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Dr. Niklas Fourberg
Katrin Marques-Magalhaes
Dr. Lukas Wiewiorra

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WIK Wissenschaftliches Institut für
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Rhöndorfer Str. 68
53604 Bad Honnef, Germany
E-Mail: info@wik.org
www.wik.org

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They Are Among Us: Pricing Behavior of Algorithms in the Field *

Niklas Fourberg[1,2,†] Katrin Marques Magalhaes[1,‡] Lukas Wiewiorra[1,§]

[1] Wissenschaftliches Institut für Infrastruktur und Kommunikationsdienste (WIK)

[2] Duesseldorf Institute for Competition Economics (DICE)

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Abstract

We analyze pricing patterns and price level effects of algorithms in the market segments for OTC-antiallergics and -painkillers in Germany. Based on a novel hourly dataset which spans over four months and contains over 10 million single observations, we produce the following results. First, price levels are substantially higher for antiallergics compared to the segment of painkillers, which seems to be reflective of a lower price elasticity for antiallergics. Second, we find evidence that this exploitation of demand characteristics is heterogeneous with respect to the pricing technology. Retailers with a more advanced pricing technology establish even higher price premiums for antiallergics than retailers with a less advanced technology. Third, retailers with more advanced pricing technology post lower prices which contradicts previous findings from simulations but are in line with empirical findings if many firms compete in a market. Lastly, our data suggests that pricing algorithms take web-traffic of retailers' online-shops as demand side feedback into account when choosing prices. Our results stress the importance of a careful policy approach towards pricing algorithms and highlights new areas of risks when multiple players employ the same pricing technology.

Keywords:Algorithmic pricing, Collusion, Artificial intelligence

JEL Classification:C13, D83 ,L13 ,L41

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†Email: N.Fourberg@wik.org; Wissenschaftliches Institut für Infrastruktur und Kommunikationsdienste (WIK), Rhöndorfer Str. 68, 53604 Bad Honnef, Germany.

‡Email: K.marques-magalhaes@wik.org; Wissenschaftliches Institut für Infrastruktur und Kommunikationsdienste (WIK), Rhöndorfer Str. 68, 53604 Bad Honnef, Germany.

§Email: L.Wiewiorra@wik.org; Wissenschaftliches Institut für Infrastruktur und Kommunikationsdienste (WIK), Rhöndorfer Str. 68, 53604 Bad Honnef, Germany.

1 Introduction

The days in which prices are chosen by humans are over, as more and more data is available to retailers in the endeavor to gain a competitive edge against rivals. Valuable information when determining prices may be cost indicators, macro-economic factors, demand side feedback but most certainly also competitors' prices. The EU Commission (2017) notes that a majority of online firms indeed track rivals' prices and two-thirds derive their pricing decision based on algorithmic software. This development is thereby not only limited to e-commerce but is also present in offline contexts as well.[1]

One the one hand, the automated analysis of these data may lead to more efficient pricing, on the other, it bears some risks to the competitiveness of markets, namely tacit collusion. The challenges associated to this have been widely discussed by scholars (Ezrachi and Stucke, 2016, 2017; Harrington, 2018, 2020; Haucap, 2021) and competition authorities alike (British Competition and Markets Authority, 2018, 2021; Bundeskartellamt and Autorité de la Concurrence, 2019). The main argument in this is that algorithms enable a form of commitment on a specific price strategy and prices being chosen in a more predictive manner. This implies a reduction in feasible strategy sets and can simplify tacitly collusive outcomes (Byrne and De Roos, 2019).

While studies based on computer simulations (Waltman and Kaymak, 2008; Calvano *et al.*, 2020) and laboratory experiments (Normann and Sternberg, 2022; Schauer and Schnurr, 2022) provided a first evidence base in recent years, empirical approaches in this field are scarce with the notable exceptions being Assad *et al.* (2020); Wieting and Sapi (2021) and Brown and MacKay (2021).

In this paper we extend upon this literature and analyze pricing patterns and price level effects in the market segments for OTC-antiallergics and -painkillers in Germany. Based on a novel and extensive hourly dataset of over 10 million single observations, we produce the following results. First, we witness a group of cross-owned retailers who exhibit concerted price choices over a large set of products. Evidence suggests that prices for these are determined by one centralized algorithm which raises concerns about collusive outcomes due to an identical pricing technology. Second, price levels are substantially higher for antiallergics compared to the segment of painkillers, which seems to be reflective of a lower price elasticity for antiallergics. Furthermore, we find evidence that this exploitation of demand characteristics is heterogeneous with respect to the pricing technology. Retailers with a more advanced pricing technology establish even higher price premiums for antiallergics than retailers with a less advanced technology. Third, retailers with more advanced pricing technology post lower prices. This contradicts numerous simulation studies (Calvano *et al.*, 2020) but is in line with experimental findings under

[1] See Assad *et al.* (2020) and "Why Do Gas Station Prices Constantly Change? Blame the Algorithms", Wall Street Journal, 8 May, 2017, available at: `https://on.wsj.com/3vRCRo3` (last accessed on 23 December, 2022) for brick-and-mortar gasoline markets. Furthermore, digital price tags in supermarket also facilitate the application of pricing technology as seen in "Surge Pricing Comes To The Supermarket", The Guardian, 4 June, 2017, available at: `https://bit.ly/3mf9IQp` (last accessed on 23 December, 2022).

mixed algorithmic and human interaction of Brown and MacKay (2021),Werner (2022) and Schauer and Schnurr (2022). Lastly, our data suggests that pricing algorithms take web-traffic of retailers' online-shops as demand side feedback into account when choosing prices.

The remainder of the paper is structured as follows. Section 2 elaborates on the relevant strands of literature to which we contribute. Section 3 sheds light on our dataset and provides summary statistics, whereas the analysis in Section 4 produces our main results. Implications of our findings for welfare and competition policy are discussed in Section 5. Finally, Section 6 concludes.

2 Literature

Our study and findings contribute primarily to the nascent literature on algorithms' effect on prices. Contributions in this field investigate algorithmic behavior in settings of simultaneous price- or quantity-competition except Klein (2021) who studies sequential actions. Examined algorithms are either of the family of learning algorithms (Waltman and Kaymak, 2008; Salcedo, 2015; Calvano *et al.*, 2020; Klein, 2021; Werner, 2022; Schauer and Schnurr, 2022) , prediction algorithms (Miklós-Thal and Tucker, 2019; O'Connor and Wilson, 2021) or include a tit-for-tat rule (Normann and Sternberg, 2022).[2] Common to all is that they study variations of human and algorithmic interaction and their ability to tacitly collude in simulation or experimental settings.

The simulation studies of Calvano *et al.* (2020), Klein (2021) and Waltman and Kaymak (2008) find that reinforcement learning algorithms can learn repeated game strategies in a Bertrand setting and tacitly coordinate on supracompetitive prices without being explicitly trained to do so. These results seem to be robust against variations in marginal costs, demand functions, number of firms and different forms of uncertainty (Calvano *et al.*, 2020). In contrast to this, Waltman and Kaymak (2008) employed a repeated Cournot oligopoly framework in their simulations and find that even algorithms which do not memorize past experienced price interactions show a tendency to collusive behavior. Klein (2021) departs from the previous studies and allows for sequential moves in price setting and restricts the feasible price set ex-ante. The result is that two algorithms converge to a stable supra-competitive Edgeworth price cycle. Thus one firm sets a higher price, which is gradually undercut for each price adaption. On average the asymmetric cycles lead to higher prices than the competitive outcome.

The recent laboratory experiments of Normann and Sternberg (2022), Werner (2022) and Schauer and Schnurr (2022) all study algorithms' effect on prices in varying combinations of human and algorithmic interaction. Except for Normann and Sternberg (2022)

[2]A tit-for-tat pricing rule is an algorithm in nature that takes a specified set of inputs (rival's and own price) and produces an output (next period's own price) according to a predefined process. This process is retaliating if the rival's price is lower and cooperating if it is equal or higher. After one round of retaliation, the tit-for-tat rule returns to the cooperation mode which is why it can be considered to be memory-one comparable to most Q-Learning approaches.

the studies produce one result in unison. Supracompetitive prices are achieved in any setting in which algorithms are involved, albeit to a lesser degree compared to pure interactions of only humans or only algorithms. Furthermore, Werner (2022) finds that conventional negative pricing effects resulting from the number of firms in the market, are more pronounced in algorithmic interaction. These results offer a contrary view on algorithms that may also facilitate competition. Subsequently, we briefly summarize the aforementioned experimental and simulation studies in Table 1.

Table 1: Relevant simulations and laboratory experiments

Study	Strategice choice	Timing	Algorithm	Competitive effect
Waltman and Kaymak (2008)	Quantity	simultaneous	Learning	Negative
Calvano *et al.* (2020)	Price	simultaneous	Learning	Negative
Klein (2021)	Price	sequential	Learning	Negative
Werner (2022)	Price	simultaneous	Learning	Positive
Schauer and Schnurr (2022)	Price	simultaneous	Learning	Positive
Normann and Sternberg (2022)	Price	simultaneous	Tit-for-tat	Negative

However, empirical evidence on algorithms and their effect on prices is scarce and the only contributions in this field are Assad *et al.* (2020), Wieting and Sapi (2021) and Brown and MacKay (2021), the latter one being the one closest related to ours. Assad *et al.* (2020) examine pricing in the German gasoline market based on a high-frequency dataset of 2,058 over a five year period. They find that AI tools increase profit margins in competitive and especially duopoly situations. Contrarily, Wieting and Sapi (2021) do not study brick-and-mortar markets but focus on pricing patterns observed on the Dutch and Belgian B2C e-commerce platform *Bol.com*. They find that for a moderate number of market participants, product prices increase when pricing algorithms compete against each other. However, using pricing algorithms is not profitable for certain firms if the number of market participants is sufficiently large. Thus, also pro-competitive effects are observable and a market efficiency argument can be made.

The empirical part of Brown and MacKay (2021) is the approach which is most closely related to ours. Similar to us, the authors use hourly data from five US online retailers for a selection of 7 drugs in the segment of antiallergics. They find that retailers which employ a more advanced pricing technology generally post lower prices. Furthermore, they witness a heterogeneity in pricing technology among firms which is reflected in price update intervals of different length. We reproduce both of these findings based on our data. Both our studies and also Klein (2021) demonstrate the importance to take asymmetric pricing technologies and the resulting sequentiality of actions into account. However, we expand upon Brown and MacKay (2021) in that we observe a larger amount of retailers as market size matters (Wieting and Sapi, 2021), and also include products from another segment of drugs, namely painkillers. Especially the focus on antiallergics restricts the analysis of Brown and MacKay (2021) to a market segment that exhibits a rather inelastic demand. We relax this narrow view and show that firms with more advanced pricing technologies are able to better exploit segment-specific demand characteristics. Furthermore, to the best of our knowledge, we are the first to complement gathered price data with web-traffic data of the retailers' online-shops to examine algorithms' reaction to traffic feedback as a proxy for demand.

Given that we observe heterogeneous price update frequencies among firms, our study also relates to the body of macroeconomic literature on menu costs and sticky prices. Different price update frequencies are well evidenced in offline brick-and-mortar settings (Nakamura and Steinsson, 2008; Klenow and Malin, 2010), whereas prices in e-commerce are updated at a higher frequency (Gorodnichenko and Talavera, 2017; Cavallo, 2017). Price data in these studies is aggregated on higher time intervals (days or weeks) compared to our hourly time frame which allows us to conjecture on the underlying pricing technology.

3 Data on pricing algorithms

3.1 Pricing algorithms: A short introduction

Algorithms in general can be understood as a programmed set of rules that map a specified set of inputs in a particular way into an output. In the context of pricing algorithms, this output would be a price value that applies to one specific product or an entire product range. The inputs which feed into the algorithmic procedure can be past or present data on demand indicators, rivals' prices or other external factors that are deemed to be informative for the pricing decision. Usually, the identification of informative parameters for the algorithm's specific purpose is carried out based on an initial data-set, the so called "training data". In this way, pricing algorithms are likely to be initially calibrated to choose prices which would maximize an own firm's profit given the historic demand parameters and price choices in the training data.

In addition to this, some algorithms can be characterized as self-learning , that is, their functional form allows for an adaption of the mapping process as response to received data points in the field. The most popular in this regard are those from the family of "reinforcement learning" of which "Q-learning" is the best known. These procedures basically exhibit a trade-off which determines whether a specific period is played with the objective to maximize profits ("exploitation") given the current optimal mapping, or "exploration" and choosing a potentially non-optimal price. Gathered data as response to a non-optimal price may be valuable in improving the current algorithmic procedure but may involve short term costs since prices may not be optimally set.

During price competition, algorithms affect two features of the underlying economic theory (Brown and MacKay, 2021). First, they automate the pricing decision and reduce costs to change prices, that is, menu costs. Calculating prices by software is much more efficient than a manual upload of a new price list. Especially, over a large set of managed products these efficiencies are substantial. Hence, it is intuitive that especially large online retailers rely on automated pricing of their products.

Second, investment in advanced pricing technology is costly and serves as a commitment device in the short-term.[3] This commitment is two-fold with respect to the specific algorithm applied and to the frequency of running the software. The specific algorithmic method stipulates a specific way how prices are determined which, in turn, commits the firm not only to a single price but a whole price strategy or strategy profile. This strategy profile contains more than one specific price at each point in time, but also best responses on counterfactual rivals' prices. Over time these non realized best response prices could be anticipated by other agents in the market given enough interactions with the algorithm. This may lead to a better anticipation of future price changes with potential effects of equilibrium price play and the state of competition. These commitment effects differ greatly from human agents who are typically bound by incentive compatibility constraints every time they are faced with a pricing decision and, hence, lack this form of commitment (Maskin and Tirole, 1988).

The second commitment concerns the frequency at which the algorithmic code runs. Firms that invest in a better pricing technology or extended computing capacities may be able to apply pricing scripts in shorter time intervals or keep it running constantly. Very short intervals of running the pricing algorithm or heterogeneity in price update cycles generally among firms may have implications for the profitability of specific strategies in competition, e.g., Edgeworth-Cycles among others. In the extreme, pricing algorithms can be running continuously and price adaptions as reactions to changes in relevant parameters can happen in real-time.

One might argue that the technical obstacles to implement such tools make them exclusive to only the technically most advanced companies. However, this is not the case as commercial solutions are increasingly available which offer automated pricing tools for a variety of platforms, including the likes of Amazon Marketplace, eBay among many others (ChannelAdvisor, 2022; Repricer, 2022; IntelligenceNode, 2022).

3.2 Data

Our data consists of 39 online retailers that offer over-the-counter (OTC) drugs in the categories of antiallergics and painkillers in Germany. We accounted for 236 different products that where offered by the set of retailers in the two categories and consist of the best selling drugs in the two specified categories. Specifically, we consider a single product to be a drug-brand-form-(variant-)size combination, such as "Ceterizin-Hexal-Tablets-20".

We collected hourly data for these products and retailers from the price comparison

[3]The commitment is only valid for a limited amount of time which is defined by the update cycle of the algorithmic programming code. Those programs are typically updated at a lower frequency than they are used to set prices. Thus, in between updates to its algorithm, the firm commits to price changes which are determined according to a fixed set of rules.

website of Billiger.de (2022) which aggregates all available offers for the products in question. Retailers and *Billiger.de* are connected via APIs that ensure a fast updating of relevant data on the comparison website.[4] Since we are interested in pricing behavior in a competitive environment and want to observe a wide range of price signals as potential input variables, we monitor price choices of a high number of competing retailers instead of only focusing on large players. Relying in this regard on a price comparison website offers the advantage that web-scraping scripts do not need to be set up and maintained individually for each retailer but only once. This less error-prone approach resulted in almost no scraping downtime and a near complete hourly time series of data.

The observational period of our sample spans over more than four months from August 3rd to November 11th of 2022. Accounting for all products, this amounts to 10.220.147 single observations for every variable in the price data-set which makes it the largest and most comprehensive so far compared to previous empirical studies in this field. The following Subsection 3.3 elaborates on all gathered indicators and provides summary statistics on included retailers and products.

Auxiliary to the price data set is traffic data sourced from the commercially available web-traffic database of Similarweb (2022). These indicators serve as proxy variables for consumers' demand since actual purchasing data is only available to the retailers themselves. Under the assumption, that conversion rates from visiting a website to a successful purchase are not structurally different between retailers, traffic data is a good approximation.[5] Traffic data in general is always measured in relation to a specific url or webpage. In our case these are the respective root-url pages of the online retailers and include any traffic from subsequent urls in the website tree. Hence, our traffic data-set is aggregated on retailer level and is measured daily in contrast to our hourly product level price data. Naturally, this implies the assumption that traffic of the entire online retailer is representative of individual product page traffic. We are confident, that there is no structural heterogeneity between retailers in that some are able to direct root traffic over-proportionally to specific products than others. Although individual fluctuations may exist, the overall traffic level should be a good indicator for the traffic level of individual product pages. Section 3.3 offers summary statistics also on available traffic variables and retailers.

[4]We are not concerned that sourcing from a third-party website leads to a structural selection bias of our data. Retailers have to fulfill certain quality criteria in order to be listed on Billiger.de, but these are comparable to other listing sites and are easy to satisfy even for smaller players. This includes even some small drug stores that primarily operate a brick-and-mortar store and just sell their excess inventory online. Additionally, we do not miss any large online retailers for considered drugs that may be not be listed for some reason.

[5]We are not aware of studies that focus on web-traffic data quality in this regard, but one can argue that intermediate to larger retail platforms are able to maintain higher conversion rates than small ones. This may be due to a larger product portfolio that enables "one-stop-shopping" behavior, a more efficient web-design or professional customer service. We can control for some of these additional quality dimensions, but of course cannot rule out all of them. However, the availability of reliable web-traffic data is skewed towards the larger platforms anyhow. Sparse traffic data is frequent for smaller retailers which restricts associated analyses on larger ones for which these concerns are less pressing.

3.3 Summary statistics

The 236 products offered by the 39 retailers in our sample translate to 6426 unique product-retailer combinations. Naturally, this number is product from the depth of retailers' product portfolios. More than half of the retailers in our sample offer 85% or more of the products. Table 2 displays this for a selection of the most popular retailers in Germany. The heterogeneity in the depth-ratio of offered products becomes evident: While the drugstore chain *Rossmann* offers only one product of the selected medications, *Medpex* has over 97% of the investigated products in store. However, the number of available products cannot be used to infer the size of the retailer as a whole, since the product selection in our study is restricted and chosen ex-ante. A full list of the product range for each shop is provided in the Appendix, see Table 8.

Table 2: Retailers' product portfolio depth - Selection

Retailer	No. of products	Depth-ratio
Rossmann	1	0.42 %
Shop Apotheke	65	27.43 %
Amazon Marketplace health & Personal Care	94	39.66 %
DocMorris Apotheke	222	93.67 %
Medpex	232	97.89 %

Summary statistics for the hourly price data is presented in Table 3. Sparseness of the hourly price data is rather limited except for indicators concerning shop ratings as these are only available for approximately half the retailers in the sample. Retailers for whom this information is available are rather well rated. $Shop\_Rating$ exhibits a range from 55 to 100, with a mean rating of 87. The $No\_Shop\_Ratings$ varies from one to 155 ratings being placed by customers.

Data on price variables are complete. The average product $Price$ in the sample is 8.74€ with a minimum value of only 0.01€. Products which post a very cheap headline price are often accompanied by rather high $Shipping\_Cost$ such that the range of $Total\_Price$ is narrower.[6] The cost of delivery is on average $3,66$ €, with free shipping being also widely available in the data. The $Availability$ of a product is measured as the number of working days which are approximately needed for the delivery, with the maximum value simple being non-availability of the product. Given this, delivery of the average product takes slightly more than two working days.

While the aforementioned variables are directly sourced from *Billiger.de*, the indicator of $Pricechange\_dummy$ is self-calculated. This dummy variable takes the value 1 if a price change occurred compared to the previous hour of the same product-retailer combination. On can see from Table 3 that the average likelihood of a price change of a given product-retailer combination is 0.6% per hour.

[6]The strategic substitution between headline prices and shipping costs is also reflected in a correlation coefficient of -0.27. Figure 5 in Appendix B displays a correlation matrix for a selection of main variables.

Table 3: Summary statistics - hourly price data

Variable	Mean	Std.Dev.	Min.	Max.	No.Obs.	Measurement
Shop_Rating	87	13.596	55	100	5,026,745	Integer $\in [0, 100]$
No_Shop_Ratings	30	42.958	1	155	5,026,745	Count
Price	8.735	7.701	0.01	76.40	10,220,147	Value in €
Shipping_Cost	3.662	1.334	0	5.00	10,220,147	Value in €
Total_Price	12.40	7.430	0.57	76.40	10,220,147	Value in €
Package_Size	33.8	30.938	1	129	9,903,548	Count
Pricechange_dummy	0.006	0.080	0	1	10,213,721	Binary $\{0, 1\}$
Availability	2.127	3.476	0	-	10,220,147	Count
Category	0.457	0.498	0	1	10,220,147	Binary $\{0, 1\}$
Month	9.26	-	8	11	10,220,147	Integer $\in [1, 12]$
Day	14.82	-	1	31	10,220,147	Integer $\in [1, 31]$
Hour	11.76	-	0	23	10,220,147	Integer $\in [0, 23]$
Minute	24.54	-	0	59	10,220,147	Integer $\in [0, 59]$
Days_passed	50.48	-	0	102	10,220,147	Count
Hours_passed	1,210	-	0	2,458	10,220,147	Count
Weekday	4.097	-	1	7	10,220,147	Integer $\in [1, 7]$
Hour_of_week	87.09	-	1	168	10,220,147	Integer $\in [1, 168]$
Ptech	2.38	-	1	4	10,132,663	Integer $\in [1, 4]$

Whether a specific product is a painkiller or an antiallergic is indicated by $Category$. This variable takes the value 0 for painkillers and 1 if a given product is an antiallergic. The mean value of 0.457 directly indicates the relative proportion between the two product groups which is rather balanced. For completeness Table 3 includes time related variables whose interpretation is rather straightforward.[7]

Analogously, summary statistics for the daily web-traffic data is presented in Table 4. Data for these variable is more sparse as not all the retailers' websites are large enough and receive enough traffic to be consistently gathered by our provider Similarweb (2022). All web-traffic data are count variables apart from $Avg\_Visit\_Duration$ which is measured in seconds and the fractional indicators of $Bounce\_Rate$ and $Desktop\_Share$.

4 Data analysis

4.1 Frequency of pricing decisions

Previous work of Brown and MacKay (2021) showed that the frequency of price changes is one dimension which is indicative of the underlying pricing technology being used. In this sense, the more frequent price changes are, the higher the likelihood that these are carried out automatically. They find for their limited data-set of five retailers and 59

[7]Please note that the variable of $Ptech$ is a categorial variable developed as part of analyses to the observed frequencies of price updates in Section 4.1. We include it here for completeness but postpone its discussion to the aforementioned section.

Table 4: Summary statistics - daily web-traffic data

Variable	Mean	Std.Dev.	Min.	Max.	No.Obs.	Measurement
Unique_Visitors	41,716	53,642.61	5,008	350,514	123,285	Count
Visits	45,241	61,406.83	5,003	403,919	128,636	Count
Page_Views	106,918	233,575.9	232	2,609,576	273,784	Count
Pages_per_Visit	4.628	3.34	1	56	273,784	Count
Bounce_Rate	0.53	0.179	0.04	1	272,327	Ratio
Avg_Visit_Duration	185.0	165.099	0	3,288	307,006	Seconds
Desktop_Share	0.37	0.135	0.07	1	258,623	Ratio

products three distinct pricing patterns of constant, daily and weekly price updates.

Generally, we reproduce these results also based on our data as the selection of retailers in Figure 1 indicates.[8] Among the retailers in our data, we find update frequencies which are consistent with hourly or a constant update process, a daily and weekly cycle and those that do not exhibit any structural pattern. In the extreme case of products sold by *Amazon* on its own Marketplace (Retailer-15170), during every hour of the week, prices of more than 10% of the entire product portfolio changed. A prime example for a daily update pattern is *Medpex.de* (Retailer-762) which is the largest retailer in the sample based on web-traffic parameters. Figure 1 displays in the third tile that price changes for this retailer occur mainly every weekday between 6:00 to 12:00 a.m. CET. A weekly pricing interval is observed by usually intermediate to small retailers of which *Beraterapotheke* (Retailer-14695) has a very distinct pattern. Almost all price changes are implemented on Tuesdays between 6:00 and 10:00 a.m. CET which affect approximately 7 % of the retailer's offered products. Finally, update frequencies of a large number of retailers do not follow any systematic pattern, which is exemplarily shown for *Mediherz.de* (Retailer-3622). Those retailers change prices only for a small subset of their offered products and they do so at different times within a week.

Establishing a very high frequency of price updates necessitates a more advanced technology that both calculates new prices and also implements them on the retailer's platform. Given this, one can generally deduce from the observed price frequencies the degree of automation and the advancement of the pricing technology. We assign, therefore, all retailers of the sample to one of four categories with respect to their pricing technology ("Ptech"). This $Ptech$ variable takes the value 1- for constant or hourly price frequencies, 2 - daily , 3 - weekly and 4 - no regularity in price changes. [9] Table 5 summarizes this and displays the distribution of retailers in our sample across these categories.

[8]The selection of retailers in Figure 1 highlights the most distinct pricing patterns to visualize different underlying pricing technologies. The selection is not misleading since there are numerous other retailers that exhibit similar patterns to those included in the figure. Price frequency plots for all retailers of the sample are displayed in Figure 6 in the Appendix.

[9]Please note that the hourly update frequency in category ($Ptech = 1$) is only limited by the gathering frequency of our web-scraping script and could actually be even more frequent. For instance, if a retailer would update prices every 15 minutes, we would just observe the last price which is posted after 60 minutes. Faster update intervals are, hence, not observable.

Figure 1: Frequency of price changes

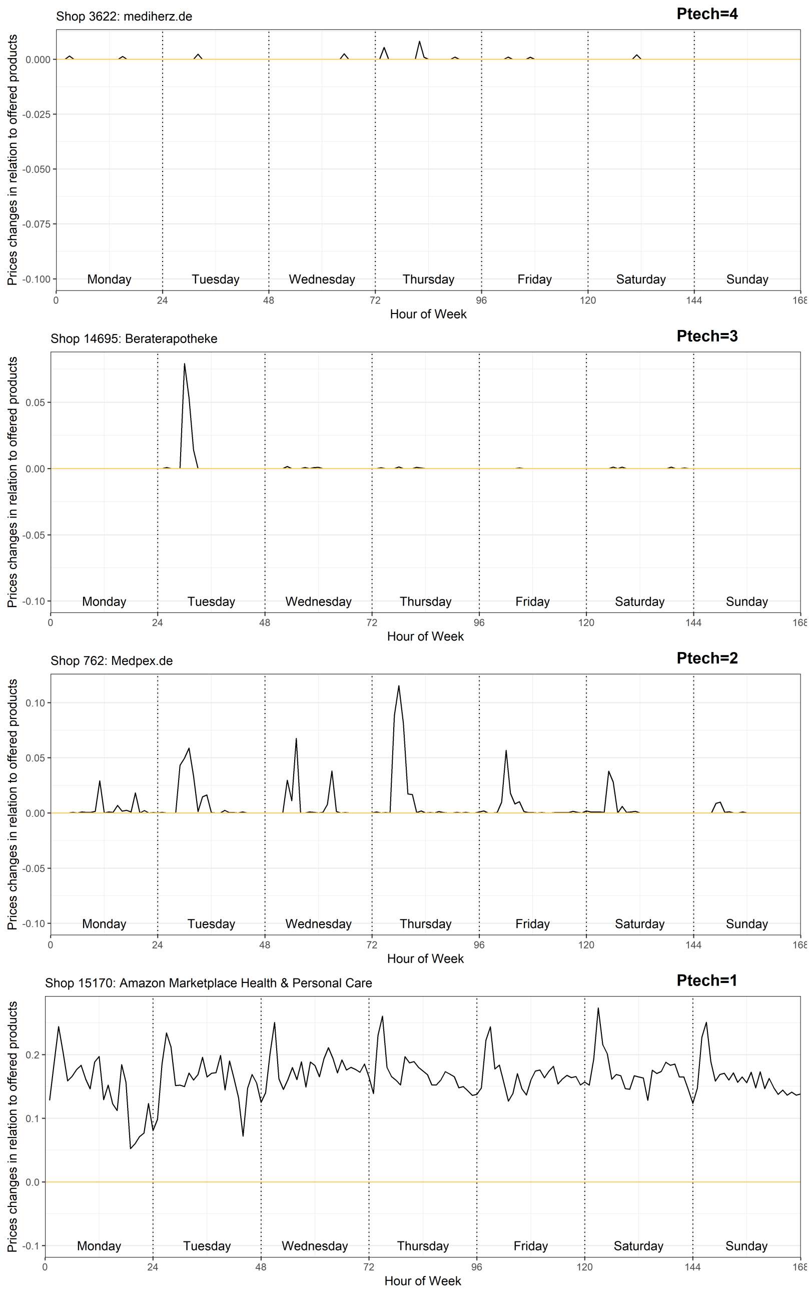


Table 5: Pricing technology category

	Update frequency	No. Observations
Ptech=1	Hourly (or faster)	7
Ptech=2	Daily	8
Ptech=3	Weekly	12
Ptech=4	No Pattern	11

We formulate our findings concerning the observed update frequencies as a first stylized fact.

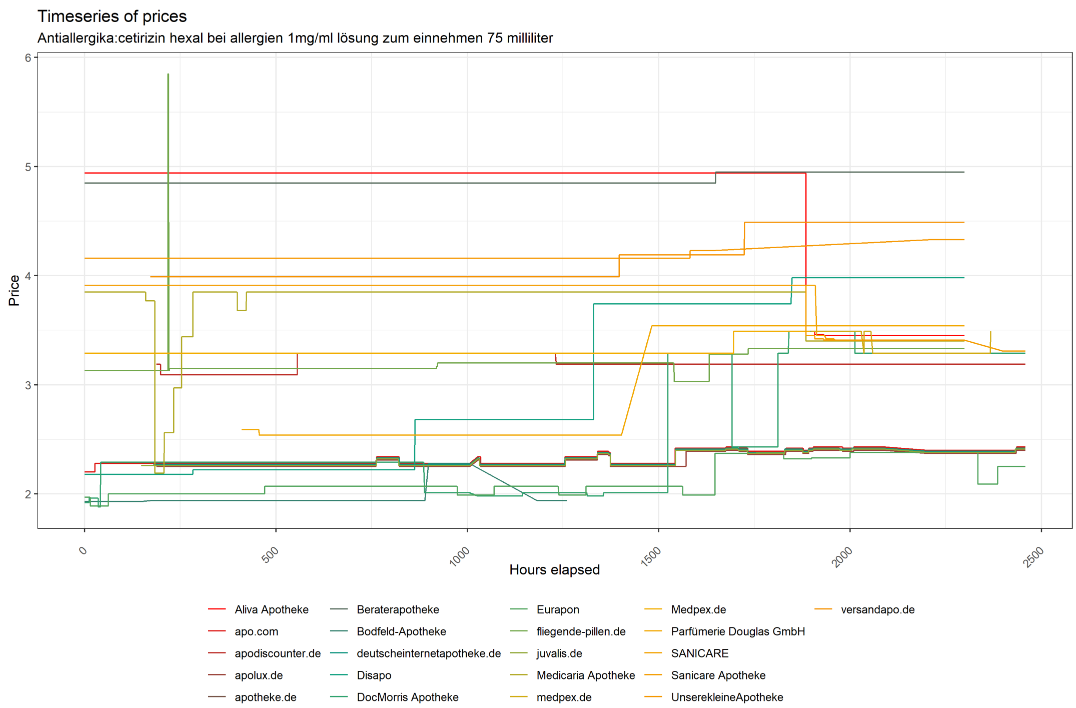
Stylized Fact 1: *Online retailers of the sample differ with respect to their price update intervals. We observe distinct patterns of no systematic update frequency, weekly, daily and hourly intervals.*

4.2 Collusive price patterns

Collusion through price algorithms is a major concern among practitioners and scholars alike. The degree of collusion is regularly assessed through analyzing price levels, which we will also tackle subsequently in Section 4.3. However, another indication of this conduct is also concerted price actions. Firms which increase and decrease prices at the same points in time could point to some form of communication taking place. Such pricing patterns may be different to the overall market's price level and do not necessarily involve all market participants. Hence, it seems promising to us to take on a more explorative approach to the pricing data initially before analyzing price level effects.

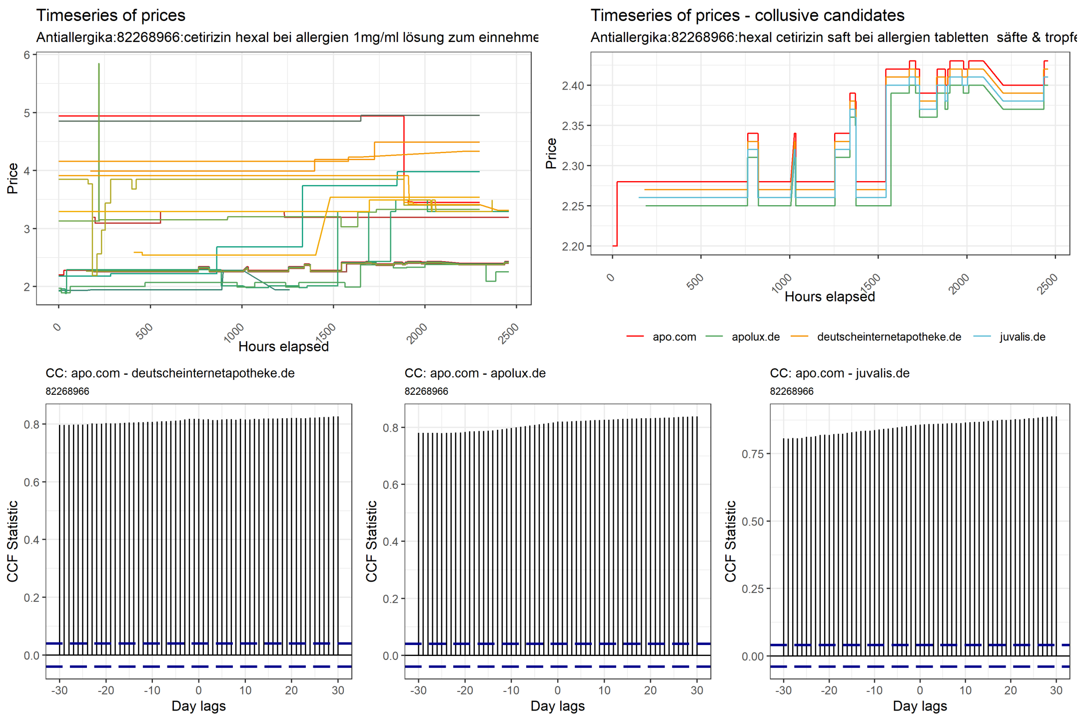
For this purpose Figure 2 displays the time series of selling prices for the product of *Ceterizin-Hexal-Juice* (Product-82268966) over the course of each hour of the observational period. Excluded are prices of retailers who kept their price constant during this time frame. Although we only include time-variant price curves, only few retailers change prices regularly for this exemplary product and price levels range from 2€ to 5€.

Figure 2: Time series of prices - Product: 82268966



Furthermore, what appears to be a bold line at the bottom of the pricing range in Figure 2 are actually price curves of retailers that are almost identical and behave in a concerted fashion. These for retailers consist of *apo.com* (Retailer-26948), *apolux.de* (Retailer-27349), *deutscheinternetapotheke.de* (Retailer-27347) and *juvalis.de* (retailer-27345). The subsequent Figure 3 highlights this in more detail as price curves from the upper-left panel are filtered for the aforementioned retailers in the upper-right panel.

Figure 3: Concerted price actions - Product: 82268966



This produces two key features of the pricing behavior of these retailers. First, price changes in both directions occur either within the same hour or are delayed by only a few. Secondly, if prices are constant for a period of time, there is a clear ordinal sequence starting with Retailer-26948 pricing highest to Retailer-27349 charging the lowest price. In conjunction with this, prices of Retailer-26948 are significantly cross correlated for every retailer pair. This applies to present day price values but also lagged and leaded values of up to 30 days after or prior. The bottom panel in Figure 3 exhibits that the cross-correlation coefficients exceed 0.8 for every Retailer-26948 pair. This concerted pattern is not exclusive to the highlighted Product-82268966, but is observable for the largest proportion of products commonly offered by the retailers. Figure 7 in the Appendix shows this for another example (Product-82250331) in similar detail, whereas Figure 8 displays concerted price curves for a wider selection of products.

If we recall the two features of this behavior, that is, a clear ordinal structure of prices and simultaneous adaption of prices, one can deduce that it is highly likely the group of retailers use the identical pricing algorithm. Prices have to be determined by the same process which reacts to external parameters in the same fashion. All retailers of this group share the same understanding when prices need to be updated, in which direction and while keeping the ordinal structure intact. Furthermore, the simultaneity of price changes implies that the update frequency has to be identical. Given that all observe an external shock in one relevant parameter at the same time, only a common update frequency would lead to simultaneous price changes as response.

The main explanation for this concerted pricing behavior is, however, that the entire group of retailers is cross-owned by one parent entity of ApoGroup (2022) which operates multiple online retail pharmacies in the German market. Hence, it is safe to assume that observed prices are not the result of independent but identically calibrated algorithms but only one which determines some form of core price. Individual retailer prices are then derived from this price via a retailer-specific linear weighting factor which perfectly explains the ordinal structure.[10]

Although this may alleviate the concerns about illegal collusive activity among the group, it nevertheless showcases pricing behavior that may result if competing market players use identical pricing technology. Given that commercial offers of these software are already available this may be worrisome and could pose a threat to competitiveness of markets. The same pricing software can easily be sold to multiple firms who may be competitors. A harmful harmonization of prices does not have to be the result of algorithms learning to do so, but because identical automated pricing solutions will react in a similar fashion to common shocks. We summarize this as our second stylized fact and discuss potential implications for competition policy in Section 5.

Stylized Fact 2: *An identical pricing algorithm is used by a group of cross-owned retailers. This common algorithm leads to a concerted price level and simultaneous price updates. A harmonization of prices does not have to be the result of self-learning algorithms but may also result from identical pricing solutions, which are commercially available.*

4.3 Price level effects

While the analysis of the hourly price data already provided insights on concerted price actions, a market's degree of collusion is usually assessed with respect to its price level. To analyze effects on prices we combine the hourly price data and the daily web-traffic data. Naturally, to align the different aggregation levels of both data sets, we build daily product-retailer specific averages of all price related variables. Consequently, the previously reported 10.220.147 observable price points reduce by approximately $\frac{23}{24}$.

[10] In our opinion, such near identical price curves as observed for Product-82268966 are highly unlikely the result of two or more independent algorithms, even if they are of the same functional form and are calibrated on the identical set of training data. The main reason for this is, that rival's prices would most likely be an important input parameter. These values differ dependent on which retailer's perspective is taken and, hence, would lead to a different optimal price. Furthermore, if we assume that maximizing revenue or profits is part of the algorithm's objective function, it may not be optimal for Retailer-26948 to constantly price highest given that all run at the same high frequency.

Estimation of price level effects rests on our linear model specification that is characterized by the following Equation 1.

$$log(Price_{ijt}) = \beta_1 X_{ijt} + \beta_2 W_{jt} + \beta_3 C_i + \beta_4 T_j + \gamma_i + \gamma_t + \epsilon_{ijt} \quad (1)$$

We include $log(Price_{ijt})$ as dependent variable and regress this on X_{ijt} as the vector of product-retailer-day specific variables from the price data. These consist of $Shop\_Rating$ and $Shipping\_Cost$. W_{jt} is the vector of relevant web-traffic indicators which are retailer-day specific and include the $Unique\_Visitors$ of the online retailer, the $Avg\_Visit\_Duration$ and total $Page\_Views$. Depending on the specification, W_{jt} includes also lagged versions of the aforementioned variables. C_i includes only a product specific $Category$ variable which distinguishes between antiallergics and painkillers. T_j includes retailer specific information and currently includes only the $Ptech$ variable stemming from analyses in Section 4.1. In addition, we include also γ_i to account for product specific fixed effects that influence different levels in price. This is complemented by the inclusion of time-varying fixed effects γ_t to filter out non-observable time trends that are common to all retailers and products. Hence, regression coefficients can be interpreted as the relative impact on the price level within a specific product-day combination.[11]

Web-traffic variables of W_{jt} serve as a proxy for general demand that the retailers of our sample are facing. Usually, the inclusion of both price and demand indicators raise valid concerns about the endogeneity assumption of the model being violated due to the reverse causality that exist between the two. However, we do not share these concerns in this particular case for two reasons. First, we are not including product demands, e.g., purchased units, directly as they are simply not available but only traffic which includes also non-purchasing interactions. Second, prices are product-retailer-time specific $(Price_{ijt})$ whereas web-traffic is only on retailer level (W_{jt}). The overall traffic a retailer's website receives probably influences the pricing decision of single products, but not that a single product price may have influence on aggregate visits or visit duration. To put it differently, traffic of one product site enters on average only with a factor of $\frac{1}{n-1}$ into total web-traffic, with n being the total set of web-pages under the root url. Given large product portfolios of the retailers, also outside of our sample, n is easily in the thousands or tens of thousand for some of them. Hence, we are confident that the direction of influence from retailer specific web-traffic to product-retailer specific prices is unidirectional.

Table 6 presents the estimation results from our specification in (1). In the left baseline specification which includes no lagged variables, a retailer's rating enables him to charge 4.01% higher price for 10 additional rating points.[12] There seems to be an inverse relationship with respect to the charged shipping costs as 1€ higher costs results on av-

[11]Given our log-level structure, estimated regression coefficients can be translated into percentage marginal effects according to $\%\Delta Price = 100 \cdot \left(\exp^{\beta} - 1\right)$. However, for values of $-0.1 < \beta < 0.1$ this can be approximated to be $\%\Delta Price = 100 \cdot \beta$.

[12]The variable $Shop\_Rating$ takes on values from 0 to 100. Furthermore, Tables 3 and 4 present information on units of measurement for all variables of the data set.

erage to price cut of 2.86%. Probably, it is a strategic decision to put different weight on a lower headline price and consequently charge shipping costs accordingly. The strongest marginal effect on the price level is exerted by the category dummy variable. Since $Category = 1$ for antiallergics, the 1.469 log point increase translates to antiallergics being priced higher by a substantial margin of 334.49%. Given that we already account for product FE, we suspect that this finding is indicative of structural differences in the elasticity of demand between the two market segments. Naturally, a lower price elasticity for antiallergics implies a larger pricing power for retailers in this segment, consistent with Lerner (1934) and his seminal index as measure of market power. We provide a discussion on this interpretation in Appendix A .

Another important result from the baseline model is that a more advanced pricing technology leads to lower prices on average. Recall that retailers with slower or unstructured update cycles are in groups with higher values of $Ptech$. Hence, starting from the fastest price technology, each group comparison beyond the first exhibits prices which are higher by 6.18% (0.060 log points).[13] Hence, this result does not support the fear of a higher price level due to algorithmic pricing that may be comparable to collusion. Furthermore, this aligns with the only other empirical finding of Brown and MacKay (2021) who show this for a smaller subset of products and retailers in the US. We summarize previously stated findings as our first set of main results.

Result 1: *The price level depends positively on the retailer's rating, and negatively on shipping costs. Prices are substantially higher for antiallergics, which seems to be reflective of a lower price elasticity and higher market power of retailers in this segment compared to painkillers.*

Result 2: *Retailers with a faster, probably more advanced pricing technology post lower prices. Price differences between each of the pricing technology groups are on average* 6.18%*. We find no support for a more collusive price level due to pricing algorithms.*

Web-traffic's effect on the price level seems to be twofold. On one side the actual number of visitors to a retailer's online shop is negatively associated to the price level. On the other, however, measures of the intensity of visits, that is, how long visitors have stayed ($Avg\_Visit\_Duration$) and how many total pages ($Page\_Views$) have been viewed in the process, have a positive impact on prices. In this context we want to emphasize the interpretation of the $Avg\_Visit\_Duration$ as likelihood that a given visit ends with a purchase decision. Naturally, the longer a visitor interacts with an online shop, the more likely it is she found products to her liking, the more products are in her shopping cart, and simply more sunk cost have been paid during the shopping process.[14] Given that visit duration

[13]This implies the assumption that price level effects between different values of $Ptech$ are linear which does not necessarily have to be the case. However, in alternative specifications that include dummy variables of $Ptech \in \{1, 2, 3\}$, we do not find qualitatively different results. Hence, for the sake of better readability of regression tables, we opt for the current representation.

[14]There are some aspects that would also result in higher visit duration but could potentially reduce the

Table 6: Price level effects

	Dependent variable: log(Price) (1)	(2)
Shop_Rating	0.004***	0.002***
	(0.0001)	(0.0001)
Shipping_Cost	−0.029***	−0.030***
	(0.001)	(0.001)
Ptech	0.060***	0.032***
	(0.002)	(0.003)
Category	1.469***	1.461***
	(0.022)	(0.023)
Unique_Visitors	−0.00000*	−0.00000***
	(0.00000)	(0.00000)
Avg_Visit_Duration	0.0001***	0.00004***
	(0.00001)	(0.00001)
Avg_Visit_Duration_lag1		0.00004***
		(0.00001)
Avg_Visit_Duration_lag2		0.00003***
		(0.00001)
Avg_Visit_Duration_lag3		0.00003***
		(0.00001)
Avg_Visit_Duration_lag4		0.00004***
		(0.00001)
Avg_Visit_Duration_lag5		0.0001***
		(0.00001)
Avg_Visit_Duration_lag6		0.0001***
		(0.00001)
Page_Views	0.00000***	0.00000***
	(0.000)	(0.000)
Page_Views_lag1		0.00000***
		(0.000)
Page_Views_lag2		0.00000***
		(0.000)
Page_Views_lag3		0.000
		(0.000)
Page_Views_lag4		0.000**
		(0.000)
Page_Views_lag5		0.000
		(0.000)
Page_Views_lag6		0.00000***
		(0.000)
Constant	−0.526***	−0.378***
	(0.028)	(0.030)
Product FE	Yes	Yes
Period (Day) FE	Yes	Yes
Observations	81,291	72,645
Log Likelihood	26,931.820	24,374.050
Akaike Inf. Crit.	-53,229.640	-48,104.110

Note: *p<0.1; **p<0.05; ***p<0.01

is measured in seconds, the marginal effect of a 100 seconds longer visit would equate to a price increase by 1.01%.

The first baseline specification in Table 6 only considers traffic data of the same day to explain effects on the price level. However, from our Stylized Fact 1 in Section 4.1 we know that update cycles are heterogeneous among retailers. Only retailers who run their pricing algorithm on an constant or hourly basis ($Ptech = 1$) can reliably incorporate traffic feedback into prices the same day. Consequently, for all other retailers, traffic of the previous day or multiple days still contains unused and informative feedback which has not been transformed into price updates yet. To account for this, we also include lagged versions of the intensive margin traffic indicators in the second specification of Table 6. Specifically, we include historic values of up to 6 days prior, such that we capture effect from web-traffic of an entire week. This aligns with the longest regular (weekly) update frequency which we have observed in the sample.

While effects of non-traffic variables remain qualitatively unchanged, it becomes clear that historic values of $Avg\_Visit\_Duration$ have a significant positive effect on prices. This applies especially to lags of 5 and 6 days prior as their marginal effects are 2 to 3 times larger than those of more recent points in time. We summarize these findings as our second main result.

Result 3: *The price level depends negatively on extensive margin of web-traffic (users) whereas the intensive measures have a positive impact. Especially historic values of users' average visit duration from 5 to 6 days prior, have a significant impact as these align with weekly update cycles of retailers.*

Hitherto, the analysis developed the price level effects based on the full sample. To qualify our results further, we look for heterogeneity of in these effects with respect to different factors. Among the first which come to mind is the retailers' pricing technology.[15] We have seen that more advanced pricing leads generally to a lower price level, but how other channels are affected by it remains unclear. For this, we conduct our specification from Equation 1 separately for subsamples of $Ptech \in \{1, 2, 3\}$. Regression results for all three models are displayed in Table 7. [16]

The first noteworthy heterogeneous effect is present with respect to the price difference between antiallergics and painkillers ($Category$). While the baseline effect of a price

likelihood of a purchase. Consider a retailer's website that is poorly structured and desired products are not easy to find. Then it would be possible that a longer visit duration is indicative of a lower probability of a purchase. However, retailers' websites in the sample are structured similarly and we found the time investment to find test products to be comparable. Hence, we feel confident in ruling out this aspect.

[15] We have also looked at effect heterogeneity with respect to the different product categories of antiallergics and painkillers. However, subsample regressions do not produce qualitatively different results. Table 9 in Appendix B displays these estimation results.

[16] We exclude retailers with irregular and most likely non-automated price updates ($Ptech = 4$) from this analysis. These retailers are also comparably small and exhibit web-traffic that is consistently below the threshold to be tracked by our data provider Similarweb (2022). We do not find any heterogeneous effects with respect to non-traffic variables for these retailers. Similarly, we have only few retailers with the fastest pricing technology in the sample ($Ptech = 1$) for which traffic data is largely sparse.

Table 7: Price level effects - pricing technology subsamples

	Dependent variable:		
	log(Price)		
	(Ptech=1: Hourly)	(Ptech=2: Daily)	(Ptech=3: Weekly)
Shop_Rating		0.016***	−0.0001
		(0.0002)	(0.0001)
Shipping_Cost	−0.317***	0.008***	−0.021***
	(0.017)	(0.001)	(0.001)
Category	1.722***	1.421***	0.762***
	(0.068)	(0.022)	(0.019)
Unique_Visitors	−0.00004	−0.00000***	−0.00000
	(0.0001)	(0.00000)	(0.00000)
Avg_Visit_Duration		0.00001	0.00002
		(0.00002)	(0.00001)
Avg_Visit_Duration_lag1		0.00002	0.00003**
		(0.00002)	(0.00001)
Avg_Visit_Duration_lag2		0.00000	0.00005***
		(0.00001)	(0.00001)
Avg_Visit_Duration_lag3		0.00001	0.00004**
		(0.00001)	(0.00001)
Avg_Visit_Duration_lag4		0.00001	0.0001***
		(0.00001)	(0.00001)
Avg_Visit_Duration_lag5		0.00000	0.0002***
		(0.00002)	(0.00001)
Avg_Visit_Duration_lag6		−0.00000	0.0001***
		(0.00002)	(0.00001)
Page_Views		0.00000**	0.00000**
		(0.000)	(0.00000)
Page_Views_lag1		0.000	0.000
		(0.000)	(0.000)
Page_Views_lag2		0.000	−0.000
		(0.000)	(0.000)
Page_Views_lag3		−0.000*	0.000
		(0.000)	(0.000)
Page_Views_lag4		0.000	−0.000
		(0.000)	(0.000)
Page_Views_lag5	−0.00000	0.000	−0.000
	(0.00002)	(0.000)	(0.000)
Page_Views_lag6		0.00000***	0.000
		(0.000)	(0.000)
Constant	1.042	−1.614***	1.023***
	(0.826)	(0.035)	(0.032)
Product FE	Yes	Yes	Yes
Period (Day) FE	Yes	Yes	Yes
Observations	424	42,917	29,304
Log Likelihood	688.387	19,048.530	14,842.330
Akaike Inf. Crit.	-946.774	-37,455.050	-29,066.670
Note:			*p<0.1; **p<0.05; ***p<0.01

premium still persists for all pricing technologies, it becomes more pronounced the more advanced the technology is. Retailers of group $Ptech = 3$ post antiallergics prices which are, on average, higher by 114.26% (0.762 log point). This price premium extends for retailers with daily update frequencies ($Ptech = 2$) to 314.13% (1.421 log point) and reaches its pinnacle for the fastest technology at 459.57% (1.722 log point). This differentiated effect suggests that more advanced pricing technology not only enables faster update cycles and shorter reaction times, but that the calculation of prices takes demand characteristics better into account. Whether algorithms calculate price elasticities of market segments explicitly or just evaluate demand-side indicators that are reflective of the concept, is not assesable to us. Regardless of how opportunities of pricing power are identified, it just matters that they are. A stronger exploitation of positions of market power due to algorithms, naturally raises questions of expected rent allocations and, lastly, welfare implications. We address these in the discussion in Section 5. Subsequently, we summarize and formulate our fourth main result.

Result 4: *Price premiums for antiallergics are differentiated with respect to the pricing technology. Retailers with the fastest technology establish premiums of* 459.57% *compared to only* 114.26% *for retailers with weekly cycles. This suggests that more advanced algorithms are better able to asses and exploit underlying demand characteristics of market segments when choosing prices.*

Web-traffic's baseline effect showcases the importance of historic values for the price level. However, if we consider price technology subsamples, this effect becomes more nuanced. Given that web-traffic data is too sparse for retailers with the fastest technology, we restrict the analysis to the comparison between retailers with daily and weekly update frequencies. For retailers that change prices daily, only traffic of the given day exert a significant influence. This is an intuitive result as the maximum delay with which traffic feedback is translated into prices is one day. Information from historic traffic values which are older than one day are already outdated and have already been accounted for in previous price updates. The same intuition holds true for retailers who update prices weekly ($Ptech = 3$). For those, traffic data of the entire prior week is significantly influential, perfectly aligning with their update schedule. The largest marginal effect is exerted by lags of order 5 or higher such that, for instance, a 100s longer average visit duration 5 days prior is associated with a higher price level by 2.00% at a given day. We summarize this as our last main result.

Result 5: *The effect of the average visit duration on prices is heterogenous in the pricing technology. The influence of historic traffic values coincides with the frequency of the update schedule.*

5 Discussion of Results

Our second result does not support collusion fears and stands in contrast to the findings of simulation studies of Waltman and Kaymak (2008) and Calvano *et al.* (2020). However, it aligns with results of experimental approaches of mixed human and algorithmic interactions (Werner, 2022; Schauer and Schnurr, 2022) and empirical investigations so far (Brown and MacKay, 2021). Although prices of retailers with a more advanced pricing technology are not elevated, concerns about collusive outcomes still persist. Nurtured are these fears by our second stylized fact and the witnessed concerted pricing behavior of a group of cross-owned retailers. Prices of these retailers follow a clear ordinal pattern and price changes occur simultaneously as response to a common shock in input parameters. Given that all retailers are owned by the same company, it is likely that one identical algorithm determines prices for all retailers of the group which dismisses suspicions of illegal conduct. However, we see this development as problematic for two reasons.

First, if prices of multiple market participants behave near identical, the predictability of the general price level within a market increases. This predictability of price reactions can be crucial in establishing tacitly collusive agreements in the long run. Normann and Sternberg (2022) show in their treatment variations on different uncertainties regarding employed algorithmic structures, that these indeed affect cooperation rates and price levels. If one considers a learning algorithm in such an environment, a higher predictability of rivals' price responses should lead to a lower attractiveness of the exploration state compared to exploitation. Exploration is simply not as necessary if a multitude of market participants behave similarly due to the same price technology. Consequently, learning algorithms would converge faster to a purely exploitative play, which constitutes a faster path to potentially higher prices as simulation studies suggest (Waltman and Kaymak, 2008; Calvano *et al.*, 2020).

The second concern is about pricing technology being increasingly available on a commercial basis. In this study we witnessed centralized algorithmic price setting only for a group of cross-owned retailers. However, the commercial distribution of these tools could create a similar situation in which retailers employ the same pricing technology, only now with the exception that they are independent entities and potentially competitors. Sellers of pricing technology could, therefore, become a de-facto facilitator of concerted price reactions loosely comparable to industry associations as collusive ringleader-platforms. However, more evidence on the behavior of commercially available price technology is needed to qualify this concern.

Based on our fourth result one can carefully conjecture on welfare effects and implications for rent allocation. Our finding suggests that retailers with more advanced pricing technology seem to be better in assessing demand characteristics of market segments and exploiting them. Economically, it is irrelevant whether algorithms are able to calculate concepts such as price elasticities explicitly. It suffices if they derive comparable conclusions from simpler demand side indicators. These conclusions could be that consumers in specific demand segments have only few other product alternatives or cannot postpone their consumption to a later point in time. According to classical welfare theory of Hotelling (1938), Hicks *et al.* (1986) and Schwartzman (1960), higher prices in cases of rather inelastic demand (such as antiallergics) imply lower welfare losses, since demand reactions are muted. As Worcester (1975) puts it: "The lower the elasticity, the smaller the output distortion and the smaller the welfare loss for a given [...] price mark-up." Although losses in welfare may not be substantial if algorithms exploit inelastic demands, the distortion in the allocation of rents is. Large price premiums, as evidenced in this study, lead to a very asymmetric distribution of rents, with consumers getting the short end of the deal. However, further empirical research based on real demand data is warranted to solidify these conjectures.

6 Conclusion

In this paper we analyze pricing patterns and price level effects of algorithms in two market segments of OTC drugs in Germany. Based on a novel and extensive hourly dataset of over 10 million single observations we discover the following stylized facts on pricing behavior. First, retailers differ significantly with respect to the frequency with which they update prices. Distinct patterns are that of constant updating, daily, weekly and non-regular updating cycles (Brown and MacKay, 2021). Second, we witness a group of cross-owned retailers that exhibit concerted price choices over a large set of products. Evidence suggests that prices for these are determined by one centralized algorithm which raises concerns about collusive outcomes due to identical pricing technology.

For the investigation of price level effects, we combine our hourly price level data with daily web-traffic from the retailers' online shops. Based on this evidence we produce the following main results. First, price levels are substantially higher for antiallergics compared to the segment of painkillers, which seems to be reflective of a lower price elasticity for antiallergics. Furthermore, we find evidence that this exploitation of demand characteristics is heterogeneous with respect to the pricing technology. Retailers with the fastest update cycles establish even higher price premiums for antiallergics than retailers with a less advanced technology. Second, retailers with more advanced pricing technology post lower prices. This contradicts numerous simulation studies (Calvano *et al.*, 2020) but is in line with experimental findings under mixed algorithmic and human interaction of Brown and MacKay (2021),Werner (2022) and Schauer and Schnurr (2022). Lastly, our data suggests that pricing algorithms take web-traffic as demand side feedback into account when choosing prices. Intuitively, historic values of web-traffic are important which align with the update cycle of the respective pricing technology. Our results have implications for competition policy and qualify the concerns on algorithmic collusion.

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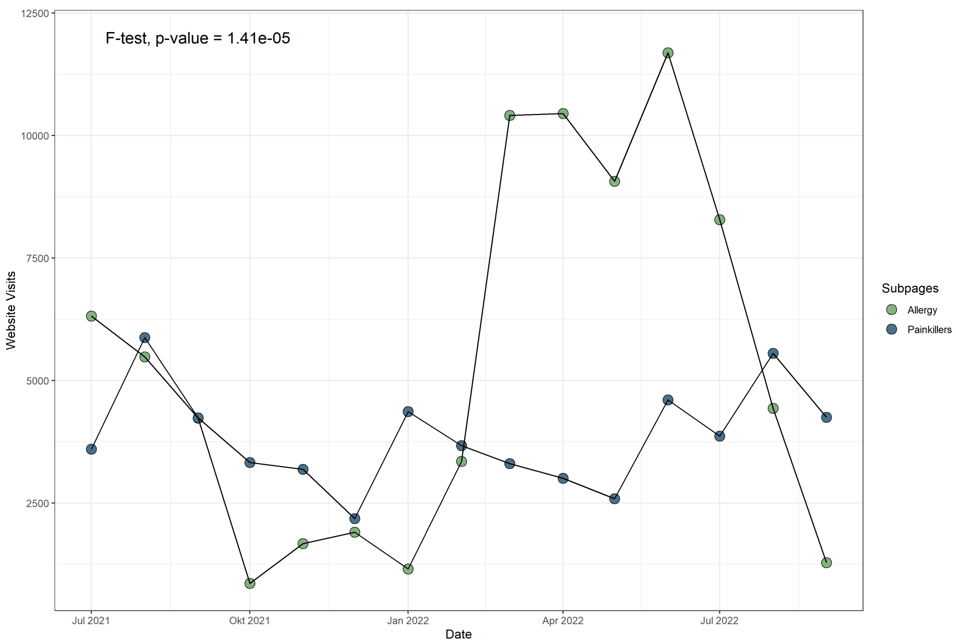
Appendix A: Demand characteristics antiallergics & painkillers

This study focuses on online retailers in the OTC market, in which demand is considered to be non-urgent. In case of severe pain or allergic symptoms, consumers would almost certainly visit the next brick-and-mortar apothecary or drug store. The online demand for OTC drugs are therefore of more forward-looking consumers.

Nevertheless, demand patterns seem to be different between the two segments of antiallergics and painkillers due to seasonality effects. While painkillers are in rather constant demand throughout the year, there is a distinct allergy season. Especially, consumers who suffer from a pollen or grass allergy are battling symptoms mainly from March through September, depending on their specific allergens. Based on this, consumers in the segment of antiallergics should know when they are going to need their medication and shop in advance. However, it seems that only a minority will do so, which can be derived from Figure 4. The displayed website visits are from the respective allergy and painkiller subpages of the most frequented online retailer in the data set *Medpex* (Retailer-762).

Figure 4: Web Visits of category subpages - Medpex (Retailer-762)



For the months of March through August of last year, website visits are clearly elevated aligning with the most common allergy seasons of pollen and grasses in Germany. Apparently a significant portion of consumers act myopic in their consumption timing in the sense of Gabaix and Laibson (2006) which has also been evidenced in numerous other contexts (Poterba, 1988; Busse *et al.*, 2013; Williams, 2016). Consequently, consumers in the segment of antiallergics are less able to postpone their purchase because they know that they are going to need their medication soon. The economic interpretation of this would be a less price elastic demand function compared to the demand segment of painkillers which exhibits no seasonality and a rather constant interest over a yearly timeframe. Naturally, a less elastic demand implies that firms do not loose as much demand in response to a potential price increase. This implies a larger market power for sellers according to Lerner (1934). In the context of price algorithms, it should be rather undisputed that some demand side parameters of specific products enter into the calculation process of prices. However, it is less clear to which extent more profound demand characteristics of whole market segments or even price elasticities are identified and exploited.

Appendix B: Additional graphics and tables

Table 8: Retailers' product portfolio depth

Retailer	No. of products	Depth-ratio
fixmedika.de	1	0.42
Rossmann	1	0.42
Schwabenpillen.de Versandapotheke	1	0.42
Elisana - Meine Stammapotheke im Internet	2	0.84
internet-apotheke-freiburg	4	1.69
Meine-Nicolai-Apotheke	20	8.44
Shop Apotheke DE	47	19.83
Amazon Marketplace Health & Personal Care	92	38.82
Parfümerie Douglas GmbH	126	53.16
arzneidoc.de	127	53.59
mediherz.de	129	54.43
Volksversand Versandapotheke	138	58.23
Paul-Pille	156	65.82
apo-mathildenhoehe	163	68.78
ahorn24.de	178	75.11
aposalis	185	78.06
Preisapo	187	78.90
Eurapon	198	83.54
Beraterapotheke	205	86.50
Bodfeld-Apotheke	205	86.50
apodiscounter.de	206	86.92
SANICARE	207	87.34
apotheke4you	208	87.76
deutscheinternetapotheke.de	212	89.45
apotheke.de	214	90.30
DocMorris Apotheke	214	90.30
juvalis.de	214	90.30
apo.com	216	91.14
apolux.de	216	91.14
versandapo.de	216	91.14
Disapo	218	91.98
Medicaria Apotheke	219	92.41
Sanicare Apotheke	220	92.83
Aliva Apotheke	221	93.25
fliegende-pillen.de	221	93.25
vitenda.de	221	93.25
UnsereKleineApotheke	226	95.36
Medpex.de	231	97.47

Figure 5: Correlation matrix of selected variables

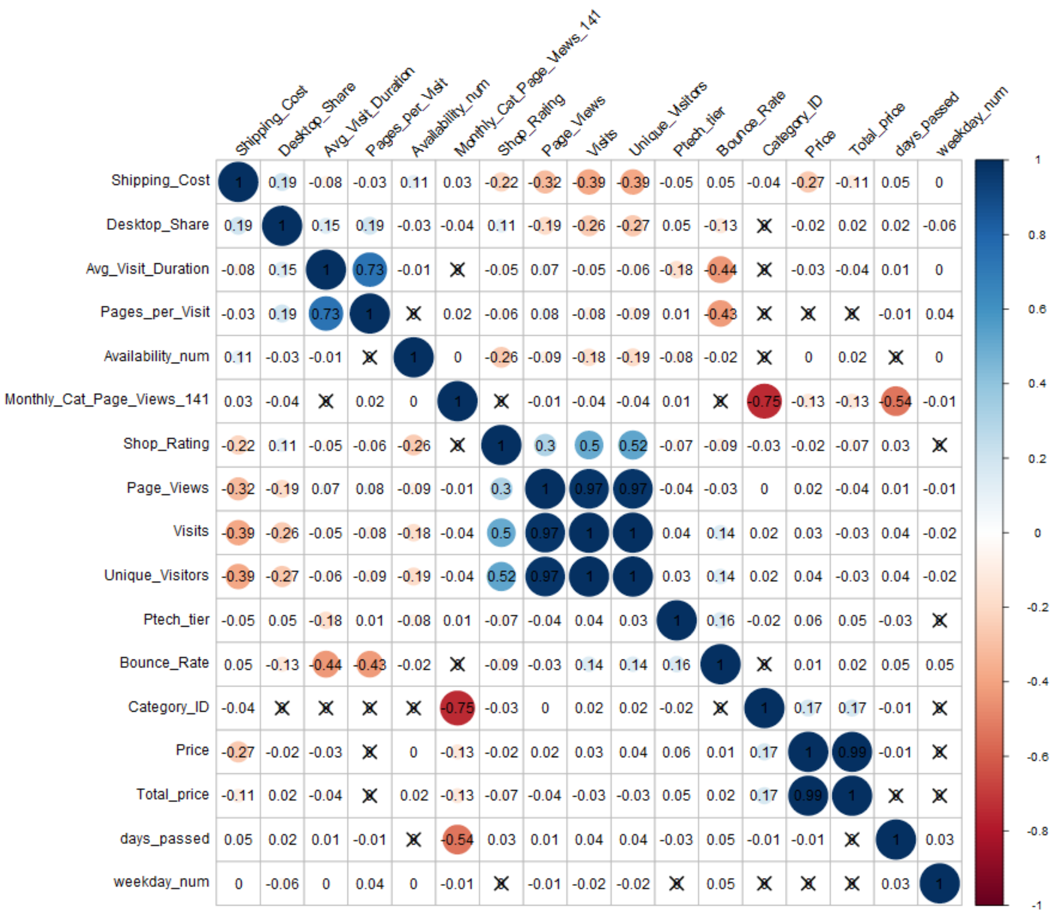


Figure 6: Frequency of price changes - all retailers

Figure 7: Concerted price patterns - Product:82250331

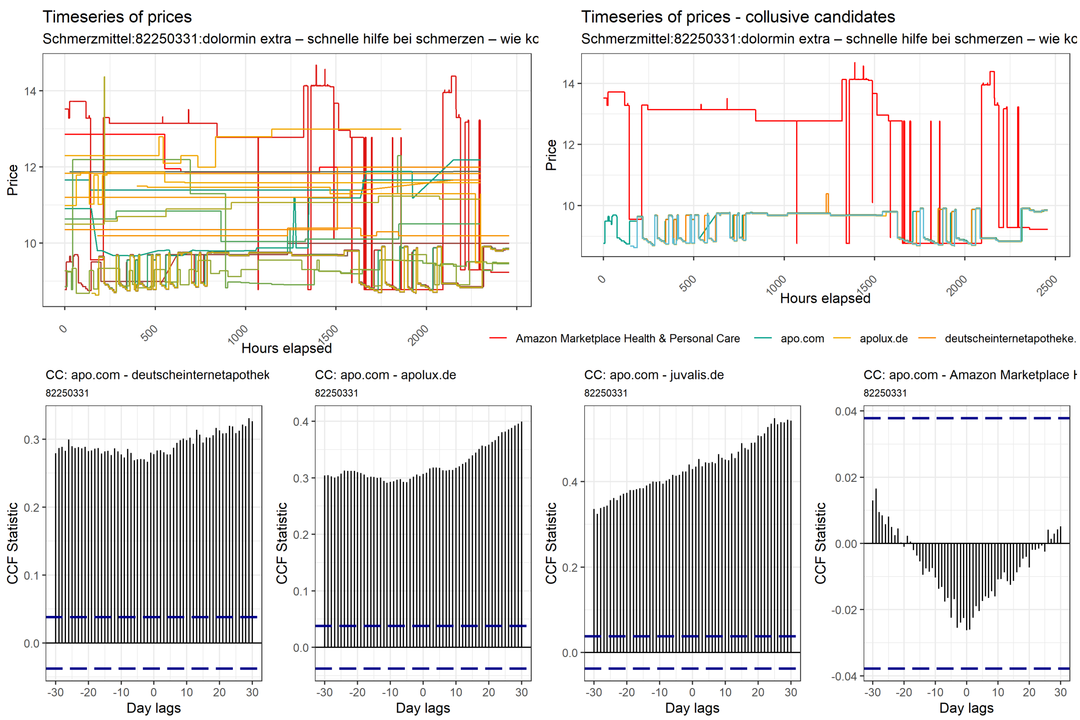


Figure 8: Concerted price patterns - Product Selection

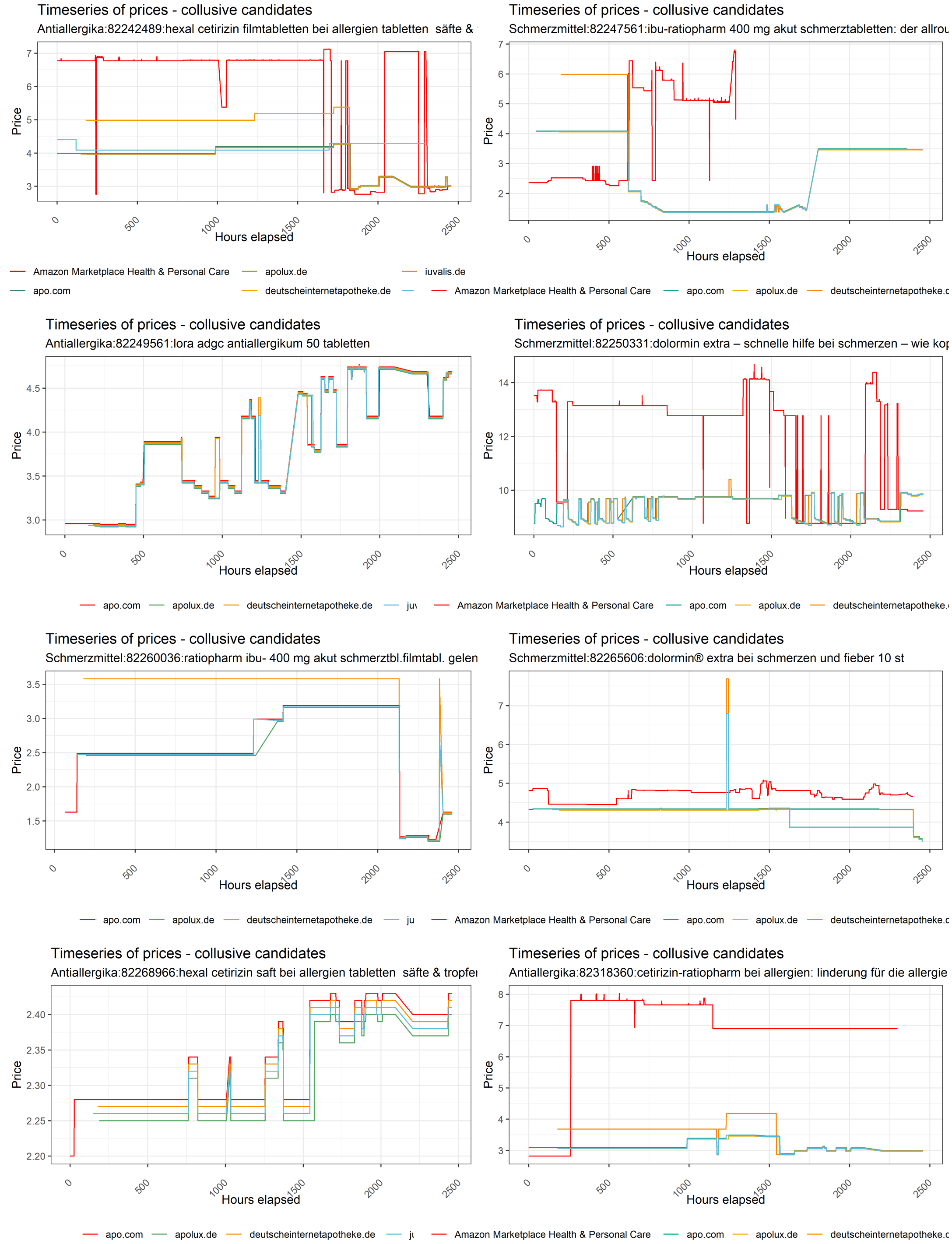


Table 9: Subsamples Category

	Dependent variable:	
	log(Price)	
	(Category=1: Painkillers)	(Category=2: Allergy)
Shop_Rating	0.004***	0.001***
	(0.0001)	(0.0002)
Shipping_Cost	−0.021***	−0.038***
	(0.001)	(0.001)
Ptech	0.046***	0.017***
	(0.003)	(0.004)
Unique_Visitors	−0.00000***	−0.00000***
	(0.00000)	(0.00000)
Avg_Visit_Duration	0.00004***	0.00005***
	(0.00001)	(0.00002)
Avg_Visit_Duration_lag1	0.00004***	0.00004**
	(0.00001)	(0.00002)
Avg_Visit_Duration_lag2	0.00003**	0.00004**
	(0.00001)	(0.00002)
Avg_Visit_Duration_lag3	0.00003**	0.00004***
	(0.00001)	(0.00002)
Avg_Visit_Duration_lag4	0.00002**	0.0001***
	(0.00001)	(0.00002)
Avg_Visit_Duration_lag5	0.0001***	0.0001***
	(0.00001)	(0.00002)
Avg_Visit_Duration_lag6	0.00003***	0.0001***
	(0.00001)	(0.00002)
Page_Views	0.00000***	0.00000**
	(0.000)	(0.00000)
Page_Views_lag1	0.00000***	0.00000*
	(0.000)	(0.000)
Page_Views_lag2	0.00000***	0.00000**
	(0.000)	(0.000)
Page_Views_lag3	0.000	0.000
	(0.000)	(0.000)
Page_Views_lag4	0.00000**	0.000
	(0.000)	(0.000)
Page_Views_lag5	0.000*	0.000
	(0.000)	(0.000)
Page_Views_lag6	0.00000***	0.00000***
	(0.000)	(0.000)
Constant	1.512***	2.708***
	(0.017)	(0.032)
Product FE	Yes	Yes
Period (Day) FE	Yes	Yes
Observations	39,232	33,413
Log Likelihood	19,041.940	6,992.347
Akaike Inf. Crit.	-37,665.870	-13,588.690
Note:		*p<0.1; **p<0.05; ***p<0.01

WIK Wissenschaftliches Institut für
Infrastruktur und Kommunikationsdienste GmbH
Rhöndorfer Str. 68
53604 Bad Honnef, Germany
www.wik.org

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