The Evolution of Nominal Rigidities in Online and Multichannel Markets

Pol Vilà & Josep Vilalta

Advisor: Jordi Galí

Universitat Pompeu Fabra

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Abstract

Sticky prices of consumer goods are a key element for ensuring the effectiveness of monetary policy. This paper studies price rigidity in a set of large retailers operating in Spain: four well-established multichannel firms (MediaMarkt, IKEA, Decathlon and Abacus) and Amazon as a purely online benchmark.

Using a novel technique we gather data in order to describe the dynamics of price changes by firm and channel and estimate several models of the price adjustment rate. We find that, in the aggregate, the price adjustment rate of multichannel retailers is similar to Amazon's, but once MediaMarkt is excluded the adjustment rate of Decathlon, IKEA and Abacus is substantially lower than Amazon's.

Furthermore, we show a partial convergence of the adjustment frequency of multichannel firms towards Amazon's levels during the 2020–2022 period, in line with the increase in the weight of the online channel following COVID-19.

Contents

1 Introduction

Price rigidity for consumer goods is a key element for understanding the transmission of monetary policy and its effect on inflation. In a frictionless world, with perfectly flexible prices, rational agents, and fully competitive markets, a change in the interest rate or in the money supply would only relabel prices and wages in nominal terms, but would have very limited real effects. The usefulness of monetary policy for stabilising the business cycle therefore depends on the existence of rigidities and frictions in price setting.

Traditionally, the literature has analysed this using data from physical stores and point-of-sale scanners (Klenow and Kryvtsov, 2008), but the expansion of e-commerce and multichannel models raises a natural question: to what extent have online channels made prices more flexible? And, in particular, how does the price-setting behaviour of a purely digital giant such as Amazon compare with that of firms which, although they have a digital presence, also have a physical component?

Several studies using online price microdata find a higher frequency of adjustments and smaller price changes than in traditional CPI or offline retail data. They suggest that digitalisation and e-commerce reduce price rigidity and that, therefore, there is a downward trend in the rate of price adjustment, even though the effect is heterogeneous across sectors and distribution channels (Cavallo, 2018; Strasser et al., 2023).

We contribute to this recent literature in two ways: (i) we show that the upward trend in the frequency of price adjustment increased especially during the COVID-19 period, and (ii) we do so by proposing a novel method of data collection, which can be extended to other studies.

This paper studies price rigidity and the frequency of price adjustment for a set of large retailers operating in Spain: four well-established multichannel firms (MediaMarkt, IKEA, Decathlon and Abacus) and Amazon as a purely online benchmark. Our aim is twofold. First, we construct a price panel with tens of thousands of products, comparable across firms and over a sufficiently long time span. Second, we use this panel to describe differences in pricing policies across channels and to analyse to what extent a greater weight of the online channel is associated with a higher frequency of price updates.

Methodologically, we combine two data sources. For the multichannel firms, we use a retrospective web scraping method based on the Wayback Machine, which allows us to reconstruct the price history of each product without first defining an exhaustive dictionary of references or programming bots to crawl the websites on a regular basis. For Amazon, we use the database distributor Keepa, which provides complete time series of the daily price for each reference. To ensure comparability, we restrict the sample to products that share categories across firms, filter out very short episodes, and harmonise the observation frequency by applying an episode-based strategy and a temporal thinning of Amazon's data based on a Bernoulli process calibrated using the traditional firms.

The descriptive analysis shows highly heterogeneous patterns of price rigidity across firms. The estimated survival curves indicate that MediaMarkt changes the price of around three out of four products at least once during the first week of the episode, which is consistent with a very concentrated pattern of updates related to weekend effects or weekly discount calendars. In contrast, IKEA, Decathlon, Abacus and Amazon follow a pricing policy in which updates are much more spread out over time. For Amazon, moreover, the curve is clearly convex: among the products that keep their price fixed during the first months, the probability of a first change falls markedly, suggesting that prices which survive initially tend to be particularly rigid.

To quantify these differences, we estimate models of the price-adjustment rate using both a Poisson specification and a discrete-time hazard model. With reference fixed effects, the adjustment rate declines with the length of the spell since the last change and, within products, with the price level. By contrast, when we use category rather than reference fixed effects, structurally more expensive categories exhibit a significantly higher adjustment rate, indicating that within-product and between-category forces operate in opposite directions.

Across channels, having a physical store presence is associated with less frequent price adjustments. That is, Amazon adjusts prices more often than most traditional retailers. Considering the group of multichannel firms as a whole, we estimate that their price-adjustment rate is about 15% lower than Amazon's, although this difference is not statistically significant. However, excluding MediaMarkt from the group, the gap becomes much larger: the adjustment rate of Decathlon, IKEA and Abacus is around 84% lower than Amazon's, with very strong statistical significance. At the firm level, these three retailers show significantly negative coefficients relative to Amazon, whereas MediaMarkt displays an adjustment rate that exceeds Amazon's.

Finally, we show a clear pattern around the COVID-19 pandemic. Between 2020 and 2022 we observe the adjustment frequency of multichannel firms converging towards Amazon's levels, in line with the hypothesis that greater reliance on online channels goes hand in hand with a more flexible pricing policy. In the case of IKEA, this increase in the frequency of updates is partially reversed once customers return to physical stores. Decathlon shows an upward trend throughout all years in the sample, which becomes stronger during this period. MediaMarkt, for its part, increases the frequency of adjustment during COVID-19 and maintains it in the following years, becoming the firm with the apparently most flexible pricing policy in the sample.

The paper is organised as follows. Section 2 describes the choice of firms and the treatment of observed prices; Section 3 explains in detail the construction and harmonisation of the database; Section 4 presents the empirical analysis of price rigidity, both descriptive, econometric and over time; and the final section summarises the main conclusions.

2 Selection of firms

To select the multichannel firms, we have taken a number of factors into account. We look for firms that are fully established in the multichannel market, update prices in their physical stores and online at the same time, cover different sectors, carry overlapping products and have been in the market for some time.

Thus, all traditional firms must be fully multichannel[1], that is, all products sold physically in stores must also be sold on the website. The literature has established that, for many sectors, the differences between online and offline prices are negligible (in particular, Cavallo (2017)). We adopt this conclusion in order to treat the prices observed on websites as representative prices for each firm, thereby allowing a solid comparison across all firms.

In addition, the firms must belong to sectors that are as differentiated as possible in order to have a representative sample of the market letting compare a much larger number of products.

Finally, we must take into account that the analysis of price adjustment requires products to have been on the market for several years, so the corresponding firm must have some track record and cannot be a new entrant.

2.1 Multichannel retailers

To carry out the analysis, the multichannel firms that we consider most suitable are MediaMarkt, IKEA, Decathlon and Abacus, since they meet all the requirements mentioned above.

MediaMarkt is a German company founded in 1979. It is a chain of stores devoted mainly to the sale of IT products, household appliances and consumer electronics. It is one of the leading firms worldwide in this regard, and it is also a reference in Spain, where it has 112 physical stores and captures 21,5% of the market share, with a turnover of more

[1] Hereafter, we will refer to this group indistinctly as “traditional firms”, “multichannel firms”, “suppliers” or “retailers”.

than 2.500 million euros (MediaMarkt, 2025).

IKEA is a Swedish multinational company dedicated to the sale of household goods, especially furniture. Founded in 1943, it currently has a turnover of around 2.000 million euros in Spain, having sold more than 164 million products in 2025. With a workforce of more than 9.000 employees, it receives around 50 million visitors per year in its stores. Its online channel is even more successful, with more than 200 million visits per year (IKEA, 2025).

Decathlon is a French company that sells sports equipment. It was founded in 1976 and currently has a turnover of slightly more than 2.000 million euros in Spain, accounting for 11,4% of the group's total turnover. It has 171 physical stores throughout the country and a workforce of more than 10.000 employees (Decathlon, 2025).

Abacus Cooperativa is a Catalan cooperative founded in 1968, specialised in the sale of educational, publishing and office products. It has a strong presence in Catalonia, the Valencian Community and the Balearic Islands, and is the market leader especially in Catalonia, where it captures 30% of the market share (Abacus, 2024).

2.2 Amazon

Amazon is a US company whose business activity is based on e-commerce, selling all kinds of products through its website. Founded in 1994, its turnover has grown exponentially over the last 10 years, making it one of the most highly valued companies in the world today. Between 2023 and 2024 alone, its net profits increased by 95%, reaching around 57.000 million euros, according to data reported by Amazon (2024). Its business model is based on commercialising products, whether its own or, mainly, of third parties[2], through its website, so that it is a purely online company. In Europe alone, in 2020 there were more than 150.000 companies from all sectors using this platform (Amazon, 2021).

In short, regarding the choice of Amazon as an online firm comparable to the others, we are dealing with a company with more than 30 years of history, a leader in e-commerce

[2]The fact that it sells similar products from different suppliers and that consumers can compare them all at once is a factor that we consider relevant as a determinant of the frequency of price adjustment.

and one that covers all the sectors in which the multichannel firms operate, making it ideal for carrying out the study. In addition, it allows us to access a large amount of data that we would hardly obtain for other players in its market.

2.3 Definition of prices and treatment of discounts

One source of debate in the literature is whether to include sales periods in studies of price dynamics. The main difficulty that is identified is that, in international studies, seasonal sales may not be synchronised across countries, which introduces bias into the analysis (Gautier et al., 2024; Nakamura and Steinsson, 2008).

Taking advantage of the fact that our study is limited to a single country, we will take as the price the minimum that is accessible to all consumers at the time of observation. In this way, we also incorporate the case of "always-on-sale" stores, since ignoring those discounts would introduce bias. By contrast, we exclude conditional promotions (e.g. discount cards, coupons or volume discounts), because they are not available to all consumers.

3 Data and panel construction

This section describes how we construct the database that makes it possible to compare the pricing policies of Amazon and the large multichannel retailers.

For the case of MediaMarkt, IKEA, Decathlon and Abacus, we present a novel strategy for data gathering. It consists in a retrospective scrapping method based on the Wayback Machine to reconstruct price histories from archived copies of product pages. This allows us to obtain long time series without having to define ex ante a closed catalogue of references. From these copies, we organise the information in a product–date–category panel and define common categories across firms that will later ensure the comparability of goods.

For Amazon, by contrast, we start from the complete daily price series provided by Keepa and focus on selecting, within its catalogue, the products that are genuinely comparable with those of the traditional retailers.

The last step is to homogenise all the series: we redefine price trajectories in terms of episodes of activity and thin out Amazon's data through a stochastic process calibrated on the multichannel firms. The result is a unified panel in which the observed differences in the frequency of adjustment can be interpreted as real differences in pricing policy, rather than as a consequence of different data-collection calendars.

3.1 Data collection from multichannel retailers

3.1.1 Introduction to retrospective web scrapping

For the traditional firms, we propose a web scrapping method that is considerably different from what is usually done in the literature (see Cavallo and Rigobon (2016), Metcalfe et al. (2016) and Cavallo (2017)). When large-scale digital price indices, robots are used to perform regular searches on the websites of products that have previously been identified through offline channels.

Other smaller-scale studies have used different methods to construct time series for specific products using retrospective data. Kaul (2022) studies the evolution of the price of pizza in two local restaurants, and Jones and Haynes (2022) use the price of a hamburger to approximate the local inflation rate. Both of them use the Wayback Machine[3] to collect the data.

3.1.2 Sampling strategy and method

The method we use seeks to build a panel with tens of thousands of products and a relatively long time dimension, comparable to those in the academic literature discussed above. At the same time, we use methods similar to those in articles that focus on specific products: instead of carrying out a prospective analysis in which we program robots that take product references as input and return cross-sectional information at the moment of the search, we program a robot that, for each predetermined supplier, searches for the entire stock of products that have appeared on its website (a functionality known as "crawling") and downloads their full price history in a single operation.

Therefore, by using this Wayback-Machine-based method we avoid (a) having to build beforehand, via offline channels, a constantly updated dictionary of references, and (b) having to make periodic searches on the target websites.

3.1.3 Raw data and initial filters

The raw data resulting from the pure scrapping process is summarised in Table 1. In this paper, a "reference" identifies each specific variant of a product (colour, size, etc.). For simplicity, we also use "product" in this same sense.

[3]The Wayback Machine (Internet Archive) is a digital archive of the web that preserves and makes available snapshots of webpages at different points in time. Snapshots are obtained by automatic crawls and on-demand requests, so availability may vary because of site restrictions (e.g. robots.txt) or technical constraints. More information on its use as a research tool can be found in Haans and Mertens (2024).

Table 1: Composition of the database by firm and repetition threshold.

	Threshold (r)					
	$r \geq 0$	$r \geq 10$	$r \geq 25$	$r \geq 50$	$r \geq 100$	$r \geq 250$
ABACUS						
Total observations	555.469	261.903	85.219	14.307	1.168	0
Different references	123.302	14.583	2.422	225	10	0
MEDIAMARKT						
Total observations	1.816.554	1.678.640	1.437.066	1.060.494	545.365	29.398
Different references	76.928	37.063	21.878	11.177	3.709	107
IKEA						
Total observations	333.105	262.265	185.846	139.516	85.778	14.502
Different references	29.304	7.872	2.678	1.300	531	46
DECATHLON						
Total observations	716.824	534.540	266.866	90.051	9.836	0
Different references	74.727	24.260	6.653	1.341	86	0

Notes: r represents the number of observation per reference.

In the first column ($r \geq 0$) we report the number of products obtained without applying any filter. We see that the quantities differ quite substantially across firms.

The remaining columns show the number of references that exceed the observation threshold indicated in the column heading. We therefore face a trade-off between maximising the number of different references in the sample (quantity of observations) and maximising the ratio of observations per product (quality of observations).

To remain flexible, and bearing in mind that we later apply other, more precise filters, from now on we drop products with fewer than 10 observations.

3.1.4 Category assignment

With the aim of classifying products and searching for matches across firms, we assign each product to a category using different methods, depending on the structure of the websites from which we extract the information. Mainly, the classification is done automatically by a robot that extracts it from the URL, taking advantage of the fact that URLs usually contain the product classification. In some exceptional cases, however, we have had to assign the category manually, based on the product's name and characteristics.

In this way, the retailer-specific categories are what we call *nodes*. For each node, we compute the number of products that belong to it.

3.2 Data collection from Amazon

The data from Amazon is collected via the database distributor Keepa. This service allows us, under certain constraints, to access a large amount of information on products sold exclusively on Amazon. Therefore, we do not need to carry out any scrapping in order to obtain the historical price series.

3.2.1 Sampling strategy and method

To build a complete panel, products need to be comparable across suppliers so that we can compare the overlaps between them. For this reason, we have placed a lot of emphasis on ensuring that the products we download from Amazon are comparable with those of the traditional firms. We have designed the data-collection method around this objective.

Schematically, the procedure for searching Amazon's products is based on:

1. Searching the nodes defined in Section 3.1.4 and storing information for 10 products for each of them. Thus, each node is assigned 10 products that are representative of Amazon.

2. For each representative product, we extract its category tree, which consists of a set of categories starting at a high aggregation level and becoming increasingly specific.

   For each node, we assign the mode at each level of the tree to obtain a representative one[4].

[4] By way of example, a keyboard from MediaMarkt would be assigned the node "teclado con cable". That node would be assigned the category tree `Informática > Accesorios > Teclados, ratones y periféricos de entrada > Teclados`.

3. Aggregating categories at level 2 (specific enough to identify products but broad enough to guarantee overlap[5]), we search among the bestsellers of the category for the number of ASINs (*Amazon Standard Identification Number*) required by each node (see 3.1.4).

4. Once the products have been identified, we download their price histories.

3.2.2 Raw data

The raw data from Amazon has a structure that differs from that of the multichannel firms, as a result of the way in which it is obtained.

The most important difference is that we have complete information on the daily price series of each product; that is, we do not have observation noise caused by scrapping. Table A1 reports the number of products obtained as a result of searching nodes for each multichannel firm.

3.3 Panel harmonisation

At this point, the panels are very heterogeneous across firms, especially regarding the frequency of observation of the data. In order not to overestimate the frequency of adjustment for those firms with more frequent observations[6], we harmonise the panels through three steps: (i) defining episodes of product activity, (ii) calculating the daily probability of observing the product during this activity period, and (iii) applying this structure to Amazon's panel.

3.3.1 Treatment of traditional retailers' data

As a consequence of the limitations of scrapping, our data for the multichannel firms has periods in which products are not observed. This lack of observations does not in itself

[5]Table A3 shows the number of categories that overlap at each level.

[6]If the density of observations is higher, it is more likely that you observe more price changes, especially if the changes have a V-shaped pattern, as the literature suggests (see Chevalier et al. (2003) and Klenow and Kryvtsov (2008)).

imply that the product has been discontinued or no longer exists, but rather that the robot has not been able to find it.

Definition of episodes

To prevent these periods of inactivity from leading us to underestimate the probability of observing the product, we use the concept of an *episode* and treat as different products those that have several clusters of activity separated by periods of inactivity[7].

Filtering of relevant episodes

We keep as "relevant episodes" (hereafter simply "episodes") those that have more than 25 observations and a minimum duration of 30 days. Table A2 shows the number of episodes and products that remain after applying this filter, together with the results obtained for different minimum numbers of products per episode.

Observation's probability calculation

For each product we calculate the daily probability of observation, conditional on the period being active (which is equivalent to calculating the probability of observing it within an episode, $P(obs)_i = \frac{\#obs_i}{\#days_i}$).

We use the average probability to apply a random Bernoulli process in which we decide whether each observation within the episode is kept in the panel or not (with independence between observations).

[7] To identify periods of inactivity, we use the distribution of the gap between observations. We consider that two clusters of activity are separated by a period of inactivity if two consecutive observations are separated by more than twice the interquartile range of the distribution for the specific product.

3.3.2 Application to Amazon

At this point, we go back to the nodes defined in Section 3.1.4 and to the category tree assigned to them in Section 3.2.1.

Aggregating all episodes by category, we compute a set of relevant statistics in order to homogenise Amazon's panel, trying to make it resemble the apparent randomness in the distribution of the multichannel firms. The result is Table A4, which contains information on the frequency of observation and the duration of episodes for each representative category.

Episodes' duration

To ensure that Amazon's products have a duration similar to that of the traditional firms, we split the time series of each Amazon product into episodes following the distribution of durations found for the traditional firms (third block of columns in Table A4), imposing that it follows a normal distribution $N(\mu_d, \sigma_d)$.

Observations' density

In the second block of columns in Table A4 we report the mean (weighted by episode length) and median probability of observing the products.

We use the mean probability to apply a random Bernoulli process in which we decide whether each observation within the episode remains in the panel or not (independently across observations).

Number of episodes

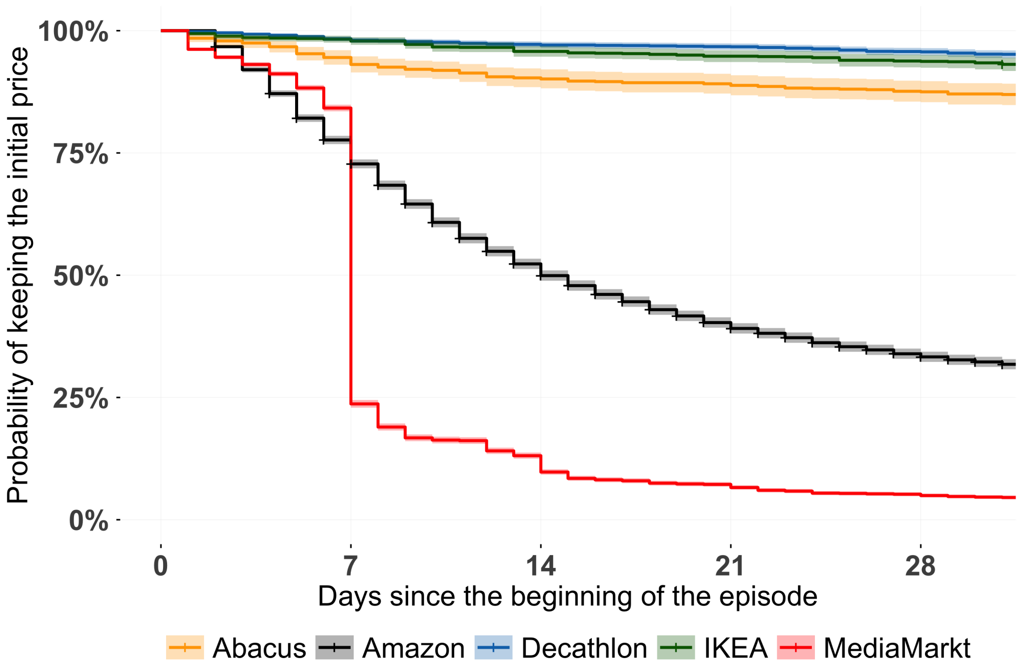
Finally, we keep only a number of Amazon episodes that is comparable with that of the traditional firms. We do so by prioritising the maximisation of the number of different ASINs, rather than maximising the number of episodes for a small set of references.

4 Empirical analysis of price stickiness

4.1 Descriptive evidence on price rigidity

Before turning to the analysis of the factors that influence the frequency of price adjustment and to identifying differences across firms, it is useful to look at what the apparent pricing policy of each of them is. With this aim, Figures 1 and 2 show, for each firm, the probability that a product's price remains unchanged over time.

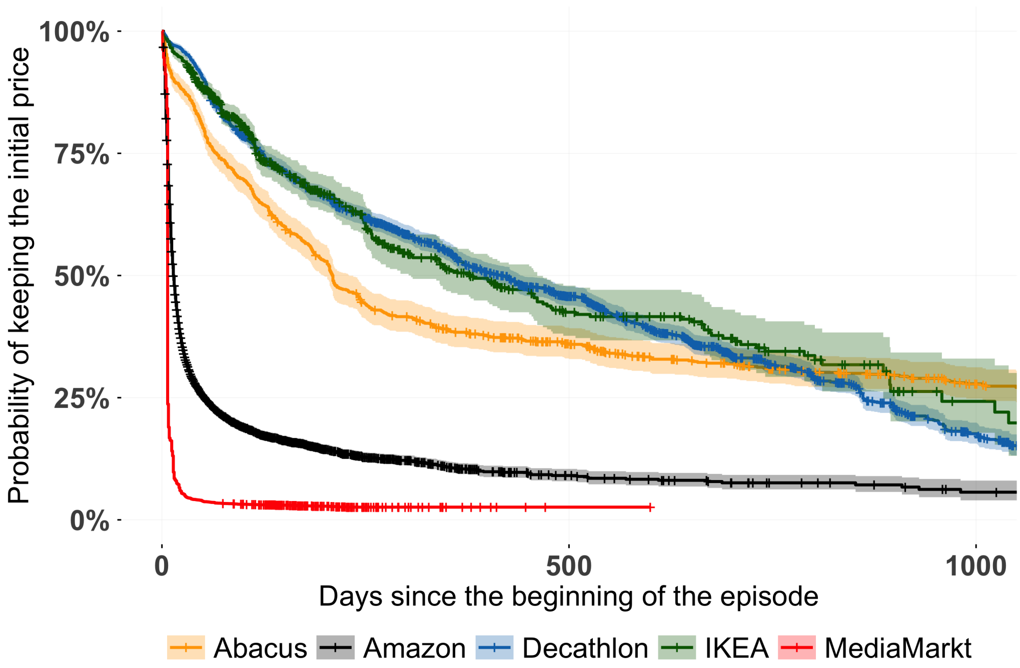
Figure 1: Price survival curve by firm (30 days)



Note: Non-parametric (Kaplan–Meier) descriptive estimate of the time to the first price change by firm (unit: product–episode). The X-axis shows the days since the beginning of the episode and the Y-axis the probability of keeping the day-0 price without any change. Covariates are not controlled for and no causal interpretation is made.

Figure 1 focuses on the first 30 days of the episode. As can be seen, MediaMarkt changes prices at least once during the first week for nearly three out of every four products, causing price survival to drop sharply (consistent with what the literature has described as the weekend effect or with weekly adjustment patterns (Warner and Barsky, 1995)). In contrast, the other firms appear to follow a continuous and more evenly distributed pricing policy, with updates occurring largely independently across days.

Figure 2: Price survival curve by firm (1,000 days)



Note: Non-parametric (Kaplan–Meier) descriptive estimate of the time to the first price change by firm (unit: product–episode). The X-axis shows the days since the beginning of the episode and the Y-axis the probability of keeping the day-0 price without any change. Covariates are not controlled for and no causal interpretation is made.

Figure 2 shows the same survival curve as above, but extending the horizon up to 1,000 days. In this case we can see the long-run evolution, which reinforces the apparent dynamics of each firm's price-changing policy.

Except in the case of Decathlon, all survival curves display a certain convex shape, indicating that in the later part of the distribution, among the products that have kept their price unchanged up to that point, the pace of changes is lower than at the beginning. This pattern is particularly pronounced for Amazon, where if prices do not change during the first months, they take much longer to change for the first time.

4.2 Differences in the frequency of price adjustment

4.2.1 Duration effect

Several studies by the European Central Bank and Eurosystem national central banks have analysed how unobserved heterogeneity across producers or products can introduce a heterogeneity bias (frailty bias) in duration models applied to price setting and inflation. In other words, if different firms or goods have very different probabilities of adjusting their prices, the aggregate measure of the price-change hazard may appear to decline over time: the more flexible units are more likely to adjust prices earlier, leaving in the sample only the most rigid ones (Álvarez et al., 2005; Baudry et al., 2007; Kiefer, 1988).

Figure 3: Comparison of the duration coefficient

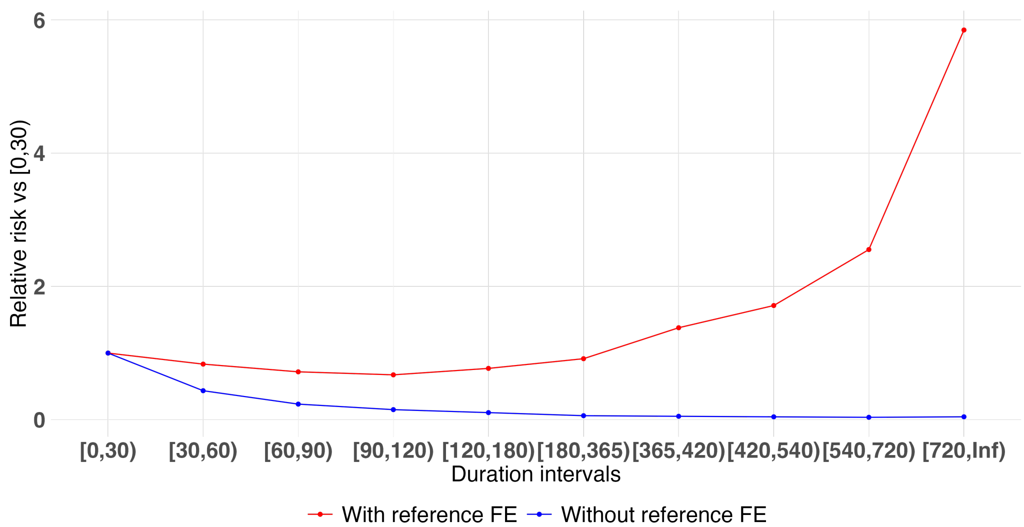


Figure 3 plots the duration coefficient, split into intervals, for two different models: one that controls for reference and therefore captures its heterogeneity (in red), and a second one that does not (in blue). We clearly observe that the model controlling for reference is sensitive to a variation in the effect of duration on the update rate: during the first year, the relative hazard compared to the first month is lower, whereas once this threshold is crossed, it increases exponentially[8]. This pattern is consistent with what has been

[8]Table A6 reports the estimated coefficients for each interval.

documented in the literature (e.g. Fabiani et al. (2005)). In contrast, the alternative model does not capture this variation.

4.2.2 Differences across firms

Table 2: Frequency of price adjustment by channel and specification

	(1) Controls	(2) All retailers	(3) Excl. MediaMarkt
Duration	-0.1357***	-0.3397***	-0.2675***
	(0.0098)	(0.0145)	(0.0179)
Price	-0.0736**	0.1351***	0.0956***
	(0.0224)	(0.0106)	(0.0113)
Traditional		-0.1664*	-1.835***
		(0.0673)	(0.0828)
Fixed-Effects:			
Month	Yes	Yes	Yes
Reference	Yes	No	No
Category	No	Yes	Yes
Model	Poisson (log)	Binomial (cloglog)	Binomial (cloglog)
S.E.: Clustered	Ref. & Month	Ref. & Month	Ref. & Month
Weights:	None	Retailer	Retailer
Offset:	ln(Δ t)	ln(Δ t)	ln(Δ t)
Observations	1,005,437	1,123,853	692,180
Squared Cor.	0.29764	0.29046	0.26717
Pseudo R2	0.22380	0.31373	0.32409
BIC	1,101,526.0	411,627.0	389,884.1

Notes: The dependent variable is the frequency of price adjustment (update rate), with an offset $\ln(\Delta t)$. Duration and Price are in logs. Column (1) is estimated using Poisson regression (log link) with month and reference fixed effects; standard errors are clustered by reference and month; no weights are applied. Columns (2) and (3) are estimated using a binomial model (complementary log–log link) with month and category fixed effects; standard errors are clustered by reference and month; both specifications include retailer weights. Column (1) and (2) are estimated on the complete sample, and column (3) excludes MediaMarkt. *Traditional* is an indicator for multichannel firms, excluding MediaMarkt in column (3). "Squared Cor." is the squared correlation between observed and fitted values; "Pseudo R2" refers to McFadden's R^2; the BIC is reported for model comparison. Robust standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Column (1)

Column (1) is used to characterise the controls and does not include any variable that compares firms across channels (we leave out any "retailer identity" variable). To avoid the heterogeneity bias described in Section 4.2.1, we estimate a Poisson model with fixed effects by reference and by month–year, with standard errors clustered in two dimensions (reference and month), and we drop perfectly predicted groups.

A key element of the specification is the temporal offset $\log \Delta t_{it}$, which normalises by the exposure time between observations and allows us to interpret the model in terms of a rate of adjustment per unit of time. Without the offset, firms with denser records (i.e. more days grouped together) could exhibit an artificially higher hazard simply because we accumulate more potential changes within each interval.[9]

Formally:

$$y_{it} \sim \text{Poisson}(\mu_{it}), \quad \log \mu_{it} = \alpha_i + \delta_m + \beta_D \log(\text{dur}_{it}) + \beta_P \log(\text{price}_{it}) + \underbrace{\log \Delta t_{it}}_{\text{offset}},$$

This is equivalent to:

$$\log\left(\frac{\mu_{it}}{\Delta t_{it}}\right) = \alpha_i + \delta_m + \beta_D \log(\text{dur}_{it}) + \beta_P \log(\text{price}_{it}),$$

so that we compare the adjustment rate (instantaneous probability of change) per unit of time rather than the raw number of changes.

The fixed effects α_i capture unobserved heterogeneity at the reference level, and the month–year fixed effects δ_m capture common seasonality.

In this framework, the coefficients are interpreted as conditional elasticities of the update rate. The coefficient for duration is $\hat{\beta}_D = -0.1357^{***}$, meaning that a 1% increase in duration is associated with an approximate 0.136% reduction in the expected update rate. The effect of the price level is $\hat{\beta}_P = -0.0736^{**}$, indicating that a 1% increase in price is

[9] This is because the expected counts μ_{it} increase mechanically with the length of the interval and, without normalisation, the model would confound a higher number of days with a higher instantaneous probability of change.

associated with a 0.074% reduction in the rate.

These relationships are purely associative and are conditioned by the fixed effects and the temporal offset in the specification.

Columns (2) and (3)

Columns (2) and (3) compare Amazon's update frequency with that of the traditional retailers. We estimate a discrete hazard[10] with category and month–year fixed effects, and two-way clustered standard errors (reference and month). In both specifications, we normalise by the exposure time between observations, so the coefficients are interpreted as update rates per unit of time.

Column (2) assigns equilibrium weights to each retailer within the traditional group so that every firm receives the same total weight in the estimation. Thus, the coefficient for Traditional reflects the average across firms (not across observations).

Column (3) keeps the same structure but excludes MediaMarkt from the sample and assesses the heterogeneity within the traditional channel.

Formally:

$$\log\big(-\log(1-p_{it})\big) = \kappa_i + \delta_m + \beta_D \log(\mathrm{dur}_{it}) + \beta_P \log(\mathrm{price}_{it}) + \beta_R R_i + \log \Delta t_{it},$$

where $p_{it} = \Pr(\mathrm{change}_{it} = 1)$, κ_i are category fixed effects, δ_m are month-year fixed effects, and R_i identifies the traditional retailers included in each column[11]. This specification is equivalent to assuming a discrete hazard of the form

$$p_{it} = 1 - \exp\{-\Delta t_{it} \lambda_{it}\}$$

where

$$\lambda_{it} = \exp\{\kappa_i + \delta_m + \beta_D \log(\mathrm{dur}_{it}) + \beta_P \log(\mathrm{price}_{it}) + \beta_R R_i\}$$

[10] By discrete hazard we mean the binomial implementation with a complementary log–log link and a temporal offset.

[11] Thus, R_i includes Decathlon, IKEA, Abacus, and MediaMarkt in the specification of column (2), and only the first three in column (3).

interpreting λ_{it} as the rate of price adjustment per unit of time.

To prevent a single traditional retailer with many more rows from dominating the estimation, we reweight the data so that each traditional firm has the same total weight. If n_r is the number of observations for retailer r within the traditional group, $N_{\text{trad}} = \sum_{r \in \text{trad}} n_r$ is the total number of traditional observations, and R_{trad} is the number of traditional firms, we assign to each observation:

$$w_i = \begin{cases} \dfrac{N_{\text{trad}}}{R_{\text{trad}}\, n_r} & \text{if } R_i = 1 \ (r_i \in \text{Traditional}), \\ 1 & \text{if } R_i = 0 \ (r_i = \text{Amazon}), \end{cases}$$

so that the contribution of each traditional firm to the likelihood is identical, independently of the number of references or observations it contributes. The weights differ between columns (2) and (3) due to the exclusion of MediaMarkt.

In this exercise, we interpret the coefficients as changes in the price-update rate (the probability of changing prices per unit of time). Duration is not discussed because, when including category fixed effects, heterogeneity bias may arise (we rely on the result in column (1)). For the price level, the estimate $\beta_P = 0.1351^{***}$ indicates that a 1% higher average price within the category corresponds approximately to a 0.135% higher update rate[12].

Regarding the channel, the coefficient for traditional retailers is $\hat{\beta}_R = -0.1664^{*}$, which implies a hazard ratio of $e^{\hat{\beta}_R} \approx 0.847$, an update rate about 15.3% lower than Amazon's, though only marginally statistically significant. Consequently, we interpret this retailer differential as moderate and imprecisely estimated: the pattern suggests a lower update rate than Amazon, but the evidence is not strong enough to draw firm conclusions.

When we separate MediaMarkt from the other traditional retailers (column (3)), the interpretation becomes more nuanced. For the coefficient of Traditional (excluding the

[12] The sign change between (1) and (2)–(3) is consistent with the source of variation that identifies $\hat{\beta}_P$. In (1), with reference fixed effects, $\hat{\beta}_P$ is identified from within variation: it compares the same product at moments when its price is higher or lower, and we find that when a reference's price increases, its update rate tends to fall (negative sign). By contrast, in (2)–(3), with category FE, $\hat{\beta}_P$ also incorporates between variation (differences across references and retailers). If the structurally more expensive references or channels also have higher update rates, the between component is positive and may dominate the within component, generating the positive sign.

German firm), we obtain $\hat{\beta}_R = -1.835^{***}$, which translates into $HR = e^{\hat{\beta}_R} \approx 0.16$, that is, an update rate about 84% lower than Amazon's, with strong statistical significance. This suggests that the weakness of the result in (2) stems from the specific weight of MediaMarkt within the traditional group[13]. Once it is excluded, the shortfall in the update rate of the other traditional retailers relative to Amazon is clear, substantial, and significant. As before, these effects are associative and conditioned by the fixed effects and the temporal offset.

4.3 Time patterns and the COVID-19 shock

Figure 4: Time evolution of the frequency of price adjustment by firm

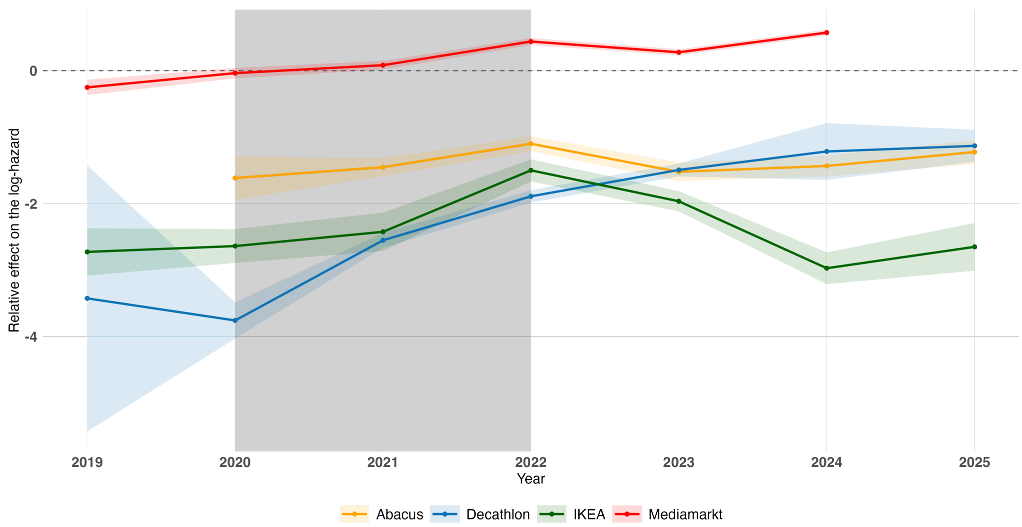


Figure 4 shows the time evolution of the frequency of price adjustment for each firm in the sample, taking as a reference Amazon's adjustment frequency in 2017.

As we can see, although each firm behaves differently, they all follow a common pattern between 2020 and 2022: there is a clear convergence of the multichannel retailers' adjustment frequency toward Amazon's. This is consistent with the hypothesis that greater reliance on online channels leads to more frequent price adjustments, a pattern driven by

[13] Table A5 presents the same model specification but estimates a separate coefficient for each traditional retailer, allowing the individual difference of each of them relative to Amazon to be compared.

the surge in online sales and the closure of physical stores following the outbreak of the COVID-19 pandemic.

For IKEA, it is particularly remarkable that its adjustment frequency rises sharply during the pandemic years, but then decreases substantially once customers return to in-store shopping. In the case of Decathlon, we also observe a substantial increase in the update frequency during the pandemic, but unlike IKEA, this higher frequency persists in the following years, even increasing considerably. For MediaMarkt, we see that its frequency was lower than Amazon's before COVID, caught up with it in 2020, and surpassed it in the subsequent years, becoming the retailer that updates prices the most frequently. Figure A1 provides a comparison of each firm's price-adjustment frequency before and after the onset of the pandemic.

5 Conclusions

This paper has documented marked differences in price rigidity between Amazon and four large multichannel firms operating in Spain. Using a homogeneous historical database, we have shown that Amazon (and, at present, also MediaMarkt) adjusts prices much more frequently than IKEA, Decathlon and Abacus, and that these patterns have evolved around the COVID-19 pandemic. In particular, we observe the adjustment frequency of multichannel firms converging towards Amazon's levels during the years in which the online channel gains weight, which suggests that digitalisation not only changes how goods are sold, but also how prices are set and updated.

Beyond these descriptive and econometric results, the implications for the interpretation of inflation and for the transmission of monetary policy (in the spirit of Baley and Blanco (2021)) in economies where e-commerce has a growing weight may be important. If an increasingly large share of consumption is concentrated in firms with relatively flexible prices, the aggregate response of the price index to demand and supply shocks may be faster than what data based only on traditional commerce would suggest. At the same time, the coexistence of sectors with very different price rigidity may generate important composition effects over the cycle. This would imply that, in the case of a shock on the weights of each channel, the policy-maker should take into account the different flexibility they show.

A natural line for future research would be to use the facts documented here to calibrate a model with two sectors: a "traditional" sector, with high price rigidity, and a "purely online" sector, with much more flexible prices (following Aoki and Yoshikawa (2007)). A framework of this kind would make it possible to study how economic activity changes as the weight of the online sector increases over time, as well as to assess the extent to which monetary policy needs to adapt to this new structure. Other possible extensions include introducing heterogeneity across product categories, exploring the role of temporary promotions and sales, and combining our data with quantity information in order to link pricing policy directly to demand behaviour.

References

Abacus. Abacus y las principales empresas de papelería del estado crean la asociación del sector de la papelería. https://abacus.cat/es/abacus-asociacion-sector-papeleria/, May 2024. Sala de prensa.

Luis J Álvarez, Pablo Burriel, and Ignacio Hernando. Do decreasing hazard functions for price changes make any sense? *Eurosystem Inflation Persistence Network*, 2005.

Amazon. Las pymes triunfan en amazon: más de 60 millones de productos vendidos en 2020, 100 cada minuto. https://www.aboutamazon.es/noticias/apoyo-a-las-pymes/las-pymes-triunfan-en-amazon-mas-de-60-millones-de-productos-vendidos-en-2020-100-cada-minuto, May 2021. Sala de prensa.

Amazon. Nuestro impacto económico en españa. https://www.aboutamazon.es/noticias/inversiones-y-creacion-de-empleo/nuestro-impacto-economico-en-espana, May 2024. Sala de prensa.

Masanao Aoki and Hiroshi Yoshikawa. *Reconstructing macroeconomics: a perspective from statistical physics and combinatorial stochastic processes*. Cambridge University Press, 2007.

Isaac Baley and Andrés Blanco. Aggregate dynamics in lumpy economies. *Econometrica*, 89(3):1235–1264, 2021. doi: https://doi.org/10.3982/ECTA17344. URL https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA17344.

Laurent Baudry, Hervé Le Bihan, Patrick Sevestre, and Sylvie Tarrieu. What do thirteen million price records have to say about consumer price rigidity? *Oxford Bulletin of Economics and Statistics*, 69(2):139–183, 2007. doi: https://doi.org/10.1111/j.1468-0084.2007.00473.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1468-0084.2007.00473.x.

Alberto Cavallo. Are online and offline prices similar? evidence from large multi-channel retailers. *American Economic Review*, 107(1):283–303, 2017.

Alberto Cavallo. More amazon effects: online competition and pricing behaviors. Technical report, National Bureau of Economic Research, 2018.

Alberto Cavallo and Roberto Rigobon. The billion prices project: Using online prices for measurement and research. *Journal of Economic Perspectives*, 30(2):151–178, 2016.

Judith A Chevalier, Anil K Kashyap, and Peter E Rossi. Why don't prices rise during periods of peak demand? evidence from scanner data. *American Economic Review*, 93 (1):15–37, 2003.

Decathlon. Decathlon alcanza los 2.094 millones de euros de facturación y un crecimiento del 47% en los negocios circulares. https://saladeprensa.decathlon.es/?corporativos=decathlon-alcanza-los-2-094-millones-de-euros-de-facturacion-y-un-crecimiento-del-47-en-los-negocios-circulares, July 2025. Sala de prensa.

Silvia Fabiani, Martine Druant, Ignacio Hernando, Claudia Kwapil, Bettina Landau, Claire Loupias, Fernando Martins, Thomas Mathä, Roberto Sabbatini, Harald Stahl, et al. The pricing behaviour of firms in the euro area: New survey evidence. 2005.

Erwan Gautier, Cristina Conflitti, Riemer P. Faber, Brian Fabo, Ludmila Fadejeva, Valentin Jouvanceau, Jan-Oliver Menz, Teresa Messner, Pavlos Petroulas, Pau Roldan-Blanco, Fabio Rumler, Sergio Santoro, Elisabeth Wieland, and Hélène Zimmer. New facts on consumer price rigidity in the euro area. *American Economic Journal: Macroeconomics*, 16(4):386–431, October 2024. doi: 10.1257/mac.20220289. URL https://www.aeaweb.org/articles?id=10.1257/mac.20220289.

Richard F. J. Haans and Marc J. Mertens. The internet never forgets: A four-step scraping tutorial, codebase, and database for longitudinal organizational website data. *Organizational Research Methods*, pages 1–29, 2024. doi: 10.1177/10944281241284941. URL https://madoc.bib.uni-mannheim.de/68472/1/haans-mertens-2024-the-internet-never-forgets-a-four-step-scraping-tutorial-codebase-and-database-for-longitudinal.pdf. Consultat el 2025-11-09.

IKEA. Ikea en españa alcanza los 1.986 millones de euros de facturación, 2025. URL https://www.ikea.com/es/es/newsroom/corporate-news/ikea-en-espana-alcanza-los-1-986-millones-de-euros-de-facturacion-puba0858260/. Noticias de IKEA.

Jacque Jones and Monica Haynes. Measuring inflation with the cheeseburger price index. Bureau of Business and Economic Research, Labovitz School of Business and

Economics, University of Minnesota Duluth, 2022. URL https://lsbe.d.umn.edu/articles/cheeseburger. Consultat el 2025-09-15.

Greta Kaul. More dough: Twin cities pizza prices are taking a bigger slice out of your wallet. *MinnPost*, 2022. URL https://www.minnpost.com/economy/2022/03/more-dough-twin-cities-pizza-prices-are-taking-a-bigger-slice-out-of-your-wallet/. Consultat el 2025-09-15.

Nicholas Kiefer. Economic duration data and hazard functions. *Journal of Economic Literature*, 26:672–676, 02 1988.

Peter J Klenow and Oleksiy Kryvtsov. State-dependent or time-dependent pricing: Does it matter for recent us inflation? *The Quarterly Journal of Economics*, 123(3):863–904, 2008.

MediaMarkt. Mediamarkt españa crece a doble dígito y supera los 2.500 m € de facturación. https://assets.ctfassets.net/osyynfyvlyjc/47j7kkZ4kHNvxenhqQZ0D/36890a97f3d871527bbeb0c31fe334b3/PresentaciÃČ_n_de_Resultados_Febrero_2025.pdf, February 2025. Sala de prensa.

E Metcalfe, T Flower, T Lewis, M Mayhew, and E Rowland. Research indices using web scraped data: Clustering large datasets into price indices (clip). *London: Office of National Statistics (ONS)*, 2016.

Emi Nakamura and Jón Steinsson. Five facts about prices: A reevaluation of menu cost models. *The Quarterly Journal of Economics*, 123(4):1415–1464, 2008.

Georg Strasser, Elisabeth Wieland, Paweł Macias, Aneta Błażejowska, Karol Szafranek, David Wittekopf, Jörn Franke, Lukas Henkel, and Chiara Osbat. E-commerce and price setting: evidence from europe. *ECB Occasional Paper*, (2023/320), 2023.

Elizabeth J. Warner and Robert B. Barsky. The timing and magnitude of retail store markdowns: Evidence from weekends and holidays. *The Quarterly Journal of Economics*, 110(2):321–352, 1995. ISSN 00335533, 15314650. URL http://www.jstor.org/stable/2118442.

A Appendix

Table A1: Number of Amazon ASINs comming from each retailer

	Number of references
Abacus	2382
Decathlon	3091
IKEA	5058
Mediamarkt	13384

Notes: Since Amazon products were found through nodes linked to each retailer, this table shows how many references were identified as reflections of the traditional ones.

Table A2: Number of episodes by thresholds.

Company	Threshold	Observations	Products	Episodes	Median gap (IQR, days)	Median episode duration (days)
Abacus	10	93809	4016	4936	7.0 (2.0–50.0)	500.0
Abacus	**25**	**27864**	**898**	**912**	**6.0 (2.0–49.0)**	**910.0**
Abacus	50	817	15	15	4.0 (1.0–38.8)	1244.0
Abacus	100	0	0	0	NA (NA–NA)	NA
Decathlon	10	252462	9426	12860	5.0 (2.0–32.0)	293.0
Decathlon	**25**	**90741**	**2746**	**2793**	**5.0 (2.0–35.0)**	**696.0**
Decathlon	50	5935	107	107	4.0 (2.0–29.0)	1041.0
Decathlon	100	0	0	0	NA (NA–NA)	NA
IKEA	10	89844	2478	3292	1.0 (1.0–12.0)	271.0
IKEA	**25**	**57186**	**1099**	**1322**	**1.0 (1.0–2.0)**	**79.0**
IKEA	50	21833	260	282	1.0 (1.0–1.0)	90.5
IKEA	100	6159	42	42	1.0 (1.0–1.0)	174.0
Mediamarkt	10	986461	24014	47687	7.0 (4.0–7.0)	101.0
Mediamarkt	**25**	**434513**	**8786**	**11432**	**7.0 (2.0–7.0)**	**190.0**
Mediamarkt	50	112239	1614	1668	7.0 (2.0–7.0)	342.0
Mediamarkt	100	11220	102	102	7.0 (1.0–7.0)	558.5

Notes: The table reports the number of observations, products, and episodes that remain after applying the minimum observation threshold per episode. It also shows the median and interquartile range of the spacing between observations that results from each filter, as well as the median duration of the episodes (in days).

Table A3: Summary of categories and overlap by level

			Overlap by number of retailers				
Level	Total categories	Shared	1 retailer	2 retailers	3 retailers	4 retailers	Prods/cat
0	25	76.0%	24.0%	36.0%	24.0%	16.0%	541
1	136	35.3%	64.7%	29.4%	5.9%	0.0%	99
2	**257**	**17.9%**	**82.1%**	**15.6%**	**1.9%**	**0.4%**	**51**
3	337	12.2%	87.8%	11.3%	0.9%	0.0%	35
4	253	9.1%	90.9%	8.3%	0.8%	0.0%	35
5	68	11.8%	88.2%	11.8%	0.0%	0.0%	30
6	12	8.3%	91.7%	8.3%	0.0%	0.0%	60
7	1	0.0%	100.0%	0.0%	0.0%	0.0%	5

Notes: A category is considered shared if it has ≥ 2 retailers (ref. level 2).

Table A4: Probabilitay of observation and episode's duration per category

	Coverage		**Observation frequency**		**Episode duration (days)**	
Categoty	N. products	N. episodes	Weighted freq. (%)	Median freq (%)	Median ep. dur. (d)	SD ep. dur. (d)
Accesorios para portátiles y netbooks	1476	1817	17.71	18.31	201.5	83.8
Batidoras, robots de cocina y minipicadoras	1057	1366	17.14	18.24	217.4	107.0
Accesorios (Cuidado y limpieza del hogar)	518	531	5.03	4.85	623.8	289.4
Accesorios (Fitness y ejercicio)	518	531	5.03	4.85	623.8	289.4
Televisores	402	500	18.67	18.95	204.5	83.5
Acampada y senderismo	392	502	12.43	18.05	293.0	229.5
Ropa de hombre	389	394	5.00	4.96	606.3	291.2
Móviles	313	355	17.40	18.79	208.7	91.5
Ciclismo	297	302	4.97	4.64	656.8	258.4
Zapatos	294	300	4.92	4.84	654.5	303.6
Accesorios (Audio y vídeo portátil)	288	378	17.93	18.68	236.1	118.2
Auriculares	274	357	15.81	17.75	229.3	119.8
Acción y aventura	273	309	17.28	18.00	209.4	85.9
Cables y accesorios	229	314	16.88	18.29	212.6	137.2
Almacenamiento de datos externo	226	343	16.90	18.39	239.4	147.6
Cafeteras	226	274	15.39	16.75	217.8	94.6
Accesorios (TV, vídeo y home cinema)	211	339	17.25	18.61	241.2	192.1
Accesorios (Ferretería)	211	339	17.25	18.61	241.2	192.1
Accesorios (Accesorios)	211	339	17.25	18.61	241.2	192.1
Aspiradoras	181	211	16.21	17.54	216.8	93.8
Afeitado y depilación	177	259	17.97	18.57	203.4	78.7
Impresoras	170	214	15.69	17.99	235.4	128.4

Table A4: Probabilitay of observation and episode's duration per category *(continued)*

	Coverage		**Observation frequency**		**Episode duration (days)**	
Categoty	N. products	N. episodes	Weighted freq. (%)	Median freq (%)	Median ep. dur. (d)	SD ep. dur. (d)
Teclados, ratones y periféricos de entrada	164	244	16.26	18.55	225.2	176.0
Monitores	158	183	18.78	19.25	196.5	88.6
Salón	146	193	13.75	81.16	305.0	511.4
Deportes acuáticos	128	128	4.47	4.46	769.0	261.8
Juegos electrónicos portátiles	125	174	17.07	19.21	243.3	184.0
Cuidado del cabello	125	177	17.16	18.50	208.2	88.1
Senderismo y Ocio al Aire Libre	119	127	5.78	5.83	543.3	283.3
Dormitorio	117	142	10.69	22.12	394.0	477.6
Campanas extractoras	116	156	16.98	17.94	224.6	117.2
Accesorios (Comunicación móvil y accesorios)	111	147	16.05	18.00	217.3	204.6
Tablets	109	135	17.30	18.44	196.3	93.1
Portátiles tradicionales	99	118	18.47	19.38	181.0	67.3
Lavadoras	88	120	17.86	18.91	207.4	85.0
Microondas	86	120	17.78	18.65	214.4	99.3
Lectores de eBooks	84	118	19.33	19.24	195.6	76.6
Juegos	83	97	18.60	18.83	173.3	59.4
Ropa de cama y almohadas	78	92	32.05	81.61	133.4	235.6
Reproductores y grabadores de DVD	76	99	17.26	18.51	224.6	154.3
Accesorios (Hombre)	75	75	3.97	3.97	752.0	244.3
Congeladores	75	94	18.32	18.71	200.9	71.8
Movilidad urbana	75	76	4.89	4.69	654.5	276.7
Torres	72	79	19.47	19.54	181.0	80.2
Juego de mesa	72	83	6.22	5.53	574.0	483.3

Table A4: Probabilitay of observation and episode's duration per category *(continued)*

	Coverage		**Observation frequency**		**Episode duration (days)**	
Categoty	N. products	N. episodes	Weighted freq. (%)	Median freq (%)	Median ep. dur. (d)	SD ep. dur. (d)
Accesorios (PC)	70	93	17.70	18.85	221.8	116.9
Ficción contemporánea	70	72	4.23	4.53	748.8	370.0
Masaje y relajación	68	87	9.70	12.44	365.7	264.0
Suplementos para deportistas	67	67	5.39	5.66	608.4	235.8
Smartwatches	66	72	13.09	18.53	259.0	213.9
Accesorios para impresoras	65	94	10.83	11.69	319.2	221.4
Calefacción	63	90	18.58	18.70	202.9	101.4
Ropa	62	65	5.53	5.17	566.9	345.8
Biografías y autobiografías	59	59	4.11	4.36	775.2	278.2
Lectura y escritura	59	59	3.27	3.71	980.4	406.7
Carrera y maratón	57	61	4.76	4.60	657.6	325.1
Excursionismo y actividades al aire libre	57	57	4.52	4.53	684.4	240.4
Aprendizaje temprano	56	57	3.59	4.15	794.6	504.3
Ciclismo	54	54	4.25	4.60	739.6	223.3
Cestos y cubos	53	76	15.26	67.90	294.4	511.9
Limpieza interdental	53	68	17.77	18.18	199.7	75.0
Fútbol	51	51	3.90	3.81	792.0	213.1
Juegos	49	61	13.20	16.15	239.9	185.3
Materiales	49	50	3.24	2.95	968.8	543.7
Juegos	47	66	16.99	19.39	236.8	137.5
Sets de construcción	47	51	4.82	5.66	614.4	378.3
Bienestar y vida sana	46	46	2.67	2.49	1205.7	359.8
Deportes acuáticos	45	45	3.76	3.91	824.1	193.8

Table A4: Probabilitay of observation and episode's duration per category *(continued)*

	Coverage		**Observation frequency**		**Episode duration (days)**	
Categoty	N. products	N. episodes	Weighted freq. (%)	Median freq (%)	Median ep. dur. (d)	SD ep. dur. (d)
Caza, pesca y tiro	44	44	3.31	3.35	882.2	218.0
Oficina	44	52	11.89	14.98	324.9	364.0
Lámparas	44	50	13.13	58.11	316.3	493.8
Entrenamiento y coaching	42	42	5.77	5.69	548.1	291.2
Sartenes y ollas	39	52	15.07	19.10	261.2	252.8
Accesorios para tablets	38	42	14.79	17.49	205.5	108.1
Centros de planchado	38	64	18.24	18.76	230.9	120.3
Cepillos de dientes y accesorios	38	49	17.71	18.81	179.5	74.4
Accesorios (Xbox Series X y S)	37	47	17.32	18.95	202.6	88.4
Pizarras	36	37	3.10	3.73	1012.4	430.7
Almacenamiento y organización de la colada	35	52	27.42	41.71	199.4	202.9
Bolígrafos y recambios	34	34	3.72	4.73	760.4	357.8
Merchandising, estatuas y bustos	34	38	15.50	18.66	228.0	132.4
Relojes	34	35	6.45	7.08	521.4	326.1
Lavadoras y secadoras todo en uno	33	39	17.51	18.38	200.7	78.7
Secadoras	33	44	19.73	19.80	204.3	76.7
Películas	33	33	4.00	5.08	755.4	494.5
Conjuntos	32	32	3.44	4.06	869.1	410.9
Cocina	31	35	5.67	41.94	587.9	751.3
Purificadores de aire	31	45	26.02	19.63	145.5	129.2
Papeles, envolturas y bolsas	31	34	26.61	76.92	208.8	281.4
Almacenamiento de alimentos	30	35	14.40	17.30	274.6	345.4
Humidificadores	30	36	18.00	18.50	205.1	72.9

Table A4: Probabilitay of observation and episode's duration per category *(continued)*

	Coverage		**Observation frequency**		**Episode duration (days)**	
Categoty	N. products	N. episodes	Weighted freq. (%)	Median freq (%)	Median ep. dur. (d)	SD ep. dur. (d)
Accesorios (Equipaje y accesorios de viaje)	29	42	19.80	18.21	213.7	97.3
Desarrollo de habilidades motoras	28	29	3.89	4.11	804.9	419.6
Calentadores de agua y piezas	28	38	18.73	18.84	233.7	117.2
Almacenamiento de datos internos	28	41	19.91	20.23	215.3	108.0
Electrodomésticos especializados y utensilios eléctricos	27	36	17.45	18.79	203.2	101.4
Accesorios de escritorio y productos de almacenamiento	27	37	7.03	17.82	439.1	487.1
Cuidado de la piel	27	38	18.47	17.90	171.7	54.1
Pilas	26	27	15.28	16.42	245.0	102.3
Arquitectura	25	25	3.61	4.03	773.2	264.1
Almacenaje de ropa y de armario	24	27	7.55	15.99	548.3	742.0
Hornos de pared	24	33	12.36	18.09	300.8	287.3
Zapatos	23	23	5.68	6.20	559.3	281.1
Freidoras	23	28	15.73	16.56	215.4	61.8
Cuchillos de cocina	23	27	16.38	17.41	200.1	57.0
TV y multimedia	23	24	16.94	19.43	216.7	90.5
Tenis	23	23	3.20	3.39	865.9	150.7
Barbacoas	23	30	19.37	20.31	223.2	114.6
Enchufes y accesorios	23	30	16.78	17.79	244.1	155.1
Planchas y centros de planchado	22	28	19.34	18.49	214.4	108.1
Cojines y accesorios	22	24	65.89	87.21	71.3	95.6
Espejos	22	37	21.31	20.38	222.9	162.7

Table A4: Probabilitay of observation and episode's duration per category *(continued)*

	Coverage		**Observation frequency**		**Episode duration (days)**	
Categoty	N. products	N. episodes	Weighted freq. (%)	Median freq (%)	Median ep. dur. (d)	SD ep. dur. (d)
Musculación	22	22	11.15	18.23	270.3	260.6
Accesorios para tarjetas de memoria	22	43	19.42	19.34	194.7	76.2
Lavavajillas tamaño estándar	22	30	16.32	17.71	206.3	109.5
Arte y manualidades	21	21	2.39	2.26	1311.0	321.7
Grapadoras y punzones	21	21	2.51	2.26	1263.9	422.7
Joyería y maquillaje	20	20	2.50	2.67	1163.2	321.7
Básculas de cocina	20	28	17.43	17.06	225.0	68.7
Sandwicheras	20	30	19.07	19.16	194.1	69.2
Planchas de vapor verticales	20	27	19.18	18.82	205.1	89.3
Recursos para planes de estudios	20	20	4.77	15.83	718.1	700.8
Tocadiscos	19	26	19.17	18.54	191.6	61.3
Alfombras, almohadillas y protectores	19	22	21.40	89.02	192.7	498.2
Airsoft	19	19	3.44	3.46	804.9	196.9
Deportes de invierno	19	19	4.54	4.54	724.7	205.0
Termos	18	24	19.22	18.73	166.7	46.6
Papel y manualidades con papel	18	18	3.77	3.66	795.6	527.4
Placas	18	20	12.02	18.09	259.6	242.1
Ciclismo	17	18	11.24	17.00	265.8	199.4
Proyectores	17	20	19.32	19.54	194.8	79.5
Accesorios de baño	17	17	4.25	14.93	677.5	822.1
Estructuras, baldas y cajones	17	21	6.28	5.08	610.3	680.8
Material escolar	16	16	3.06	2.70	916.1	496.2
Vajilla	16	22	25.27	84.46	187.5	474.1

Table A4: Probabilitay of observation and episode's duration per category *(continued)*

	Coverage		**Observation frequency**		**Episode duration (days)**	
Categoty	N. products	N. episodes	Weighted freq. (%)	Median freq (%)	Median ep. dur. (d)	SD ep. dur. (d)
Pasillo	16	19	10.68	55.28	392.3	621.6
Manicura y pedicura	16	27	18.83	18.71	192.4	73.5
Cuadernos, blocs de notas y diarios	15	15	2.64	2.57	1123.9	535.3
Desarrollo y cuestiones personales y sociales	14	14	2.79	2.94	1136.8	408.6
Otras marcas de ropa	14	14	2.75	3.56	1037.4	402.6
Destructoras de papel y documentos	14	30	18.58	18.59	191.5	74.2
Creación de álbumes de recortes	14	14	2.61	2.31	1159.7	492.1
Cuidado dental de bebés y niños	14	19	19.11	19.20	223.1	100.1
Música	13	13	2.38	2.22	1192.5	379.4
Poesía	13	13	1.82	1.79	1528.0	187.5
Cómics y novelas gráficas	13	13	2.26	2.11	1230.4	361.2
Desarrollo personal y autoayuda	11	14	8.06	8.96	427.9	364.9
Literatura y ficción	11	12	7.14	9.28	502.8	600.7
Tostadoras	11	17	20.13	20.65	193.2	95.6
Máquinas de cardio	11	11	16.30	18.56	174.5	50.8
Utensilios y accesorios	11	19	18.15	18.37	192.0	71.8
Marcos, álbumes de fotos y accesorios	11	11	25.41	86.67	149.5	242.3
Dispositivos internos	10	11	18.27	18.59	207.5	74.7
Accesorios para aspiradoras	9	13	58.12	60.38	75.3	42.0
Bar	9	13	4.10	2.61	754.4	868.0
Decoración de ventanas	9	11	13.46	22.08	291.7	359.7
Jarrones	9	9	2.34	1.89	1290.7	509.3
Béisbol	9	9	7.46	7.50	405.1	135.8

Table A4: Probabilitay of observation and episode's duration per category *(continued)*

	Coverage		**Observation frequency**		**Episode duration (days)**	
Categoty	N. products	N. episodes	Weighted freq. (%)	Median freq (%)	Median ep. dur. (d)	SD ep. dur. (d)
Ganchos	9	11	12.20	43.33	263.1	326.8
Organizadores de herramientas	9	11	43.01	84.51	122.2	122.0
Juguetes deportivos	8	8	3.01	4.44	913.1	503.3
Juguetes para Bebés	8	8	3.53	3.81	937.6	736.2
Gofreras	8	14	19.25	19.05	198.5	78.0
Comedor	8	8	7.11	23.04	527.8	546.5
Accesorios y repuestos	8	11	20.08	19.98	209.6	108.4
Recipientes para plantas y accesorios	8	8	3.10	2.60	1032.0	579.2
Marionetas de dedos	7	7	1.81	1.83	1476.0	102.9
Velas y candelabros	7	8	12.29	85.90	383.5	772.2
Accesorios decorativos	7	7	3.24	2.27	1097.6	530.5
Climatización	7	11	18.11	18.37	187.7	75.2
Material de construcción	7	7	13.95	84.78	275.6	299.5
Artistas individuales	7	7	3.45	5.47	765.4	461.3
Fotografía y vídeo	6	6	2.51	2.11	1136.3	423.3
Educación y consulta	6	6	3.84	5.13	724.7	391.5
Aprendizaje y enseñanza de idiomas	6	6	3.10	3.70	934.2	325.4
Cristalería	6	7	43.91	86.00	125.6	158.9
Cubos	6	6	3.32	3.18	928.2	701.5
Decoración de temporada	6	6	6.72	6.53	404.5	47.0
Lápices	6	6	2.67	2.35	1111.3	592.7
Construcciones magnéticas	6	6	2.93	3.60	966.0	534.5
Paraguas y sombra	6	7	86.67	87.45	75.0	27.2

Table A4: Probabilitay of observation and episode's duration per category *(continued)*

	Coverage		Observation frequency		Episode duration (days)	
Categoty	N. products	N. episodes	Weighted freq. (%)	Median freq (%)	Median ep. dur. (d)	SD ep. dur. (d)
Energía solar	5	5	2.58	2.23	1146.8	454.2
Cartuchos de filtrado para el agua	5	10	100.00	100.00	36.5	6.9
Caza	5	5	2.91	2.97	947.0	128.9
Sistemas de seguridad para el hogar	5	8	19.38	100.00	181.9	411.9
Tablas para picar	5	5	29.64	88.44	355.6	484.9
Dispensadores de agua fría y fuentes	5	6	9.29	42.37	299.5	509.1
Coches y coches de carreras	5	5	2.59	3.64	1058.4	559.8
Recambios y accesorios para lavavajillas	5	13	19.55	19.74	230.2	106.3
Consulta	4	4	2.69	2.56	1123.5	600.9
Guías de estudio y repaso	4	4	1.51	1.51	1772.0	31.3
Biografías y memorias	4	4	2.63	2.38	1113.8	276.9
Material de escritura y dibujo	4	4	11.29	46.86	496.0	466.6
Ciencias	4	4	3.49	4.70	901.8	622.5
Muñecos y figuras de acción	4	4	2.34	2.52	1218.2	475.8
Murales adhesivos y pegatinas de pared	4	4	4.95	5.08	546.0	46.1
Calzado	4	4	3.42	3.56	811.0	158.7
Ciclocomputadores	4	4	5.28	5.02	634.5	310.2
Accesorios de baño	4	4	27.93	42.37	117.2	81.6
Costura	4	4	2.16	2.23	1227.0	564.9
Tratamientos para sala acústica	4	4	4.12	4.43	679.2	510.1
Equipos e instrumental de laboratorio	4	6	44.35	55.51	113.5	101.0
Guías turisticas	3	3	1.73	1.60	1558.3	309.1
Muebles	3	3	3.64	3.24	686.0	156.8

Table A4: Probabilitay of observation and episode's duration per category *(continued)*

	Coverage		**Observation frequency**		**Episode duration (days)**	
Categoty	N. products	N. episodes	Weighted freq. (%)	Median freq (%)	Median ep. dur. (d)	SD ep. dur. (d)
Estantes y soportes	3	3	5.70	53.06	696.0	1100.8
Soportes y fundas para asiento	3	3	86.73	94.59	37.7	3.1
Felpudos	3	3	100.00	100.00	36.0	0.0
Golf	3	3	3.53	3.68	782.7	160.4
Esquí	3	3	1.99	1.82	1240.0	140.3
Ferretería y cerrojos para puertas	3	3	9.24	65.79	328.3	496.8
Textiles de baño	3	3	9.18	86.67	381.3	589.6
Textiles de cocina	3	4	80.99	81.62	60.5	29.5
Bombillas LED	3	3	3.97	3.76	797.0	568.6
Agendas y calendarios	3	3	3.12	3.92	960.7	479.8
Archivadores y accesorios	3	4	81.43	84.30	70.0	41.6
Cuentos, fábulas y mitos	3	3	2.82	2.45	1053.3	359.0
Paneles solares	3	4	17.34	19.15	252.2	61.1
Cojines	3	3	89.71	90.77	45.3	17.9
Animales de peluche	3	3	24.64	78.85	161.0	188.8
Economía	2	2	4.62	4.63	530.5	48.8
Puzzles	2	2	1.79	1.81	1732.5	142.1
Circuitos y playsets para coches de juguete	2	2	2.88	3.51	1370.0	650.5
Baberos	2	2	94.44	95.83	54.0	25.5
Mochilas	2	2	65.54	75.60	88.5	51.6
Zapatos	2	2	3.04	3.27	821.5	306.2
Espátulas, paletas y cucharas de cocina	2	3	71.43	70.98	53.7	23.0
Salvamanteles	2	2	3.57	9.37	785.0	851.4

Table A4: Probabilitay of observation and episode's duration per category *(continued)*

	Coverage		**Observation frequency**		**Episode duration (days)**	
Categoty	N. products	N. episodes	Weighted freq. (%)	Median freq (%)	Median ep. dur. (d)	SD ep. dur. (d)
Regletas	2	2	2.17	3.04	1335.5	962.4
Herramientas manuales	2	2	1.53	1.53	1568.0	0.0
Accesorios de iluminación	2	2	3.21	3.24	1448.5	265.2
Iluminación de seguridad	2	2	11.32	19.47	450.5	446.2
Iluminación de techo	2	2	4.01	4.09	761.5	205.8
Rotuladores y subrayadores	2	2	92.91	95.05	63.5	38.9
Material de educación infantil	2	2	2.32	2.62	1076.5	485.8
Tambores de mano	2	2	2.22	4.30	1194.0	1134.2
Gestión de cable eléctrico	2	2	2.56	2.92	1054.0	569.9
Dulces, chocolates y chicles	2	2	3.86	4.13	634.0	236.2
Astronomía	1	1	81.16	81.16	69.0	0.0
Certificaciones	1	1	8.09	8.09	346.0	0.0
Cristianismo	1	1	85.29	85.29	34.0	0.0
Altavoces	1	1	4.78	4.78	669.0	0.0
Fantasía y ciencia ficción	1	1	6.92	6.92	419.0	0.0
Delantales y guardapolvos	1	1	3.07	3.07	912.0	0.0
Pistas para canicas	1	1	4.23	4.23	733.0	0.0
Trenes	1	1	22.12	22.12	113.0	0.0
Dance y electrónica	1	1	1.90	1.90	1261.0	0.0
Accesorios (Accesorios para coche)	1	2	94.52	94.52	36.5	9.2
Colchones y mantas para cambiador	1	3	90.23	90.23	44.3	9.1
Ropa de cama	1	1	2.88	2.88	834.0	0.0
Accesorios y cuidado de zapatos	1	1	2.06	2.06	1797.0	0.0

Table A4: Probabilitay of observation and episode's duration per category *(continued)*

	Coverage		Observation frequency		Episode duration (days)	
Categoty	N. products	N. episodes	Weighted freq. (%)	Median freq (%)	Median ep. dur. (d)	SD ep. dur. (d)
Molinillos de café	1	1	76.09	76.09	46.0	0.0
Moldes	1	1	85.90	85.90	78.0	0.0
Cubertería	1	1	100.00	100.00	36.0	0.0
Utensilios de bar	1	1	81.16	81.16	69.0	0.0
Bacas y portaequipajes	1	1	2.87	2.87	836.0	0.0
Infantil	1	1	1.98	1.98	1566.0	0.0
Fragancias para el hogar	1	1	14.20	14.20	176.0	0.0
Fundas	1	1	81.82	81.82	33.0	0.0
Baloncesto	1	1	2.88	2.88	1077.0	0.0
Dardos y dianas	1	1	2.03	2.03	1673.0	0.0
Interruptores y reguladores de intensidad	1	1	2.41	2.41	1077.0	0.0
Fontanería de cocina	1	1	1.14	1.14	2286.0	0.0
Camas y almohadas hinchables y accesorios	1	1	80.39	80.39	51.0	0.0
Basura y reciclaje	1	1	86.81	86.81	91.0	0.0
Tronas y asientos	1	1	1.80	1.80	1720.0	0.0
Tratamientos de frío y calor	1	1	80.56	80.56	36.0	0.0
Tizas	1	1	90.11	90.11	91.0	0.0
Accesorios (Instrumentos de viento)	1	1	3.64	3.64	907.0	0.0
Rompecabezas	1	1	1.72	1.72	1749.0	0.0
Herramientas de mano	1	1	100.00	100.00	30.0	0.0
Fundas para muebles de jardín	1	1	80.56	80.56	36.0	0.0
Carnes de cerdo	1	1	1.59	1.59	1571.0	0.0
Cervezas	1	1	85.90	85.90	78.0	0.0

Table A4: Probabilitay of observation and episode's duration per category *(continued)*

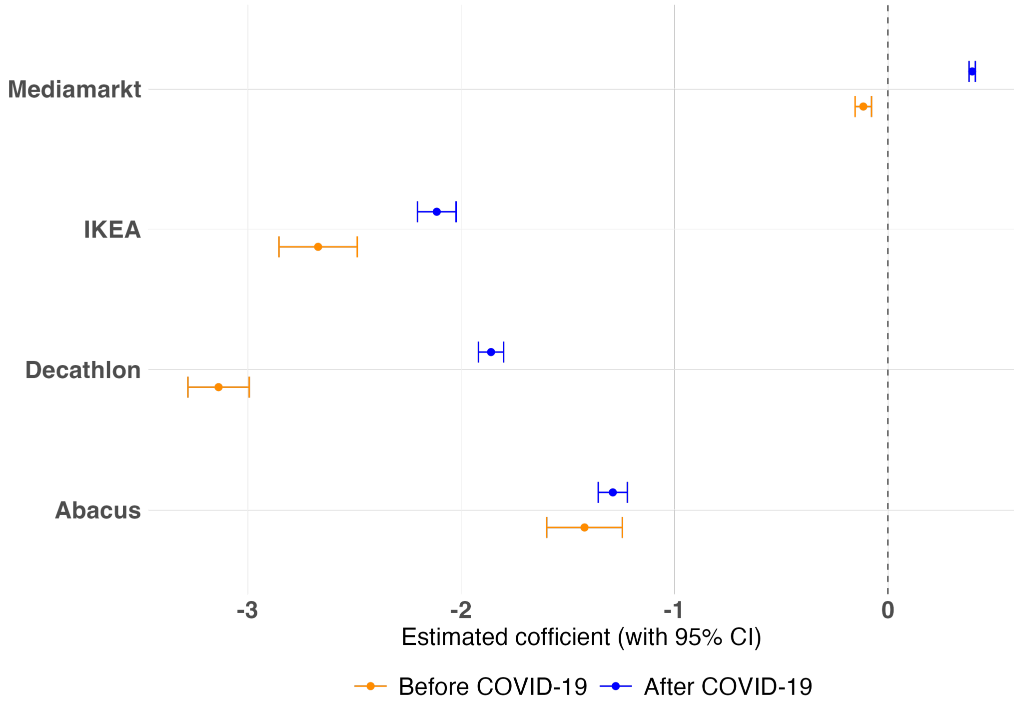
	Coverage		**Observation frequency**		**Episode duration (days)**	
Categoty	N. products	N. episodes	Weighted freq. (%)	Median freq (%)	Median ep. dur. (d)	SD ep. dur. (d)
Mezclas para repostería	1	1	1.65	1.65	1454.0	0.0
Maquillaje	1	2	84.51	84.51	71.0	28.3
Cableado y conectividad	1	1	93.33	93.33	30.0	0.0
Comederos y bebederos	1	1	85.90	85.90	78.0	0.0
Modelismo y maquetas	1	1	100.00	100.00	36.0	0.0
Lavavajillas compactos	1	1	16.88	16.88	160.0	0.0
Barnices, selladores y tintes	1	1	80.43	80.43	46.0	0.0
Paños de limpieza	1	1	82.61	82.61	46.0	0.0
Pulverizadores y accesorios	1	1	93.75	93.75	48.0	0.0

Table A5: Differences in adjustment frequency across retailers

	Coefficients
Duration	-0.3309*** (0.0132)
Price	0.0979*** (0.0110)
Abacus	-1.327*** (0.1657)
Decathlon	-1.983*** (0.1600)
IKEA	-2.183*** (0.1188)
MediaMarkt	0.3372*** (0.0601)
Fixed-Effects:	
Month	Yes
Category	Yes
S.E.: Clustered	Ref. & Month
Offset:	ln(Δ t)
Observations	1,123,853
Squared Cor.	0.31457
Pseudo R2	0.30912
BIC	774,497.7

Notes: The dependent variable is the frequency of price adjustment (update rate), with an offset $\ln(\Delta t)$. Duration and Price are in logs. The estimation is made using a binomial model (complementary log-log link) with month and category fixed effects; standard errors are clustered by reference and month. It is estimated on the complete sample. The retailer-specific variable measures each retailer's difference relative to Amazon. "Squared Cor." is the squared correlation between observed and fitted values; "Pseudo R2" refers to McFadden's R^2; the BIC is reported for model comparison. Robust standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.
We observe that all traditional retailers except MediaMarkt update their prices at a significantly lower rate than Amazon (negative coefficient).

Figure A1: Temporal evolution of the price-adjustment frequency by firm (before and after COVID)



Notes: This figure compares the estimated coefficient of the difference in the price-update rate for each traditional retailer relative to Amazon, distinguishing between the years before and after the declaration of the COVID-19 pandemic (using March 13, 2020 as the reference date).
The results confirm what we observe in Figure 4: all retailers show a sharp increase in their price-update frequency (especially Decathlon), and MediaMarkt surpasses Amazon after the pandemic.

Table A6: Estimated coefficient for the different time intervals

	Duration effect
[30,60)	-0.1813*** (0.0087)
[60,90)	-0.3305*** (0.0155)
[90,120)	-0.3954*** (0.0226)
[120,180)	-0.2613*** (0.0268)
[180,365)	-0.0882* (0.0346)
[365,420)	0.3221*** (0.0679)
[420,540)	0.5384*** (0.0713)
[540,720)	0.9372*** (0.0844)
[720,Inf)	1.766*** (0.1140)
Fixed-Effects:	-
Mes	Yes
Reference	Yes
S.E.: Clustered	Reference
Observations	1,088,601
Squared Cor.	0.26726
Pseudo R2	0.19855
BIC	1,159,599.8

Notes: The dependent variable is the frequency of price adjustment (update rate), with an offset $\ln(\Delta t)$. Duration is in logs and its effect is measured relative to the first month. The model is estimated using a binomial specification (complementary log–log link) with month and reference fixed effects to avoid heterogeneity bias; standard errors are clustered by reference and month. "Squared Cor." is the squared correlation between observed and fitted values. "Squared Cor." is the squared correlation between observed and fitted values; "Pseudo R2" refers to McFadden's R^2; the BIC is reported for model comparison. Robust standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.
We observe that the update rate decreases significantly relative to the first month, but rises sharply after the first year.