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Everyday Regular Prices in a Multi-Product Retailer *

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Abstract

Using a novel dataset from a large grocery retailer in a European country that never engages in temporary sale promotions, we establish that prices behave very similarly to regular prices set by retailers engaging in temporary promotional sales. We find evidence of state-dependent price setting in a multi-product firm when estimating the responsiveness of prices to exogenous demand shifts. The 'everyday regular prices' dataset is characterized by a more than trivial share of small price changes, and low synchronization of price changes across items. Price rigidity, selection and the extent of state-dependence are heterogeneous across items. Pricing of top sales items is more flexible and state-dependent compared to items that represent a small share of total revenues, a result consistent with price setting in a multi-product firm characterized by rational inattention. This result implies that inferences about firm-level price setting mechanisms from price microdata may be inaccurate if heterogeneity in price setting within the same firm is not taken into account.

Keywords: price setting, multi-product firm, state-dependence, synchronization, rational inattention, promotional price, regular price

Jel Codes: E31, D22, E4, E32

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1 Introduction

The ability of monetary policy to affect the response of the economy to business cycle shocks depends on the adjustment mechanism of prices and wages. It is essential for monetary policymakers to have appropriate models of how firms adjust their prices, and to understand how prices react to changes in aggregate economic conditions. Evidence from item-level retail price data documents higher price flexibility than what is suggested by the behaviour of aggregate inflation, and by estimates of the impact of monetary policy shocks on the real economy (Golosov and Lucas, 7). For instance, retail prices are estimated to change once every 4.3 months in Bils and Klenow [2004] based on BLS consumer prices, while estimates of new-Keynesian inflation equations or business cycle models based on aggregate data return much longer median price durations. However, a large share of price changes in individual-item prices are actually temporary sales promotions, that is, price transitions which are later reversed, and which occur around a recurrent price level, defined as the 'reference price' in Eichenbaum, Jaimovich and Rebelo [2011]. Changes in individual-item regular prices (that is, changes that exclude temporary sales promotions) are instead less frequent. Dropping temporary price cuts in BLS price data, Nakamura and Steinsson [2008] find that regular prices change about every 7-11 months, and Kehoe and Midrigan [2015] measure regular price durations of 14.5 months when eliminating both temporary price cuts and price increases.

Temporary sales promotions do not necessarily respond to shocks nor convey true price flexibility (Nakamura and Steinsson [2013]). Thus, the presence of promotions in price micro-data hinders the assessment of key features of retailers' price-setting behaviour relevant for monetary policy-making, such as the sensitivity of prices to changes in the state of the economy or the degree of selection in firms' optimal price choices.[1] One approach to assess the implications of micro-price evidence for the transmission of monetary policy has been to develop price setting models able to account for changes in both temporary and regular prices (Midrigan, [2011], Alvarez and Lippi, [2020]).

We take a different approach and analyze the price-setting behaviour of a large grocery retailer in Europe that never engages in temporary promotions, and follows instead a EDLP (everyday low-price) strategy. A profit-maximizing EDLP retailer will choose a price-setting strategy consistent with the array of models developed in the literature where all price changes follow a single price-setting behaviour, without the need to take a stand on the different incentives to adopt temporary or regular price changes. We verify that at low enough frequencies the EDLP pricing behaviour is comparable with the behaviour of the competitors who engage in temporary price changes (labeled as 'promo-

[1]For example, a higher frequency of price changes translates into more immediate transmission of monetary policy shocks to prices, and a smaller impact on real variables. A higher degree of price-selection implies that firms adjust first the prices of products further away from the optimal price, resulting in relatively large price-changes, and lowering the response of real variables.

tional pricing' strategy), supporting the hypothesis that EDLP and promotional pricing provide similar pricing to customers when high-frequency price-changes are averaged out.

We provide two sets of results. First, we analyze the EDLP price-setting behaviour, summarizing overall statistics, and focusing on small price changes, price-changes synchronization, and estimating the response of prices to a demand shifter. The extent of small price changes and price-changes synchronization is especially relevant to the impact of monetary policy on real variables. A high degree of price synchronization weakens the selection effect in many multi-product price-setting models, since paying a single menu cost allows many prices to be adjusted contemporaneously, including prices that may be not far away from their optimal level. This in turns is consistent with the existence of many small price changes, and with a strong effect of monetary policy on real variables. Alvarez and Lippi [2014] is an example of a multi-product firm model with full price synchronization. On the contrary, partial or no synchronization is consistent - generally speaking - with a stronger selection effect, where firms adjusts first prices which are further away from the optimal level, making the pass-through of monetary policy into prices much faster (as in Golosov and Lucas, 2007). It is readily apparent that temporary sales in the data hinders the understanding of the amount of selection present multi-product retailer data.

Second, we show that pricing behaviour is heterogeneous across the product distribution, and hinges critically on the revenue share of items sold. This implies that high-revenue items price-setting resembles models with a high degree of selection. Even if overall the empirical data is consistent with low-price synchronization and a high implied degree of selection, firm pricing behaviour may be driven by a small portion of all the items sold. We verify the heterogeneity hypothesis across all our statistics and panel estimates.

Our finding can be summarized as follows.

Posted prices are very sticky. The hypothesis that the frequency of price adjustment for a EDLP seller would be higher than the one for regular prices in retailers engaging in promotional pricing is not supported by the data. Our estimate for the frequency of price changes (about 10% per month) is comparable to what has been found in the literature for regular prices (*i.e.*, posted price records excluding temporary promotions). This finding validates the use of reference prices, discussed in Eichenbaum et al. [2011] to assess the impact of retailers' pricing behaviour on the aggregate economy. In this sense, EDLP retailers may be described as implementing 'everyday reference prices'. Overall our data contain a more than trivial share of small price changes, , as well as a very low amount of synchronization of price changes across products.

We provide evidence of state-dependence in pricing, a feature found also in Eichenbaum et al. [2011], Gagnon [2009], Vavra [2014], Alvarez et al. [2019]). These papers though do not conclusively resolve the issue of how to handle promotional prices - whether the extent of state-dependence relevant for the transmission of monetary policy should be estimated including promotional prices in the data. Based on our EDLP data where this concern doesn't apply, we find that item-specific prices respond to changes in lagged aggregate demand shifts.this end, we estimate a set of regressions of prices on an exogenous demand shifter and find that in the EDLP data prices increase when lagged demand increases. Moreover, we find that this result is also statistically significant when we estimate the same regressions on national-average price indices from weekly scanner data of the EDLP retailer's competitors. We also estimate the price reaction to macroeconomic conditions at the extensive and the intensive margins. We find that an increase in the demand indicator raises the probability of a price increase.

Our dataset includes sales volume by item. Over the whole sample, 10% of products account for over half of the total revenue, and the top 25% of products by sales account for over 80% of revenues. We investigate the hypothesis that pricing behaviour is heterogeneous across products, and we find that pricing of top sales items is more flexible, displays higher state-dependence, a higher share of small price changes and higher price-changes synchronization compared to low-sales items. The results are strengthened when we examine 'private label' items - that are branded and marketed directly by the retailer. This pricing behaviour is consistent with price setting in a multi-product firm that may rationally choose to be inattentive, for some items more than for others, to information that is costly to acquire, absorb, or process as in Reis [2006]. A multi-product price-setter may find optimal to more often revise and change prices of items that have a larger weight in the firm revenue stream, minimizing in this way the loss incurred when failing to optimally adjust any given price. Overall this set of results imply that assessing the impact of reatilers' pricing behaviour on the propagation of shocks based on the full product assortment may be misleading.

This paper relates to a vast literature on analyzing item-level data sets to discriminate across price-setting models. There is an active debate in the literature regarding the relevance of promotional prices for the aggregate dynamics of the economy. Bils and Klenow [2004] argue that promotions respond to shocks. Some empirical support for this view has been provided by Kryvtsov and Vincent [2020]. However, Kehoe and Midrigan [2015] find that promotional prices, which are by definition temporary, contribute less than regular prices to inflation. Moreover, since promotional prices are for the most part time-dependent 'comeback prices' orthogonal to aggregate conditions, as suggested by Nakamura and Steinsson [2008], they contribute little to the extent of price rigidity which is relevant for the transmission of monetary policy to real variables. Also Midrigan [2011] argues that temporary discounts and regular price changes follow different adjustment mechanisms, so that there is little interaction among the two types of price changes. Coibion et al. [2015] show that promotions are acyclical and are not more frequent under recessionary macroeconomic conditions. Similarly, Anderson et al. [2017] find evidence that temporary promotions follow sticky plans, typically agreed by retailers and manufacturers up to a year in advance, so that they are basically unresponsive to macroeconomic shocks. We contribute to this debate by studying an item-level dataset where we do not need to disentangle whether promotional sales events respond to demand conditions and to aggregate macroeconomic variables, or whether they do so in the same degree as regular prices.

We also connect to a large literature on synchronization of price changes across products, including. models of multi-product firm state-dependent price setting Ã la Midrigan [2011] and Alvarez and Lippi [2014]. While these models imply perfect synchronization (*i.e.*, the price of all items should adjust at the same time), there is empirical evidence in the literature of partial synchronization, in particular across similar products (Lach and Tsiddon [1996], Levy et al. [1997], Levy et al. [1999], Fisher and Konieczny [2010], Cavallo [2018]). The closest paper to our work is Bonomo et al. [2023]. These authors find that in a multi-product, multi-store daily dataset from Israel synchronization is partial, but time-dependent.

In the following, Section 2 describes the EDLP data sets, including results on small price changes and synchronization, and a panel estimate of state-dependence in price setting. Section 3 examines the price-setting heterogeneity hypothesis across revenue-ranked items. Section 4 concludes.

2 EDLP Retailer Item-level Data

2.1 Price Data Collection

Our dataset is provided by a EDLP retailer operating in a European country since many years with a very significant share of the grocery retail industry. The unique characteristic of these data is that the retailer never engages in temporary promotions. The data contain more than ten thousand different items, that can be grouped in about four hundred product categories.[2] Sales have a skewed distribution across products, despite the variety of products being consistent with the industry competition: about one sixth of total sales derive on average from about 100 items. Overall 16% of items are store-branded, private label goods, and represent about 32% of total average sales. Moreover, almost half of the 100 items generating one sixth of total sales are private label items. Monthly sales and volumes are available at the barcode level for the period October 2008 to September 2013 (60 months). For one year within that period, weekly data are also available.

We infer unit prices taking the ratio of total revenue and volume sold by product per period, across all stores included in the analysis (barcode-level prices are identical across

[2] Notice that fish, meat, fruits and vegetables are not in the data.

all stores in the analysis). This implies that if a price changed in the middle of the period the observed price is an average of the price before and after the change, weighted by the number of items purchased at the different price levels. To avoid mis-identifying or double-counting price changes that occur during the period, we follow Anderson et al. [2017] and exclude price changes less than 1-cent in magnitude and filter price changes that are in the same direction as a price change in the immediately preceding period.We only include items for which price observations are available consecutively for at least one quarter, and sold in at least 100 outlets. We also drop from the sample products whose price is missing for more than two months in a row. Finally, we drop extreme price changes, defined as larger than a factor of five. Unless otherwise specified, we weigh all results by item-average share of revenue.

Overall we clean the data following standard procedures in the grocery micro-pricing literature. The fact that price changes occur with much lower frequency than in datasets containing temporary promotions, and that statistical results from monthly and weekly data provide nearly identical empirical results, supports our choice of using the more extended monthly dataset in most of the analysis.

2.2 Comparison With Promotional Pricing Retailers Data

If the key difference between the EDLP retailer and the competitors were the absence of promotional sales, we would expect the EDLP pricing not to diverge significantly from the industry average over long enough time-periods. To compare the data of the EDLP retailer with the grocery supermarket retail sector at the national level, we exploit Nielsen data for the same country and same period.[3] We are able to exactly match 82 items (*i.e.*, same product, brand, and pack content) belonging to 37 categories between the two data sets. For each item, the Nielsen dataset reports the 4-week national average revenue and sales-volume, from which an average price is obtained. The Nielsen sample covers November 2009 to October 2011. [4]

The EDLP retailer is a significant player in the retail sector of the country, with an average market share for the matched product categories of 25%, and a standard deviation equal to 0.12 .Matched items within this set of product categories have similar market shares to the retailer's market share for the overall matched product categories, and constitute therefore a reasonable subsample of all the product-category items.

[3]The Nielsen dataset is accessed through the ECB Statistics Directorate and is described in "Grocery prices in the Euro area", ECB, 2015. These data include 582 products (including 'private labels' items across all product categories) belonging to 45 product categories. For more details on Nielsen data, please refer to Anderton et al. [2011].

[4]The matched categories are: 100% fruit juice, refrigerated 100% fruit juice, all-purpose cleaner, automatic dishwasher detergent, baby food, baby food cereals, beer, bouillon, butter, cat food, chewing gum, chocolate countline, chocolate tablet, deodorant, diapers, dog food, dry pasta, ground coffee, ice cream, instant coffee, laundry detergent, margarine, refrigerated milk, uht milk, panty liners, paper towels, rice, shampoo, sugar, tinned peas, tinned tuna, toilet tissue, toothpaste, water sparkling, water still, soups wet, whiskey.

We build for each matching item a price ratio between the EDLP retailer price and the national average national price. The cross-sectional distribution of price ratios has a symmetric distribution centered around 1 implying that prices are similar. Figure 1 shows the distribution of price ratios at each date. On average the EDLP retailer has persistently slightly lower prices than the average price for the same items at the national level in each period. The interquartile range across all the products shows the retailer's prices in nearly all months are within a narrow [-4%, +2%] band of the national average

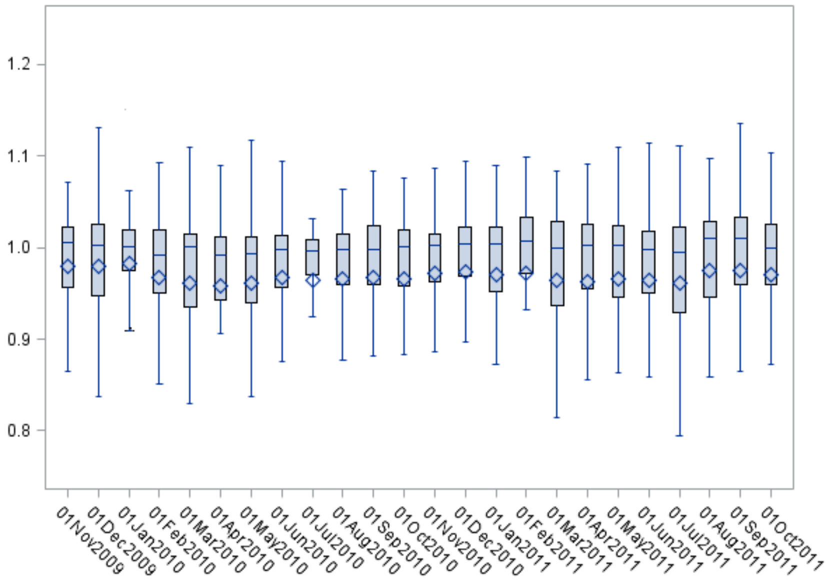

Figure 1: Boxplots of relative prices of the EDLP retailer with respect to the national average compute from Nielsen data: range, interquartile range, median and average of the distribution by month, for 82 barcode- matched products within 37 product categories.

Finally, monthly inflation largely co-moves, with a correlation for the mean price change equal to 0.6 . Overall, we conclude that price levels and price dynamics over the longer horizon for the EDLP retailer is consistent with the behaviour of the industry.

2.3 Price-changes Statistics

Despite the fact that the EDLP retailer does not engage in promotions, we find that the price updating characteristic of transaction prices are similar to what the literature finds for regular prices. Table 1 reports that 9.8% of prices change each month and 3.1% each week in the weighted sample.[5] These frequencies of price changes are between the frequency of price changes found for regular prices of Israeli stores by Bonomo et al.

[5]The mean and median implied duration of a price spell are respectively about 10 and 12 months. Figure 3 in the appendix plots the hazard function and its confidence intervals. The price hazard function is downward sloping up to 15 months and flattening for longer horizons, similarly to Nakamura and Steinsson [2008]'s hazard function for processed food prices.

[2019] (11.5% for monthly prices and 4.3% for weekly prices) and those found for regular prices based on BLS monthly data (6.9%, while including also temporary promotions raises the updating frequency to 22%) and based on Dominick's weekly data (2.9%, and 33% when including temporary promotions) computed by Kehoe and Midrigan [2015].[6] Not surprisingly, price increases are slightly more frequent than price decreases (54% of both monthly and weekly price changes). Table 1 also shows that the absolute size of price decreases tends to be larger than that of price increases.

	monthly data		weekly data	
	unweighted	weighted	unweighted	weighted
frequency of price changes (%)	7.0	9.8	2.3	3.1
frequency of price increases (%)	3.3	5.1	1.1	1.7
frequency of price decreases (%)	3.7	4.7	1.2	1.4
N	376,135		350,120	
mean price increases (%)	8.3	7.0	7.4	6.0
median price increases (%)	5.6	5.2	4.1	3.8
N	12,571		3,863	
mean price decreases (%)	-14.5	-8.1	-11.3	-6.9
median price decreases (%)	-7.3	-5.6	-5.2	-4.3
N	13,613		4,335	

Table 1: Extensive and intensive margin of price flexibility in monthly and weekly data.

Table 2 compares basic statistics of the EDLP dataset with Bhattarai and Schoenle [2014] and Midrigan, [2011]. Table 3 compares the EDLP dataset distribution of regular price changes with the data reported in Table 1 from Midrigan [2011] calculated in our data. Overall, summary statistics of the EDLP dataset are aligned with the statistics reported in the literature for grocery item-level data.

	EDLP data		Bhattarai & Schoenle (2014)	Midrigan (2011)			
	Monthly	Weekly	(n=10 products)	AC Nielsen		Dominick's	
Statistics				All	No Sales	All	No Sales
$\text{Std}(\lvert\Delta p_i\rvert)/[\lvert\Delta p_i\rvert]$	1.5	1.7	1.55	0.68	0.72	0.84	0.81
$\text{Kurtosis}(\Delta p_i)^*$	17.15	21.8	17	3.0	3.6	4.1	4.5

Table 2: Comparison of statistics from Table 2 in Alvarez & Lippi (2014). (*) Note that kurtosis is calculated based on actual price changes, not in absolute values.

[6]Computing the statistics excluding observations that are flagged by sales (symmetric) V-shaped filters with a 1, 2, or 3-month window, similar to 'filter B' in Nakamura and Steinsson [2008], does not significantly change the results in the table. See the Appendix.

Moments	EDLP data	Midrigan (2011)
10th percentile size regular price changes	0.01	0.03
25th percentile size regular price changes	0.03	0.05
50th percentile size regular price changes	0.06	0.09
75th percentile size regular price changes	0.13	0.13
90th percentile size regular price changes	0.24	0.21

Table 3: Comparison of statistics from Table 1 in Midrigan [2011]. Percentiles are calculated based on absolute values of price changes.

2.4 Small Price Changes

Models of multi-product price setting, like Alvarez and Lippi [2014], typically imply the existence of a non-trivial number of small price changes, which have been documented by empirical results at least since Klenow and Malin [2010]. Small price changes are also frequent in the EDLP dataset. Table 4 shows the frequency of price changes small in absolute number and small relative to the average price change, for the sample unweighted and revenue-weighted. In the monthly weighted sample, we find that price changes' frequencies which are small relative to average price changes are in line with the frequency found by Midrigan [2011] based on Dominick's scanner data.

	monthly data		weekly data	
% of price changes with:	unweighted	weighted	unweighted	weighted
$\lvert\text{price changes}\rvert \leqslant 1\%$	0.7	0.8	0.6	0.5
$\lvert\text{price changes}\rvert \leqslant 2\%$	1.2	1.7	0.8	0.9
$\lvert\text{price changes}\rvert \leqslant 3\%$	1.8	2.7	1.0	1.2
$\lvert\text{price changes}\rvert < \frac{1}{2}\mathbf{E}\lvert\text{price changes}\rvert$	46.5	36.4	50.4	41.8
$\lvert\text{price changes}\rvert < \frac{1}{4}\mathbf{E}\lvert\text{price changes}\rvert$	24.9	16.4	35.6	21.4

Table 4: Percentages of small price changes in monthly and weekly data. Weighted statistics use as weight a given product's average monthly revenue as share of average total monthly revenue.

Following the literature, we compute statistics for 'standardized' price changes so as to account for heterogeneity in price behaviour across product families, corresponding to store 'aisles'. We standardize the price change measure as

$$z_{ift} = \left.\frac{\pi_{ift} - \bar{\pi_f}}{\sigma_f}\right|_{\pi_{ift} \neq 0}$$

where z_{ift} is the standardized price change measure of product i in product family f at time t, $\pi_{ift} = 100 \cdot (\ln P_{ift} / \ln P_{if(t-1)})$ is the log price difference, while $\bar{\pi_f}$ and σ_f respectively are the unweighted average and standard deviation of price changes within family of products f across the whole period. The standardized price change measure and the moments used are all evaluated for non-zero price changes.

Table 5 reports the results. As one would expect, the revenue-weighted statistics are of similar magnitude to the ones reported for raw price changes. Bonomo et al. (2023) reports similar magnitudes for U.S. retailers data.

	Monthly		Weekly	
% of price changes with:	unweighted	weighted	unweighted	weighted
$\lvert$price changes$\rvert < \frac{1}{2}\mathbf{E}\lvert$price changes$\rvert$	35.1	33.2	42.1	36.4
$\lvert$price changes$\rvert < \frac{1}{4}\mathbf{E}\lvert$price changes$\rvert$	16.8	15.6	23.7	20.6

Table 5: Small standardized-price change statistics on monthly and weekly data. Weighted statistics use as weight a given product's average monthly revenue as share of average total monthly revenue.

2.5 Price-changes Synchronization

To study whether synchronization or staggering of price changes prevails in the EDLP data, we compute the fraction of price changes that takes place in every period. Perfect staggering implies that the fraction of price changes is identical in all periods. In case of perfect synchronization, instead, all products move at the same time. Therefore, in each period either the fraction of price changes is 1 or 0. Notice that the series of the fractions of price changes in the case of perfect staggering and that of perfect synchronization have the same mean, but different standard deviation. In particular, the former has standard deviation equal to 0. Fisher and Konieczny [2010] suggest measuring synchronization as the percentage difference of the actual standard deviation and the perfect synchronization case.

Based on this intuition and transposing the computation proposed by Dias et al. [2005] to the case of synchronization of price changes of different items within the firm rather than of the same product across competitors, we compute the Fisher-Konieczny index as:

$$FK = \sqrt{\frac{1}{T}\frac{\sum_{t=1}^{T}(h_t - \bar{h})^2}{\bar{h}(1-\bar{h})}}$$

where h_t is the ratio of price changes at period t relative to the number of products available that time period and $\bar{h}$ is the average over time of those ratios: $\bar{h} = \sum_{t=1}^{T} h_t/T$. By construction $FK = 0$ when prices across items are perfectly staggered and $FK = 1$ when they are perfectly synchronized.

Overall, the percentage difference from perfect staggering is about 6.5%. Fisher and Konieczny [2010]'s measure suggests therefore limited synchronization in price changes. However, a standard deviation close to 0 may also result from a situation where there is no perfect staggering, but rather heterogeneity in price setting across products. This would be the case if, for instance, prices of many items never change and prices of a few products change very often. We address this issue in a later section.

2.6 State-dependent price setting in a multi-product firm

The fact that firms change prices whenever the economic conditions attain a critical level has been extensively documented using micro data (*e.g.*, Eichenbaum et al. [2011] for changes in costs, Karadi and Reiff [2019] in VAT, and Gagnon [2009], Vavra [2014], Alvarez et al. [2019] in inflation). We investigate whether the EDLP price-setting strategy is consistent with state-dependent price setting estimating the responsiveness of prices to the economic conditions. In order to explore the extent to which everyday regular prices react to economic conditions, we test whether prices adjust in response to exogenous shifts in demand. We first normalize monthly prices by their (over time) average:[7]

$$P_{ist} = \frac{p_{ist}}{\mathbf{E}\left[p_{is}\right]} \tag{1}$$

where i is the item, s is the product category, and t is the monthly date. We then regress the price index P_{ist} on item and date fixed effects as well as on a demand shifter:

$$P_{ist} = \mu_i + \mu_t + \beta X_{s\tau} + \varepsilon_{ist} \tag{2}$$

where μ_i are item and μ_t time fixed effects, respectively. Demand is proxied by sales in our data[8] of items belonging to the same product category s as item i in a given time period τ, normalized by its over time average.[9] More precisely, the demand index $X_{s\tau}$ is a ratio with numerator equal to the sales for product category s divided by the number of items in that category in a given time period τ, and the denominator equal to the average value of the numerator over time. Table 6 shows the results with τ corresponding to the previous period (column I), to the previous period two-month moving average (column II) and to the previous period three-month moving average (column III), all standard errors are clustered at the item level. This is consistent with Alvarez et al. [2011], who suggest that price reviews should not depend on contemporaneous variables. Fabiani

[7]This normalization aims to avoid over-weighting expensive items. Kaplan and Menzio [2015] and Anderson et al. [2017] adopt the same normalization.

[8]Ideally, the independent variable would be the national demand for product categories. However, we do not exploit Nielsen data at the national level in this exercise for several reasons. Beyond restricting the time period available for the analysis, we would have to significantly shrink the number of items, since we only have access to national sales for a few product categories. Overall, national sales and the EDLP retailer's have a correlation of 82% therefore, we can be confident in using EDLP retailer's sales data in the estimation.

[9]Table 15 in the appendix shows that these results are robust to an alternative demand shifter that does not take into account the varying number of items belonging to product category over time. The choice of the preferred demand shifter depends on the extent to which new items are believed to be substitutes of others in the category or not. In the former case, sales of a product category should not be affected by the fact that the number of items varies over time, while in the latter sales should increase (decrease) when the number of items increases (decreases). Since we find a positive correlation between the number of items and sales within product categories, we favor the hypothesis that the appearance of new items in a category does not simply reallocate demand within the category and therefore our preferred demand index takes the number of items of product categories into account.

et al. [2006] provides evidence that the median firm in several Euro Area countries changes its price one to three months after a demand shock and even a bit longer in the country where the EDLP retailer is located.

EDLP retailer price index	I	II	III
lagged product category sales index	0.0347***		
	(0.0042)		
lagged MA2 product category sales index		0.0457***	
		(0.0051)	
lagged MA3 product category sales index			0.0539***
			(0.0058)
constant	0.9873***	0.9745***	0.9665***
	(0.0042)	(0.0051)	(0.0057)
item FE	✓	✓	✓
time FE	✓	✓	✓
N.obs	360,204	349,561	338,922
R-squared within	0.070	0.072	0.075

Table 6: Estimated coefficients of demand shifts. Dependent variables: item price indexes of the EDLP retailer.
Note: Standard errors are clustered at the item level.

Identification relies on cross-sectional variation across different product categories. The idea is inspired from Coibion et al. [2015], who exploit cross-sectional variation across stores in unemployment rates. Two conditions are necessary for identification. First, shifts in demand need to be exogenous. Therefore, product categories need to be large enough, so that a change in sales is not endogenous to the change in price of any item.[10] Second, product categories need to be poor substitutes. Indeed, if they are perfect substitutes, a shift in demand in one product category would have general equilibrium effects on demand for other product categories as well, and cross-sectional variation would be compromised. Indeed, the extent to which prices react to the shifter depends on the degree of imperfect substitutability across product categories. Similarly, the extent to which prices react to local unemployment depends on the degree of imperfect mobility of workers across local areas in Coibion et al. [2015]

Table 6 suggests that prices increase when lagged demand increases. In other words, if demand for a product category increased last month, the price of an item belonging to that category would likely go up. Notice also, comparing the estimated coefficients in columns [I], [II], and [III], that the magnitude of the reaction to demand shifts is monotonic with the length of the time period considered. That is, the longer demand

[10] For this reason, all items belonging to categories in which one item alone represents more than 20% of sales of its product category are dropped. As a consequence, 16 product categories are dropped in this exercise, corresponding to less than 4% of total sales of the retailer. Table 16 in the appendix shows that the result are robust to a more stringent 15% criterion, although the sample size shrinks.

has been increasing, the more prices increase as well.

The coefficient of the lagged MA2 product category sales index (column II) in Table 6 suggests that, if sales of a category are 20% above their mean (which corresponds to one standard deviation of the independent variable), then prices of items belonging to that category would be on average about 1% above their mean (which corresponds to a bit more than one tenth of the standard deviation of the dependent variable).[11]

The magnitude and significance of the estimated coefficients is basically unaffected by the inclusion of other variables characterising the cycle like the national monthly unemployment rate (see Table 18 in the appendix).[12]

As a robustness check, we also estimate a similar specification on price indexes at the national level. The idea is to test whether the prices of all retailers show a similar sensitivity to economic conditions. Indeed, in this case one can argue that the EDLP retailer's price setting is representative, and the fact that other retailers engage in sales basically just adds noise to price sensitivity to the economic cycle. In this robustness exercise P_{ist} in specification (2) is a national price index (based on Nielsen price data) and corresponds to the monthly average price for an item sold in supermarkets all over the country. Notice that this exercise restricts the analysis only to the time period for which we have national prices, as well as to the items available and matching with the EDLP retailer, so that the sample size shrinks accordingly. Table 7 shows the estimated coefficients for total sales for product categories with τ corresponding to the previous period (column I), to the previous period 2-month moving average (column II), and to the previous period 3-month moving average (column III).[13] Estimated coefficients are smaller and their standard errors (clustered at the item level) larger, but the overall picture is consistent with Table 6.[14]

Another possible way to investigate whether prices react to macroeconomic conditions is looking at the extensive and intensive margins of price adjustment, instead of

[11] Qualitative results are similar when the dependent and independent variables are taken in logs (instead of transformed in indexes relative to their over time mean). The coefficient of log lagged MA2 product category sales (column II) in Table 17 in the appendix suggests that a 1% increase in sales of a category increases prices of items belonging to that category on average by 4%.

[12] The inclusion of the monthly unemployment rate implies that in this specification time fixed effects are dropped. We however include year and month fixed effects. The estimated coefficients for unemployment are negative and significant. They suggest that if unemployment increases by one percentage point, prices are on average 0.2% below their mean. Notice that this does not correspond to a causal impact of unemployment on prices. Indeed, we can't proceed like Coibion et al. [2015] and exploit regional variations in unemployment due to the fact that the EDLP retailer has national pricing. However, the order of magnitude is rather similar to that estimated by Coibion et al. [2015] on effective price inflation.

[13] In the Nielsen data sometimes product categories are too narrow and therefore sales too endogenous to single items. Therefore, also in this exercise demand is proxied by EDLP retailer's sales, which overall are anyway highly correlated with the national ones.

[14] Notice that restricting the analysis only to the time period for which we have national prices and to the items available and matching with the EDLP retailer, the estimated coefficients with the EDLP retailer's data are smaller than in the whole sample. Table 19 in the appendix reports the estimated coefficients obtained by replicating the same regressions as in Table 6, but on the subsample of common period and product categories as available at the national level.

national price index	I	II	III
lagged product category sales index	0.0136		
	(0.0100)		
lagged MA2 product category sales index		0.0285*	
		(0.0114)	
lagged MA3 product category sales index			0.0444***
			(0.0128)
constant	0.9856***	0.9706***	0.9544***
	(0.0249)	(0.0259)	(0.0268)
item FE	✓	✓	✓
time FE	✓	✓	✓
N.obs	13,029	12,613	12,222
R-squared within	0.055	0.067	0.086

Table 7: Estimated coefficients of demand shifts. Dependent variable: item national price indexes.
Note: Standard errors are clustered at the item level.

looking at EDLP retailer's price indexes.[15] Results (reported in the appendix) suggest that an increase in the previous period 2-month moving average significantly enhances the probability of a price increase and diminishes that of a price decrease. The intensive margin of a price adjustment reacts in a consistent way with respect to the extensive margin, although the estimated coefficients are not significant.

3 Heterogeneity in Price-setting for a Multi-product Retailer

3.1 Price-changes Statistics: Heterogeneity Results

This section examines to what extent heterogeneity in prices across items may be consistent with a multi-product firm characterized by rational inattention as -for example - in Reis [2006].[16] In this family of models acquiring, absorbing and processing information is costly. The existence of information costs implies that price setters may optimally choose to be 'inattentive', so that prices do not always track the full-information, menu-cost optimal prices. Harris et al. [2020], for instance, suggest that two thirds of price rigidity would vanish if there was no information friction. Alvarez et al. [2011] suggests

[15]In particular, we investigate the response of frequency and size of price change (upper and lower panel of Table 20, respectively) to a change in previous period 2-month moving average demand. In this exercise P_{ist} in specification 2 is a dummy indicating whether a price, respectively, has changed or not (column 'price changed'), has increased (column 'price increased'), or has decreased (column 'price decreased' in the upper panel of Table 20), and is, respectively, the price change (column 'price change'), the price increase (column 'price increase'), the price decrease (column 'price decrease' in the lower panel of Table 20).

[16]An alternative interpretation could be related to behavioral industrial organization, in terms of behavioral consumers Ã la Della Vigna and Malmendier [2004] or behavioral firms Ã la Della Vigna and Gentzkow [2019]. The uniformity of prices across stores belonging to the same retail chain has also been studied by Berardi et al. [2017], Hitsch et al. [2019], and Berardi [2019].

that the maximum period length between two price reviews is a decreasing function of the loss incurred when failing to adjust. Costain and Nakov [2011] study the distribution of retail price adjustments under the assumption that firms are more likely to adjust their prices when doing so is more valuable. In particular, the main assumption of their model is that the probability of adjustment is a smooth function of the gain from adjustment. Mackowiak and Wiederholt [2009] develop a rational inattention model in which price setting firms decide, subject to a constraint on information flow, whether to pay attention to idiosyncratic or aggregate conditions.

The added value of our results is in providing evidence that for a multi-product firm price-setting is heterogeneous across the revenue distribution, since failing to adjust prices may be more costly for some items than for other ones. If items are not all equally important for a firm, we expect that information costs are more often paid to adjust prices of the most relevant ones. When inattention is more costly, firms are more likely to revise and change their prices. In particular, we argue that the most important items are likely to be those yielding high profits. We do not observe profits, but under the assumption that they are proxied by sales,[17] we explore whether price setting is more state-dependent for items that represent top 1%, 5% and 10% as far as their sales are concerned. Among those, we also explore the price setting of private labels items, which are arguably characterized by particularly high profit margin.

Many studies have shown that price rigidity is very heterogeneous across products (see Dhyne et al. [2006] for Europe or Berardi et al. [2015] for France). Our data are no exception. The median monthly frequency of price changes across product categories is 5.2%, but the standard deviation is large and the 95^{th} to 5^{th} percentile ratio is 8.7. At the item level, about 30% actually never changed price over the whole period.[18]

We split items into quantiles sorting products into equal-numbered deciles of the full product distribution, where products are ranked by revenue. For example, the top decile contains the top 10% of products (c. 1,079 SKUs) by average monthly revenue, so that we can ensure equally-sized item-number deciles. Table 8 reports the key statistics of the distribution by revenue.

	Top				
	1%	5%	10%	20%	25%
Revenue share	16.9%	38.9%	53.5%	70.6%	80.1%

Table 8: Quantiles are defined such that the top 1% group consists of the 1% of products with the highest average revenue. All percentiles have an equal number of products.

[17]If the price setter targets in general an average markup, then sales are indeed a proxy for profits. Alternative assumption, however, could be that top sales items are consumers' preferred ones because they offer the best price-quality within a product category. In this case, they would be the items with the smallest markup. However, the reasoning stays similar: the pricing of items that are particularly important for consumers should be more important to the price setters.

[18]Bonomo et al. [2019] also find that 40% of regular prices don't change once in 4 years.

Tables 9 and 10 report statistics of the extensive and intensive margins of price changes. Top sales items are characterized by price changes that are more frequent and smaller in absolute value. In particular, this tendency is stronger for the very top sale products. For instance, 12% of the top 1% sales items change prices each month, versus 9.8% in the whole sample. Also private label items that yield top 1% sales have a higher frequency of price changes than other items (10.9%). At the same time, the absolute size of mean (and median) price increases is smaller, respectively 5.6 (4.2) and 5.2 (3.7), compared to 7 (5.2) in the whole sample. Similarly, the absolute value of mean (and median) price decreases is smaller, respectively 6.1 (4.6) and 6.9 (4.2), compared to 8.1 (5.6) in the whole sample.

	Quartiles sorted by revenue (monthly)			
	Q4	Q3	Q2	Q1
frequency of price changes (%)	10.6	6.6	6.1	5.7
frequency of price increases (%)	5.6	3.3	2.7	2.3
frequency of price decreases (%)	5.0	3.3	3.4	3.4
N			370,223	
mean price increases (%)	6.9	8.0	8.4	9.9
median price increases (%)	5.1	5.9	5.3	5.4
N			12,389	
mean price decreases (%)	-7.4	-10.4	-16.7	-24.9
median price decreases (%)	-5.5	-6.5	-7.4	-12.0
N			13,340	

Table 9: Extensive and intensive margin of price flexibility in monthly and weekly data. Results for quartiles based on within-quartile item-weighing

As far as small price changes are concerned, Table 3.1 suggests that overall they tend to be more frequent among top sales products than for the other ones (reported in

	top1%	top5%	top10%	top1%	top5%	top10%
		sales items			sales private label items	
% frequency of price changes	12.0	12.2	11.6	10.9	8.7	7.8
% frequency of price increases	6.5	6.5	6.2	6.4	4.9	4.4
N.obs	5,200	24,101	46,550	2,522	9,861	18,504
% mean price increases	5.6	6.4	6.6	5.2	5.4	5.7
% median price increases	4.2	4.7	4.9	3.7	4.0	4.2
N.obs	306	1,524	2,674	139	374	615
% mean price decreases	-6.1	-6.9	-7.0	-6.9	-7.0	-7.1
% median price decreases	-4.6	-5.0	-5.2	-4.2	-4.3	-4.6
N.obs	292	1,366	2,381	113	327	505

Table 10: Extensive and intensive margin of price flexibility for top sales items.

Table 4). Moreover, the incidence of small price changes is monotonically decreasing in the share of sales represented by items. The small price change statistics are calculated for different percentiles, based on price changes standardized with regards to a given product's family.

	Percentiles		
% of price changes with:	Top 1%	Top 5%	top 10%
$\lvert$price changes$\rvert$ $< \frac{1}{2}\mathbf{E}\lvert$price changes$\rvert$	43.2	35.8	34.6
$\lvert$price changes$\rvert$ $< \frac{1}{4}\mathbf{E}\lvert$price changes$\rvert$	21.2	16.7	16.2
... As a percentage of N =	567	2,794	4,939

Table 11: Small standardized price change statistics on monthly data for given quantile groups. Note that moments are weighted by share of average monthly total revenue. Average price change is calculated across all quantile groups.

3.2 Price-changes synchronization: Heterogeneity Results

In order to assess whether heterogeneity in price rigidity across items is driving our result, we compute the Fisher and Konieczny [2010]'s measure of synchronization across different deciles of the items ranked by revenue distribution. Synchronization appears much stronger among top sales products than for the other ones. Indeed, the Fisher and Konieczny [2010]'s index computed among items that represent the top 1%, 5%, 10%, 20% sales decreases as the revenue share of each ranked deciles falls. Synchronization of price changes among private label items that represent the top 10%, 5%, and 1% of sales is even higher.[19]

	Top				Bottom		All
	1%	5%	10%	20%	80%	90%	100%
FK-index	0.184	0.106	0.099	0.086	0.068	0.067	0.067
N	567	2,794	4,939	8,508	17,221	20,790	25,729
Revenue share	16.9%	38.9%	53.5%	70.6%	29.4%	46.5%	100%

Table 12: Quantiles are defined such that the top 1% group consists of the 1% of products with the highest average revenue. N indicates the total number of price changes across the whole period within the quantile group.

We also compute the Fisher and Konieczny [2010]'s measure of synchronization limiting the sample to items for which the price changes some minimum number of times. By imposing stronger homogeneity of price rigidity on our sample, we limit the role that heterogeneous price setting can play and we thus have a better assessment of the extent of price change synchronization across products. Figure 2 shows that indeed dropping

[19]Notice that the Fisher and Konieczny [2010]'s index computed for all private label items is larger than for other products (11.6% versus 6.5%) and increases further when dropping products whose prices change very rarely.

products whose prices change very rarely, dramatically increases the measure of synchronization. Similarly, Bonomo et al. [2019] find 30% higher synchronization with the FK index for items with mean frequency of price changes in the top quartile of the distribution. Importantly, the set of products with a larger number of price changes are mostly overlapping with the top sale products by revenue.

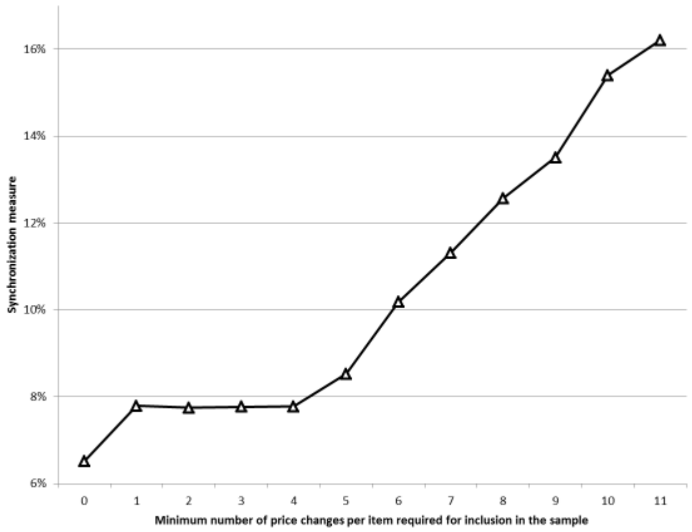

Figure 2: Fisher and Konieczny [2010]'s measure of synchronization when limiting the sample to items that have an increasing minimum number of price changes.

It seems likely that in a firm pricing more than ten thousand items, one should not expect very high level of synchronization of price changes across all items. Even online prices exhibit a rather low synchronization level of price changes across goods within a seller, as documented by Gorodnichenko et al. [2018]. However, the empirical literature tends to find synchronization across similar products (Lach and Tsiddon [1996], Levy et al. [1997], Levy et al. [1999], Fisher and Konieczny [2010], Cavallo [2018], Anderson et al. [2017]). We find support for synchronization at the aisle level by computing the Fisher and Konieczny [2010]'s measure at the product category level. Indeed, no product category exhibits price synchronization below 10%, one fifth between 10 and 20%, the vast majority between 20 and 30%, and another fifth between 30 and 40%. Overall, the mean FK index at the aisle level is 29.1% and the median 25.6%. Moreover, the finer the product category level the stronger synchronization within it.

EDLP retailer price index	top1%	top5%	top10%	top1%	top5%	top10%
		sales items			sales private label items	
lagged MA2 prod.cat.	0.1117***	0.0839***	0.0698***	0.1571**	0.1412***	0.1156***
sales index	(0.0308)	(0.0128)	(0.0098)	(0.0522)	(0.0278)	(0.0216)
constant	0.9183***	0.9424***	0.9542***	0.8882***	0.8858***	0.9109***
	(0.0335)	(0.0130)	(0.0100)	(0.0583)	(0.0294)	(0.0223)
item FE	✓	✓	✓	✓	✓	✓
time FE	✓	✓	✓	✓	✓	✓
N.obs	4,396	21,966	43,124	2,474	9,532	17,754
R-squared within	0.177	0.149	0.128	0.305	0.272	0.237

Table 13: Estimated coefficients of demand shifts. Dependent variable: top sales item price indexes of the EDLP retailer.
Note: Standard errors are clustered at the item level.

3.3 Pricing State-dependence: Heterogeneity Results

Table 13 shows the estimated coefficients resulting from running specification (2) in the subsample of top sales items (left panel) and of those that are also private labels (right panel). Prices of top sales items, and especially private label ones, react more to demand changes than the other products. Notice that the size of the coefficient for the previous period 2-month moving average demand is almost three times larger for 1% top sales items than that for the overall sample reported in Table 6 and almost four times for private label top 1% sales items. We find that the estimated coefficients are monotonically decreasing in the share of sales represented by each product-group.

4 Conclusions

Typically retail price setters engage in temporary sales promotions, hindering the analysis of pricing models, since the setting of temporary sale prices may be orthogonal to the regular price optimization of the retailer, and respond differently to the state of the economy. We exploit the 'everyday low prices' strategy from a large grocery retailer in a European country and establish that pricing behaviour is akin to the one found for regular, non-promotional prices of other retailer. Our panel estimates provide evidence consistent with state-dependence price setting in a multi-product firm. Product-specific prices are responsive to changes to aggregate demand shifts.

Price rigidity and the extent of state-dependence are heterogeneous across items. We find that pricing of top sales items is more flexible and state-dependent. Indeed, the extent to which prices react to an exogenous shift in demand is more than twice for 1% top sales items when compared to the results for the overall sample and about four times for private label top 1% sales items. Our findings are consistent with state-dependent price setting in a multi-product firm that minimizes the loss incurred when failing to adjust prices and focus its price-setting resources on items yielding higher revenues.

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Appendix

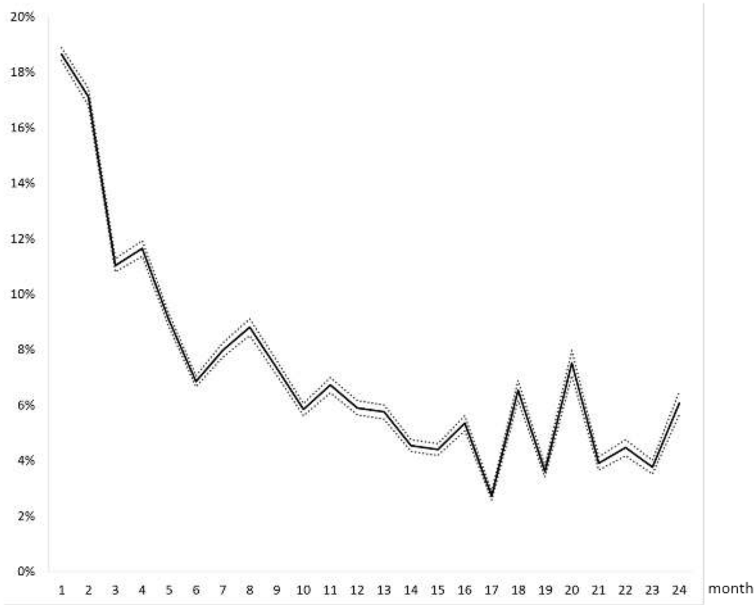

Figure 3: Hazard function and confidence intervals of monthly prices.

	monthly data			weekly data		
	excluding V-shaped flagged observations with a window of					
	1-month	2-month	3-month	1-month	2-month	3-month
% frequency of price changes	8.9	8.5	8.3	3.0	2.9	2.9
N	373,125	371,488	369,853	349,513	349,142	348,741
% mean price increases	6.9	7.0	7.0	6.1	6.2	6.2
% median price increases	5.1	5.2	5.2	3.9	3.9	3.9
N	11,271	10,841	10,583	3,615	3,499	3,460
% mean price decreases	-8.1	-8.1	-8.0	-7.1	-7.1	-7.0
% median price decreases	-5.7	-5.6	-5.7	-4.6	-4.7	-4.7
N	11,903	11,186	10,481	3,976	3,836	3,676

Table 14: Extensive and intensive margin of price flexibility in monthly and weekly data when excluding observations that are flagged as sales by (symmetric) V-shaped filters with a 1, 2, or 3-month window as well as the following data observation (*i.e.*, prices that fully revert after 1, 2, or 3 months).

EDLP retailer price index	I	II	III
lagged product category sales index	0.0285***		
	(0.0037)		
lagged MA2 product category sales index		0.0400***	
		(0.0047)	
lagged MA3 product category sales index			0.0495***
			(0.0055)
constant	0.9928***	0.9783***	0.9679***
	(0.0039)	(0.0050)	(0.0058)
item FE	✓	✓	✓
time FE	✓	✓	✓
N.obs	360,204	349,561	338,922
R-squared within	0.066	0.068	0.070

Table 15: Robustness with respect to an alternative demand index that does not correct for the number of items belonging each product category. Dependent variables: item price indexes of the EDLP retailer.
Note: Standard errors are clustered at the item level.

EDLP retailer price index	I	II	III
lagged product category sales index	0.0265***		
	(0.0037)		
lagged MA2 product category sales index		0.0361***	
		(0.0045)	
lagged MA3 product category sales index			0.0435***
			(0.0052))
constant	0.9935***	0.9823***	0.9749***
	(0.0041)	(0.0050)	(0.0055))
item FE	✓	✓	✓
time FE	✓	✓	✓
N.obs	343,489	333,293	323,100
R-squared within	0.057	0.057	0.058

Table 16: Robustness with respect to an alternative trimming criterion that drops product categories in which one item alone represents more than 15% of its category sales. Dependent variables: item price indexes of the EDLP retailer.
Note: Standard errors are clustered at the item level.

EDLP retailer log price	I	II	III
lagged product category log sales	0.0384***		
	(0.0046)		
lagged MA2 product category log sales		0.0464***	
		(0.0052)	
lagged MA3 product category log sales			0.0533***
			(0.0058)
constant	0.2881***	0.1890**	0.1045
	(0.0554)	(0.0628)	(0.0694)
item FE	✓	✓	✓
time FE	✓	✓	✓
N.obs	360,204	349,561	338,922
R-squared within	0.064	0.065	0.067

Table 17: Robustness with respect to log-log model. Dependent variables: item log prices of the EDLP retailer.
Note: Standard errors are clustered at the item level.

EDLP retailer price index	I	II	III
lagged product category sales index	0.0324***		
	(0.0041)		
lagged MA2 product category sales index		0.0436***	
		(0.0050)	
lagged MA3 product category sales index			0.0521***
			(0.0057)
unemployment rate	-0.0023***	-0.0022**	-0.0024***
	(0.0007)	(0.0007)	(0.0007)
constant	1.0218***	1.0116***	1.0215***
	(0.0100)	(0.0105)	(0.0175)
item FE	✓	✓	✓
month and year FE	✓	✓	✓
N.obs	360,204	349,561	338,922
R-squared within	0.062	0.064	0.067

Table 18: Robustness with respect to the inclusion of monthly unemployment rate. Dependent variables: item price indexes of the EDLP retailer.
Note: Standard errors are clustered at the item level.

EDLP retailer price index	I	II	III
lagged product category sales index	0.0329***		
	(0.0058)		
lagged MA2 product category sales index		0.0434***	
		(0.0070)	
lagged MA3 product category sales index			0.0514***
			(0.0082)
constant	0.9807***	0.9681***	0.9593***
	(0.0056)	(0.0071)	(0.0084)
item FE	✓	✓	✓
time FE	✓	✓	✓
N.obs	93,852	90,132	86,439
R-squared within	0.051	0.052	0.055

Table 19: Estimated coefficients of demand shifts, restricting the analysis only to the time period for which we have national prices and to the items available and matching with the EDLP retailer. Dependent variables: item price indexes of the EDLP retailer. Note: Standard errors are clustered at the item level.

extensive price adjustment	price changed	price increased	price decreased
lagged MA2 product category sales index	0.09115***	0.60338***	-0.57111***
	(0.00012)	(0.00015)	(0.00017)
item FE	✓	✓	✓
time FE	✓	✓	✓
N.obs	263,760	197,971	208,830

intensive price adjustment	price change	price increase	price decrease
lagged MA2 product category sales index	4.84805***	0.22690	1.90529
	(0.76805)	(0.78077)	(1.11028)
constant	-2.38166*	7.08387***	-8.95108***
	(1.10958)	(1.06694)	(1.61968)
item FE	✓	✓	✓
time FE	✓	✓	✓
N.obs	24,606	11,849	12,757
R-squared within	0.066	0.028	0.061

Table 20: Estimated coefficients of demand shifts. Dependent variable: price changes (upper panel) and size of price changes (lower panel) of the EDLP retailer.