WORKING paper

BANQUE DE FRANCE
EUROSYSTÈME

Everyday Regular Prices

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December 2020, WP 746

ABSTRACT

Analysing French firms over 1991-2016, we find first that since the beginning of the century, one or two downward significant productivity breaks have occurred in all industries, both at the frontier and for laggard firms, suggesting a decline in the contribution of technological progress to productivity growth. Second, the median labour share is always higher for the laggard firms than for the frontier firms, with a sharp decrease from the mid-1990s to 2008, and an increase from 2008 onwards. Third, factor reallocation decreased significantly in the 2000s, at the time when we observed an increase in productivity dispersion, with a growing productivity gap between frontier and laggard firms. It appears also that reallocation has been lower on average over the whole period for sectors with a high import share, which can be related to the impact of global value chains.

Keywords: Price Setting, Multiproduct Firm, State-Dependence, Synchronization, Rational Inattention, Sales Price, Regular Price

JEL classification: E31, D22, E4, E32

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Financial support from the Fondation Banque de France, from HEC Montreal, and from the Social Sciences and Humanities Research Council of Canada is gratefully acknowledged. A special thanks to Alejandro Bernales, to the PRISMA research network members, and to participants to the ECB DG-Research internal seminar participants for very useful comments. The views expressed in this paper are solely those of the authors and should not be interpreted as reflecting the views of Danmarks Nationalbank, the Banque de France, or the European System of Central Banks.

NON-TECHNICAL SUMMARY

The ability of monetary policy to affect the dynamics of the economy in response to business cycle shocks depends on the adjustment process of prices. Microeconomic evidence documents higher price flexibility than what is suggested by aggregate inflation: Prices change often, but a large share of price adjustments are actually temporary sales, that is, price transitions which are later reversed. Regular prices are instead much more rigid. It is an open debate in the literature whether sales are relevant from a macroeconomic perspective. If they are time-dependent `comeback prices' that follow sticky plans that are basically unresponsive to macroeconomic shocks, they contribute little to price flexibility relevant for the transmission of monetary policy. Inference on the firms' pricing behaviour, and their responsiveness to monetary policy and to changes in demand, is therefore hard to extract from micro price data in general, since it is unclear whether sales event respond to demand conditions and to aggregate macroeconomic variables - and whether they do so in the same degree as regular prices.

Using a novel dataset from a large supermarket retailer in a European country that never engages in temporary sales, we establish that prices are actually as sticky as regular prices. Circumventing the debate on whether sales have to be included or excluded from price adjustments, we find evidence consistent with state-dependence price setting in a multiproduct firm. In particular, our data exhibit responsiveness of prices to changes to aggregate demand shifts, a more than trivial share of very small price changes, and synchronization of price changes across items especially within the same product category. Price rigidity and the extent of state-dependence are heterogeneous across items. In particular, we find that pricing of top sales items (and even more of private label ones) 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 with respect to that for the overall sample and about four times for private label top 1% sales items that are private labels (arguably characterized by particularly high profit margin). This is consistent with price setting in a multiproduct firm that may rationally choose to be inattentive to information that is costly to acquire, absorb, or process for some items more than for others ones. Indeed,multiproduct price setter may more often revise and change prices of items that are more important for the firm, minimizing in this way the loss incurred when failing to adjust.

Figure: Both price cyclicality and synchronization are stronger for private label items and monotonically decreasing in the share of sales that items represent.
The grey bars represent the estimated coefficients of price sensitivity to previous period 2 month moving average demand (left vertical axis). The blue bars represent the Fisher and Konieczny (2000)'s index of synchronization (right vertical axis). Dark colors correspond to all brand items, while light colors to private labels items only.

Prix Toujours 'Réguliers'

RÉSUMÉ

Exploitant une base de données de prix qui ne contient pas de changements temporaires de prix (car issue d'une enseigne qui ne fait ni promotions ni soldes), nous trouvons que la rigidité des prix est comparable à celle des « regular prices ». Sans faire des hypothèses controversées sur l'inclusion ou l'exclusion des prix promotionnels, nous trouvons que les ajustements sont cohérents avec les modèles state-dépendants des firmes fixant les prix de plusieurs biens, en termes de sensibilité au cycle économique, petits changements de prix et synchronisation, particulièrement entre produits similaires. La rigidité des prix et la state-dépendance de leur dynamique sont hétérogènes entre produits. En particulier, les prix des biens générant les revenus les plus importants (et encore plus si de la marque de distributeur) quant à eux sont plus flexibles et state-dépendants, ce qui est cohérent avec une fixation des prix rationnellement inattentive de la part d'une entreprise multi produit.

Mots-clés : fixation des prix, entreprise multi produit, state dépendance, synchronisation, inattention rationale, soldes

1 Introduction

The ability of monetary policy to affect the dynamics of the economy in response to business cycle shocks depends on the adjustment of prices. Microeconomic evidence documents higher price flexibility than what is suggested by aggregate inflation. For instance, prices change once every 4.3 months in Bils and Klenow [2004] based on BLS consumer prices. However, a large share of price adjustments are actually temporary sales, that is, price transitions which are later reversed. Regular prices (*i.e.*, excluding temporary sales) are instead much more rigid. Dropping temporary cuts in BLS price data, Nakamura and Steinsson [2008] find that regular prices change about every 7-11 months and Kehoe and Midrigan [2015] dropping as well temporary price increases get to regular price durations of 14.5 months. Thus, the presence of sales in the microeconomic data hinders the assessment of price rigidity (Nakamura and Steinsson [2013]).

While sales are clearly an interesting phenomenon from a marketing point of view, it is an open debate in the literature whether they are relevant from a macroeconomic perspective. Taking into account prices during temporary sales makes sense if they respond to shocks and convey true price flexibility. Bils and Klenow [2004], for instance, argue that sales respond to shocks. Some empirical support for this view has been provided by Kryvtsov and Vincent [2020]. However, Kehoe and Midrigan [2015] note that sales prices, which are by definition temporary, contribute less than regular prices to inflation. Moreover, if they are time-dependent 'comeback prices' mostly orthogonal to aggregate conditions, as suggested by Nakamura and Steinsson [2008], they contribute little to price flexibility relevant for the transmission of monetary policy. Also Midrigan [2011] argues that temporary discounts and regular price changes are performed at different levels, so that there is little interaction among the two types of price changes. Coibion et al. [2015] show that sales are acyclical and not more frequent under tough macroeconomic conditions. Similarly, Anderson et al. [2017] find empirical evidence that temporary sales follow sticky plans, typically agreed by retailers and manufacturers up to a year in advance, so that they are basically unresponsive to macroeconomic shocks. Inference on firm pricing behaviour, and its responsiveness to monetary policy, is therefore hard to extract from micro price data in general, since it is unclear whether sales events respond to demand conditions and to aggregate macroeconomic variables - and whether they do so in the same degree as regular prices.

Using a novel dataset from a large supermarket retailer in Europe that never engages in temporary sales and sets uniform national prices, we find that their posted prices are very sticky (Section 2.1). The frequency of price changes (about 10% per month) is actually comparable to what has been found in the literature for regular prices (*i.e.*, posted price records excluding temporary sales). In this sense, an Everyday Low Price (EDLP) retailer exhibits everyday regular prices.

Section 3 provides evidence of state-dependence, a feature of price setting that has already been extensively documented (*e.g.*, Eichenbaum et al. [2011], Gagnon [2009], Vavra [2014], Alvarez et al. [2019]), but without clearing up all possible doubts concerning whether sales should be included or excluded from the data. Based on our EDLP data where this concern doesn't apply, we find that item-specific prices respond to changes in aggregate lagged demand shifts. This result holds but is weaker for prices at the national level, consistently with the idea that the prices of other retailers (that engage in sales) add noise to the sensitivity of micro prices to economic conditions. In addition, our data exhibit a more than trivial share of very small price changes, as well as some synchronization of price changes across products, which are consistent with a multi-product firm state-dependent price setting à 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]). Similarly, we find stronger synchronization of price changes within product categories.

Finally, we show that price rigidity and the extent of state-dependence is heterogeneous across items. In particular, we find that pricing of top sales items (and even more of private label ones) is more flexible and state-dependent (Section 4). This 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 à la Reis [2006]. Indeed, a multi-product price setter may more often revise and change prices of items that are more important for the firm, minimizing in this way the loss incurred when failing to adjust.

2 Everyday regular prices: retail prices, yet no temporary sales

2.1 Every Day Low Price retailer's data

We exploit scanner data of an EDLP retailer operating in a country of the Euro Area. The unique characteristic of these data is that the retailer never engages in temporary sales. Another feature is that it sets uniform national prices.

Our data contain more than ten thousand different items, that can be grouped in about four hundred product categories.[1] Despite the large number of products, the weights in terms of sales are heterogeneous and about one sixth of total sales derive on average from about 100 items. One particular type of items are private label goods. Overall 16% of items are private labels and they represent about 32% of total sales on average. 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 scanner data are also available.

One difficulty when inferring posted prices from scanner data is that each unit price obtained dividing sales by volumes corresponds to a weighted average of transaction prices for the item over the period. This implies that if a price changed in the middle of the period then 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 double-counting price changes that occur during the period,

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

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.[2]

Another difficulty is that it is possible that there were no transactions for an item in a given period and thus no unit price can be computed. We follow Anderson et al. [2017] and restrict attention to items consecutively observed at least one quarter. However, this is a rare event in our data due to national pricing. Except for items without missing price information, we trim those sold in less that 101 stores.

We also drop from the sample products whose price is missing for more than two months in a row. We carried forward the remaining missing prices. Finally, we drop extreme price changes, defined as larger than factor 5.

Unless otherwise specified, we weight all results by item average share of revenue.[3]

2.1.1 Comparison with other retailers

To compare the data of the EDLP retailer with the context of the retail sector at the national level, we exploit Nielsen data for the same country and same period.[4] 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.[5]

The EDPL retailer is a rather big player in the retail sector of the country. Indeed, its average market share for the matched product categories is 25% with a standard deviation of 0.12 and is fairly stable over the period.Matching items within those product categories exhibit similar market shares and constitute therefore somewhat a representative subsample.As far as matching items allow to compare, price levels and aggregate dynamics appear to be reasonably similar. To see how the retailer's prices compare to the national average prices of the same items, we built 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), though the EDLP retailer is slightly cheaper than the average at the national level. Figure 2 shows the distribution of price ratios at each date. This suggests that 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.[6] Finally, monthly inflations largely

[2]While it is still debatable whether scanner data are the best suited to identify price changes (entailing consequences on the assessment of the frequency of price changes, the incidence of small price changes, or the extent of synchronization, see for instance Cavallo [2018]), we are reasonably confident that the procedure filtered out potential double-counting. Indeed, results on monthly and weekly data (arguably less sensitive to double-counting issues) appear consistent.

[3]Weighting by volumes instead of revenues provides similar results.

[4]For more details on Nielsen data, please refer to Anderton et al. [2011].

[5]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.

[6]The comparison refers to the period for which we have both sources of data and excludes items that are observed only for a short period.

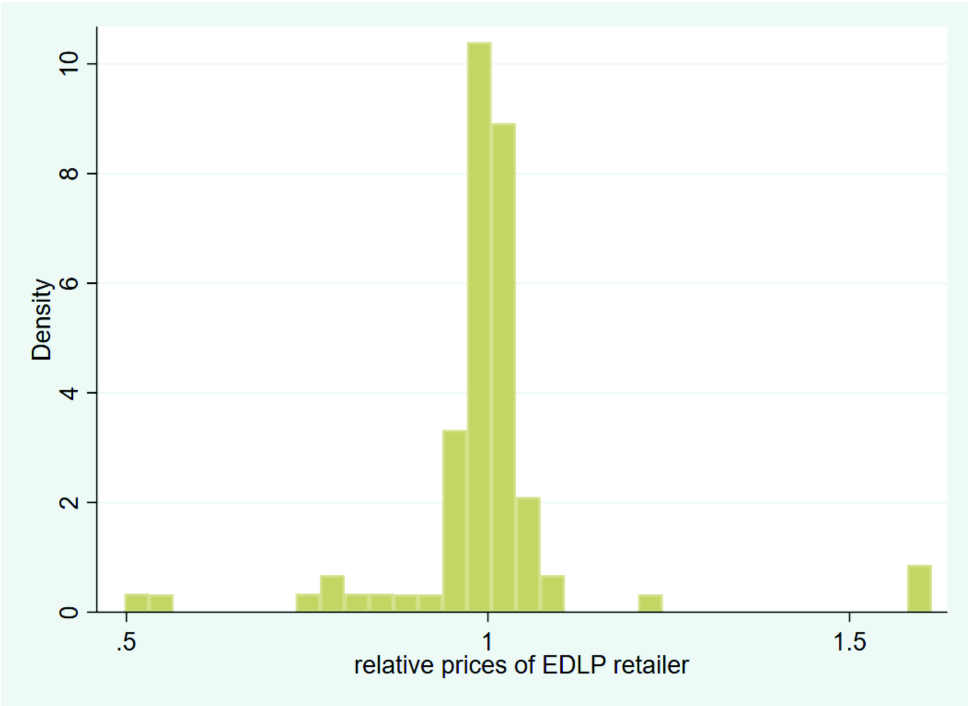

Figure 1: Distribution of relative prices of the EDLP retailer with respect to the national average.

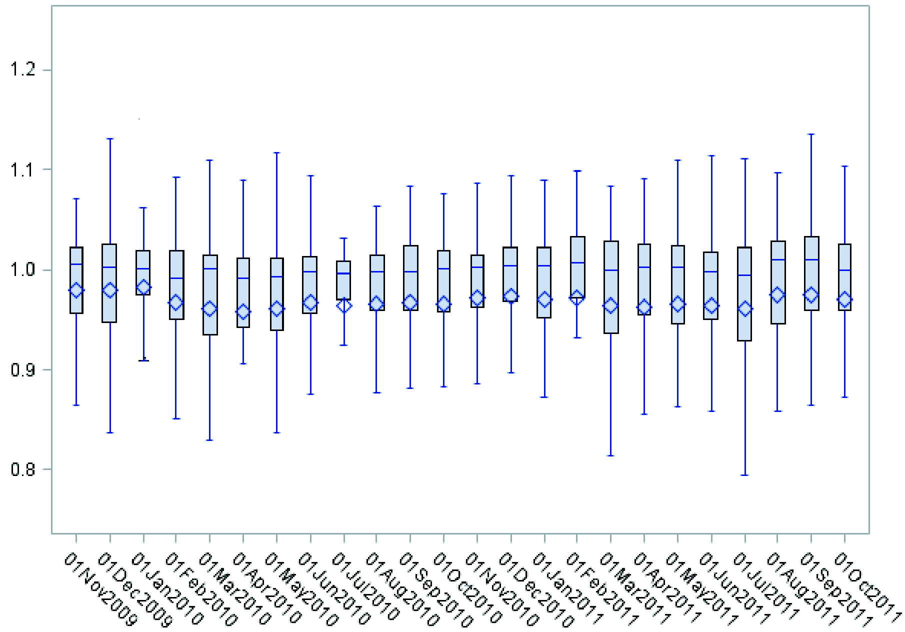

Figure 2: Boxplots of relative prices of the EDLP retailer with respect to the national average.

co-moves (see Figure 3)[7]

[7]The two series are indeed correlated by more than 60%.

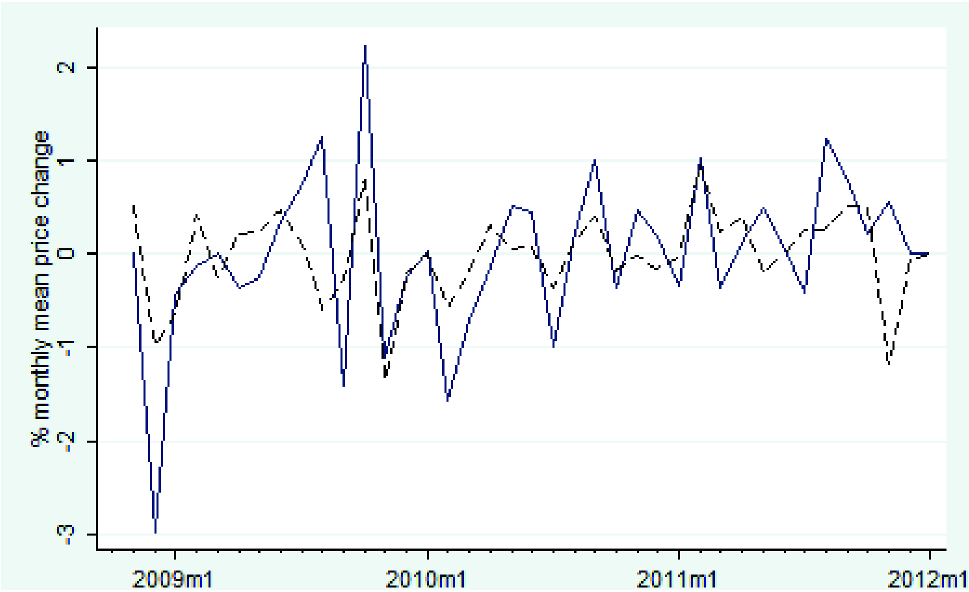

Figure 3: Percentage monthly average price changes, as computed based on matching items in our data (solid blue line) and in Nielsen data (dotted black line).

2.2 Everyday Low Price rigidity

As the EDLP retailer does not engage in sales, one could have imagined that its posted prices exhibit a higher degree of flexibility than what has been found in the literature for regular prices (*i.e.*, posted price records excluding temporary sales). However, this is not the case: we find that posted prices of the EDLP retailer are actually as sticky as regular prices reported in the literature. In a sense, the retailer is characterized by everyday regular prices.

Table 1 reports that 9.8% of prices change each month and 3.1% each week in the weighted sample.[8] These frequencies of price changes are between the frequency of price changes found for regular prices of Israeli stores by Bonomo et al. [2019] (11.5% monthly and 4.3% weekly) and those found for regular prices based on BLS monthly data (6.9%, compared to 22% for all price changes) and based on Dominick's weekly data (2.9%, compared to 33% for all price changes) computed by Kehoe and Midrigan [2015]. Notice that the average frequency of price changes for processed food in the country computed by Dhyne et al. [2006] based on monthly CPI data on an earlier period in the country is larger, at about 18%. 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.[9]

[8] The mean implied duration is thus about 10 months. Figure 10 in the appendix plots the hazard function and its confidence intervals. The downward sloping and then flattening shape is similar for instance to Nakamura and Steinsson [2008]'s hazard function for processed food.

[9] Table 8 in the appendix reports similar statistics for the extensive and intensive margin of price flexibility in monthly and weekly data when excluding observations that are as flagged by sales (symmetric) V-shaped filters with a 1, 2, or 3-month window as well as the following observation (*i.e.*, prices that fully revert after 1, 2, or 3 months) in the same spirit as 'filter B' in Nakamura and Steinsson [2008]. Price rigidity appears very similar, like in Dedola et al. [2019].

	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
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.

Figure 4 shows seasonal patterns of price adjustments. The frequency of price changes is seasonal (left panel of Figure 4) and so is the size of price decreases. However, this is not the case for the size of price increases (right panel of Figure 4).

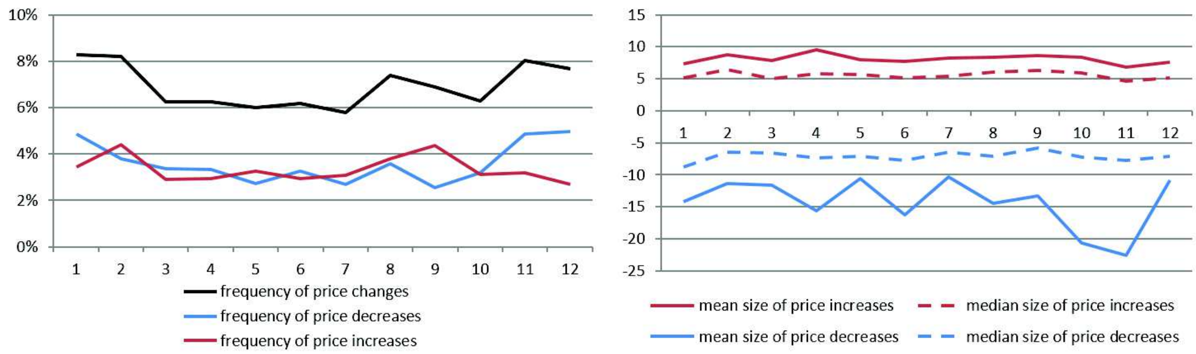

Figure 4: Frequency and size of price changes by month of the year.

Figure 5 shows the evolution over time of the average extensive and intensive margin (upper and lower panel, respectively). Beyond seasonal movements, the frequency of price decreases peaked at the end of 2009 and 2012, when the absolute size of price decreases was particularly large. The frequency and the size of prices increases remained instead remarkably stable the whole period.

In conclusion, the absence of sales in the EDLP retailer, does not result in posted prices being more flexible than regular prices elsewhere. Its posted prices are indeed as sticky as other retailers regular prices and therefore they can be described as everyday regular prices.

3 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).

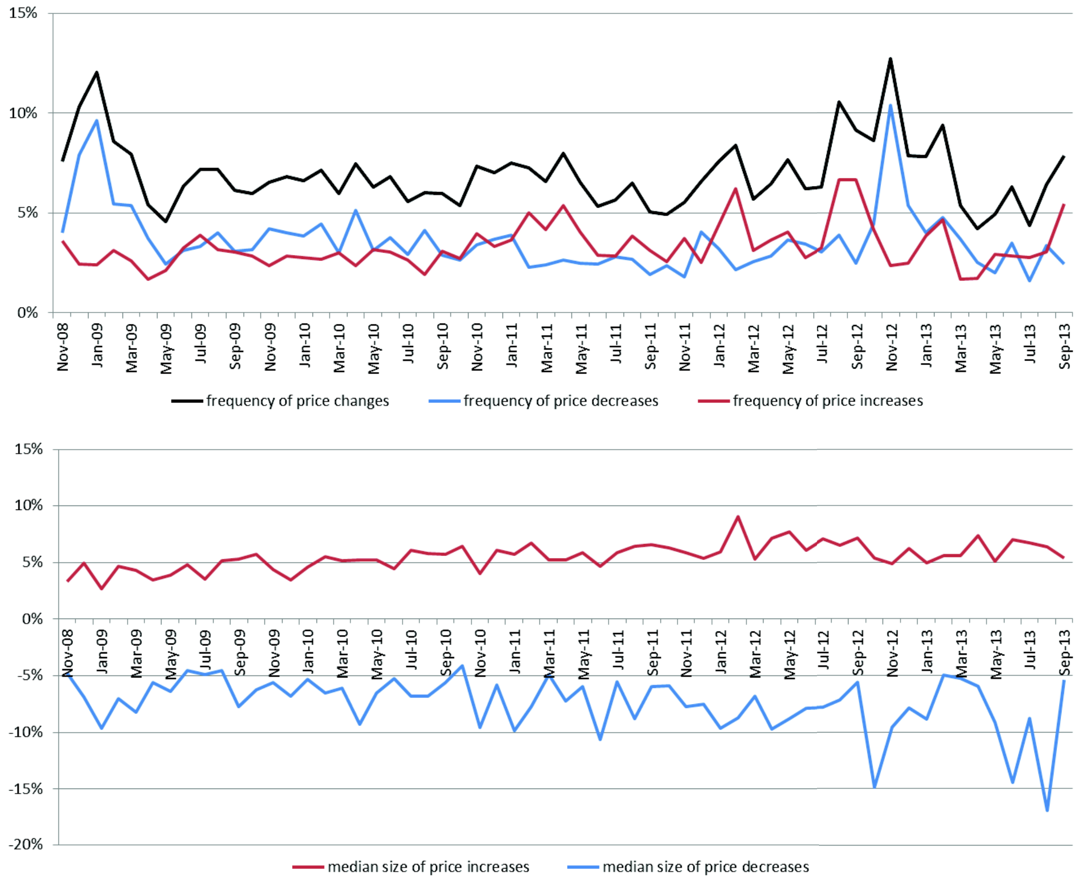

Figure 5: Frequency and size of price changes over time.

However, the literature does not clear up all possible doubts concerning the role played by sales, if any.

The strength of working with everyday regular prices is that the investigation of price setting is not wrecked by doubts about how to properly treat temporary sales. In other words, we do not need to worry about whether regular and sale prices react in a similar way and have similar implications, for instance in terms of monetary policy transmission. We are therefore able to investigate price setting, without any dilemma about including or excluding sale prices.

We first investigate whether everyday regular price are consistent with state-dependent price setting in terms of responsiveness of prices to the economic conditions. The last part of the section focuses on the existence of small prices changes and synchronization of price changes across items, which are consistent with price setting in a multi-product firm à la Alvarez and Lippi [2014].

3.1 Responsiveness to 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:[10]

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

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[11] of items belonging to the same product category s as item i in a given time period τ, normalized by its over time average.[12] 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 2 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 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.

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.[13] Second, product categories need to be poor substitutes. Indeed, if they are perfect substitutes, a shift in demand in one product category would

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

[11] 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.

[12] Table 9 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.

[13] 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 10 in the appendix shows that the result are robust to a more stringent 15% criterion, although the sample size shrinks.

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

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.[14]

Table 2 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 has been increasing, the more prices increase as well.

The coefficient of the lagged MA2 product category sales index (column II) in Table 2 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).[15]

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[16] (see Table 12 in the appendix).[17]

[14]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].

[15]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 11 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%. However, prices and sales data are in very different scales and these coefficients seem thus less intuitive to interpret.

[16]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.

[17]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

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 3 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).[18] Estimated coefficients are smaller and their standard errors (clustered at the item level) larger, but the overall picture is consistent with Table 2.[19]

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

Another possible way to investigate whether prices react to macroeconomic conditions is looking at the extensive and intensive margins of price adjustment, instead of looking at EDLP retailer's price indexes.[20] Results (reported in the appendix) suggest that an increase in the previous period

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.

[18] 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.

[19] 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 13 in the appendix reports the estimated coefficients obtained by replicating the same regressions as in Table 2, but on the subsample of common period and product categories as available at the national level.

[20] In particular, we investigate the response of frequency and size of price change (upper and lower panel of Table 14, 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

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.

3.2 Small price changes and synchronization

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].[21] This is what, indeed, is suggested by Figure 6, representing the cumulative distribution of the absolute value of price change size against that of a normal distribution in monthly (left panel) and weekly data (right panel).

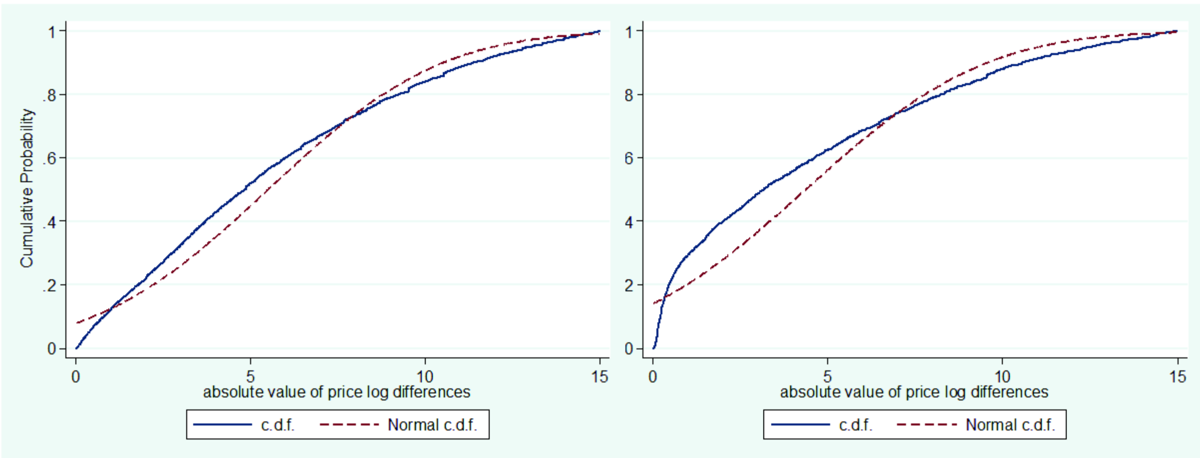

Figure 6: Cumulative distribution of the absolute value of price changes in monthly (left panel) and weekly data (right panel).

The same conclusion emerges from Table 4. Less than 2% of weighted monthly absolute value price changes are smaller or equal to 2%. We also compute the percentage of price changes that are smaller than a half and a fourth of the mean absolute value price changes. In the monthly weighted sample, we find that those are, respectively, slightly more than a third and an eighth of all price changes, which is similar to the proportions found by Midrigan [2011] based on Dominick's scanner data.

Some degree of synchronization of price changes is also expected from multi-product price setting. In order to see whether synchronization or staggering of price changes prevails in the 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,

'price increased'), or has decreased (column 'price decreased' in the upper panel of Table 14), 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 14).

[21] Notice that many small price changes are however not expected in a state dependent model where a firm sets the price of only one good, while they are in a standard time dependent one à la Calvo.

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

Table 4: Percentages of small price changes (among price changes) in monthly and weekly data.

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. 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 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 7 shows that indeed dropping 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.

It seems likely that in a firm pricing more than ten thousand items, one should not expect

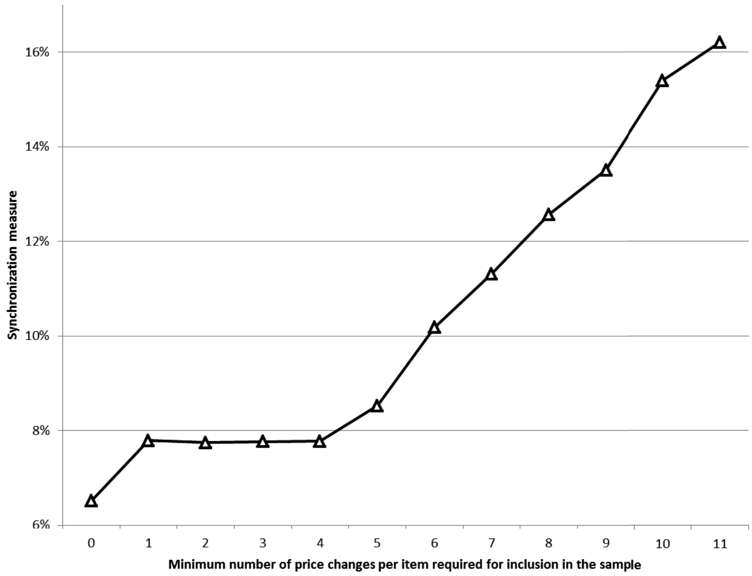

Figure 7: Fisher and Konieczny [2010]'s measure of synchronization when limiting the sample to items that have an increasing minimum number of price changes.

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% (see Figure 8). 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.[22]

4 Price setting heterogeneity and rational inattention in a multi-product firm

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

[22] Figure 11 in the appendix shows that going from 79 categories to 417 subcategories implies that only 3.4% exhibit synchronization below 10%, 25.2% between 30 and 40%, 21.6% between 40 and 50%, and 37.5% above 50%. The mean FK index at the product subcategory level is 48% and the median 44%. In conclusion, price setters appear to heavily synchronize price changes of similar products.

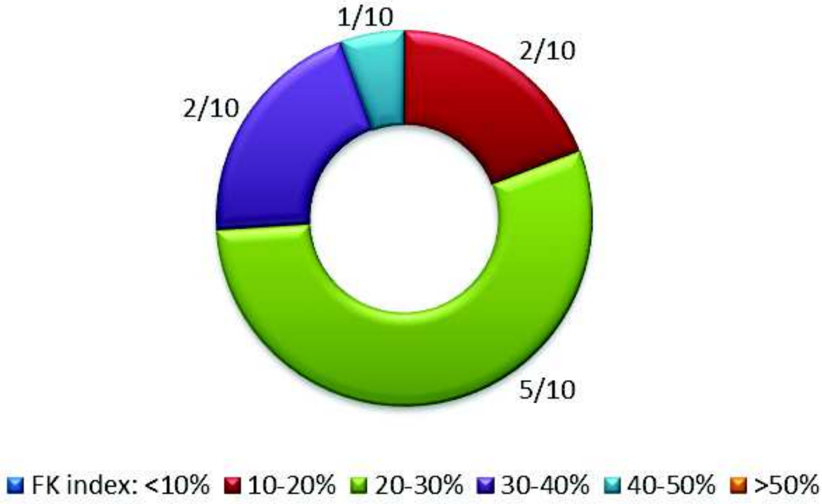

Figure 8: Fisher and Konieczny [2010]'s measure of synchronization within product categories.

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.[23]

This section examines to what extent heterogeneity in prices across items may be consistent with a multi-product firm characterized by rational inattention à la Reis [2006].[24] The idea is that 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 underlying 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 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 twist in this paper is the argument that for a multi-product firm failing to adjust 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

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

[24] An alternative interpretation could be related to behavioral industrial organization, in terms of behavioral consumers à la Della Vigna and Malmendier [2004] or behavioral firms à 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].

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

observe profits, but under the assumption that they are proxied by sales,[25] 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.

Table 5 reports statistics of the extensive and intensive margins of price changes. Comparing it with Table 1 reveals that 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.

Table 6 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 2 and almost four times for private label top 1% sales items. In particular, Figure 9 graphically shows that the estimated coefficients are monotonically decreasing in the share of sales represented by items (the grey bars correspond to the sensitivity of prices to demand shifts for all items in dark grey and for private labels in light grey).

As far as small price changes are concerned, Table 7 suggests that overall they tend to be more frequent among top sales products than for the other ones (reported in Table 4). Moreover, the

[25] 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.

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 6: 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.

	top1%	top5%	top10%	top1%	top5%	top10%
% of price changes with:		sales items			sales private label items	
$\lvert$price changes$\rvert \leqslant 1\%$	0.9	0.9	0.8	0.7	0.4	0.4
$\lvert$price changes$\rvert \leqslant 2\%$	2.6	2.2	2.1	2.9	2.0	1.7
$\lvert$price changes$\rvert \leqslant 3\%$	3.9	3.5	3.3	3.9	2.9	2.5
$\lvert$price changes$\rvert < \frac{1}{2}\mathbf{E}\lvert$price changes$\rvert$	30.2	32.0	32.9	35.3	33.7	34.2
$\lvert$price changes$\rvert < \frac{1}{4}\mathbf{E}\lvert$price changes$\rvert$	11.5	13.9	14.4	9.5	11.3	11.5

Table 7: Percentages of small price changes (among price changes) for top sales items.

incidence of small price changes is monotonically decreasing in the share of sales represented by items.

Synchronization also 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 10%, 5%, and 1% of sales is respectively 9.7%, 10.3%, and 17.4% (compared to 6.5% for all items). Synchronization of price changes among private label items that represent the top 10%, 5%, and 1% of sales is even higher (respectively 16.3%, 17.8%, and 25.7%).[26] The blue bars in Figure 9 graphically show that the extent of synchronization is monotonically decreasing in the share of sales represented by items (for all items in dark blue and for private labels in light blue).

5 Conclusions

A long ongoing debate in the price setting literature concerns whether firms' decision to change their prices is state-dependent. One element complicating the assessment is that typically price setters temporarily engage in sales and it is not clear whether those temporary price changes should be included or excluded from the analysis of nominal rigidities. We exploit 'everyday regular prices'

[26]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 (see Figure 12 in the appendix, compared to Figure 7 for all items).

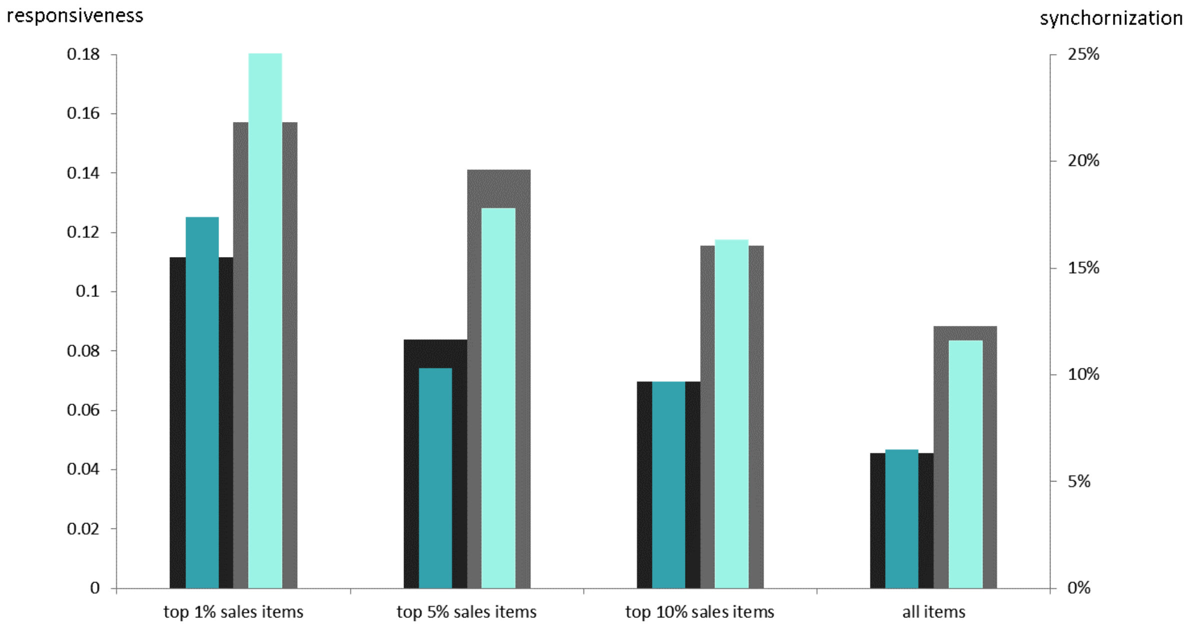

Figure 9: State-dependent price setting in a rationally inattentive multi-product firm. Both price responsiveness to economic conditions and synchronization are stronger for private label items and monotonically decreasing in the share of sales that items represent. The grey bars in the background represent the estimated coefficients of price sensitivity to the previous period 2-month moving average demand (left vertical axis). The blue bars represent the Fisher and Konieczny [2010]'s synchronization index (right vertical axis). Darker colors correspond to all brand items, while lighter colors to private labels items only.

from a large supermarket retailer in a European country and establish that prices are actually as sticky as regular prices. We also find evidence consistent with state-dependence price setting in a multi-product firm. In particular, our data exhibit responsiveness of product-specific prices to changes to aggregate demand shifts, a more than trivial share of very small price changes, and some synchronization of price changes across items especially within the same product category.

Price rigidity and the extent of state-dependence are heterogeneous across items. In particular, 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 with respect to that for the overall sample and about four times for private label top 1% sales items that are private labels. This is consistent with state-dependent price setting in a multi-product firm that minimizes the loss incurred when failing to adjust and thus cares more for items yielding higher profits.

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Appendix

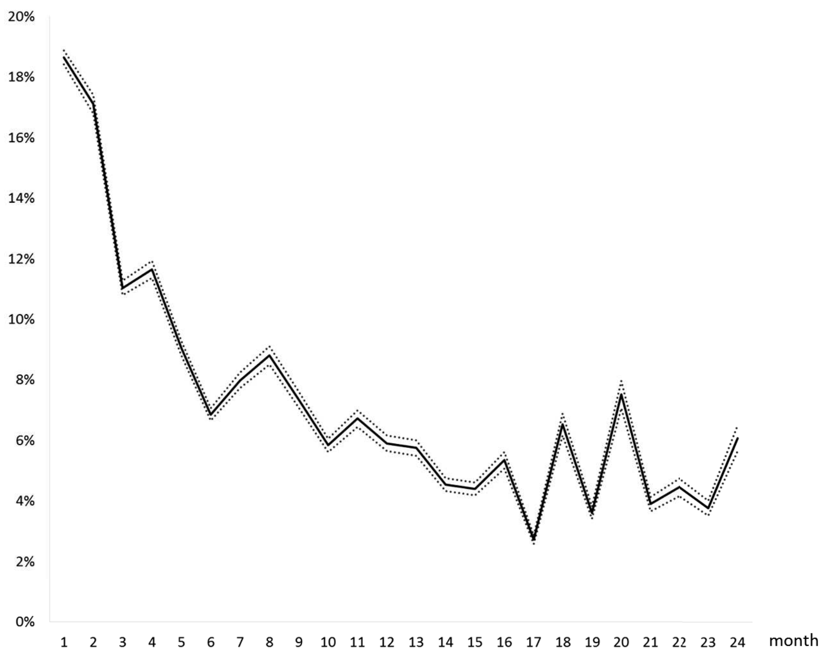

Figure 10: Hazard function and confidence intervals of monthly prices.

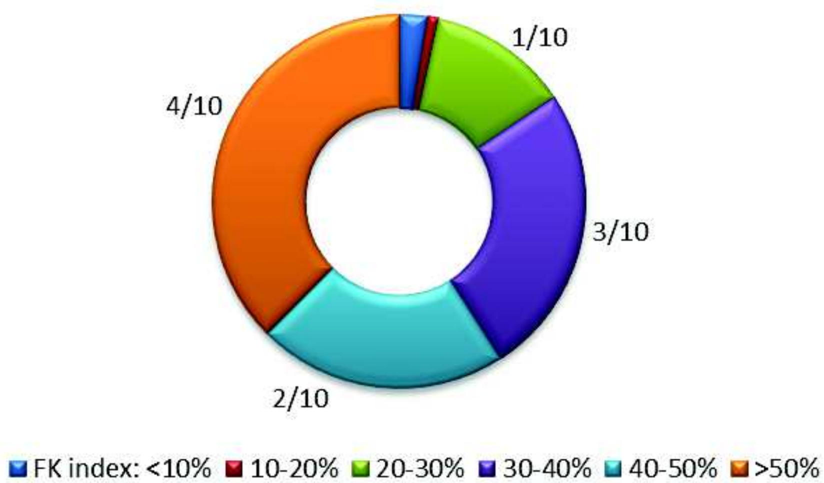

Figure 11: Fisher and Konieczny [2010]'s measure of synchronization within product subcategories.

	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 8: 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 9: 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 10: 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 11: 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 12: 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 13: 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 14: Estimated coefficients of demand shifts. Dependent variable: price changes (upper panel) and size of price changes (lower panel) of the EDLP retailer.

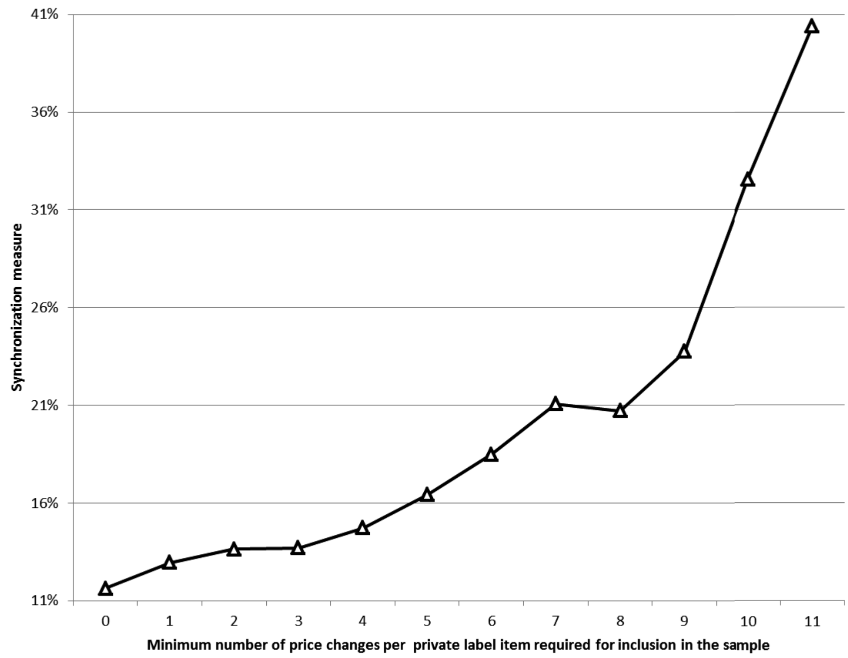

Figure 12: Fisher and Konieczny [2010]'s measure of synchronization when limiting the sample to items that have an increasing minimum number of price changes for private label items.