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 *Bol.com*, the largest online marketplace in the Netherlands and Belgium. Based on more than two months of pricing data for around 2,800 popular 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. We are first to document that 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, algorithms benefit from each other's presence: Prices are particularly high if two algorithms bid against each other and there is a medium number of sellers in the market. With a sufficient number of competitors, algorithmic sellers reduce the Buy Box price and compete particularly fiercely. We also identify several algorithmic pricing patterns that are often associated with collusion. Such patterns may serve as valuable screens for anti-competitive practices. Algorithmic sellers are more likely to win the Buy Box, and therefore carry disproportionate relevance for consumers and welfare. Overall, our findings call for careful policy with respect to pricing algorithms, that considers both the risk of collusion and the need to preserve potential efficiencies.

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 the potential of algorithmic sellers to sustain collusion on an online retail platform.

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).

Compatible with algorithmic collusion, we see particularly high prices if algorithms price against each other. Algorithmic sellers therefore seem to benefit from each other's presence. Moreover, we find that algorithmic pricing pays off: Algorithmic sellers win the Buy Box - the slot reserved for the most promoted seller - significantly more often than traditional sellers. Moreover, we find that algorithmic pricing is associated with higher average Buy Box prices.

We also qualitatively explore our dataset and structure the price data into several reoccurring 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 with 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 a detailed econometric analysis of algorithmic pricing and present qualitative results. 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]

[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'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 *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* (in Dutch: *koopblok*): 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)).

From a competition perspective, this is very interesting. 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 whether the presence of reprice engines is associated with supra-competitive 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

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

indicators Bol measures, such as on-time delivery, telephone accessibility, completeness of product description, track-and-trace information and seller cancellations (ChannelEngine (2018)).

At the time of our crawls, *Bol.com* determined for each product a weekly maximum price, above which the product cannot be offered for sale. For establishing the maximum price, Bol considered among other factors the price range of the product, historic prices, the prices of the sellers in the market and the number of sellers. If a seller's price for the product exceeded the maximum price, Bol could set the product's status to *"unpublished"* (Bol.com (2021a,e)).

The maximum permitted sales price is relevant for our analysis because it creates variation in our data even for non-algorithmic sellers and even in monopoly markets: sellers may enter or exit the market if their (possibly even constant) prices may slip above or below the maximum permitted price, as the latter may change with time.

2.3 Re-Pricer Software

The term *algorithmic pricing* is used interchangeably in different contexts. It is worth discussing the main types of pricing algorithms.[3]

The simplest pricing algorithms are pure *pricing rules*, that enable retailers set different prices depending on the market context. Often, 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 optimiza-*

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

tion 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 (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.

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*

[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.

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

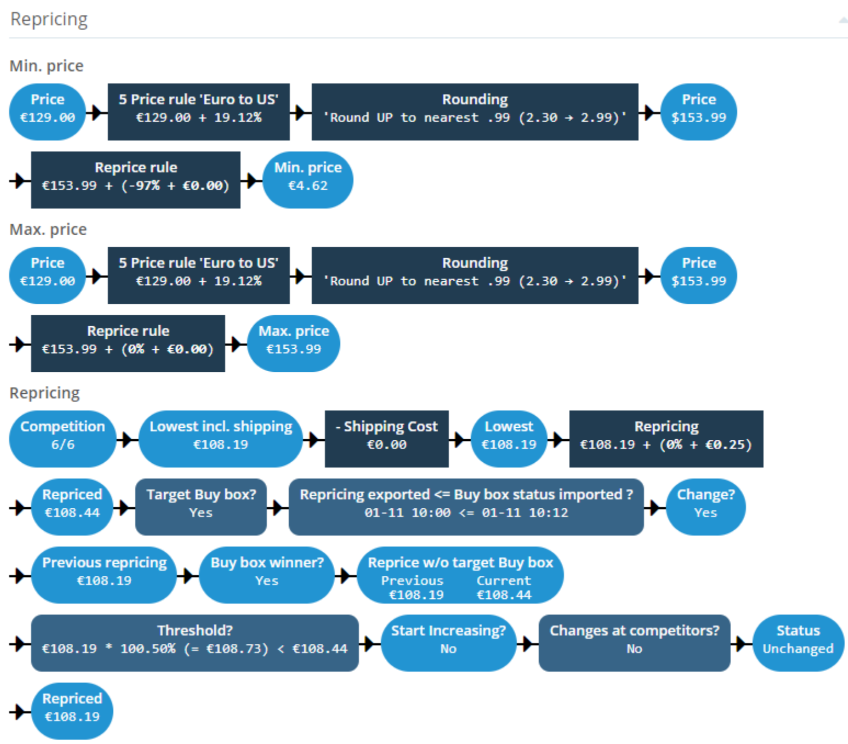


Figure 1: ChannelEngine repricing rule illustration. Reproduced from `https://help.channelengine.com/article/47-repricer`, retrieved on the 17th of September 2021.

are "entitled" to while keeping the price high instead of racing to the bottom" (IndustryNews (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. 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.

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.

[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 such announced maximum prices may serve as focal points for collusion (Knittel and Stango (2003)).

[8]Despite the attention from competition authorities (Konkurransetilsynet.no (2021), 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.

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), 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) and 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]

[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.

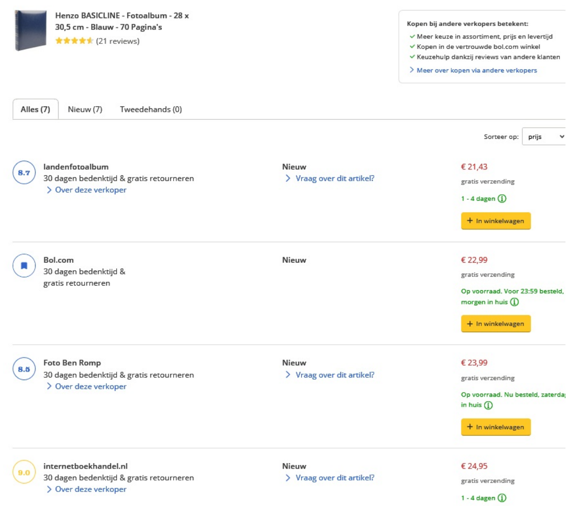


Figure 3: The *compare all sellers* page.

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:

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 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.

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

[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.

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 Section 6.2 as well as 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 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, as we explain in detail in Section 6.2, 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 bot hcrawls. 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.

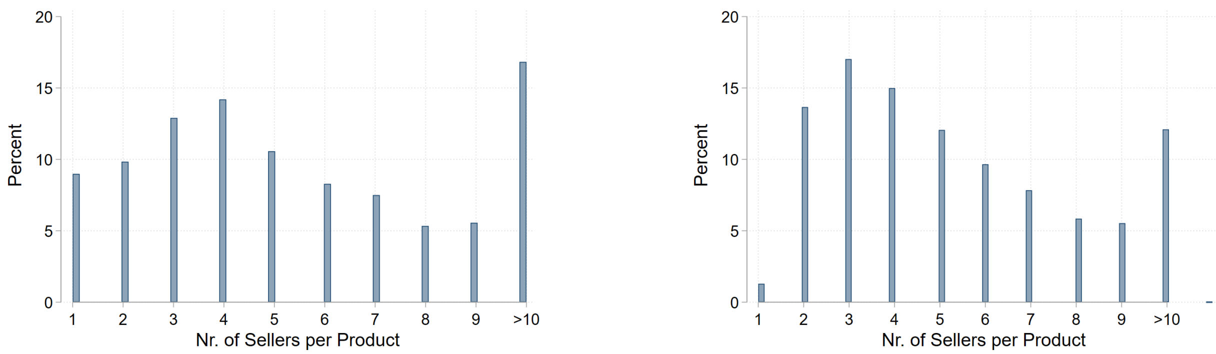


Figure 4: Number of sellers per product. Left: Crawl 1, Right: Crawl 2.

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.

5.2 Price Changes

In Table 2 we focus on some properties with respect to the price changes we observe in our data.[12] As we can see, the median price correction is downwards by four cents. We further measure the time elapsed between price changes in between own price changes or between own and competitors' price change. The latter aims at depicting the reaction time after a

[12]For crawl 1, statistics on price changes for crawl 2 are available upon request.

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

Table 1: Summary Statistics

rival's price change.[13] The median time elapsed after the last own price change is two days and half a day after a rival's price change, respectively.

Looking at the distribution of price changes in the left panel of figure 6, further interesting details become apparent. Downward (*upward*) price corrections are often assumed pro (*anti*)-competitive (Brown and MacKay, 2020). In this light, note that the distribution of price changes has a light skew towards positive price changes for very small price corrections. Further note that we find both moderate and extreme deviations in both positive and negative price changes.

[13]Figure A.2 in the Appendix depicts the time elapsed between price changes against the total number of price changes per product-seller-pair. As we can see, accounts that change prices often, also seem to change prices fast.

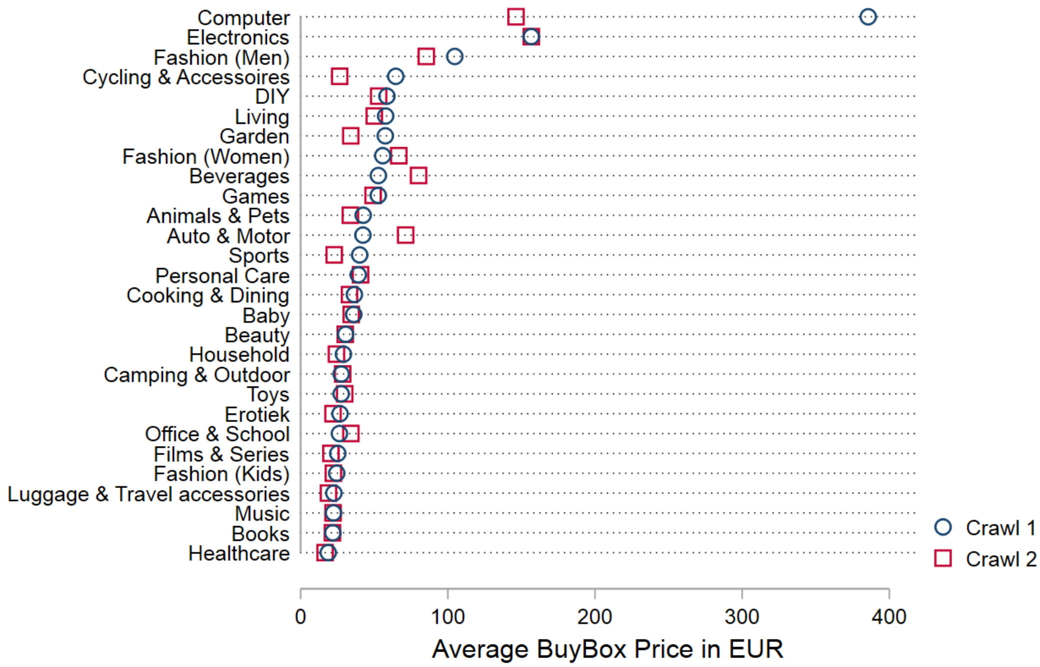


Figure 5: Average Buy Box price by category

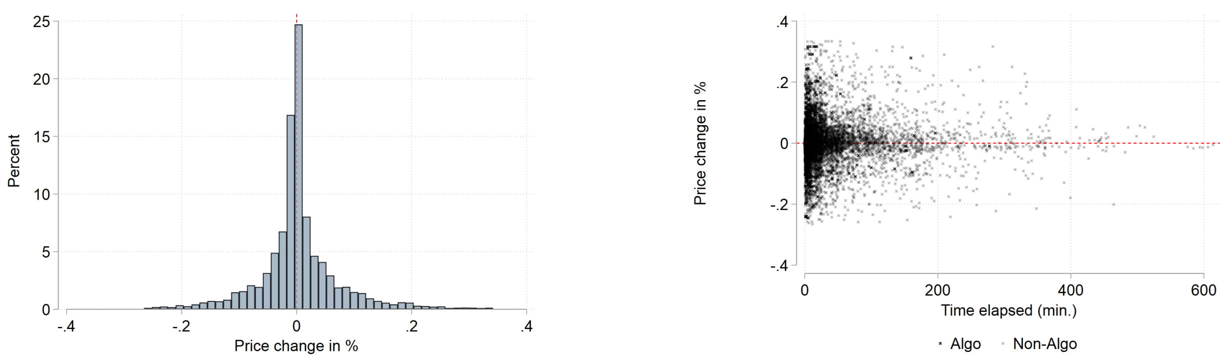


Figure 6: Distribution of price changes in percent (left) and time elapsed between price changes over value of price change in percent (right) (Crawl 1).

	Median	sd	1st	99th
Total amount of price changes per product / seller pair	9.00	36.43	2.00	143.00
Price change in EUR	-0.04	6.44	-15.00	14.01
Hours elapsed: Last own price change	48.09	104.84	1.12	466.42
Hours elapsed: Last comp. price change	12.45	47.19	0.41	234.97
N	4812			
Share of product-seller pairs with min. one price change	.50			

Table 2: Summary Statistics: Price changes for product-seller-pairs with at least one price change (Crawl 1)

We now turn to the question to identify algorithmic sellers.

5.3 Identifying Algorithmic Sellers

We do not directly observe which sellers rely on automatic pricing tools.[14] 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, 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*

[14]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.

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 5.4, 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.[15]

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: as seen in Figure 8, this criterion yields the highest number of algorithmic sellers and hence minimizes the risk of failing to label sellers as

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

algorithmic. At the same time, 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. The left panel in Figure 7 indicates that most product-seller pairs experience few price changes, if at all.[16] 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.

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. Intuitively, a seller who aims at offering the lowest price at all times would need to target the minimum price for a certain product. Such behavior therefore could be an indication of pricing algorithms being used. Following Chen et al. (2016) we investigate two reference price series: The lowest price of seller j at any point in

[16] Note that we detect algorithmic pricing on the *product-seller* level. We regard pricing as algorithmic on products where sellers apply an active, automated re-pricing strategy. But this approach also implies that a seller may have products on which it is regarded as algorithmic (where prices change often) and other products where it is labeled as non-algorithmic (with less frequent price changes). In Section 6.2 we provide robustness checks and further analysis for our definition of algorithmic sellers.

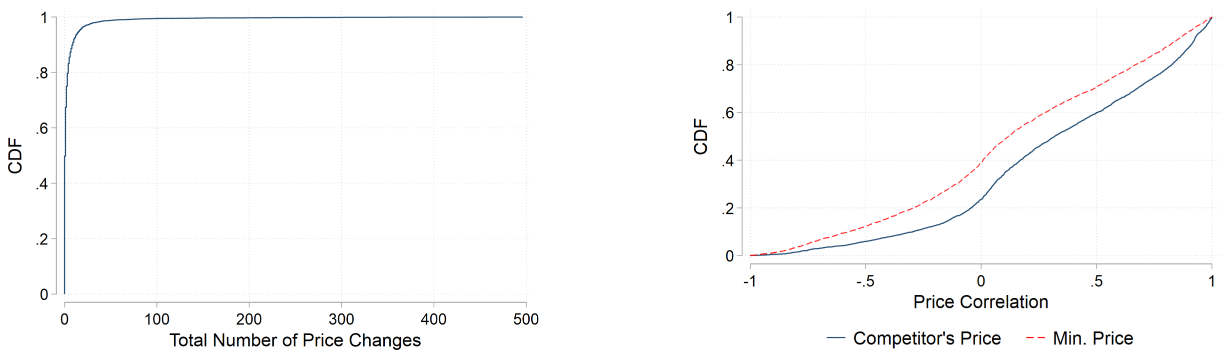


Figure 7: CDF of the number of total price changes (left) and price correlations (right).

time t for product i and the price of any competitor $k \neq j$ on the same product i. As Chen et al. (2016), if seller j is itself offering the minimum price on product i at a certain time t, we take the second lowest price as reference.

We calculate Spearman's rank correlation coefficients for each seller-product pair with the time series of the minimum price from the perspective of seller j, ρ_{ji}^{min}, as well as a correlation matrix with 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. For both the number of price changes criterion as well as the price-correlation criterion we need cut-offs that separate algorithmic sellers from traditional rivals. The right panel in Figure 7 shows the distribution of the price correlation criteria. As we can see, these distributions have no long-tail.

Figure 8 shows the number of product-seller pairs in Crawl 1 that are flagged algorithmic under different combinations of screening criteria and threshold values. The solid line in both figures represents the number of algorithmic sellers exclusively based on the number of price changes as baseline criterion. The dashed lines combine the price changes criterion with minimum price correlation (left panel) and competitors' price correlation (right panel) taking different correlation coefficients as cut-offs.

Both graphs have a *'knee'* at around 15-20 price changes per crawl. We conservatively choose 20 price changes per crawl as a threshold above which we regard a seller as algorithmic in Crawl 1. Due to the higher frequency in Crawl 2, we chose 40 price changes as the cut-off

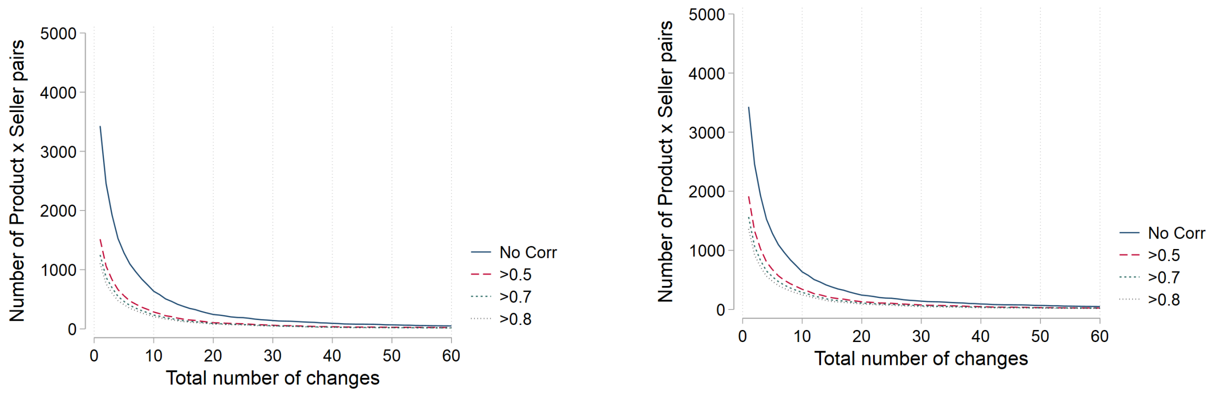


Figure 8: Number of algorithmic sellers by change threshold. Left panel: correlation with minimum price. Right panel: Correlation with rivals' price.

for the second wave of the data.[17] To further refine this measure, we combine cut-offs of the number of price changes with measures of price correlation - the minimum price and the strongest price correlation with any competitor. Following Chen et al. (2016) we choose a correlation threshold of 0.7 and confirm the sensitivity of these values in the Appendix.

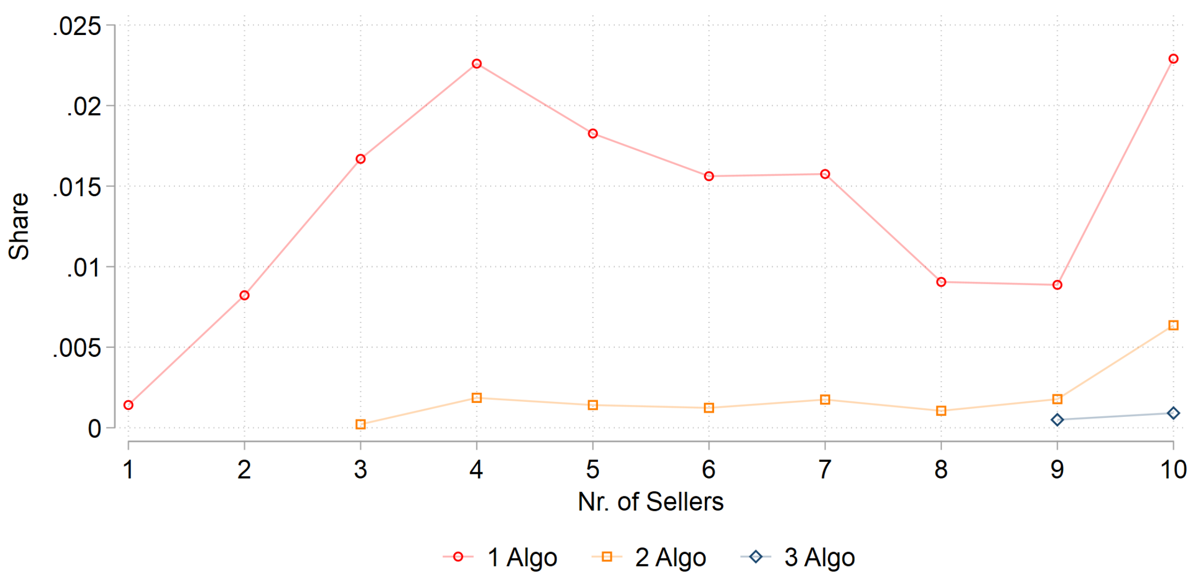


Figure 9: Share of algorithmic sellers over total number of sellers

Figure 9 shows the distribution of algorithmic sellers over the total number of sellers. For this figure we rely on the number of price changes as underlying criterion on algorithmic

[17]We chose this cutoff based on the 'knee' in Crawl 2.

pricing. We observe the highest share of algorithmic sellers for intermediate numbers of total sellers per product. 2% of our observations in the sample correspond to products with one observed algorithmic seller among four competing sellers.[18].

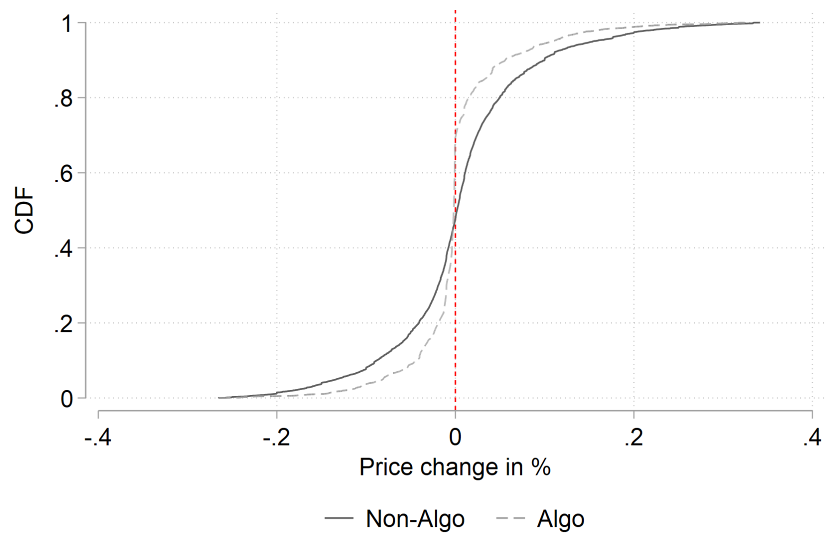


Figure 10: CDF of price changes in percent for algorithmic sellers vs. non-algorithmic sellers (Crawl 1).

In Figure 10 we depict the CDF of price changes in percent for algorithmic and non-algorithmic sellers separately. As we can see, there is more (*less*) probability mass for the algorithmic (*non-algorithmic*) sellers for positive price changes. In other words, upward price corrections are more prevalent in algorithmic seller accounts[19].

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. In Section 6.2 we provide robustness checks using other heuristics to identify algorithmic sellers.

5.4 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,

[18]The peak with ten total sellers is due to the fact that this category includes *ten or more*
[19]This finding appears to be in line with Brown and MacKay (2020).

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.[20]

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 11a).

2. **Rockets and feathers**: The price shoots up rapidly, and then gradually and slowly

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

decreases, often reaching the starting point (Figure 11b).

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 12a).

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 12b).

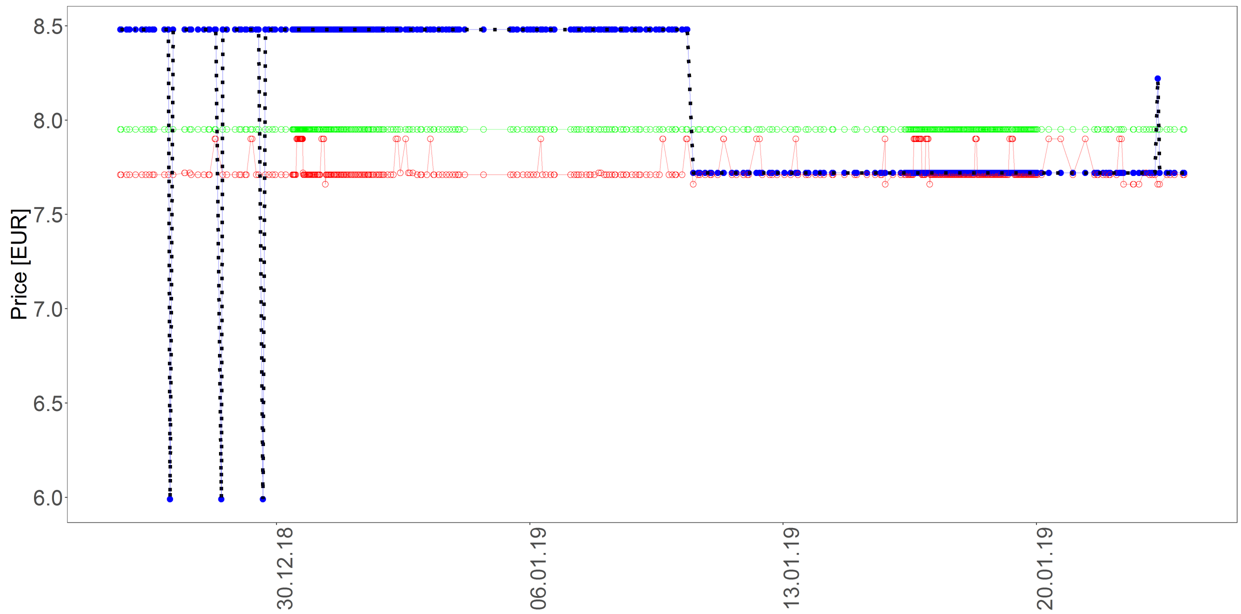
5. **Random jumps**: The price changes frequently in a seemingly random manner (Figure 13).

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.

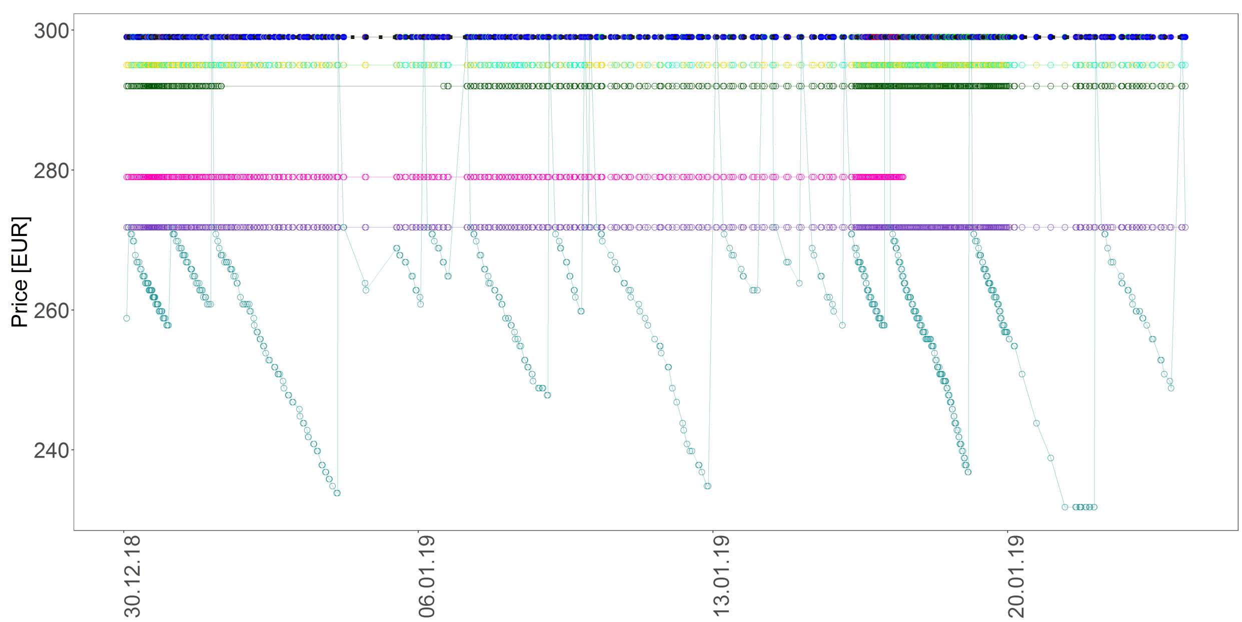
Price jitters are also documented by Chen et al. (2016) on Amazon, who conclude *"the very rapid price 'jitters' are likely caused by transient inconsistencies in Amazon's infrastructure, rather than actual price changes by sellers."*

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 and Bol, independently. Second, we observed some of the affected products over time and never encountered any inconsistencies.[21] 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

[21] 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.

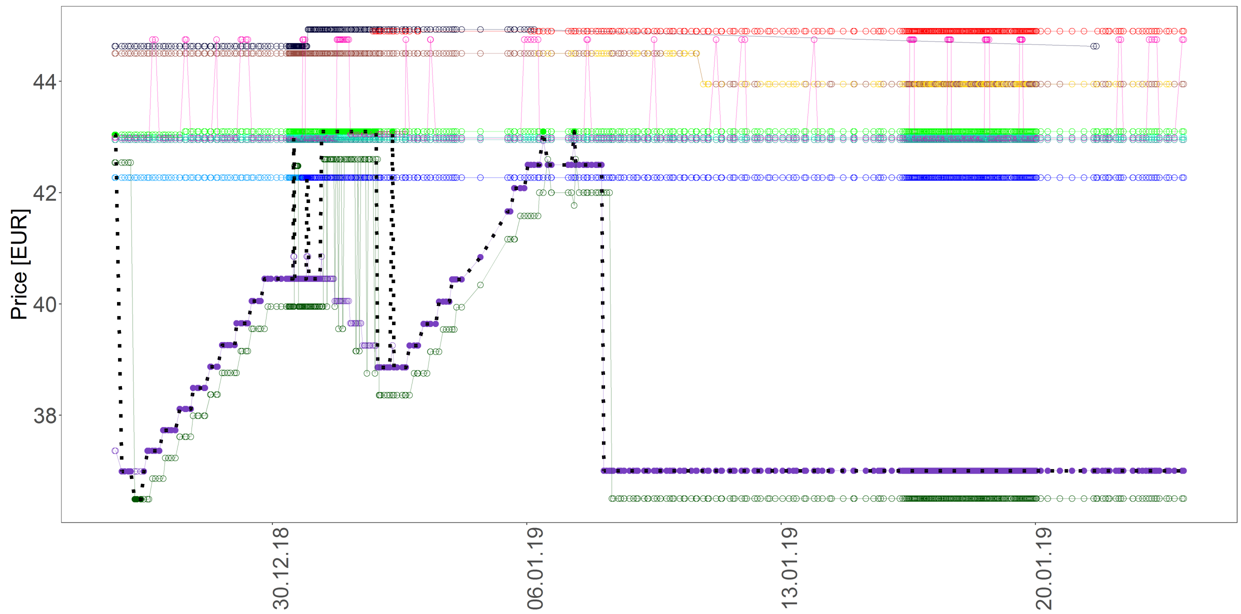


(a) Jitter up and down

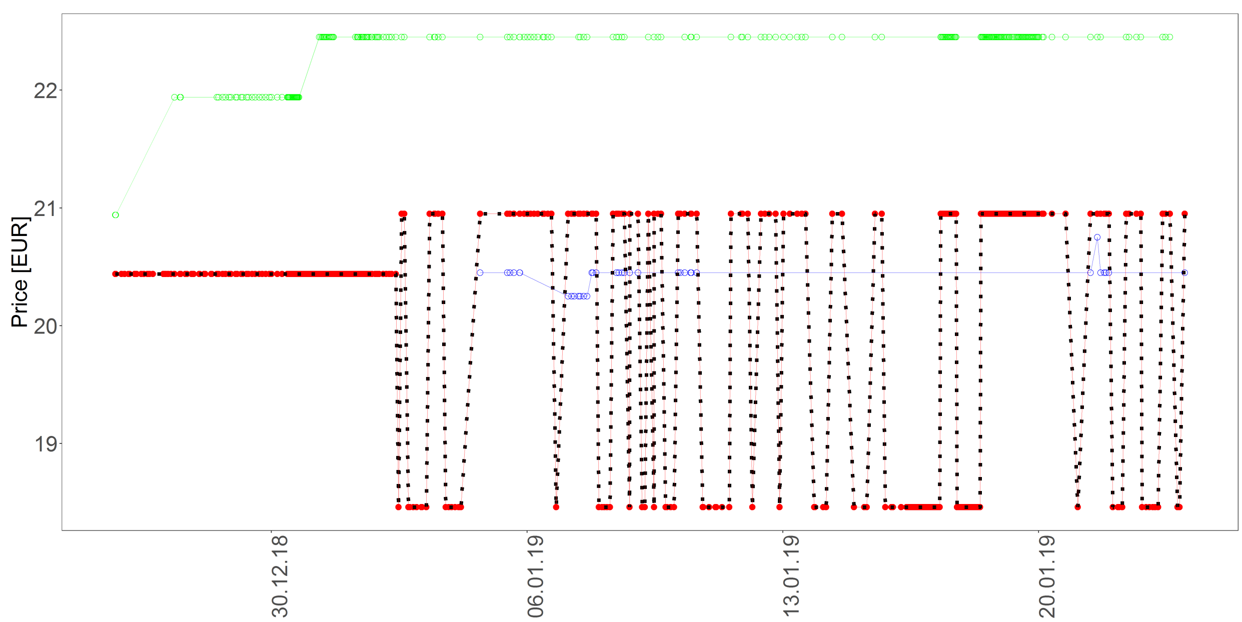


(b) Rockets and feathers

Figure 11: Sample price patterns



(a) Balloons and rocks



(b) Alternating Prices

Figure 12: Sample price patterns - continued

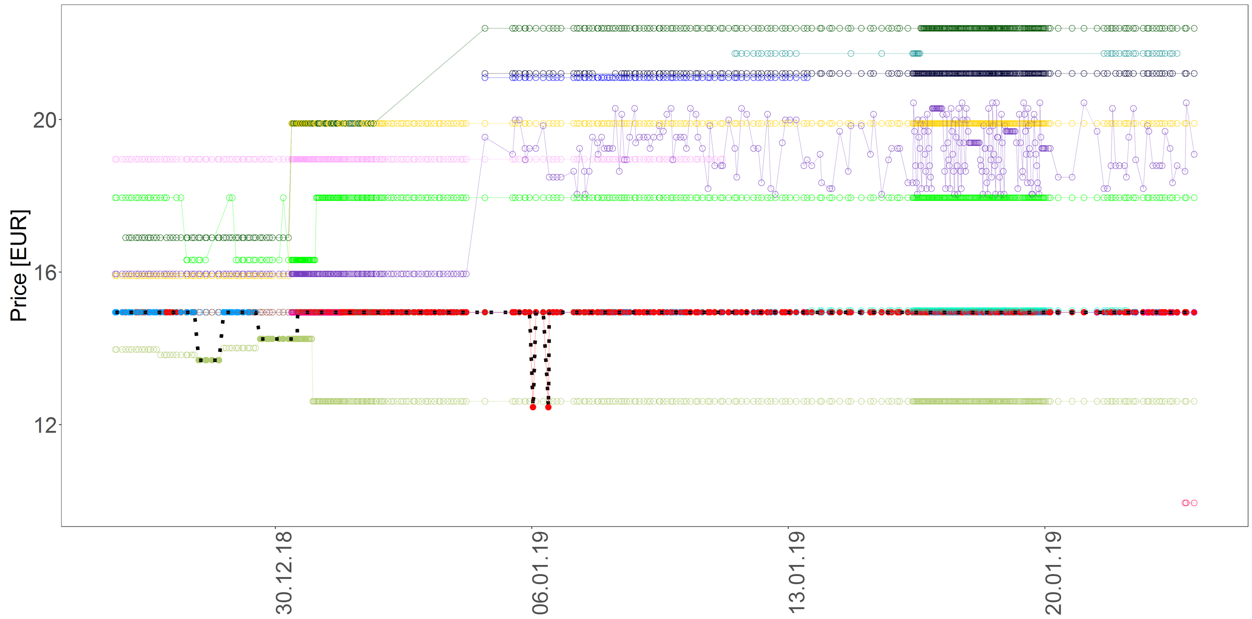


Figure 13: Sample price pattern - Random Jumps

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 deviating 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.[22]

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.[23]

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

[23]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.

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.[24] 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)).[25]

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.* 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

[24] 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.

[25] 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*).

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 12a.

In Figure 12a 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.

Algorithm 1 Dark Purple seller

Initialize $Price_t \leftarrow MC$
if *"Environment is favourable"* **then**
    if "*I Am the Buy Box Seller*" **then**
        $Price_t \leftarrow Price_{t-1} - \epsilon$
    else
        $Price_t \leftarrow Price_{t-1} + \epsilon$
    end if
else
    $Price_t \leftarrow MC$
end if

Algorithm 2 Dark Green seller

Initialize $Price_t \leftarrow MC$
if "*I Am the Buy Box Seller*" **then**
    $Price_t \leftarrow Price_{BuyBox} - \epsilon$
else
    $Price_t \leftarrow Price_{t-1}$
end if

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 12a), 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 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 12a *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 12a, 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 *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

[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.

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. In the third sub-section we examine the effects of algorithmic pricing on a seller's propensity to win the Buy Box.

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 - 2900 electric toothbrush, in double-pack."*[29] Nevertheless, sellers are somewhat differentiated,

[28] The behavior of *Dark Purple* and *Dark Green* sellers in Figure 12a 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.

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

for example in terms of 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 also 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 5.3. We further control for the seller rating scaled between 0 and 10 as well as the delivery time.

We add product-date fixed effects (i, d). The inclusion of fixed effects help 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 Box price varies by the degree of competition on a certain product, we estimate Equation 1 by looking at sub-samples cut at different levels of competition. In a similar vein, we re-estimate Equation 1 by adding interaction terms between sets of indicator variables for the total number of sellers and the number of algorithmic sellers. This allows us to delineate the average marginal effect of replacing a traditional seller with an algorithmic seller while holding the number of competitors constant.

Results

We present results on how the presence of algorithmic sellers effects the Buy Box price and how this effect changes with different degrees of competition. We measure the intensity of competition for each product by the number of sellers offering the product for sale at every given period, $N.Comp$.[30] The results are summarized in Table 4. Coefficients on the number of algorithmic sellers by the number sellers are plotted in Figure 14.

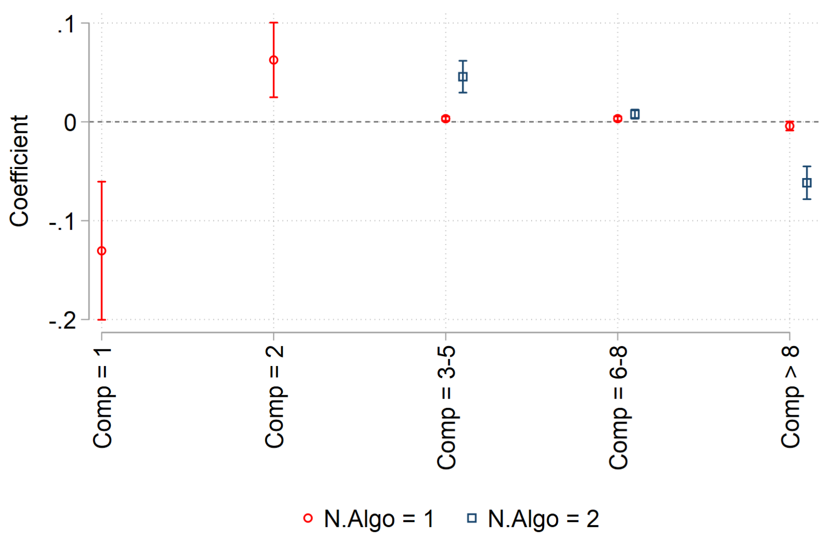


Figure 14: Buy Box Price by Subsamples. Algorithmic Pricing: Price Changes (Crawl 1).

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 number of price changes for a specific product-seller-pair. In section 6.2, we discuss results using other criteria to flag algorithmic sellers.

From the first column of Table 4, the Buy Box price decreases by 13% if the monopolist

[30] Note that this variable is top-coded and $NComp = 10$ includes 10 or more competitors.

	(1)	(2)	(3)	(4)	(5)
	Comp = 1	Comp = 2	Comp = 3-5	Comp = 6-8	Comp > 8
(1) Algorithmic Pricing: Price Changes only					
Bol comp.=1	-0.0581***	-0.228***	-0.142***	-0.0796***	-0.145***
	(-3.31)	(-12.42)	(-33.46)	(-18.65)	(-26.94)
N.Algo=1	-0.130***	0.0626**	0.00322**	0.00327**	-0.00420
	(-3.66)	(3.25)	(2.85)	(2.89)	(-1.81)
N.Algo=2			0.0457***	0.00780***	-0.0616***
			(5.56)	(3.34)	(-7.28)
Rating	-0.0213	0.00112	-0.0122***	0.00738*	-0.0268***
	(-0.50)	(0.55)	(-5.88)	(2.11)	(-4.63)
Deliverytime	0.00275***	-0.000164	-0.00105***	0.00217***	-0.00462***
	(3.84)	(-1.12)	(-3.31)	(3.67)	(-5.03)
Constant	3.773***	3.513***	3.527***	3.367***	3.513***
	(10.02)	(170.83)	(189.14)	(107.90)	(68.66)
N	104981	156384	317755	99307	73527
R2	1.000	1.000	1.000	1.000	0.999
ProductxTime FE	Y	Y	Y	Y	Y
Algo	Changes	Changes	Changes	Changes	Changes

t statistics in parentheses

Dependent Variable: Bbox Price. Robust SE. Crawl

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

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

seller is algorithmic, compared to the case of a traditional seller acting in the same position. This effect is larger in magnitude but preserved if we also incorporate price correlation with competitors into our measure of algorithmic pricing.[31]

The finding that pricing algorithms reduce prices by around 13% in monopoly markets is surprising, novel and deserves explanation. It stands in strong contrast with 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

[31] In the Appendix we show the sensitivity to this coefficient over different thresholds with both the number of price changes and the correlation coefficient with rivals' prices. In Figure A.9, we see that the coefficient further increases if our measure of algorithmic prices becomes *more* conservative, requiring higher correlation and more price changes. As such, we rather under- than overestimate effects on the Buy Box price.

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.6 and A.7 in the Appendix). If anything, algorithmic sellers are slightly over-represented in middle price ranges. 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.[32] 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.[33] 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

[32]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.

[33]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`, 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."*

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 monopoly level. This is a downward adjustment, as we find, if humans initially set these prices excessively high.[34] 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.3). 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 competitive products. In column 2, we present effects for duopoly products. One algorithmic seller competing with a traditional rival is associated with a 6% increase in the Buy Box price.

Interestingly, for intermediate levels of competition (3-5 sellers), we find that the Buy Box price is only very mildly affected if a single seller is algorithmic, but increases to 4%

[34]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.*"

if two algorithmic sellers are present. This finding is compatible with tacit collusion: with 3-5 sellers in the market, algorithms benefit from each other's presence, resulting in a higher Buy Box price.

The price increase due to two algorithmic sellers remains preserved, but becomes smaller with 6-8 competitors. Finally, as the total number of competitors increases to eight or more, two algorithms in the market go hand-in-hand with a significant price reduction. To sum up, consistently with tacit collusion, with medium number of competitors two algorithmic agents in the market lead to increased Buy Box prices. With a high number of rivals, algorithmic sellers compete fiercely, reducing the Buy Box prices.

In a similar vein, we re-estimate Equation 1 using an interaction term between the number of algorithmic sellers, $N.Algo$, and the number of sellers, $N.Comp.$ for product i in time t. In Figure A.8, we plot the average marginal effects from this interaction term. Results confirm previous results form the analysis by sub-samples discussed earlier as we see the largest increase in Buy Box prices for an intermediate amount of sellers, once two algorithmic sellers are present.

We sum up our findings regarding the effect of algorithmic agents on the Buy Box price in competitive markets. We document that, *ceteris paribus*, algorithmic pricing may be associated with a higher Buy Box price. This is particularly the case when two algorithmic agents meet in markets with intermediate competition ($4-6$ sellers) relative to a situation with traditional sellers only. In contrast, we find that algorithmic monopolies see on average lower prices than a traditional equivalent. Overall, this amounts to an inverted-U shaped relationship between Buy Box price and competition when algorithmic sellers are present.

6.2 Robustness and Further Checks

Before moving on to the analysis of how algorithmic pricing affects the probability to win the Buy Box, we conduct several robustness checks to validate our results on prices. We look at alternative ways to flag algorithmic sellers, confirm our results with the second crawl of our data and change the dependent variable into percentage margins above the all-time minimum price for a product.

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 the analysis so far, we flagged a specific *product-seller*-combination algorithmic if prices changed sufficiently often. As a further refinement, we now add price correlations with competing sellers to the number of price changes, as discussed in section 5.3. Doing so results in a labeling product-seller pairs as algorithmic if prices change often *AND* closely follow competitors. Analogous to Table 4, Table 5 repeats the analysis of the previous section.

The main results remain robust to including price correlations in defining algorithmic pricing. The inverted-U shaped relationship remains intact. For an intermediate degree of competition (3-5 sellers), we see Buy Box prices increasing by around 4%. The result that algorithmic prices are lower than *human prices* in single-seller products also prevails. With very intense competition (8 sellers or more), Buy Box prices are lower if algorithmic agents are present.

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 *product-seller* level. For example, the same seller may be labeled algorithmic on some products, but not on others. One may argue that a seller with access to re-pricer software should be regarded as algorithmic on all products, not just on those where prices change sufficiently fast or in line with rivals. We address this concern by robustness checks repeating much of the above analysis by defining a seller as algorithmic on all of her products, if she behaves as algorithmic (i.e. changes prices sufficiently often) on one product.

In essence, this analysis changes the composition of the control group. When defining algorithmic pricing on a product-seller-level, the (algorithmic) treatment group so far included only products of sellers where prices change often. The (non-algorithmic) control

	(1) Comp = 1	(2) Comp = 2	(3) Comp = 3-5	(4) Comp = 6-8	(5) Comp > 8
(2) Algorithmic Pricing: Price Changes and Price Corr. with Comp.					
Bol comp.=1	-0.0586***	-0.232***	-0.142***	-0.0796***	-0.147***
	(-3.38)	(-12.06)	(-33.45)	(-18.65)	(-27.01)
N.Algo=1	-0.184***	0.0300	-0.00364*	-0.00293**	-0.0161***
	(-6.70)	(1.47)	(-2.32)	(-2.64)	(-3.34)
N.Algo=2			0.0396***	-0.00291*	-0.0237**
			(7.59)	(-2.48)	(-2.96)
Rating	-0.0214	0.00175	-0.0122***	0.00725*	-0.0270***
	(-0.50)	(0.80)	(-5.86)	(2.07)	(-4.66)
Deliverytime	0.00275***	-0.000159	-0.00110***	0.00209***	-0.00436***
	(3.83)	(-1.08)	(-3.47)	(3.53)	(-4.74)
Constant	3.774***	3.513***	3.528***	3.370***	3.513***
	(10.02)	(169.97)	(189.22)	(108.01)	(68.61)
N	104981	156384	317755	99307	73527

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Dependent Variable: Log Buy Box Price.

Table 5: Buy Box Price by Subsamples (Crawl 1)

group in turn included 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.

In this robustness check we take as treatment group all products of sellers who have one product with frequent price changes. The control group in turn consists of only products of sellers who set relatively stable prices on all their products. Extending the definition of algorithmic pricing to a seller-wide level shifts products with algorithmic sellers setting stable prices into the treatment group. This latter group of products is large, as shown in Table 6.

Table 6 displays the number of distinct product-seller pairs for different *levels* of definitions for algorithmic pricing.[35] The first column counts the number of products-seller pairs

[35] The underlying cut-off is unchanged at 20 price changes to flag a product-seller combination algorithmic.

	(1)	(2)	(3)
Product-Seller Pairs	243	4,455	4,212

Table 6: Number of Product-Seller pairs at different levels of algo. price definitions. (1) Product-seller pair definition of algorithmic pricing, (2) Seller-level definition of algorithmic pricing, (3) Product-seller pairs with evidently algorithmic sellers and few price changes.

that see many price changes and are accordingly flagged algorithmic. The second columns contains the number of product-seller pairs if the seller behaves *algorithmic* on at least one other product. The third column is a subset of the second column, including only products where the algorithms sets stable prices.

Note that columns 2 and 3 are similar in size and large compared to column 1. When applying a seller-wide definition of algorithmic pricing, the treatment (*algorithmic*) group contains a large number of products for which prices change only few times.

Along these lines, we run two further tests. First, we flag sellers algorithmic if they apply algorithmic pricing on at least one of their products. This incorporates the idea that once a seller subscribes to re-pricer software, re-pricing capability in principle applies to all products of the seller.

The results are presented in Table A.2. It is worth noting that this definition of algorithmic sellers is broader, and flags more sellers as algorithmic. We now have up to 8 competing algorithmic sellers per product. The reason is that the new algorithmic seller definition includes also products where prices do not change particularly often, and there are many sellers who set such - relatively stable - prices on some products.

The main insight from Table A.2 is that algorithmic sellers under this definition are not associated with higher Buy Box prices. We investigate further why this is the case.

To do so, we inspect how results change in a further comparison, looking at the subset of algorithmic sellers with relatively stable prices and contrasting them to sellers who never set algorithmic prices (i.e. prices are relatively stable on *ALL* products). This compares sellers who *cannot* set algorithmic prices (e.g. because they do not use a re-pricer software) with sellers who *choose not to* set algorithmic prices on some products, whereas they can and do so on other products. As we can see in Table A.3, algorithmic sellers in this comparison do not yield higher Buy Box prices than those sellers who always set stable prices.

We consider this an important result: On products where sellers with algorithmic-capabilities *choose* not to change prices frequently, the prices of algorithmic sellers are not higher than those of non-algorithmic rivals. This insight is important, because it implies that 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.

The fact that on products with relatively stable prices algorithmic sellers are not associated with higher prices than non-algorithmic rivals also explains why in Table A.2 most coefficients turn out insignificant: Adding a very large group of products to the treatment group where prices are similar to those in the control group dilutes the effect of algorithmic agents. The latter unfolds primarily on the relatively small subset of products where these algorithmic sellers change prices frequently. Since our aim is to *screen* for potentially harmful algorithmic pricing, we conclude that the comparison on the product-seller level in Section 6 is informative and relevant.

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 and estimate the equation by subsamples cut at the level of competition.

Results in Table A.8 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 40%. Under intermediate competition, margins above the minimum price increase particularly strongly if there are two algorithmic sellers competing.[36]

Second Crawl

To verify that our results obtained in Crawl 1 remain preserved over time, we repeat the main analysis in the second crawl of our dataset, obtained approximately a year after Crawl 1. Table A.4 is the counterpart to Table 4 using the second crawl of the data. As in Crawl 1, we find strong price increases for products under the presence of algorithmic sellers. Notably, in duopolies of two algorithmic sellers, the Buy Box price is 6% more expensive compared to the counterfactual of a non-algorithmic duopoly.

Note that we do not have sufficient observations to include single-seller products in Crawl 2. The reason is, as explained in Section 5.1, that Crawl 2 includes the same products as Crawl 1, and the initially single-firms products saw entry in the year that elapsed between the two crawls.

Overall, the main results reported based on Crawl 1 prevail in Crawl 2: algorithmic sellers tend to be associated with higher prices under medium competition. While there is some indication of lower algorithmic prices with a high number of algorithmic sellers, overall increased algorithmic prices emerge even stronger in Crawl 2 than in Crawl 1.

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

6.3 Algorithmic Pricing and 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 (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.[37] We provide a detailed econometric analysis to investigate this hypothesis on Bol.com.

We test the hypothesis that algorithmic sellers are more likely to win the Buy Box than traditional rivals by estimating 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.[38]

Variable Bol indicates whether the platform operator *Bol.com* is competing for product i. Most importantly, variable $Algo$ indicates whether seller j is tagged algorithmic for product i according to the criteria described in section 5.3.

We aim at isolating the effect of algorithmic pricing from a different number of sellers competing. Hence, again, variable $NComp$ counts the number of competitors offering product i at time t. Other controls $\mathbf{X}$ that vary with the product, seller and time include *seller rating* and *delivery time*.

We estimate Equation 3 using a probit-specification. To ensure that results are not biased by unobserved seller and product heterogeneity, we also rely on a linear probability specification and include a set of product, date and seller fixed effects.

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

[38] We log-transform because prices are highly left-skewed.

Results

Table A.1 presents the results for the first crawl for Equation 3. As before, specifications 1 to 3 differ in the criteria used to define algorithmic sellers: The number of price changes only (1), the number of price changes plus correlation with competitors' prices (2) and the number of price changes combined with the correlation with the minimum price (3).

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. This result is robust for different measures of algorithmic pricing shown across columns.

We can also confirm a general competition on the Buy Box as the probability of winning decreases with the number of competitors. Moreover, keeping the number of firms in the market fixed, *Bol*'s presence as competitor *reduces* the probability of winning the Buy Box. Our results remain intact also in the data from the second crawl (see Table A.5 in the Appendix).

In the last three columns of Table A.1 we can confirm our results from the probit-specification in a linear model. In the linear probability specification we can also rely on a set of product-, seller- and date-specific fixed effects in order to control for unobserved heterogeneity beyond prices, delivery times and the seller rating.

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 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 over the number of sellers per product. This is shown in Figure 15, for different criteria used to define sellers as algorithmic.

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 20 to 25 percentage points compared to being a non-algorithmic seller in a similar duopoly market. This result is very robust across different definitions of algorithmic pricing, as shown in the three panels in Figure 15.

Moving further right on the horizontal axis, 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 10 percentage points.[39]

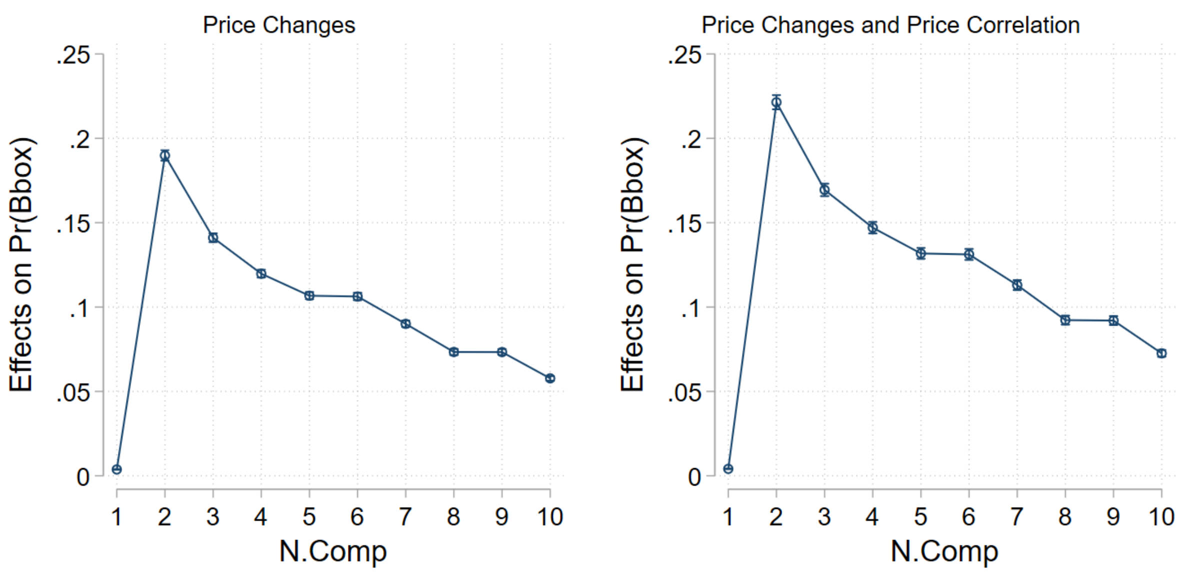


Figure 15: Probit Marginal Effects - Algorithmic seller winning the Buy Box over the number of competitors and different measures of algorithmic pricing. Left: Price changes only, Right: Price changes and comp. price correlation.

[39]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.

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).

Chen et al. (2016) also report that algorithmic sellers on Amazon appear more likely to win the Buy Box than traditional retailers. However, they explain this phenomenon by algorithmic sellers winning *"due to their feedback and sales volume."* Unlike Chen et al. (2016), we also control for rating, delivery time and a battery of product, date and seller-specific fixed effects. The fact that the coefficient for $Algo$ emerges as significant and positive in all specifications suggests that the success of algorithmic sellers to win the Buy Box is due to genuine reasons related to algorithmic pricing, beyond rating and delivery conditions.

Algorithmic sellers winning the Buy Box more often than traditional rivals is in isolation not a concern for public policy. However, it shows that algorithmic pricing deserves disproportionate attention, because consumers are exposed to the prices set by algorithmic agents disproportionately often. Combined with the finding in the previous sections that under certain circumstances algorithmic sellers are associated with higher prices, these sellers increasingly occupying the Buy Box calls for awareness from policy makers. In such cases consumers may be harmed not only by higher algorithmic prices, but also by facing such inflated prices more prominently displayed, as algorithmic sellers' increasingly occupy the Buy Box.

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 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)).[40] 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 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 13, which we observe in just 11% of affected (algorithmic) products. This pattern may indicate algorithms being *trained* as sellers experiment with different prices.

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

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 12a 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.[41] The Dark Green seller in Figure 12a 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 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

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

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: The Buy Box for an example product

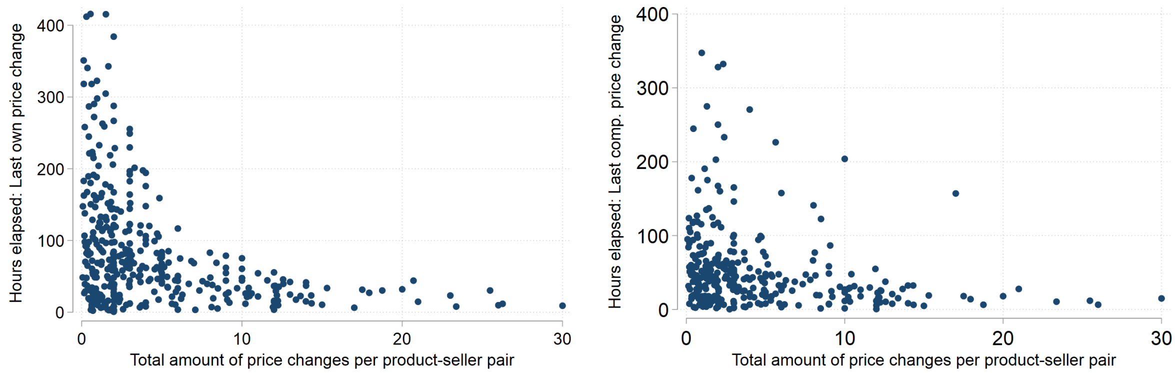

Figure A.2: Total price changes versus hours elapsed after last own (left panel) and competitor's price change (right panel) - Data from Crawl 1. Observations shown below the 99th percentile in both time elapsed and number of price changes.

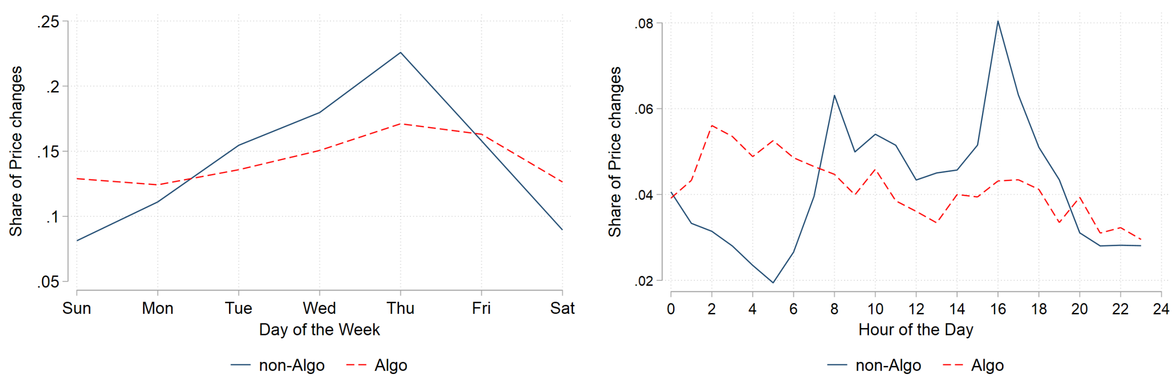

Figure A.3: Share of Price Changes by Weekday and Hour of the Day in all for Algorithmic versus Non-Algorithmic Price Changes. Product-Seller-pairs are flagged algorithmic if we document more than 20 price changes. Data from Crawl 1.

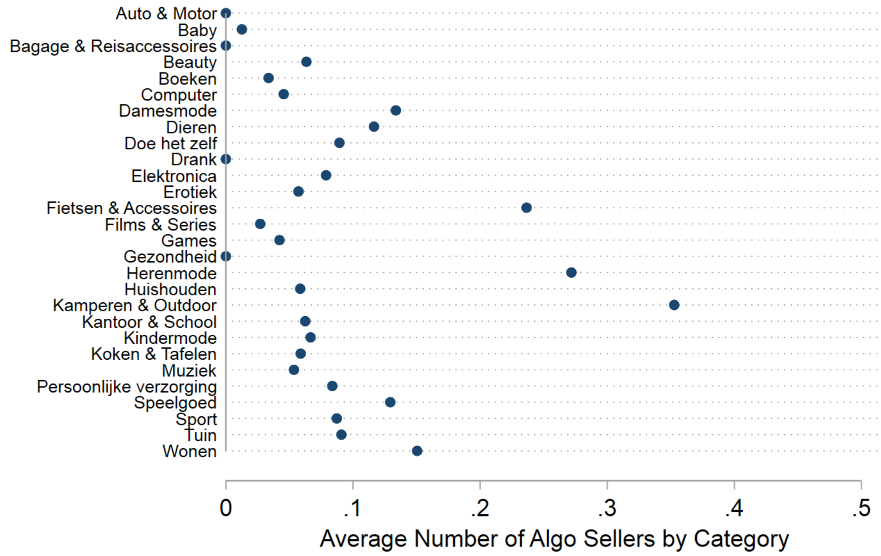

Figure A.4: Number of algorithmic sellers by Product and Product Category. Product-Seller-pairs are flagged algorithmic if we document more than 20 price changes. Data from Crawl 1.

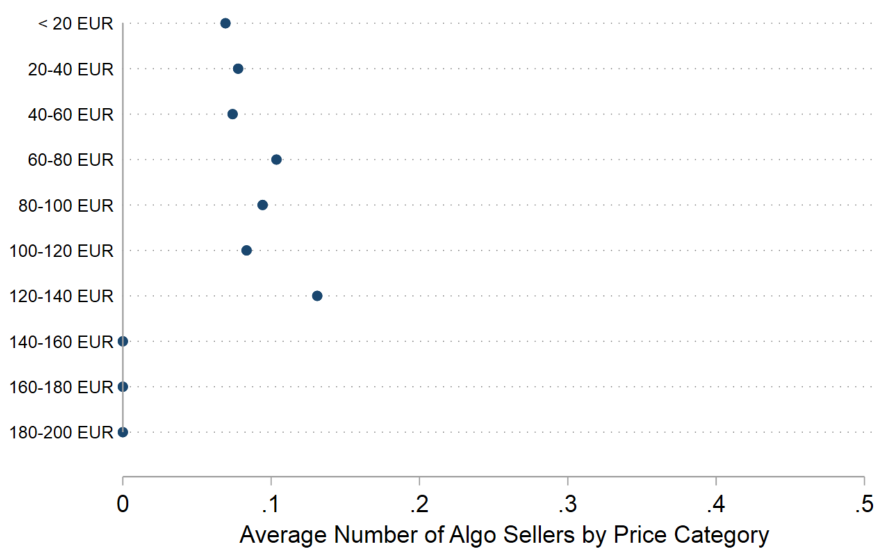

Figure A.5: Number of algorithmic sellers by Product and Price Category. Product-Seller-pairs are flagged algorithmic if we document more than 20 price changes. Data from Crawl 1.

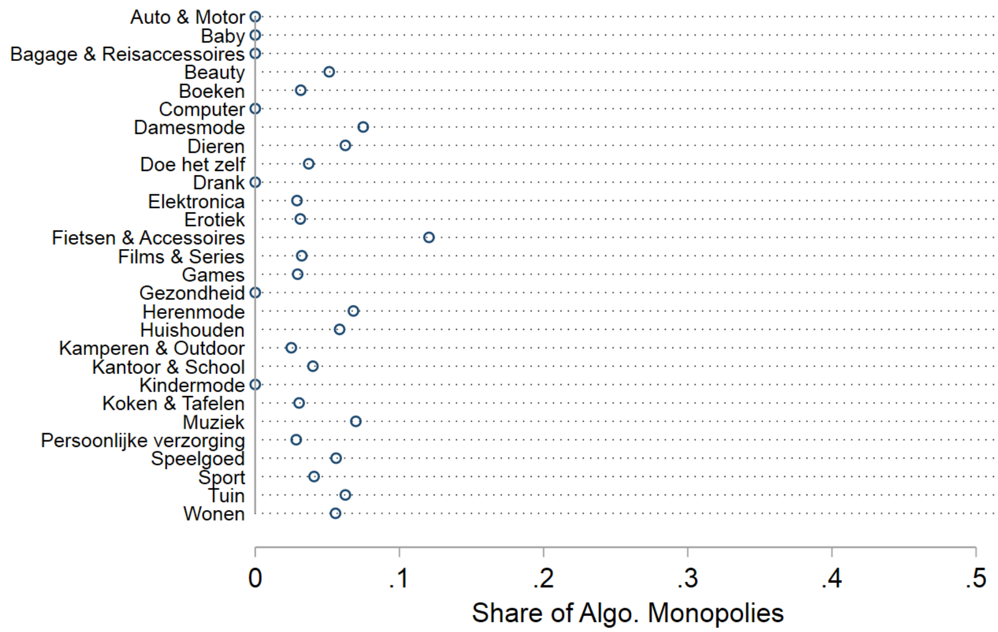

Figure A.6: Share of Algorithmic Monopolies by Product Category. Product-Seller-pairs are flagged algorithmic if we document more than 20 price changes. Data from Crawl 1.

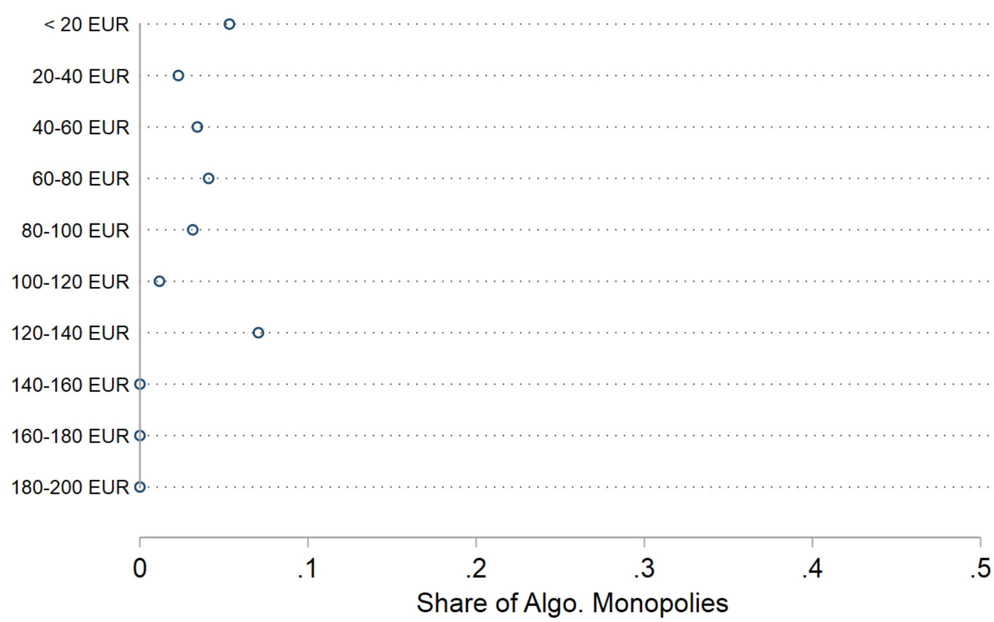

Figure A.7: Share of Algorithmic Monopolies by Buy Box Price. Product-Seller-pairs are flagged algorithmic if we document more than 20 price changes. Data from Crawl 1.

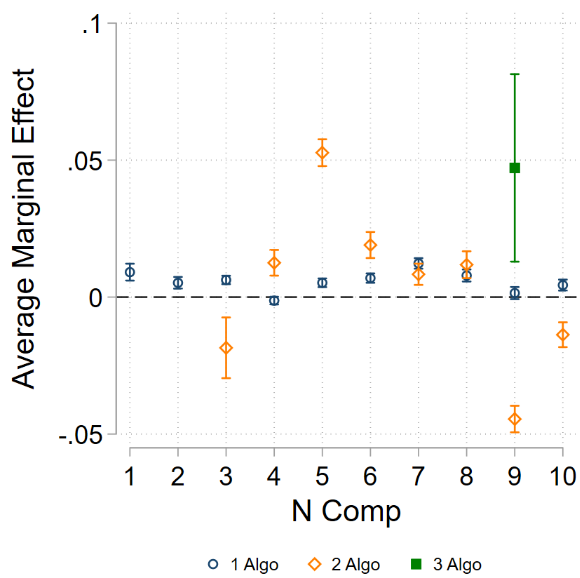

Figure A.8: Average Marginal Effects on the Buy Box Price over the total number of sellers per product using price changes only (left) and price changes with rivals' price correlations (right) as measures for algorithmic pricing.

	Probit			LPM		
	(1)	(2)	(3)	(4)	(5)	(6)
Bol comp.=1	-1.363***	-1.354***	-1.360***	-0.180***	-0.181***	-0.181***
	(-448.54)	(-447.85)	(-449.91)	(-191.15)	(-191.21)	(-191.19)
Rating	0.220***	0.216***	0.222***	0.00279**	0.00253**	0.00306***
	(58.76)	(57.84)	(59.45)	(3.00)	(2.73)	(3.30)
Price (Log)	0.00509***	0.0111***	0.00875***	-0.337***	-0.339***	-0.333***
	(3.69)	(8.08)	(6.35)	(-172.20)	(-172.58)	(-170.76)
Deliverytime	-0.0931***	-0.0945***	-0.0950***	-0.0103***	-0.0106***	-0.0104***
	(-170.33)	(-172.98)	(-173.87)	(-107.94)	(-110.62)	(-109.23)
Algo=1	0.649***	0.751***	0.824***	0.145***	0.216***	0.261***
	(126.73)	(107.73)	(105.87)	(82.77)	(82.31)	(93.98)
N.Comp=2	-4.414***	-4.435***	-4.441***	-0.553***	-0.554***	-0.553***
	(-177.02)	(-176.54)	(-176.51)	(-227.65)	(-227.27)	(-226.69)
N.Comp=3	-4.876***	-4.884***	-4.884***	-0.655***	-0.656***	-0.655***
	(-194.99)	(-193.89)	(-193.62)	(-272.16)	(-271.54)	(-270.85)
N.Comp=4	-5.098***	-5.093***	-5.095***	-0.692***	-0.694***	-0.693***
	(-203.33)	(-201.63)	(-201.40)	(-283.59)	(-282.97)	(-282.61)
N.Comp=5	-5.219***	-5.217***	-5.226***	-0.716***	-0.718***	-0.717***
	(-207.40)	(-205.80)	(-205.90)	(-288.15)	(-287.49)	(-287.29)
N.Comp=6	-5.270***	-5.268***	-5.282***	-0.721***	-0.723***	-0.722***
	(-208.64)	(-207.04)	(-207.30)	(-284.48)	(-283.83)	(-283.46)
Constant	2.631***	2.668***	2.635***	2.073***	2.083***	2.060***
	(61.18)	(62.00)	(61.13)	(191.98)	(192.90)	(191.01)
N	2553536	2553536	2553536	2553519	2553519	2553519
FE				Y	Y	Y
Algo	Changes	Comp.	Min.	Changes	Comp.	Min.

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Dependent variable: Seller own the Buy Box (binary)

Table A.1: Winning the Buy Box (Crawl 1)

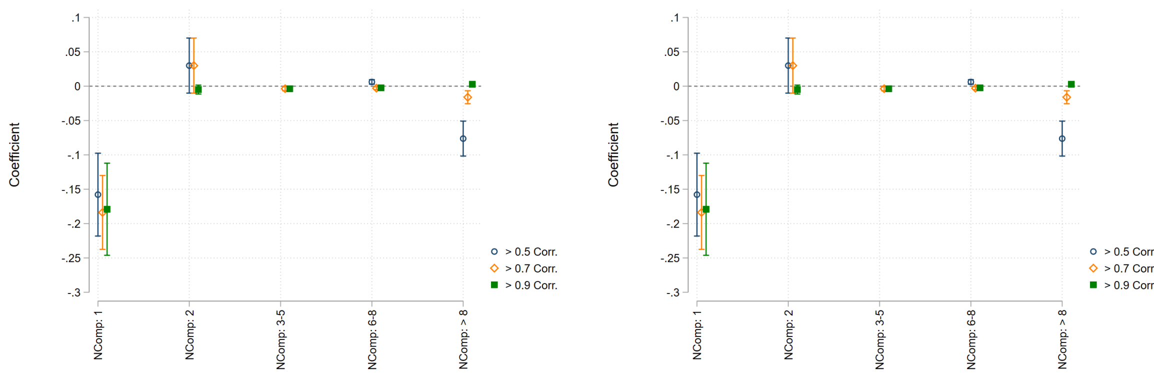

Figure A.9: Sensitivity - Coefficients on N.Algo = 1 by Subsamples over different thresholds of total *price changes* (left) and *price correlations* (right).

	(1) Comp = 1	(2) Comp = 2	(3) Comp = 3-5	(4) Comp = 6-8	(5) Comp > 8
(1) Algorithmic Pricing: Price Changes only					
Bol comp.=1	-0.0557**	-0.240***	-0.141***	-0.0815***	-0.104***
	(-2.85)	(-11.84)	(-33.03)	(-17.95)	(-18.13)
N.Algo=1	0.00901	0.0224	0.00352	0.00226	-0.169***
	(0.59)	(1.82)	(1.32)	(0.50)	(-21.58)
N.Algo=2		0.0188	0.00549*	0.00323	-0.163***
		(1.48)	(2.15)	(0.68)	(-18.02)
N.Algo=3			0.00302	0.00751	-0.138***
			(0.95)	(1.64)	(-13.83)
N.Algo=4			-0.0374***	0.0141**	-0.135***
			(-6.52)	(3.01)	(-13.62)
N.Algo=5			-0.0389***	0.00820	-0.143***
			(-6.77)	(1.66)	(-14.38)
N.Algo=6				0.00792	-0.139***
				(1.57)	(-13.75)
N.Algo=7				-0.00421	-0.236***
				(-0.70)	(-12.35)
Rating	-0.0174	0.00243	-0.0128***	0.00758*	-0.0378***
	(-0.40)	(1.10)	(-5.85)	(2.16)	(-6.48)
Deliverytime	0.00276***	-0.000175	-0.000947**	0.00232***	-0.00382***
	(3.78)	(-1.19)	(-2.99)	(3.92)	(-4.44)
Constant	3.733***	3.498***	3.529***	3.362***	3.712***
	(9.85)	(151.01)	(176.45)	(106.72)	(71.12)
N	104981	156384	317755	99307	73527
R2	1.000	1.000	1.000	1.000	0.999
ProductxDate FE	Y	Y	Y	Y	Y
Algo	Changes	Changes	Changes	Changes	Changes

t statistics in parentheses

Dependent Variable: Log Buy Box Price. Robust SE.

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

Table A.2: Log. Buy Box Price by sub-samples with alternative algo. definition (Data from Crawl 1). Seller accounts are documented algorithmic if they meet our criteria on at least one of the product offered.

	(1)	(2)	(3)	(4)	(5)
	Comp = 1	Comp = 2	Comp = 3-5	Comp = 6-8	Comp > 8
Bol comp.=1	-0.0757***	-0.218***	-0.137***	-0.0814***	-0.112***
	(-3.81)	(-11.60)	(-32.30)	(-17.84)	(-18.62)
N.Algo=1	0.0190	-0.0119	-0.00293	0.00208	-0.119***
	(1.22)	(-1.12)	(-0.86)	(0.65)	(-13.84)
N.Algo=2		-0.0136	0.000800	0.00512	-0.103***
		(-1.26)	(0.24)	(1.43)	(-10.42)
N.Algo=3			-0.0175***	0.00640	-0.0800***
			(-4.94)	(1.81)	(-7.64)
N.Algo=4			-0.0559***	0.0147***	-0.0790***
			(-8.81)	(3.92)	(-7.58)
N.Algo=5			-0.0575***	0.00303	-0.0782***
			(-9.04)	(0.68)	(-7.41)
N.Algo=6				0.00275	-0.0723***
				(0.60)	(-6.73)
N.Algo=7				-0.00928	-0.158***
				(-1.67)	(-8.10)
Rating	-0.0149	0.00246	-0.0135***	0.00563	-0.0388***
	(-0.34)	(1.46)	(-6.14)	(1.66)	(-6.54)
Deliverytime	0.00277***	-0.0000942	-0.000976**	0.00256***	-0.00214*
	(3.83)	(-0.64)	(-3.07)	(4.22)	(-2.41)
Constant	3.713***	3.507***	3.535***	3.379***	3.670***
	(9.67)	(170.83)	(176.01)	(110.40)	(68.47)
N	103218	155267	316887	99307	73527
R2	1.000	1.000	1.000	1.000	0.999
ProductxTime FE	Y	Y	Y	Y	Y
Algo	Changes	Changes	Changes	Changes	Changes

t statistics in parentheses

Dependent Variable: Bbox Price. Robust SE. Crawl

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

Table A.3: Log. Buy Box Price by sub-samples with alternative algo. definition (Data from Crawl 1). Seller accounts are documented algorithmic if they meet our criteria on at least one of the product offered - but we drop those products where they actively set prices.

	(1)	(2)	(3)	(4)
	Comp = 2	Comp = 3-5	Comp = 6-8	Comp > 8
Bol comp.=1	-0.142***	-0.141***	-0.141***	-0.116***
	(-48.33)	(-131.64)	(-84.71)	(-57.03)
Rating	0.000549	-0.00362***	0.00292*	-0.0123***
	(0.68)	(-6.77)	(2.32)	(-4.93)
Deliverytime	0.000589***	-0.000226***	0.000422**	-0.000292
	(9.54)	(-4.42)	(3.28)	(-1.45)
NAlgo=1	0.00213	0.00452***	0.00971***	0.0247***
	(0.90)	(7.49)	(10.00)	(17.64)
NAlgo=2	0.0677***	0.00313**	0.0230***	0.0239***
	(5.59)	(3.23)	(14.34)	(7.81)
NAlgo=3		-0.00805***	0.0202***	0.00719
		(-3.97)	(5.62)	(0.86)
NAlgo=4		-0.00251	0.0220***	0.000932
		(-0.82)	(5.37)	(0.11)
Constant	3.397***	3.260***	3.199***	3.299***
	(473.03)	(686.81)	(287.39)	(153.11)
N	1378695	2405856	702887	371426
R2	1.000	0.999	0.999	0.999
ProductxTime FE	Y	Y	Y	Y
Algo	Changes	Changes	Changes	Changes

t statistics in parentheses

Dependent Variable: Log. Bbox Price. Robust SE.

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

Table A.4: Buy Box Price by sub-samples (Crawl 2)

	Probit			LPM		
	(1)	(2)	(3)	(4)	(5)	(6)
Bol comp.=1	-0.271***	-0.260***	-0.263***	-0.0355***	-0.0355***	-0.0343***
	(-323.44)	(-303.98)	(-299.52)	(-114.20)	(-114.20)	(-111.81)
Rating	-0.236***	-0.246***	-0.227***	-0.0276***	-0.0276***	-0.0259***
	(-356.13)	(-366.99)	(-327.48)	(-221.87)	(-221.87)	(-206.85)
Price (Log)	-0.0148***	-0.00315***	-0.00538***	-0.00914***	-0.00914***	-0.00531***
	(-29.23)	(-6.01)	(-9.95)	(-17.26)	(-17.26)	(-9.89)
Deliverytime	-0.0364***	-0.0396***	-0.0383***	-0.00522***	-0.00522***	-0.00470***
	(-209.22)	(-221.29)	(-207.89)	(-158.72)	(-158.72)	(-141.32)
Algo=1	0.292***	0.199***	0.448***	0.00356***	0.00356***	0.0763***
	(168.84)	(71.55)	(118.43)	(5.96)	(5.96)	(74.54)
N.Comp=2	-1.187***	-0.579***	-1.315***	-0.0605***	-0.0605***	-0.0718***
	(-292.22)	(-105.68)	(-274.22)	(-31.64)	(-31.64)	(-33.77)
N.Comp=3	-1.433***	-0.763***	-1.462***	-0.0792***	-0.0792***	-0.0890***
	(-352.55)	(-139.81)	(-307.40)	(-41.56)	(-41.56)	(-42.01)
N.Comp=4	-1.675***	-1.006***	-1.686***	-0.0832***	-0.0832***	-0.0955***
	(-409.24)	(-183.49)	(-353.28)	(-43.62)	(-43.62)	(-45.04)
N.Comp=5	-1.773***	-1.112***	-1.783***	-0.0747***	-0.0747***	-0.0853***
	(-428.76)	(-201.72)	(-370.81)	(-39.03)	(-39.03)	(-40.14)
N.Comp=6	-1.894***	-1.215***	-1.892***	-0.0703***	-0.0703***	-0.0812***
	(-451.81)	(-218.73)	(-390.15)	(-36.66)	(-36.66)	(-38.15)
Constant	2.902***	2.296***	2.808***	0.503***	0.503***	0.478***
	(386.36)	(274.36)	(343.49)	(178.33)	(178.33)	(160.63)
N	17071804	16517796	15796832	16517794	16517794	15796830
FE				Y	Y	Y
Algo	Changes	Comp.	Min.	Changes	Comp.	Min.

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Dependent variable: Seller own the Buy Box (binary)

Table A.5: Winning the Buy Box (Crawl 2)

	NComp = 1			NComp = 3-6		
	(1)	(2)	(3)	(4)	(5)	(6)
Bol comp.=1	-0.0581***	-0.0573***	-0.0573***	-0.142***	-0.142***	-0.142***
	(-3.31)	(-3.30)	(-3.30)	(-33.46)	(-33.44)	(-33.44)
Rating	-0.0213	-0.0213	-0.0213	-0.0122***	-0.0122***	-0.0122***
	(-0.50)	(-0.50)	(-0.50)	(-5.88)	(-5.88)	(-5.86)
Delivery Time	0.00275***	0.00277***	0.00277***	-0.00105***	-0.00111***	-0.00111***
	(3.84)	(3.86)	(3.86)	(-3.31)	(-3.49)	(-3.49)
N.Algo=1	-0.130***	-0.207***	-0.207***	0.00322**	0.00491***	0.00381**
	(-3.66)	(-6.02)	(-6.02)	(2.85)	(3.98)	(2.98)
N.Algo=2				0.0457***		
				(5.56)		
Constant	3.773***	3.771***	3.770***	3.527***	3.528***	3.527***
	(10.02)	(10.01)	(10.01)	(189.14)	(189.01)	(188.98)
N	104981	104981	104981	317755	317755	317755
Changes	20	60	100	20	60	100

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Dependent Variable: Log Buy Box Price.

Table A.6: Sensitivity - Effect of the Number of Algorithmic sellers by different *price change* thresholds over the total number of competitors.

	NComp = 1			NComp = 3-6		
	(1)	(2)	(3)	(4)	(5)	(6)
Bol comp.=1	-0.0586***	-0.0586***	-0.0561**	-0.142***	-0.142***	-0.142***
	(-3.35)	(-3.38)	(-3.24)	(-33.44)	(-33.45)	(-33.45)
Rating	-0.0214	-0.0214	-0.0212	-0.0121***	-0.0122***	-0.0120***
	(-0.50)	(-0.50)	(-0.49)	(-5.84)	(-5.86)	(-5.78)
Deliverytime	0.00275***	0.00275***	0.00275***	-0.00108***	-0.00110***	-0.00112***
	(3.84)	(3.83)	(3.82)	(-3.41)	(-3.47)	(-3.53)
N.Algo=1	-0.158***	-0.184***	-0.179***	0.00126	-0.00364*	-0.00378*
	(-5.13)	(-6.70)	(-5.24)	(0.81)	(-2.32)	(-2.38)
N.Algo=2				0.0433***	0.0396***	-0.0059
				(8.42)	(7.59)	(-1.39)
Constant	3.774***	3.774***	3.772***	3.526***	3.528***	3.526***
	(10.02)	(10.02)	(10.01)	(189.18)	(189.22)	(189.11)
N	104981	104981	104981	317755	317755	317755
Correlation	>.5	>.7	>.9	>.5	>.7	>.9

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Dependent Variable: Log Buy Box Price.

Table A.7: Sensitivity - Effect of the Number of Algorithmic sellers by different *price correlation* thresholds over the total number of competitors.

	(1)	(2)	(3)	(4)	(5)
	Comp = 1	Comp = 2	Comp = 3-5	Comp = 6-8	Comp > 8
(1) Algorithmic Pricing: Price Changes only					
Bol comp.=1		-0.0557	-0.0226**	0.00694	-0.0101
		(-1.03)	(-2.99)	(0.73)	(-1.86)
N.Algo=1		0.431***	-0.0940***	0.00723	0.00742
		(4.67)	(-10.96)	(1.10)	(1.57)
N.Algo=2			0.121***	-0.0180	-0.107*
			(5.14)	(-1.21)	(-2.44)
Rating	0.0651	0.00808	-0.0365***	0.0148	0.0149*
	(1.64)	(0.86)	(-10.06)	(1.80)	(2.08)
Deliverytime	-0.00178*	-0.0104***	0.0233***	0.00640***	0.0153***
	(-2.57)	(-8.46)	(46.35)	(11.60)	(27.97)
Constant	1.746***	2.696***	3.389***	3.183***	3.453***
	(4.99)	(30.83)	(104.67)	(43.81)	(54.94)
N	44748	177524	880283	564999	635145
ProductxDate FE	Y	Y	Y	Y	Y
Seller FE	Y	Y	Y	Y	Y

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.8: Margin above all-time minimum Price