policy makers alike. Understanding the resulting pricing patterns helps researchers link the observed data to theoretical models of dynamic pricing. Practitioners, such as competition authorities scanning the horizon for anti-competitive behavior need to be able to identify pricing patterns that may indicate collusion, and do so in a data-sparse manner. Our graphical analysis aims at providing practical forensic economic tools that allow screening high-frequency price data for traces of collusion (Connor (2007), Zitzewitz (2012)).

To investigate the issue, we select those products where we previously identified algorithmic sellers to be present and plot the prices of all sellers as well as the Buy Box. First of all, and in line with the findings by Brown and MacKay (2020), we note large heterogeneity in price setting behavior between sellers in terms of observed patterns and price setting frequency.

We categorize five prominent and recurrent pricing patterns that are clearly characteristic to algorithmic sellers. We do not apply quantitative criteria to distinguish these patterns and instead rely on our own intuition to classify them. The resulting price pattern categories may therefore even overlap in some cases. However, most of the time they are rather clearly distinguishable to the human observer. While our categories are not exhaustive, we are convinced that they cover the most persistent pricing behavior human eye can detect in our data. We discuss the most interesting price patterns in more detail below.[19]

[19]The figures here were produced based on Crawl 1. We observe very similar pricing patterns in Crawl 2.

Algo Pattern	**Frequency** (in %)
Jitter	52
Alternate	20
Feathers and Rockets	11
Random Jumps	11
Balloons and Rocks	6

Table 3: Frequency of algorithmic price patterns in sub-sample where at least one seller has more than 20 price changes

1. **Price jitter up** and **down**: There is a rapid, transitory increase (*jitter up*) or decrease (*jitter down*) in the price of the seller. The jitter is usually in place only for a very short period of time (Figure 8a).

2. **Rockets and feathers**: The price shoots up rapidly, and then gradually and slowly decreases, often reaching the starting point (Figure 8b).

3. **Balloons and rocks**: The price increases slowly and gradually up to a point, where it collapses and falls rapidly, often reaching the starting point (Figure 9a).

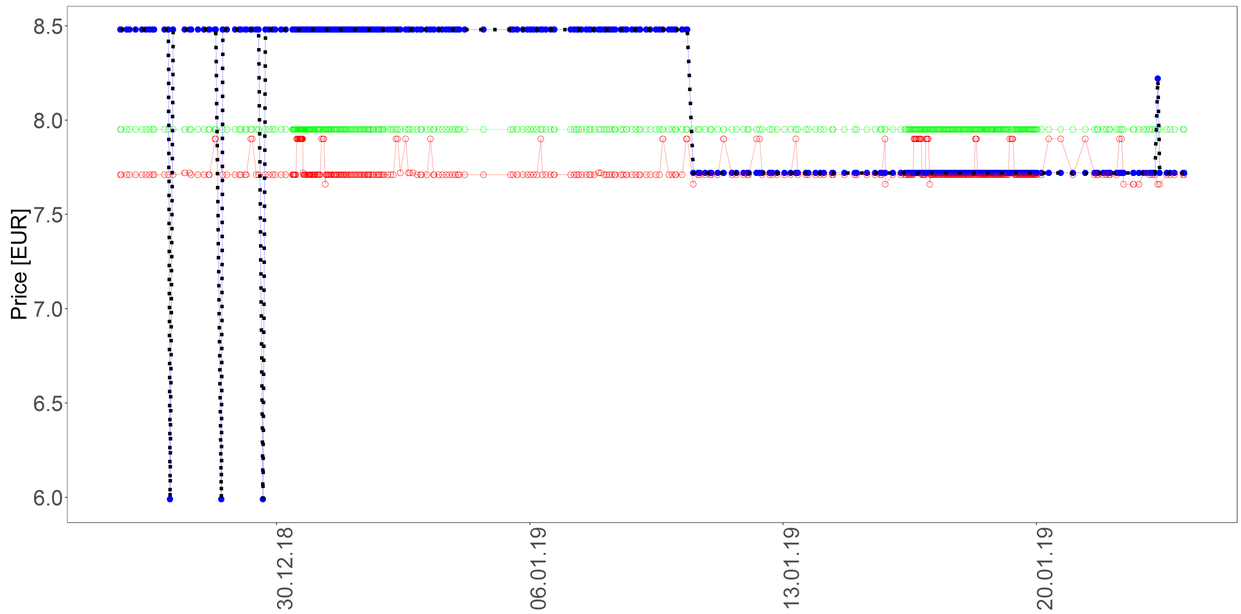
4. **Alternating price**: The price jumps up or down for a longer but transitory period between fixed bounds, after which it returns close to the earlier level (Figure 9b).

5. **Random jumps**: The price changes frequently in a seemingly random manner (Figure 10).

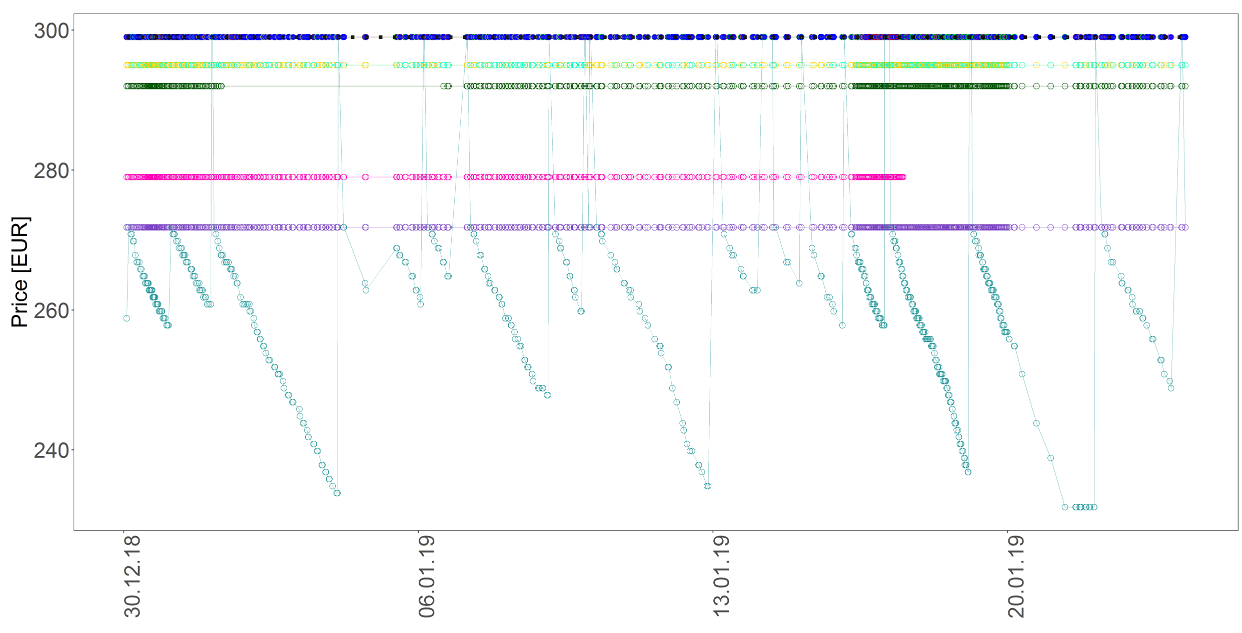
The patterns *jitter up* and *down* are rather popular. We observe either of these in about half of the 300 products selected for inspection, with the jitter pointing up and down in about equal number of cases (Table 3). While upward jitters are produced by a large number of sellers, interestingly, jitters pointing down are very typical to Bol. We see a downward jitter in 75 seller-product pairs, out of which 56 times the seller is Bol.

Price jitters are also documented by Chen et al. (2016) on Amazon, who conclude *"the very rapid price 'jitters' are likely caused by transient inconsistencies in Amazon's infrastructure, rather than actual price changes by sellers."*

We find it unconvincing that on *bol.com* these jitters would be caused by a malfunction, for many reasons. First, it would be unlikely that the same glitch slipped in both on Amazon

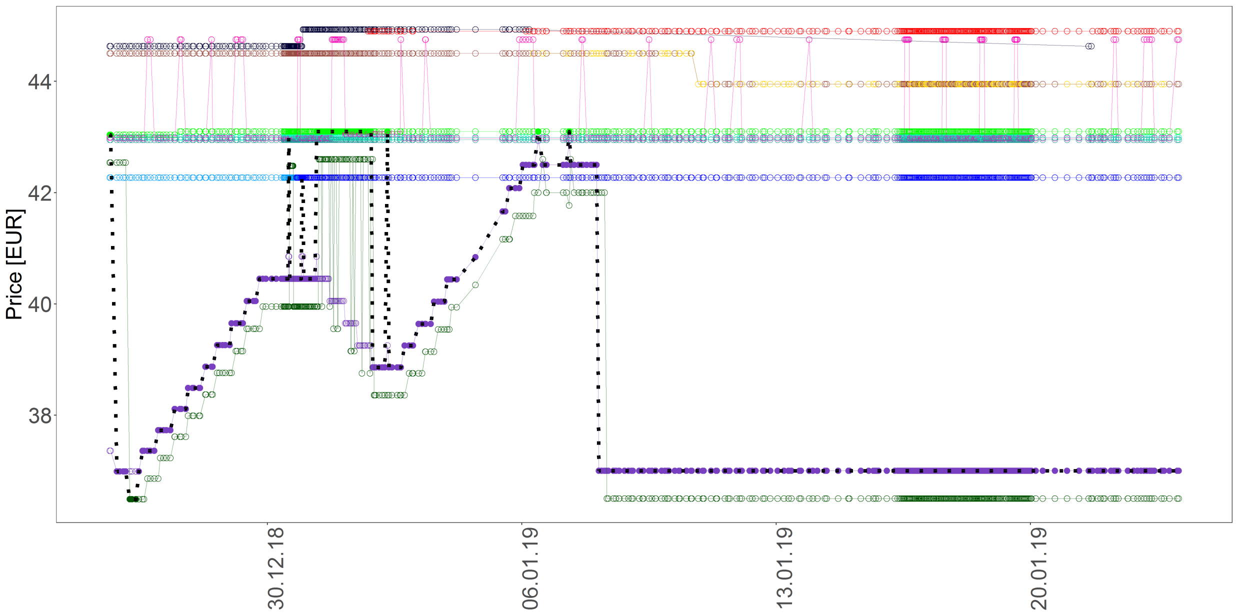


(a) Jitter up and down

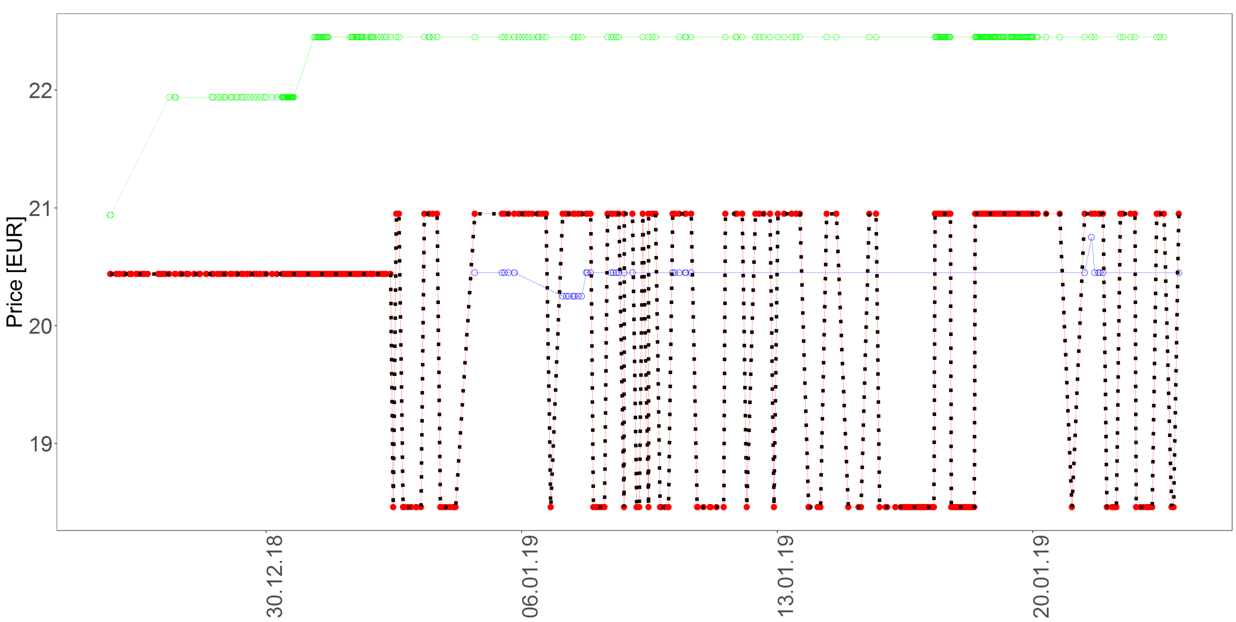


(b) Rockets and feathers

Figure 8: Sample price patterns



(a) Balloons and rocks



(b) Alternating Prices

Figure 9: Sample price patterns - continued

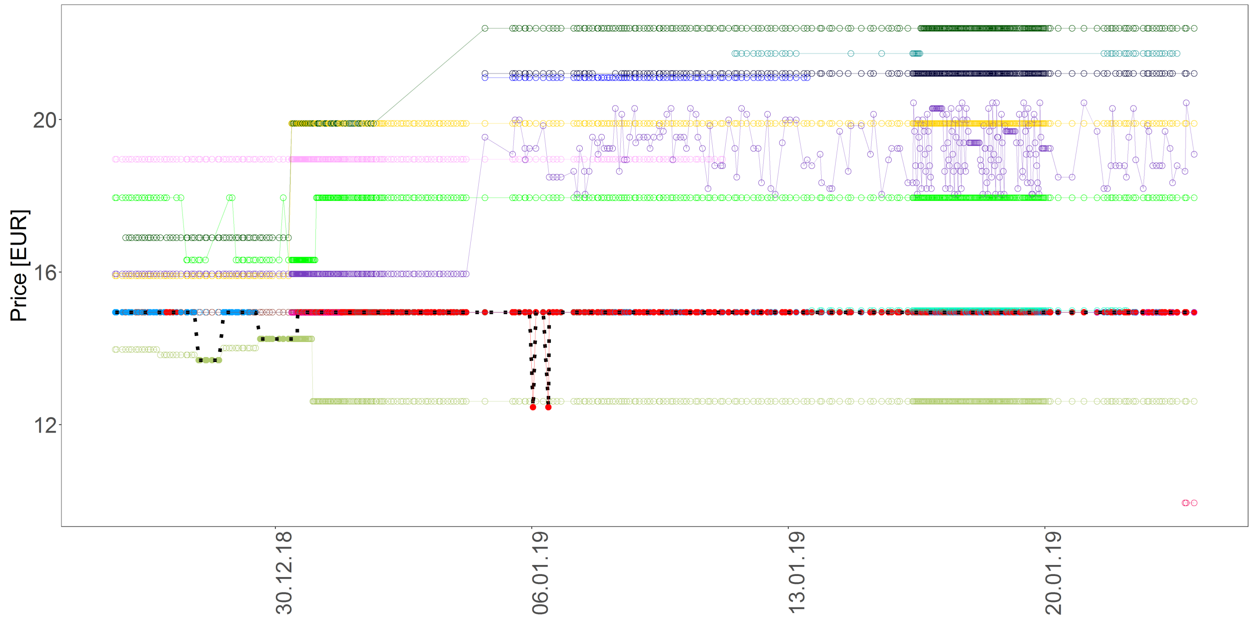


Figure 10: Sample price pattern - Random Jumps

and Bol, independently. Second, we observed some of the affected products over time and never encountered any inconsistencies.[20] Third, downward jitters are mostly (but not only) performed by Bol as the seller. It seems unlikely that different sellers would be affected differently by a platform-wide malfunction. Fourth, jitters persist in both of our crawls, with more than a year having elapsed between them. It seems unlikely that a technical error would not have been eliminated over this time. Fifth, we observe products where the jitters lead to an apparent reaction by other actors, such as a change in the Boy Box seller. This testifies that other players and the platform operator also perceived these rapid price changes. It therefore appears likely that the jitters on *Bol.com* are the result of actual pricing behavior.

A possible collusive explanation for the upward price jitters may be signalling to competitors the intent to raise prices. Byrne and De Roos (2019) document that petrol stations in Australia used price jumps *"to signal their intentions, and to create a mutual understanding of a coordinated pricing strategy among rivals."* A potentially collusive explanation of *downward* jitters may relate to signaling a firm's ability to reduce prices and punish deviat-

[20]For instance Chen et al. (2016) report the shopping basket not working during their crawl. We shopped for the crawled products several times while our crawler ran and never encountered problems with the basket.

ing rivals if needed. We would expect the seller with the lowest marginal cost to be the most likely to engage in this kind of signaling, since she is the most able to drive prices down. Consistently with this, as explained above, we observe downward jitters predominantly when the seller is Bol. It is beyond doubt that Bol is a fiercely competitive seller, one we would typically expect to have the lowest marginal costs.[21]

A further concern with downward jitters is that even absent collusion, these large transitory downward price jumps are also direct proof that the seller is pricing above cost, and does so most of the time.[22]

The pattern *rockets and feathers* is observed in about 11% of the 300 products considered. Motivated mainly by Edgeworth-cycles, this pattern is very often associated with collusion.[23] In their seminal work, Maskin and Tirole (1988) provide a dynamic competitive model that gives rise to an equilibrium with Edgeworth-cycles, and add that their *"model can be viewed as a theory of tacit collusion."* While the *rockets and feathers* pricing pattern did trigger cartel investigations (e.g. Byrne (2012)), it is debated to what extent this phenomenon emerging in a *non-cooperative equilibrium* can and should be regarded as collusive.

Rockets and feathers is also the pricing pattern that emerges in simulation studies of collusion by Q-Learning algorithms (Calvano et al. (2020) and Klein (2021a)). It has also been shown to be characteristic to collusion in gasoline markets (Eckert (2013) and Byrne and De Roos (2019)). Furthermore, most non-collusive explanations of *rockets and feathers* pricing we are aware of are based on consumer search and unexpected cost changes (Yang and Ye (2008), Cabral and Fishman (2012) and Tappata (2009)).[24]

[21] Our results in Section 6 show that Bol being present as seller has a very large effect on market outcomes, typically driving prices down.

[22] This is because for rational firms even the bottom of the downward jitter is above costs, so the fact that these price reductions are very rapid implies that most of the time the firm prices relatively far above costs.

[23] Borenstein et al. (1997) argue that retailers may prefer not to reduce prices in response to negative cost shocks and prefer to use previous prices as focal points for coordination.

[24] For example, in Tappata (2009) marginal costs change over time which influences how consumers search. When marginal cost are high, consumers expect little price dispersion and search less. If marginal cost unexpectedly drop, firms have little incentive to lower prices because consumers are not searching much (*feathers*). On the other hand, if marginal cost are low consumers expect large price dispersion and intensify search: then firms' response to a positive cost shock is to raise prices significantly (*rockets*).

We believe these models do not apply well to an online marketplace such as *Bol.com*. We observe several price changes within a short period. These changes appear unlikely to be driven by unexpected cost shocks, since marginal costs are hardly changing within a day, or even during the few weeks of our sample. We are not sure whether tacit collusion is the main reason behind the *Rockets and feathers pattern*.[25] Given the prevalence of the pattern and the fact that the price jumps tend to be significant, we however believe this pattern is a candidate for any screen for tacit collusion.

We observe a *balloons and rocks* pricing pattern in 6% of the 300 products inspected in detail. We are only aware of this pricing pattern being previously reported in energy markets (Douglas (2010) and Bremmer and Kesselring (2016)). To our knowledge it has never been described as conduct that would harm consumers, nor has it been discussed in the context of algorithmic pricing. This is somewhat surprising, because the *balloons and rocks* pricing pattern can be the outcome of very simple algorithmic rules. We explain this based on Figure 9a.

In Figure 9a two sellers display *balloons and rocks* pricing: *Dark Purple* and *Dark Green*. The pseudo-code below is an example for algorithms that would give rise to the observed prices. Of course, in reality the algorithms of these sellers may not be identical to what is presented here, and small variations would produce the same outcome. Our aim is to illustrate how simple the algorithms need to be to give rise to the observed *balloons and rocks pattern*, which, we argue, softens competition.

In words, the Dark Green seller always undercuts the Buy Box seller by a fix amount. If Dark Green wins the Buy Box (it never does in Figure 9a), she leaves the price unchanged.

The Dark Purple seller is slightly more complex as it acts as the price leader, and is experimenting: under normal circumstances (when the environment is favourable) it always increases the price by a small fixed amount as long as it holds the Buy Box. Dark Purple reduces the price period by period if she is not the Buy Box seller. This explains the pricing of Dark Purple untill the price drop (i.e. the *"rocks"* event) on the 8th of January 2019, but

[25]It is certainly not the only reason, as we observe this pattern by single sellers as well.

not the drop itself.

We investigated the price drop event on the 8th of January 2019 in detail. The most plausible explanation for *Dark Purple*'s large price reduction is an exogenous event: One day before the price drop the market saw a new entrant so that the number of competing firms increased from nine to ten. Perhaps more importantly, immediately before the price drop, the main competitor, *Dark Green*, increased its delivery time from five to six days. This led to an instant punishment in the ranking on the *compare all sellers* page, where *Dark Green* moved from the first to seventh position.[26] This in turn led to a complete reshuffle of sellers on the *compare all sellers* page.

In particular, the high-price but also high-rating sellers *Pink*, *Red*, *Brown* and *Cyan* moved to a more prominent display rank from the bottom of the list. The *Dark Purple* seller was low-price but also had a low (below-median) seller rating. The up-ranking of high-rated sellers changed the competitive environment from one where prices mattered for the ranking in the seller comparison to one where rating was more rewarded. Under these conditions, *Dark Purple* stopped experimenting and set a low fixed price to compensate for its relatively low rating (lines 8-9 in Algorithm 1 kicked in).

In summary, in Figure 9a *balloons and rocks* pricing is a combination of price-experimenting (*balloons*) and an exogenous event that changes competition fundamentally, away from price towards the quality (rating) dimension. The *Dark Purple* seller rapidly needs low prices to compensate buyers for its quality handicap (*rocks*). The *balloons and rocks* pattern of *Dark Green* is fully explained by her strategy to always follow the Buy Box seller and undercut it by a small amount.

Off-the-shelf re-pricer solutions appear perfectly capable of defining scenarios like those in our explanations of the *balloons and rocks* pattern in Figure 9a, including the environment changing due to new entry and referencing rivals with certain characteristics, such as rating and delivery time.[27]

The combination of Algorithms 1 and 2 is double-harmful to consumers: first, during

[26] The first position on the *compare all sellers* page does not always automatically go to the Buy Box seller.
[27] See ChannelEngine (2021) and Figure 1 above.

Dark Purple's experiment phase (the *balloons* period) prices are excessively high. Second, *Dark Green*'s follower strategy completely disqualifies her as a competitor, exerting as good as no pressure on *Dark Purple*, who usually wins the Buy Box, while Dark Green never does.[28]

We now move on to the detailed econometric analysis of how algorithmic pricing affect Buy Box prices, sellers' prices and eventually the propensity to win the Buy Box.

6 Econometric Analysis

Having established the prevalence of algorithmic pricing on *Bol.com*, in this Section we examine the effect of algorithmic pricing on market outcomes in further detail. In the first sub-Section, we investigate the effects of algorithmic sellers on Buy Box prices. In the second sub-Section, we investigate the robustness of these findings.

6.1 Algorithmic Pricing and the Buy Box Price

How do algorithmic agents affect the price of the Buy Box? The question is relevant in a screening exercise for algorithmic pricing. It provides useful guidance about whether policy makers should be concerned about algorithmic pricing in the first place. If algorithmic sellers are predominantly associated with low prices, there is little reason for regulatory attention. If however algorithms go hand-in-hand with increased prices, attention may be warranted.

The Buy Box is without doubt the most valuable bounty for which firms on *Bol.com* compete. In broad terms, it appears to us that the market environment on a platform such as *Bol.com* can be looked at as price competition with a slightly heterogeneous, nearly homogeneous product. There are few markets where products would be as standardized as on *Bol.com*, with nearly a dozen sellers bidding for a product as specific as an *"Oral B Pro 2 -*

[28] The behavior of *Dark Purple* and *Dark Green* sellers in Figure 9a is consistent with market sharing, whereby *Dark Green* would sell only to the most price-conscious, savvy users who click on the "*compare all sellers*" page and do not rely solely on the Buy Box.

2900 electric toothbrush, in double-pack."[29] Nevertheless, sellers are somewhat differentiated, for example in terms of their rating and delivery time.

In such an environment, we would expect prices to quickly converge towards marginal costs as the number of seller increases. The price of a seller is an important factor based on which Bol is suspected to award the Buy Box, albeit not the only one. We therefore expect the Buy Box price to converge to the appropriate marginal costs as competition intensifies.

Overall, theory about algorithmic pricing provides little certainty about whether algorithms are able to sustain higher prices or drive up competition. Our aim is to explore this question empirically. To do so, we study the effect of the presence of algorithmic sellers on the Buy Box price. We regress the following specification where the dependent variable $Log(BboxPrice)$ is the log-transformed Buy Box price of product i in period t.

$$Log(BboxPrice_{it}) = \beta_0 + \beta_1 Bol_{it} + \beta_2 N.Algo_{it} + \mathbf{X} + \mu_i \times \lambda_d + \epsilon_{it} \tag{1}$$

Bol_{it} indicates whether the platform operator competes as seller for the respective product. Most importantly, $N.Algo_{it}$ is a set of dummy variables counting the number of algorithmic sellers on product i at time t with respect to the criteria and cut-offs described in Section 5.2. We further control for the Buy Box seller rating scaled between 0 and 10 as well as the Buy Box delivery time.

We restrict the variation in the data at the level of the same product within a day. The inclusion of fixed effects helps to alleviate endogeneity concerns due to unobserved demand shocks. By including product-date fixed effects, we hope to largely eliminate time-specific demand changes. Our rich set of fixed effects also help mitigate endogeneity concerns due to unobserved product characteristics, and algorithmic sellers potentially self-selecting into certain products.

In order to establish how the effect of the presence of algorithmic pricing on the Buy

[29] `https://www.Bol.com/nl/nl/prijsoverzicht/oral-b-pro-2-2900-elektrische-tandenborstel-duopack/9200000117664163/`, retrieved on the 17th of September 2021.

Box price varies by the degree of competition on a certain product, we estimate Equation 1 by looking at sub-samples cut at the number of sellers present.

Results

We present results on how the presence of algorithmic sellers effects the Buy Box price and how this effect changes with different numbers of sellers present at every given period t. The results are summarized in Table 4. Coefficients on the number of algorithmic sellers by the number sellers are plotted in Figure 11.

The columns in Table 4 refer to the number of firms selling the product at a given time. Column 1 (Comp = 1) is the monopoly case, column 2 (Comp = 2) corresponds to the duopoly scenario and the other columns are analogous. The underlying criterion for algorithmic pricing applied here is the normalized number of price changes for a specific product-seller-pair. In section 6.2, we discuss results using other criteria to flag algorithmic sellers.

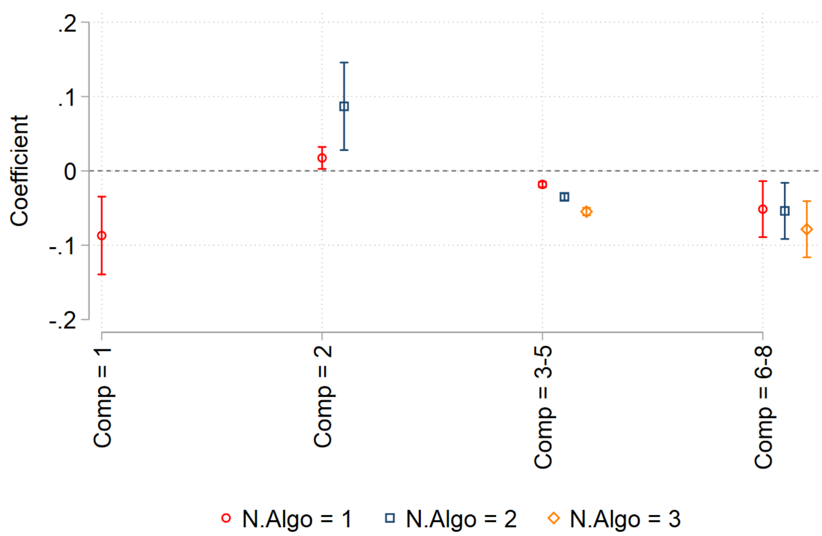


Figure 11: Buy Box Price by Subsamples. Algorithmic Pricing: Price Changes (Crawl 1).

From the first column of Table 4, the Buy Box price decreases by 9% if the monopolist seller is algorithmic, compared to the case of a traditional seller acting in the same position. This finding is surprising, novel and deserves explanation. It stands in strong contrast with

	(1)	(2)	(3)	(4)
	Comp = 1	Comp = 2	Comp = 3-5	Comp = 6-8
Bol comp.=1	-0.045***	0.093***	0.026***	-0.017***
	(-2.60)	(65.89)	(12.31)	(-6.23)
N.Algo=1	-0.087***	0.017**	-0.018***	-0.051***
	(-3.26)	(2.32)	(-9.53)	(-2.67)
N.Algo=2		0.087***	-0.035***	-0.054***
		(2.89)	(-14.39)	(-2.80)
N.Algo=3			-0.055***	-0.078***
			(-21.47)	(-4.07)
N.Algo=4			-0.071***	-0.090***
			(-25.98)	(-4.67)
Rating	-0.013	0.051***	0.044***	0.043***
	(-0.29)	(10.87)	(18.60)	(30.22)
Deliverytime	0.003***	-0.006***	-0.020***	-0.015***
	(3.84)	(-14.97)	(-74.88)	(-39.11)
Constant	3.773***	3.074***	3.196***	3.344***
	(10.07)	(62.91)	(148.26)	(147.84)
N	104742	126969	424925	262130
ProductxDate FE	Y	Y	Y	Y
Algo	2 sd	2 sd	2 sd	2 sd

t statistics in parentheses. Dependent Variable: Log Bbox Price. Robust SE.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Buy Box Price by Subsamples (Crawl 1)

the empirical results of Assad et al. (2020), who find that the adoption of algorithmic pricing software had no effect on monopoly petrol station prices. One may suspect that the price-reduction due to algorithmic sellers in monopoly markets arises because these sellers may focus on lower-price products in the first place. We exclude this explanation for at least two reasons.

First, we see no systematic relationship between the prevalence of algorithmic pricing and product categories or price classes (see Figures A.5 and A.6 in the Appendix). Second, our estimate of Equation 1 includes product fixed effects. We identify the effect of algorithmic pricing primarily by the variation of the Buy Box price *within* products. It is very unlikely that the large price reduction due to algorithms in monopoly markets would have to do with the products of algorithmic and non-algorithmic sellers being different.

We provide a simple explanation for the large monopoly algorithmic price-rebate. In markets such as petrol stations (Assad et al. (2020)), every facility has a manager who takes pricing decisions for a very narrow set of petrol products. On e-commerce marketplaces such as Bol, third-party sellers often carry tens of thousands of items.[30] While in a petrol station a manager needs to review merely 3-4 petrol product prices, pricing in thousands of products on Bol separately would clearly be a challenge even for hundreds of product managers.

The most likely practical way for how non-algorithmic sellers determine the prices of a long list of products on e-commerce platforms - at least for the first upload - seems to be applying a simple formula: by first summing up costs and then adding a margin that - for practical reasons - is likely equal for several products. External pricing tools actively recommend this *cost-plus* pricing approach.[31] Clearly, a uniform margin may not be profit-maximizing for all products. But the effort required to adjust prices for thousands of products separately can prove prohibitive for many third-party sellers.

When a traditional seller subscribes to a re-pricer, she likely starts out by uploading a list with regular product prices based on such a *cost-plus* formula. The re-pricer then takes over the pricing of individual products: it can experiment and adjust those regular prices. In monopoly markets the re-pricer algorithm may end up pushing prices downwards, at least for some products, where the regular margins may result in insufficient demand. Re-pricer ChannelEngine offers precisely this pricing procedure for monopoly products (*"if no competition"*) on Bol, by automatically setting the *"regular price, with price rules applied"* (ChannelEngine (2021)). Note that by the same mechanism, whether algorithms reduced or increased prices compared to manual sellers depends entirely on the initial bias made by the human seller. Algorithms would merely adjust the price to the profit maximizing

[30] Bol displays the number of products by seller. We browsed several arbitrary sellers to find that products typically range in the thousands, with several sellers having more than 40,000 products.

[31] See for example `https://www.woosa.com/software/bol-woocommerce-addon-price-calculator/?v=d3dcf429c679`, `https://www.shopify.com/blog/how-to-price-your-product` (both retrieved on the 1st of December 2021), explaining the procedure as follows: *"To set your first price, add up all of the costs involved in bringing your product to market, set your profit margin on top of those expenses, and there you have it."*

monopoly level. This is a downward adjustment, as we find, if humans initially set these prices excessively high.[32] Clearly, by the same mechanism algorithms could as well result in an upward price adjustment, if the human-bias meant lower-than-monopoly prices in the first place. Our findings suggests that the net effect on average is a downward adjustment of manually set prices.

Consistently with this explanation, we observe that human sellers tend to disproportionately change prices on Thursdays, and around peak office hours, at 8-9 AM and 4-6 PM (Figure A.2). In contrast, algorithmic sellers change prices evenly across various weekdays, and are predominantly at work during the night, a few hours after the the main human price upload at 4 PM. This lends some support to the view that algorithms continuously adjust human-uploaded prices.

We conclude that algorithmic agents may reduce prices, and observe this at work in monopoly markets. We explain this by automated pricing engines applying different margins product-by-product, in a more granular manner than what would manually be feasible.

We now move on to discussing the results in Table 4 for products with more than one seller present. In column 2, we present effects for duopoly products. One algorithmic seller competing with a traditional rival is associated with a 2% increase in the Buy Box price. What is more, if both sellers in that duopoly set prices through algorithms, prices are about 9% higher.

Interestingly, this observation does not hold any longer if the number of sellers increases beyond two. This finding is compatible with tacit collusion: In a duopoly, algorithmic sellers benefit from each other's presence, resulting in a higher Buy Box price. In turn, with a high number of rivals, algorithmic sellers compete fiercely, reducing the Buy Box prices. Taking into account lower prices in monopoly situations, this amounts to an inverted-U shaped relationship between Buy Box price and competition when algorithmic sellers are present (see the plotted coefficients in Figure 11).

[32] There is a rich body of business literature documenting managerial overconfidence, among others about demand (Montgomery and Bradlow (1999)), new product introduction (Simon and Shrader (2012), Markovitch et al. (2015), Feiler and Tong (2021)) and other corporate decision variables (Malmendier and Tate (2015)). Kahneman (2011) recognizes overconfidence as "*the most significant of the cognitive biases.*"

6.2 Robustness and further Results

In this section we explore the robustness of some of the results we established in the previous section.

Flagging Algorithmic Sellers: Price Changes and Price Correlations

We would like to verify how our results may depend on the heuristic used to identify sellers as algorithmic. In Table 5 we verify whether the most relevant results of our analysis (monopolies and duopolies) hold for different definitions of algorithmic pricing. So far, we have flagged a seller algorithmic if prices on of the products changed sufficiently often. At baseline, we assume that price changes that are more than *two* standard deviations above the normalized distribution are due to algorithmic pricing. In this section, we examine robustness by applying both one and three standard deviations as alternative cut-off (columns 1, 2 and 5 of Table 5).

As a further refinement, we add price correlations with competing sellers to the number of price changes, as discussed in section 5.2. Doing so results in labeling a seller as algorithmic if prices change often *and* closely follow competitors (columns 2, 4 and 6 of Table 5).

As we can see in Table 5, the results from our baseline specification mostly holds for different specifications. If anything, coefficients decrease by 1 to 2 percentage points in absolute terms as we choose a more conservative measure of algorithmic pricing.

Product-Seller Level Definition of Algorithmic Pricing

In e-commerce, sellers likely rely on algorithmic pricing software in order to manage price-setting for a broad range of products. In the analysis so far we defined pricing as algorithmic on the *seller* level. The same seller is considered algorithmic on all her products if labelled on at least one according to our criteria. We address this assumption by repeating much of the above analysis by categorizing single product-seller pairs as algorithmic.

In essence, this analysis changes the composition of the control group. When defining algorithmic pricing on a product-seller-level, the (algorithmic) treatment group includes only

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Monopolies:						
N.Algo=1	-0.11***	-0.08***	-0.09***	-0.12***	-0.08***	-0.10***
	(-3.13)	(-3.13)	(-3.26)	(-5.40)	(-3.37)	(-5.21)
(2) Duopolies:						
N.Algo=1	0.06***	0.05***	0.02**	0.03***	0.02**	0.03***
	(2.95)	(2.94)	(2.32)	(2.86)	(2.33)	(2.86)
N.Algo=2	0.09***	0.08***	0.09***	0.07***	0.07***	0.06***
	(3.69)	(3.62)	(2.89)	(2.64)	(2.74)	(2.98)
N	104742	104742	104742	104742	104742	104742
R2	1.00	1.00	1.00	1.00	1.00	1.00
ProductxDate FE	Y	Y	Y	Y	Y	Y
SD x Corr.	1sd	1sd x Corr.	2sd	2sd x Corr.	3sd	3sd x Corr.

t statistics in parentheses. Dependent Variable: Log Bbox Price. Robust SE.

Note: For the sake of brevity, other coefficients have been omitted from this table.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Robustness - Monopolies and Duopolies (Crawl 1)

products of sellers where prices change often. The (non-algorithmic) control group in turn includes products of sellers who set relatively stable prices on all products, and also similar products of sellers who do have other products (in the treatment group) that exhibit patterns of algorithmic pricing.

	1 SD	2 SD	3 SD
Always Algo	10914	10244	9835
Sometimes Algo	3453	2250	1801

Table 6: Number of Product-Seller Pairs by Algo-Definition. **Total:** 13228

Table 6 shows the number of product-seller pairs depending on whether we assume that a seller that changes prices by a significant amount applies algorithmic pricing to all her products (*always algo*) or we consider only those product-seller pairs algorithmic where we observe such behaviour (*sometimes algo*). As we can see, for a substantial number of products of algorithmic sellers prices are set in a stable manner. Only labelling product-seller pairs algorithmic where we observe such behaviour transfers such product-seller pairs from the treatment into the control group.

Table A.1 presents results for the most interesting scenarios examined in previous sections: Monopolies and duopolies.[33] As we can see, results point into the same direction although at larger magnitude.

Margins

In a screen for potentially harmful pricing behavior margins are particularly relevant, as high margins may serve as markers for collusion or sustained high prices. A drawback of our data-sparse screening approach is that we do not observe costs directly. We approximate the closest proxy to marginal costs available in our setting by the all-time minimum price observed for a certain product, assuming that marginal costs remain constant throughout our sample.

We estimate the following regression:

$$ln(Margin_{ijt}\%) = \beta_0 + \beta_1 Bol_{it} + \beta_2 N.Algo_{it} + \mathbf{X} + \mu_{id} + \phi_j + \epsilon_{ijt} \tag{2}$$

with $ln(Margin_{ijt}\%)$ corresponding to the logged percentage margin for seller j on product i above the all-time minimum price recorded for product i. In addition to product-date fixed effects, we include seller fixed effects to account for unobserved seller heterogeneity.

Results in Table A.2 and Figure A.7 on log-margins are analogous to what we have previously established on Buy Box Prices. In a duopoly situation, where only one of the sellers is algorithmic, margins increase by about 66%. If both sellers are algorithmic, prices even increase by 73%.[34] If the number of sellers increases beyond two, this effect vanishes.

Winning the Buy Box

Our hypothesis is that algorithmic sellers are *more likely* to win the Buy Box than traditional rivals. After all, this is what providers of re-pricer software promise their customers

[33] As we have substantially fewer product-seller pairs that are labelled algorithmic (see Table 6), the coefficient for two algorithmic sellers in a duopoly is now mostly omitted.

[34] Note that the inclusion of seller fixed effects absorbs the variation in the coefficients for N.Algo for monopoly products.

(ChannelEngine (2018), IndustryNews (2018), RepricerExpress (2021)). Furthermore, in a different empirical framework, Chen et al. (2016) find that algorithmic sellers tend to win the Buy Box on Amazon, except for the top rank on the price comparison page.[35]

We test the hypothesis that algorithmic sellers are more likely to win the Buy Box than traditional rivals by estimating the following Equation 3:

$$Bbox_{ijt} = \beta_0 + \beta_1 Log(Price_{ijt}) + \beta_2 Bol_{it} + \beta_3 Algo_{ij} + \beta_4 NComp_{ijt} + \mathbf{X} + \mu_{id} + \lambda_j + \epsilon_{ijt}, \quad (3)$$

where the outcome variable $BBox_{ijt}$ is binary and captures whether in period t seller j has the Buy Box for product i. $Log(Price)$ is the log-transformed price of seller j for product i at time t. Most importantly, variable *Algo* indicates whether seller j is flagged algorithmic for product i according to the criteria described in section 5.2. We further include product-date and seller fixed effects. All other variables are the same as in Section 6.1.

Table A.3 presents the results for the first crawl for Equation 3. Columns 1 and 2 show results from a linear model including seller and product-date fixed effects to account for unobserved seller heterogeneity as well as unobserved product specific demand shocks. Columns 3 and 4 present results from a probit-model. In Columns 2 and 4 the criterion for algorithmic pricing is amended with a criterion for price correlation.

The coefficient of the indicator that flags algorithmic selling (*Algo*) is significant and positive for all specifications. This indicates that using algorithmic pricing *increases* the probability of winning the Buy Box relative to prices set manually.

Moreover, keeping the number of firms in the market fixed, *Bol*'s presence as competitor *reduces* the probability of winning the Buy Box.

Lastly, it may be that Bol takes into account a seller's available stock of a certain product when awarding the Buy Box. This is unobserved to customers, rivals and the researcher and hence captured in the error term. Endogeneity concerns of our variable of interest *Algo* may

[35] See figure 26 in Chen et al. (2016).

arise if the level of stock is correlated with the application of algorithmic pricing engines. We think this is unlikely: we see little reason why algorithmic sellers would differ from non-algorithmic rivals in how they keep their product stocks up to date. Watching these stocks is a key task of any seller, no matter how sophisticated pricing tools she may use.

We next turn to the question of how competition affects the ability of algorithmic sellers to win the Buy Box. In order to investigate how the bonus of algorithmic sellers to win the Buy Box changes with more intense competition, we calculate marginal effects from a probit model over the number of sellers per product (see Figure A.8).

In a duopoly situation, using algorithmic pricing relative to manually set prices pays off tremendously: Algorithmic pricing increases the probability of winning the Buy Box by about 9 percentage points compared to being a non-algorithmic seller in the same duopoly market. As the number of competitors increases, the advantage of algorithmic pricing deteriorates gradually. However, the algorithmic bonus wears off surprisingly slowly with additional competition. In particular, even with six firms offering the product for sale, being algorithmic increases the probability of winning the Buy Box by around 5 percentage points.[36]

Our main finding in this section is that algorithmic pricing helps winning the Buy Box, and adds a bonus that remains preserved even under very strong competition, only to fade away as the number of rivals becomes very high (more than six).

Second Crawl

Lastly, we establish that previous largely hold based on the data we have gathered about a year later. According Results are presented in Table A.4.

7 Policy Discussion

To our knowledge, we are first to document that algorithmic pricing may involve efficiencies in the form of lower prices in monopoly markets. We explain this finding by the inability of

[36]This is a very large algorithmic bonus, taking as benchmark that in a six-firm market identical firms would each have a 17% probability to win.

traditional sellers to accurately determine the profit maximizing monopoly price for thousands of products in their portfolio. Algorithmic agents may start out with imperfect prices, but gradually converge to the monopoly price by experimenting.

We also find that in competitive products algorithmic sellers increase prices and benefit from each other's presence. While we document that - consistently with collusion - the presence of algorithmic sellers is associated with higher prices and margins, we are not able to reliably determine whether this price increase is due to the algorithms *"failing to learn to compete"* (Hansen et al. (2020)) or actually *"learning to coordinate"* (Calvano et al. (2020)). Some commentators (e.g. Assad et al. (2020)) argue that competition policy *"should mostly be concerned with algorithms actively learning not to compete."*

We believe competition agencies *screening* for anti-competitive behavior should be concerned with algorithmic pricing if - as we demonstrate - it results in higher prices, regardless whether and what algorithms learn to achieve such an equilibrium. Antitrust agencies rightly argue that *"companies cannot hide behind algorithms"* (Laitenberger (2017), Busse (2017)).[37] Competition policy looks at algorithmic agents applying the same criteria as to human decision makers. Whether a manager charged with collusion *"learned to coordinate"* or *"failed to learn to compete"* would likely make little difference for most judges deciding in antitrust matters.

A limitation of our analysis is that we do not *identify* collusion. We do not intend to *prove* or even allege collusion. Our aim is to investigate the likelihood of pricing algorithms to increase prices in a real market environment. We furthermore aim at creating simple screens that can be used to narrow the search for algorithmic collusion. Our descriptive results carry relevance for Competition authorities, researchers and managers scanning the horizon for potentially collusive practices: we propose a list and frequency of potentially problematic price patterns that can serve as a simple first screen to shortlist firms and products for further analysis. We do so in an extraordinarily data-sparse manner, relying solely on publicly available price information.

Overall, our impression is that sellers on *Bol.com* using re-pricer software are relatively

[37] They undoubtedly try, see Feier et al. (2021).

unsophisticated. We see little trace of complex learning behind the documented pricing patterns. The strongest evidence consistent with algorithmic learning appears to be the *random jumps* pattern illustrated in Figure 10, which we observe in just 11% of affected (algorithmic) products. This pattern may indicate algorithms being *trained* as sellers experiment with different prices.

As illustrated in Figure 1 and the pseudo-code for Algorithm 1 (Dark purple seller) and 2 (Dark green seller) above, the bulk of algorithmic pricing on Bol.com appears to consist of a finite set of *if-then* statements. A striking finding of our paper is that this apparent lack of sophistication may not make pricing algorithms less harmful. On the contrary: Our results are consistent with the view that a secret to successful collusion may lie in managers' ability to commit to simple strategies, such as leader-follower prices shown in Figure 9a via the simple *if-then* formulae in off-the-shelf re-pricer software. Overall, we cautiously side with the strand of literature that emphasizes the role of algorithmic agents as commitment devices to elevated prices (Salcedo (2015), Brown and MacKay (2020)).

While we find circumstances, where, *ceteris paribus*, algorithmic sellers drive up average prices, we observe instances where algorithmic pricing appears non-profitable for *some* algorithmic sellers.[38] The Dark Green seller in Figure 9a provides an example. This seller automatically follows Dark Purple to raise prices. But Dark Green never wins the Buy Box, and therefore appears to sell very little, unlikely to benefit much directly from the increased prices. This has practical implications for competition policy, where firms accused of algorithmic collusion may (truthfully) argue that algorithmic pricing never benefited them. It also shows the limits of forensic economics to *prove* collusion from pricing data: These techniques can serve as a useful first screen, but traditional cartel investigative tools such as unannounced inspections and formal information requests appear irreplaceable to understand whether and how algorithmic sellers work together, communicate and allocate profits.

Our econometric analysis of algorithmic prices yields nuanced results. The finding that algorithmic agents may reduce prices in monopoly markets and highly competitive products but increase prices with medium competition calls for careful policy. We document

[38]Normann et al. (2021) also report a similar finding.

that algorithmic pricing may involve pro-competitive effects. It likely simplifies price-setting product-by-product and may counter-steer human errors in overestimating demand and setting excessive prices. Also, algorithmic sellers seem to be particularly efficient and reduce prices under fierce competition. However, when competition is in a medium range, we observe both higher prices associated with algorithms as well as a range of pricing patterns that are often associated with collusion. Such pricing patterns likely deserve more detailed investigation, a message that is relevant for competition policy and managers alike.

We also find that algorithmic sellers tend to price very differently within their own product palette. On some products, they change prices frequently, and these prices are on average higher than those of comparable non-algorithmic firms. However, on a broad range of their products, algorithmic agents cannot be distinguished from non-algorithmic sellers. This also implies that (relatively) stable prices are not particularly useful markers in screening for potential algorithmic collusion. Stable prices of sellers with algorithmic capabilities are not higher than of sellers without the ability to engage in algorithmic pricing.

While in this paper we focus on "*what comes out*" of algorithms, designing appropriate policies to improve market outcomes would also require a detailed understanding of "*what goes in.*" For example, algorithms that take as input the prices of rivals may cause more harm in competitive markets than algorithms that merely experiment and observe the resulting demand (Morton (2012)). In a similar vein, understanding what happens "*inside*" the algorithm - the formula the algorithm uses to recommend a price based on the input signals - is very likely also necessary for apt policy response. Better understanding these questions constitute possible avenues for further research.

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8 Appendix

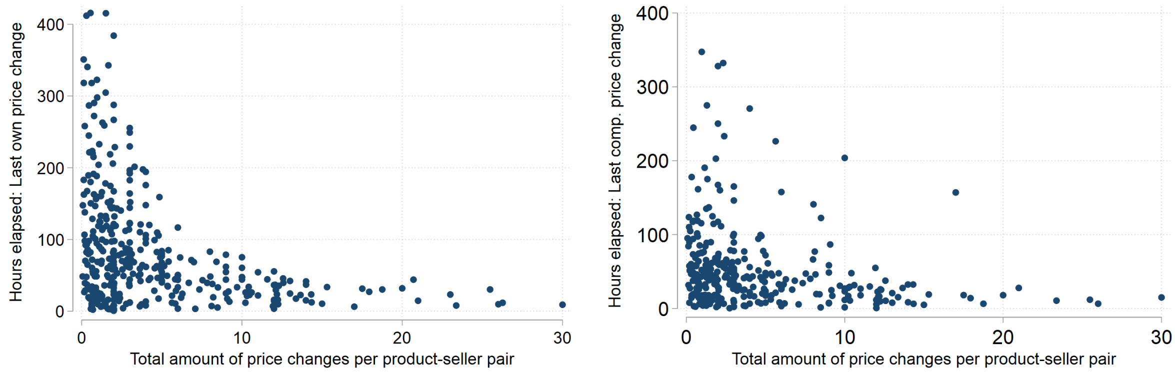

Figure A.1: Total price changes versus hours elapsed after last own (left panel) and competitor's price change (right panel) - Data from Crawl 1. Observations shown below the 99th percentile in both time elapsed and number of price changes.

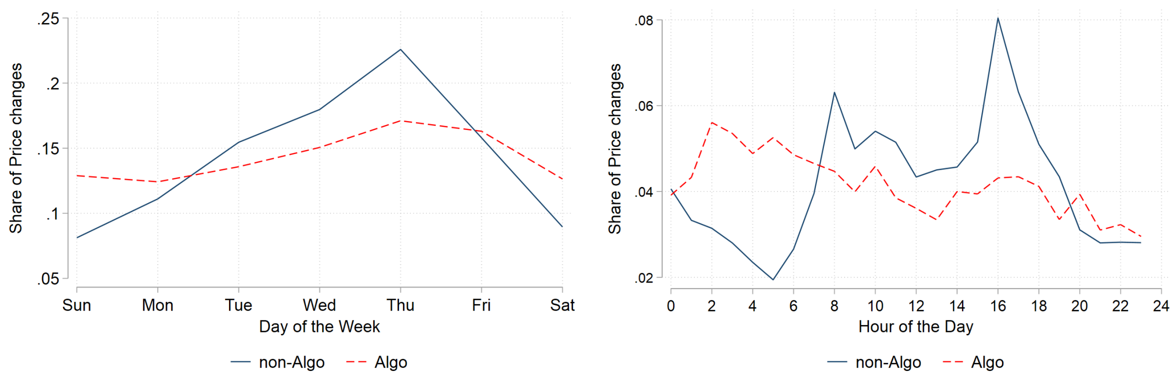

Figure A.2: Share of Price Changes by Weekday and Hour of the Day in all for Algorithmic versus Non-Algorithmic Price Changes. Product-Seller-pairs are flagged algorithmic if we document more than 20 price changes. Data from Crawl 1.

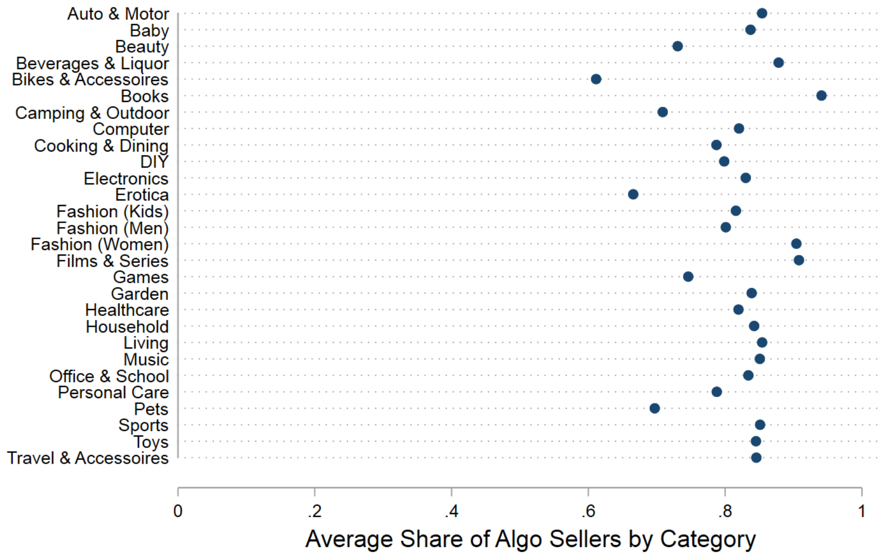

Figure A.3: Number of algorithmic sellers by Product and Product Category. Product-Seller-pairs are flagged algorithmic if we document more than 20 price changes. Data from Crawl 1.

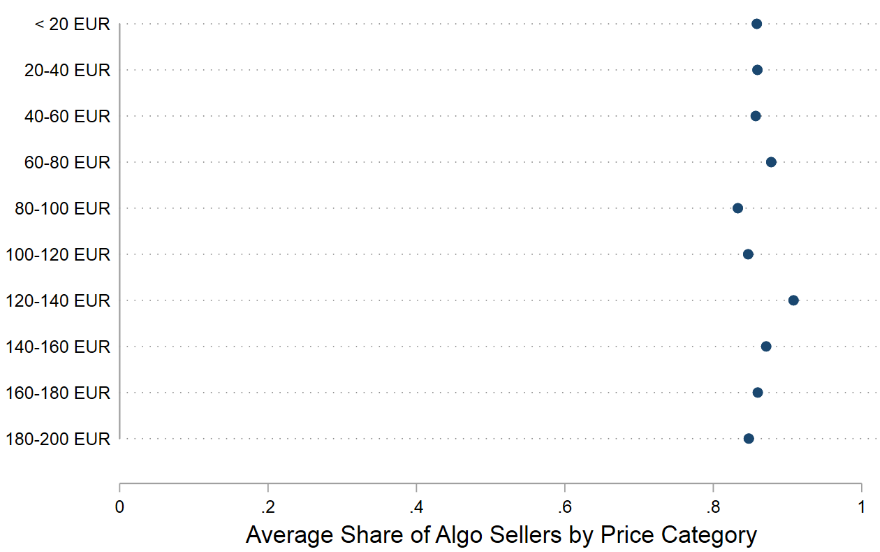

Figure A.4: Number of algorithmic sellers by Product and Price Category. Product-Seller-pairs are flagged algorithmic if we document more than 20 price changes. Data from Crawl 1.

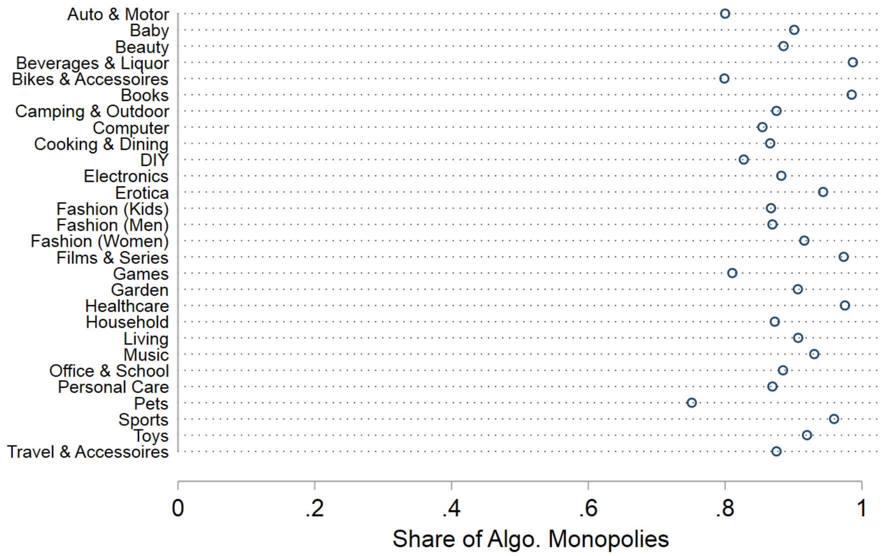

Figure A.5: Share of Algorithmic Monopolies by Product Category. Product-Seller-pairs are flagged algorithmic if we document more than 20 price changes. Data from Crawl 1.

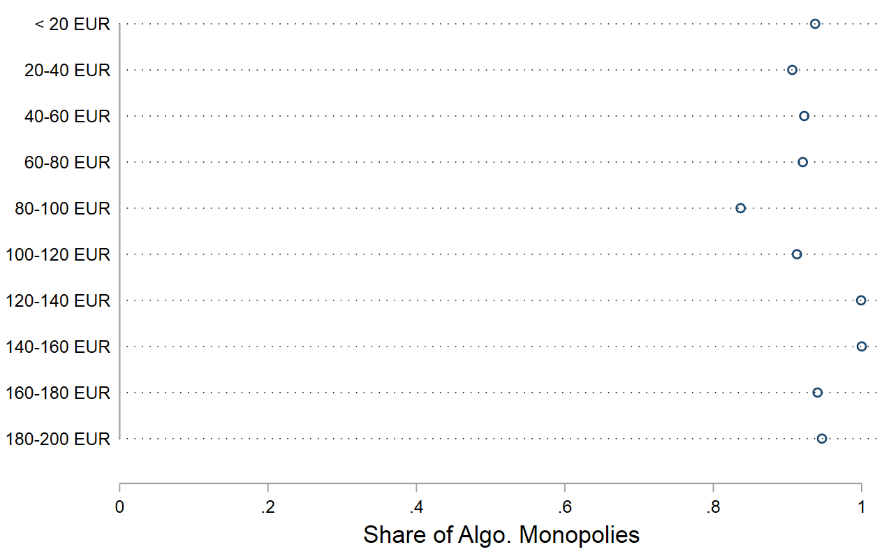

Figure A.6: Share of Algorithmic Monopolies by Buy Box Price. Product-Seller-pairs are flagged algorithmic if we document more than 20 price changes. Data from Crawl 1.

	(1)	(2)	(3)	(4)	(5)	(6)
Bol comp.=1	-0.06***	0.12***	-0.10***	0.09***	-0.05***	0.09***
	(-3.11)	(15.66)	(-5.74)	(64.57)	(-2.86)	(64.49)
N.Algo=1	-0.02	0.03***	-0.24***	0.08***	-0.12**	0.07***
	(-1.31)	(4.17)	(-10.09)	(3.39)	(-2.45)	(6.88)
N.Algo=2		0.07***				
		(6.99)				
Rating	-0.00	0.05***	0.02	0.05***	-0.01	0.05***
	(-0.10)	(10.90)	(0.46)	(10.88)	(-0.12)	(10.84)
Deliverytime	0.00***	-0.01***	0.00***	-0.01***	0.00***	-0.01***
	(3.71)	(-15.90)	(3.20)	(-15.82)	(3.70)	(-15.81)
Constant	3.64***	3.09***	3.59***	3.12***	3.72***	3.12***
	(9.33)	(76.52)	(9.12)	(75.10)	(9.77)	(74.99)
N	104742	126969	104742	126969	104742	126969
Nr. Comp	1	2	1	2	1	2
ProductxDate FE	Y	Y	Y	Y	Y	Y
SD	1sd	1sd	2sd	2sd	3sd	3sd

t statistics in parentheses

Dependent Variable: Log Bbox Price. Robust SE.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.1: Product-Seller Level Algo Definition, Monopolies and Duopolies

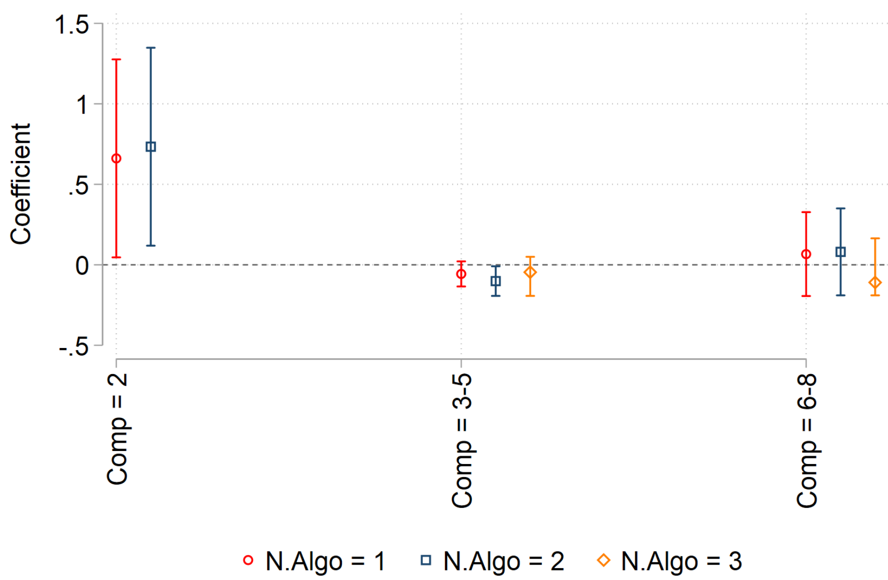

Figure A.7: Margin above min price

	(1) Comp = 2	(2) Comp = 3-5	(3) Comp = 6-8
Bol comp.=1	-0.129	0.00970	-0.00760
	(-0.74)	(0.43)	(-0.32)
N.Algo=1	0.661*	-0.0566	0.0667
	(2.11)	(-1.42)	(0.50)
N.Algo=2	0.734*	-0.101*	0.0804
	(2.24)	(-2.15)	(0.58)
N.Algo=3		-0.0456	-0.109
		(-0.94)	(-0.78)
N.Algo=4		-0.0774	-0.150
		(-1.55)	(-1.07)
Rating	0.106**	-0.280***	-0.245***
	(2.79)	(-16.21)	(-6.42)
Delivery Time	-0.0260***	0.0379***	-0.0596***
	(-8.82)	(23.35)	(-26.54)
Constant	0.134	3.835***	3.836***
	(0.31)	(24.19)	(10.78)
N	73195	312365	159845
R2	0.976	0.869	0.773
ProductxTime FE	Y	Y	Y
Seller FE	Y	Y	Y
Algo	2 SD	2 SD	2 SD

t statistics in parentheses

Dependent Variable: Margin above all-time minimum Price on product level. Robust SE.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.2: Margin above the min price

	LPM		Probit	
	(1)	(2)	(3)	(4)
Algo=1	0.0538***	0.0778***	0.322***	0.314***
	(50.73)	(42.33)	(87.24)	(75.38)
Log. Price	-0.408***	-0.407***	-0.00157	-0.00132
	(-202.85)	(-202.33)	(-1.14)	(-0.96)
Bol comp.=1	-0.177***	-0.177***	-1.360***	-1.360***
	(-73.77)	(-73.68)	(-449.41)	(-449.83)
Rating	0.00439***	0.00473***	0.221***	0.220***
	(3.94)	(4.24)	(59.32)	(58.99)
Delivery Time	-0.0118***	-0.0120***	-0.0994***	-0.0997***
	(-112.36)	(-113.83)	(-181.12)	(-181.55)
N.Comp=2	-0.492***	-0.492***	-4.314***	-4.323***
	(-99.56)	(-99.61)	(-171.09)	(-171.03)
N.Comp=3	-0.572***	-0.572***	-4.739***	-4.746***
	(-111.66)	(-111.75)	(-187.32)	(-187.12)
N.Comp=4	-0.610***	-0.610***	-4.933***	-4.937***
	(-116.02)	(-116.14)	(-194.35)	(-193.96)
Constant	2.216***	2.208***	2.513***	2.540***
	(172.54)	(171.87)	(58.26)	(58.94)
N	2552704	2552704	2553536	2553536
FE	Y	Y	-	-
Algo	2 SD	2 SD x Corr.	2 SD	2 SD x Corr.

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3: Win the Buy Box

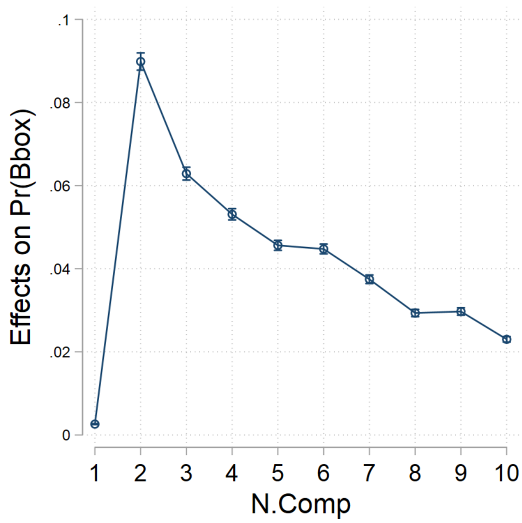

Figure A.8: Probit Marginal Effects - Algorithmic seller winning the Buy Box over the number of sellers.

	(1)	(2)	(3)	(4)
	Comp = 1	Comp = 2	Comp = 3-5	Comp = 6-8
Bol comp.=1	-0.073***	-0.019	-0.041***	-0.124***
	(-8.27)	(-1.62)	(-19.94)	(-30.96)
N.Algo=1	-0.062***	0.036*	-0.002***	0.009***
	(-4.64)	(1.76)	(-3.74)	(9.84)
N.Algo=2		0.035*	-0.022***	0.008***
		(1.71)	(-4.07)	(7.36)
N.Algo=3			-0.023***	
			(-4.20)	
N.Algo=4			-0.037***	
			(-6.76)	
Rating	0.010*	0.008***	-0.006***	-0.003***
	(1.95)	(4.66)	(-7.85)	(-3.00)
Deliverytime	0.000***	-0.001***	0.001***	0.001***
	(5.46)	(-12.28)	(13.35)	(4.44)
Constant	3.494***	3.267***	3.203***	3.230***
	(78.77)	(209.27)	(472.25)	(386.74)
N	155632	557198	1066364	318770
R2	1.000	1.000	1.000	0.999
ProductxDate FE	Y	Y	Y	Y
Algo	2sd	2sd	2sd	2sd

t statistics in parentheses. Dependent Variable: Log Bbox Price. Robust SE.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Second Crawl