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Consumer Price-Setting Behaviour: Evidence from Food CPI Microdata

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Abstract
This paper studies the price-setting behaviour in food products, using the microdata underlying the Portuguese Consumer Price Index (CPI). We document that, on average, more than one-quarter of food prices changed every month and half displayed price spells shorter than 5.3 months. Positive price changes were more frequent and had a higher magnitude than price decreases. There is a strong heterogeneity across type of industry and outlet. We find that, from 2009 to 2019, food inflation was primarily driven by the frequency of price changes rather than the magnitude, and price changes were more frequent at the producer than at the consumer level, but in a lower magnitude. Finally, we report that frequency and magnitude estimates are higher when using daily online price data, meaning that intra-month patterns in price dynamics, not captured by the official inflation statistics, are relevant.

JEL: E30, E31, D40.

Keywords: price stickiness, price-setting behaviour, consumer prices, microdata, inflation.

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1. Introduction

In macroeconomics, nominal rigidities are at the core of a large class of theoretical models. These have emerged as a solution to reconcile the debate between theory and empirical evidence on whether demand shocks have large effects on real output. Early macroeconomic models assumed that in an economy that responds efficiently to shocks, temporary demand shocks would have minimal impact on output, and monetary shocks would have no effect on output (Kydland and Prescott 1982).

Nevertheless, empirical evidence has consistently challenged these assumptions, supporting the hypothesis of "monetary non-neutrality" (see, for instance, Friedman and Schwartz (1963), Christiano *et al.* (1999), Romer and Romer (2004)) and that government spending can lead to increases in output (Blanchard and Perotti (2002), Ramey (2011), and Nakamura and Steinsson (2014)). These effects may arise due to nominal rigidities, in particular, sluggish adjustments in prices or wages when aggregate conditions change (Nakamura and Steinsson 2013), as well as from coordination failures among price setters (Ball and Romer 1991). Such factors have been, more recently, incorporated into modern business cycle models.

Research on how price adjustments happen has been active in the recent past. The seminal work by Bils and Klenow (2004) was the first to use a broad data set of prices for the United States, finding much more frequent price changes than previously known and that their frequency differed dramatically between goods. For Portugal, Dias *et al.* (2008) identified empirical stylised features of consumer price-setting behaviour over the period 1992–2001. Dias *et al.* (2015) have also identified asymmetries in the speed with which firms adjust their prices in response to positive and negative demand or cost shocks. In fact, firms may not immediately adjust the prices of their goods and services, since the decision to change prices seeks to balance a fixed cost incurred by resetting prices – menu costs – against the loss from keeping prices unchanged by misaligning with their reset values. Some producers may also refrain from adjusting prices so that households do not reassess their purchasing decisions (Rebelo *et al.* 2024).

This paper contributes to the ongoing discussion by presenting new evidence on the dynamics of food prices. Leveraging on unpublished microdata underlying the Portuguese Consumer Price Index (CPI), we offer a comprehensive analysis of how price adjustments occur for food products. We focus on the frequency and magnitude of price changes, as well as on the heterogeneities between product categories, types of goods, and different retail outlets. These insights are crucial for understanding the pass-through of aggregate demand shocks to consumer prices, which is influenced by the proportion of firms that adjust their prices (the frequency component) and the size of these adjustments (the magnitude component). We also explore how the price-setting behaviour changes over time, along the production value chain, and between monthly official data and daily data from online platforms. Our findings aim to deepen the understanding of how monetary policy affects the real economy and how inflation behaves under various economic conditions.

First, we identify five main facts about the consumer price-setting behaviour in food products between January 2009 and December 2019. Our work extends and updates the evidence available for Portugal, presented by Dias *et al.* (2008). They use a similar dataset on consumer prices for goods and services, allowing us to make comparisons over time. We also benchmark our findings within the context of the euro area, comparing them with recent evidence from other countries.[1]

We document that more than one-quarter of food prices changed every month in our analysis period. The weighted frequency of consumer price changes stands at 26.3% while the median estimate is 18.7%. Upon closer examination, distinct patterns emerge across food categories and different retail formats. There is a striking difference between unprocessed and processed goods. Although half of the products in the latter category recorded a price change, only 17.9% of the processed food items registered price adjustments on a monthly basis. At the outlet level, hyper and supermarkets exhibited a higher frequency of price changes, reaching 31.9%, while small stores and markets had less frequent adjustments.

The median duration indicates that half of the items displayed price spells shorter than 5.3 months. Positive price changes were more frequent than the negative (14.0% versus 12.3%). This difference is also found when studying the magnitude of price changes. We find that positive adjustments exhibited larger size compared to negative changes. The discrepancy in the magnitude underscores a tendency towards sharper and more substantial upward adjustments relative to downward revisions. It is also worth noting that the price changes were, in general, sizeable. The first (third) quartile of the conditional distributions of the magnitude of price increases (decreases) exhibited values typically above the average inflation rate for that period. Thus, size seems to matter on the decision to change prices.

Using other complementary datasets and looking at different time periods, we provide additional insights into the price-setting behaviour. First, when examining the dynamics over time, there was a notable stability, with the overall frequency of price changes remaining relatively constant despite economic fluctuations. Positive price adjustments were more common than negatives, and they followed a seasonal pattern, particularly peaking in the early months of the year. This implies that although prices adjust in response to economic conditions, there was a stabilizing equilibrium that regulated the rate of change, ensuring a steady adjustment process.

Furthermore, producer prices were adjusted more frequently, but the magnitude of these changes was smaller compared to consumer prices. Lastly, the comparison between monthly and daily data highlights a discrepancy in the recorded frequency and magnitude of price changes. The latter, with its higher temporal resolution, captures more frequent adjustments. This suggests that the CPI may underreport the true frequency of changes, thus being interpreted as lower-bound estimates.

1. This research project is part of the broader Price-Setting Micro Analysis (PRISMA) Research Network, involving Eurosystem national central banks and the European Central Bank (ECB).

Related Literature. Price stickiness remains a central question in Economics because the understanding of price-setting behaviour and inflation dynamics helps to evaluate the transmission of monetary policy to the real economy. The theoretical foundation of price stickiness in microeconomics is significantly shaped by the works of Ball and Mankiw (1995) and Taylor (1999). These studies explore how and why prices do not adjust instantly to changes in economic conditions. Two primary models dominate this discourse: time-dependent models, such as those proposed by Calvo (1983) and Taylor (1980), posit that firms adjust prices at fixed intervals, making the frequency of adjustments exogenous; conversely, state-dependent models, such as those by Barro (1972) and Sheshinski and Weiss (1977), suggest that firms decide both the timing and magnitude of price changes based on the state of the economy, thus treating these factors as endogenous variables.

More recently, empirical research has emerged in the literature and investigated the frequency and patterns of price adjustments across various markets and periods. Studies by Cecchetti (1986), Kashyap (1995), and Lach and Tsiddon (1992, 1996), among others, focused on small samples with a limited number of products, often revealing infrequent price changes. The seminal work by Bils and Klenow (2004) expanded this scope with a broader set of unpublished individual price data from the Bureau of Labour Statistics, used for the calculation of the U.S. CPI, uncovering more frequent price changes with significant variation across different goods. Moreover, Nakamura and Steinsson (2008) established five facts about prices in the U.S., which inspire our approach to describe the price-setting behaviour in Portugal. As they did, we also provide evidence that is both consistent and not with a benchmark menu-cost model.

The Eurosystem Inflation Persistence Network (IPN) extensively studied price stickiness in the euro area. This collaborative effort among national central banks and the ECB put together a vast array of datasets, including consumer and producer price indices and surveys on pricing behaviour.[2] The studies within the IPN, such as Fabiani *et al.* (2005) and Álvarez *et al.* (2006), provided comprehensive analyses of price stickiness across countries.[3] The PRISMA network continued this line of inquiry, further enhancing the understanding of inflation dynamics. Erwan and et al. (2022) documents five stylized facts relating to price adjustment in the euro area. Among other results, they find that for both consumer and producer prices, cross-sectoral heterogeneity is more pronounced than cross-country heterogeneity and that, consistent with idiosyncratic shocks as the main driver of price changes, aggregate disturbances affected inflation by shifting the relative number of firms increasing or decreasing prices, rather than the size of price increases and decreases.

2. Survey evidence obtained for Portugal is summarised in Martins (2010, 2015)

3. Other studies include Baumgartner *et al.* (2005) for Austria; Aucremanne and Dhyne (2004, 2005) for Belgium; Kurri (2007) for Finland; Baudry *et al.* (2004) and Fougére *et al.* (2005) for France; Hoffmann and Kurz-Kim (2006) for Germany; Veronese *et al.* (2005) for Italy; Lünnemann and Mathä (2005) for Luxembourg; Dias *et al.* (2005) and Dias *et al.* (2008) for Portugal; Álvarez and Hernando (2004), and Álvarez *et al.* (2004) for Spain; Jonker *et al.* (2004) for The Netherlands.

Outline. The paper is organized as follows. Section 2 describes the microdata used and the evolution of aggregate consumer prices. Section 3 presents the main facts on the consumer price dynamics. Section 4 and 5 complement the analysis with a description of the price-setting behaviour over time and over the production value chain. Section 6 benchmarks our main results against the ones obtained from a dataset with online daily prices. Section 7 concludes.

2. Data

We use a micro-level dataset on consumer prices for the food products, collected by Statistics Portugal (INE). This dataset includes the most granular information used to construct the aggregate CPI for Portugal, representing about 25% of the total consumption basket. The items included in our sample were carefully selected by INE to mirror consumption habits of the resident population in Portugal, thus offering a representative snapshot of the consumer spending patterns over time.[4]

The dataset spans from January 2009 until December 2019. It has a longitudinal setting: outlets are followed over time, on a monthly basis. More than 40,000 price quotes are collected every month from establishments across the country. This method ensures that all types of outlets and regions are represented in the dataset. Information on prices is collected by means of a statistical survey and reported at the outlet and product levels. As such, the unit of observation is the price of a single item in a certain outlet at a given month. Such item is followed over time within the same store. We are thus able to compute descriptive statistics on the price-setting behaviour, focused primarily on two dimensions: frequency and magnitude.

The frequency of price adjustments is defined as the proportion of times a price for an item in an outlet is changed over T observation periods. We compute the frequency of price changes at the item level, for which we use pairs of consecutive price observations within each store. We aggregate them at the monthly level, ending with a series of frequency of price changes per month. Since INE collects one price observation per month for each item, it may not capture price changes in-between two observations. Thus, our estimates should be taken as a lower-bound for the frequency of price changes. To see the relevance of this issue, we explore these intra-month price changes using daily price observations in Section 6.

When analysing the duration of price spells, which refers to the number of consecutive months in which the price level remains constant, we adopt the frequency approach for measuring price duration, as outlined by Bils and Klenow (2004) and Dias *et al.* (2008). Under the assumptions of stationarity and homogeneity, the average spell duration is calculated as the inverse of the frequency of price changes. This relationship is valid only for homogeneous data. Therefore, it can be applied to our analysis because we use data at the item and outlet level.

4. The bundle of goods and services is determined by *Inquérito às Despesas das Famílias (IDEF)*. The results of this survey are used to define the consumption structure for the panel of goods and services of the CPI corresponding to transactions carried out in the economic territory by all resident households, which are based on a monetary counterpart. (Martins 2024).

Finally, the CPI does not provide an indication of the price level, but rather of the variation in prices. As such, we analyse the magnitude of price adjustments as a percentage change, since consumer prices are displayed as indices. Because averages are very sensitive to outliers and extreme values, we have opted to present the weighted median (as well as other quartiles) of the individual averages instead of the weighted average. The only exception is the frequency of price changes, for which both the average and the median are presented.

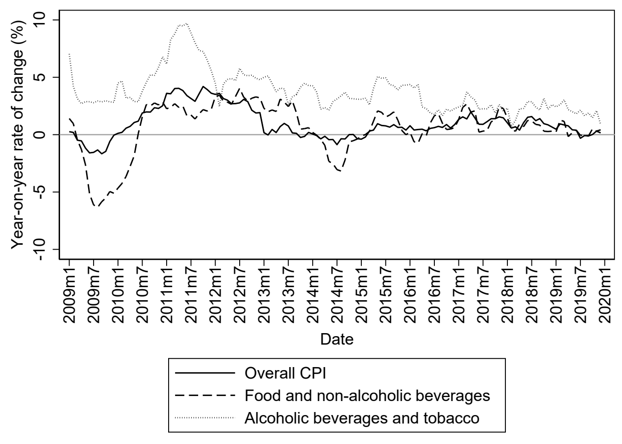
The dataset used as benchmark by Dias *et al.* (2008) differs in two key aspects. First, INE increased significantly the number of observed prices, which comes from the collection of prices for new products, additional varieties of the same products and the change from quarterly to monthly price collection for some products. Moreover, there was an improvement of the geographical coverage of the country, which is also relevant for our analysis. This means that the current dataset is more representative of all the establishments across the country as well as the households consumption structures. Nevertheless, it is important to note that this new series does not imply substantial methodological changes regarding the previous series.

We complement our study with two other micro-level datasets on food prices. First, we use producer producer prices in Section 5. This dataset is also collected by INE and its goal is to determine the monthly evolution of the transaction prices in the national and external markets of a pre-determined bundle of products, set by companies with some industrial activity. It is used to construct the aggregate Industrial Producer Prices Index (IPPI) and spans the period December 2010 to December 2019. This has also a longitudinal setting with companies headquartered in national territory whose principal or secondary activity is mining and quarrying, manufacturing, and electricity, gas and water supply being followed over time on a monthly basis. The unit of observation is the product produced in a given establishment. Items are classified using the Prodcom nomenclature at the 12-digit level (European Commission classification of industrial products) and matched at the most detailed level possible with consumer prices. For instance, one of the matches presented is the one that compares price changes in "Sugar", on the consumer side, and "Manufacture of sugar", on the producer side.

Second, we also resort to supermarket daily prices (SDP), a dataset curated by Banco de Portugal Microdata Research Laboratory (BPLIM) (2024) in Section 6. This dataset includes daily prices from the online stores of the main Portuguese retailers. The information is collected from each outlet using automated web scraping algorithms on a daily basis. For all the items sold on each retailer's website, BPLIM stores information about its name, brand, units, capacity, bar code, and price. The European Classification of Individual Consumption according to Purpose (ECOICOP) is used to classify each item into its category using the 5-digit level of disaggregation. This was done by manual inspection of the data as well as using a classification algorithm based on the item description and brand, trained on the manually classified data. We focus on the period from January 2022 until the end of 2023 as this is the period for which we have data from all retailers.

Figure 1 shows the year-on-year rate of change from January 2009 to December 2019 for the CPI (solid line), food and non-alcoholic beverages (dashed line), and alcoholic beverages and tobacco (dotted line). It provides insights into the consumer price dynamics over time within each category.

Figure 1: Consumer Price Index (CPI) over time



3. Consumer Price-Setting Behaviour

This section explores the microdata underlying the Portuguese CPI to document the main features of the consumer price-setting behaviour in the food industry. We highlight five main features derived from the empirical analysis done and benchmark them against the results previously presented in similar studies. Each fact sheds light on the mechanisms that shape the price dynamics within the Portuguese economy.

Fact 1: More than one-quarter of food prices changes every month

Table 1 reports monthly and median frequencies of price changes for all items, in the first and second columns. It also presents this information for each type of good, industry and outlet. Estimates are computed with CPI weights at the most detailed level. The overall monthly frequency of price changes is 26.3%, which means that, on average, more than one-quarter of food prices changed every a month. Moreover, the median frequency of price changes stood at 18.7%. Upon closer examination, distinct patterns emerge across food categories and retail formats.

Regarding the frequency of changes by type of good, we find a striking difference between unprocessed and processed ones. While, on average, more than half of the items in the first group changed on a monthly basis (51.3%), this happened to only 17.9% of the processed ones. Such pronounced volatility in unprocessed food prices underscores their inherent sensitivity to fluctuations in input costs, weather conditions impacting agricultural yields, and other supply-side shocks. Conversely, this pattern does not extend to processed food items, which exhibited stronger rigidity. Similar conclusions can be taken when using the median estimates.

	Monthly frequency of price changes	Median frequency of price changes	Median duration (in months)	Monthly frequency of positive price changes	Monthly frequency of negative price changes	Number of observations	Weights
Total	0.263	0.187	5.3	0.140	0.123	5 495 353	1.000
By type of good							
Unprocessed	0.513	0.593	1.7	0.259	0.254	1 640 443	0.270
Processed (excluding tobacco)	0.179	0.173	5.8	0.096	0.083	3 801 294	0.640
By type of industry							
Food and non-alcoholic beverages	0.287	0.207	4.8	0.148	0.138	5 082 941	0.842
Food	0.292	0.192	5.2	0.151	0.141	4 677 930	0.789
Bread and cereals	0.112	0.080	12.4	0.061	0.050	766 525	0.157
Meat	0.211	0.192	5.2	0.112	0.100	896 371	0.161
Fish and seafood	0.515	0.422	2.4	0.265	0.250	761 187	0.141
Milk, cheese and eggs	0.186	0.187	5.3	0.097	0.089	481 614	0.093
Oils and fats	0.258	0.260	3.8	0.135	0.124	161 756	0.037
Fruit	0.646	0.712	1.4	0.315	0.331	341 826	0.065
Vegetables	0.390	0.319	3.1	0.201	0.189	715 431	0.072
Sugar, jam, honey, chocolate and confectionery	0.148	0.162	6.2	0.078	0.069	238 759	0.037
Food products n.e.c.	0.173	0.189	5.3	0.090	0.083	314 461	0.026
Non-alcoholic beverages	0.207	0.224	4.5	0.113	0.094	405 011	0.053
Coffee, tea and cocoa	0.215	0.224	4.5	0.115	0.100	203 141	0.015
Mineral waters, soft drinks, fruit and vegetable juices	0.204	0.226	4.4	0.113	0.092	201 870	0.038
Alcoholic beverages and tobacco	0.132	0.105	9.5	0.094	0.038	412 412	0.158
Alcoholic beverages	0.172	0.158	6.3	0.097	0.075	358 796	0.068
Spirits	0.184	0.184	5.4	0.107	0.077	59 647	0.003
Wine	0.160	0.158	6.3	0.089	0.071	245 022	0.055
Beer	0.238	0.238	4.2	0.141	0.097	54 127	0.010
Tobacco	0.102	0.105	9.5	0.092	0.010	53616	0.090
By type of outlet							
Store	0.188	0.104	9.6	0.103	0.085	785 117	1.000
Market	0.197	0.065	15.3	0.100	0.097	575 863	0.783
Supermarket	0.269	0.178	5.6	0.143	0.125	2 627 865	1.000
Hypermarket	0.319	0.251	4.0	0.166	0.154	1 504 977	1.000

Source: Authors' calculations using disaggregated CPI monthly data. **Notes:** The estimates correspond to the 2009:2 to 2019:12 period. The estimates for the median duration are calculated as the inverse of the median frequency of price changes. The estimates use CPI weights at the most detailed level made available by INE and the weights have been rescaled to add to one.

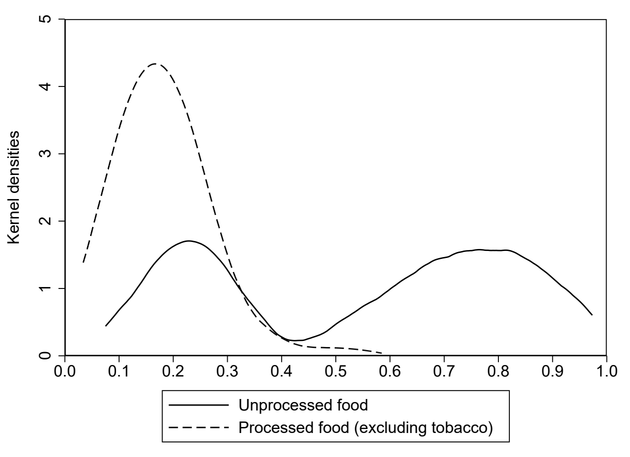
Table 1. Frequency of consumer price changes

These values point towards a strong decrease in the rhythm of adjustments in food prices, when comparing with the period between January 1997 and January 2001 in Dias *et al.* (2008). The monthly frequency drops from 36.6% to 26.3% and the median one from 32.6% to 18.7%. This trend is specific to processed food items, given that prices for unprocessed goods experienced more frequent changes between 2009 and 2019. For the processed goods, we find that the frequency of price changes decreased from 23.9% to 17.9%. We are also able to frame our estimates within the euro area. Using as comparison the results from Erwan and et al. (2022), food prices changed more frequently in Portugal than the average of the 11 countries analysed in this study as, on average, 31.4% of the unprocessed goods and 15.4% of the processed ones change every month in the euro area.

The distribution of the frequencies of price changes by type of good for each month, which is displayed in Figure 2, confirms that unprocessed food items had a bi-modal distribution around 25% and 80%. This indicates that there are products such as fruits that had very frequently price changes (almost every month) while others, such as bread and cereals or milk, cheese and eggs, changed less frequently.

Regarding processed goods, the mass of the distribution is more concentrated, with the right tail not surpassing the 60%, but still exhibiting considerable within-group heterogeneity. These patterns are similar to those in Dias *et al.* (2008), with the only difference being the fact that the centre of mass of the distribution for the processed items is now around a lower level.

Figure 2: Distribution of the frequency of price changes by type of good



Source: Authors' calculations using CPI monthly data. **Notes:** This graph illustrates the distribution of the average frequency of price changes by item. Monthly averages were computed by item and constitute the basic observation used in these graphs. The estimates correspond to the 2009:2 to 2019:12 period. The distributions were obtained by using kernel weights. No CPI weights were used.

Fact 2: Half of the items display price spells shorter than 5.3 months

The third column of Table 1 shows the median average spell durations, in months. We find that half of the items displayed price spells, which capture how long prices tend to remain unchanged, shorter than 5.3 months. The estimated spells are longer for processed food items (5.8 months) than for unprocessed ones (1.7 months). Notably, the highest median duration is found in bread and cereals, which is 12.4 months, while the shortest one is observed for fruit (1.4 months).

These findings show an increase of the median duration when compared to the period from 1997 until 2001, when it was 3.1 months for food. This difference comes mostly from the processed food as the median duration increased from 5.3 months, while for the unprocessed group it actually decreased from 2.1 months.

Fact 3: Positive price changes are more frequent than negative ones

Columns 4 and 5 of Table 1 present the monthly frequency of positive and negative price changes. Positive price changes were more frequent than negative ones – 14.0% against 12.3% – when examining all products in the sample together. As explained in Dias *et al.* (2008), these values close to each other may be a result of the seasonal nature of many items in this class, for which rises and drops in prices are expected to be equally likely. This is even more evident when filtering for the unprocessed foods as the two values are 25.9% and 25.4% for positive and negative changes. An examination of these estimates at the industry-level concludes that positive price changes were more frequent than negatives ones across all categories, with only one exception. Fruits recorded an average monthly frequency of price increases of 31.5%, while the share of products every month with price decreases stands at 33.1%. This reinforces that prices for this type of goods were highly influenced by changes in market conditions, responding in a flexible way to supply-side changes related with their seasonal nature.

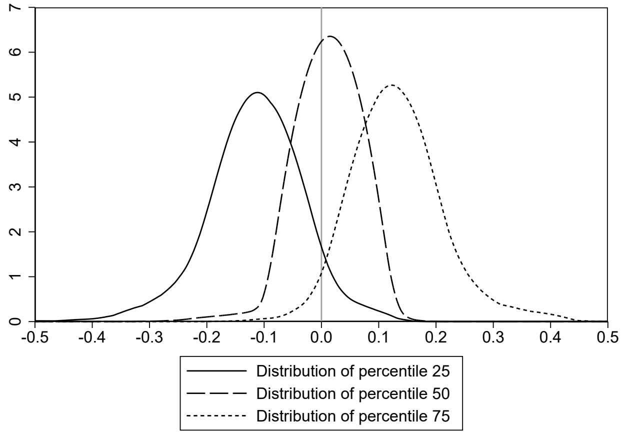
This result is also influenced by the inflationary period under analysis. For the food category, year-on-year rates of change were primarily positive from 2009 until 2019, except for some months in 2009, 2010, and 2014. As expected in a context of positive but very low inflation, the frequency of price increases surpassed that of price decreases, accounting for approximately 53% of total price changes. At the industry-level, the most significant discrepancies between the frequencies of positive and negative price changes occur in alcoholic beverages and tobacco. In this industry, positive changes made up 71% of total price changes (9.4% versus 3.8%). This downward rigidity was particularly pronounced in tobacco, where the frequency of negative price changes was only 1.0% against 9.2% for positive ones.

Fact 4: Price increases have a higher magnitude than price decreases

Table 2 presents the 25$^{\text{th}}$, 50$^{\text{th}}$ and 75$^{\text{th}}$ percentiles of the magnitudes of the price changes conditional on a change having occurred and on its sign. We find that not only price increases were more frequent, but they were also larger than price decreases, as positive adjustments had a higher magnitude than negative ones. Specifically, positive price changes had a median magnitude of 21%, whereas negative price changes had a median magnitude of -16%. It means that, not only prices increases were more frequent, they were larger than price decreases. This is corroborated when comparing the 1st and 3rd quartiles.

Here, there are two main differences vis-à-vis the magnitudes documented in Dias *et al.* (2008). Between 1997 and 2001, the median size was 9% for positive changes and -8% for the negative. These are smaller than our estimates. Furthermore, the interquartile ranges are narrower in both directions in our sample, with price changes more concentrated around the median. When comparing with the euro-area estimates in Erwan and et al. (2022), the size of price changes were much larger in Portugal for both processed and unprocessed foods. The notable divergence in this comparison is that for the euro area the median decrease was larger than the median increase, which we do not find in our results.

Figure 3: Distributions of the magnitude of price changes of percentiles 25, 50, and 75



Source: Authors' calculations using CPI monthly data. **Notes:** This graph illustrates the distribution of the 25th, 50th and 75th percentiles of the magnitudes of price changes conditional on a change having occurred. Monthly figures were computed using estimates at the outlet $\times$ item level. The estimates correspond to the 2009:2 to 2019:12 period. The distributions were obtained using kernel weights. No CPI weights were used.

Finally, we turn to the distribution of magnitudes of price changes, conditional on the occurrence of a price change (i.e., zeros were excluded). Figure 3 presents the distribution of the 25th, 50th and 75th percentiles using all items in the sample. The median distribution is tightly concentrated around a small positive value, indicating that most price changes were minor and positive. In contrast, the distributions for the percentiles 25 and 75 were more dispersed. This suggests a higher variability in price changes, with some products experiencing substantial decreases or increases. In the Appendix A.1, we present this analysis by type of good, industry and outlet.

	Magnitude of positive price changes			Magnitude of negative price changes		
	1st quartile	Median	3rd quartile	1st quartile	Median	3rd quartile
Total	0.17	0.21	0.22	−0.18	−0.16	−0.14
By type of good						
Unprocessed	0.16	0.18	0.21	−0.16	−0.15	−0.13
Processed (excluding tobacco)	0.18	0.22	0.26	−0.19	−0.18	−0.15
By type of industry						
Food and non-alcoholic beverages	0.18	0.21	0.24	−0.18	−0.17	−0.14
Food	0.17	0.21	0.22	−0.18	−0.17	−0.14
Bread and cereals	0.22	0.22	0.26	−0.19	−0.18	−0.18
Meat	0.20	0.21	0.22	−0.18	−0.17	−0.16
Fish and seafood	0.15	0.16	0.22	−0.18	−0.13	−0.12
Milk, cheese and eggs	0.16	0.21	0.25	−0.18	−0.16	−0.14
Oils and fats	0.18	0.18	0.19	−0.15	−0.14	−0.14
Fruit	0.17	0.17	0.17	−0.15	−0.15	−0.15
Vegetables	0.19	0.19	0.27	−0.18	−0.14	−0.14
Sugar, jam, honey, chocolate and confectionery	0.20	0.21	0.26	−0.20	−0.16	−0.15
Food products n.e.c.	0.22	0.28	0.28	−0.20	−0.20	−0.17
Non-alcoholic beverages	0.20	0.22	0.26	−0.19	−0.17	−0.15
Coffee, tea and cocoa	0.22	0.22	0.22	−0.17	−0.17	−0.17
Mineral waters, soft drinks, fruit and vegetable juices	0.20	0.26	0.26	−0.19	−0.19	−0.15
Alcoholic beverages and tobacco	0.04	0.04	0.17	−0.15	−0.03	−0.03
Alcoholic beverages	0.17	0.17	0.17	−0.15	−0.15	−0.15
Spirits	0.08	0.08	0.08	−0.08	−0.08	−0.08
Wine	0.17	0.17	0.17	−0.15	−0.15	−0.15
Beer	0.36	0.36	0.36	−0.22	−0.22	−0.22
Tobacco	0.04	0.04	0.04	−0.03	−0.03	−0.03
By type of outlet						
Store	0.11	0.13	0.16	−0.14	−0.12	−0.10
Market	0.10	0.11	0.15	−0.14	−0.10	−0.08
Supermarket	0.17	0.22	0.26	−0.19	−0.17	−0.14
Hypermarket	0.19	0.21	0.24	−0.18	−0.17	−0.15

Source: Authors' calculations using CPI monthly data. **Notes:** The estimates correspond to the 2009:2 to 2019:12 period. The estimates are conditional on a price change having occurred. The estimates use CPI weights at the most detailed level made available by INE and the weights have been rescaled to add to one.

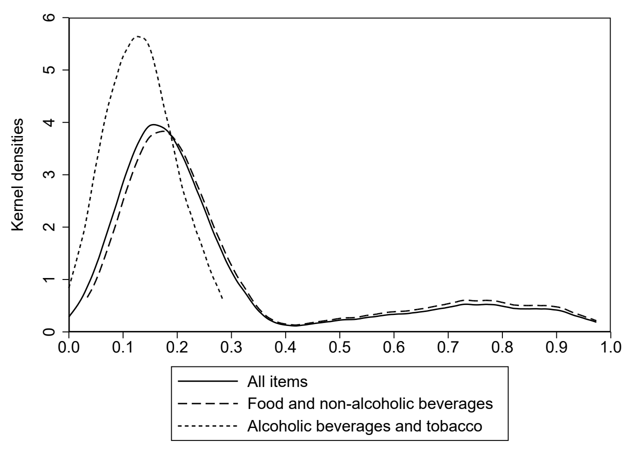
Table 2. Price rigidity: magnitude of consumer price changes

Fact 5: **Price-setting behaviour is heterogeneous at industry and outlet level**

Given the granularity of the data underlying the CPI consumer basket, it is possible to investigate the distribution of the frequency and magnitude of price changes, across several dimensions. As such, we try to understand how heterogeneous price-setting behaviour is for each of the industries and type of outlets in the sample.

Figure 4 presents the distribution of the frequency of price changes for the main industries. The distributions for food and non-alcoholic beverages exhibited a multi-modal pattern with a long tail extending towards 100%. Despite this, the majority of price adjustments happened with a frequency lower than 40%. This distribution is very close to the one with all items taken together. For the category of alcoholic beverages and tobacco, the distribution is more concentrated around the median value, which is 10.5% and around 10% of items do not registered any change in their price.

Figure 4: Distribution of the frequency of price changes by type of industry



Source: Authors' calculations using CPI monthly data. **Notes:** This graph illustrates the distribution of the average frequency of price changes by industry. Monthly averages were computed by item and constitute the basic observation used in these graphs. The estimates correspond to the 2009:2 to 2019:12 period. The distributions were obtained by using kernel weights. No CPI weights were used.

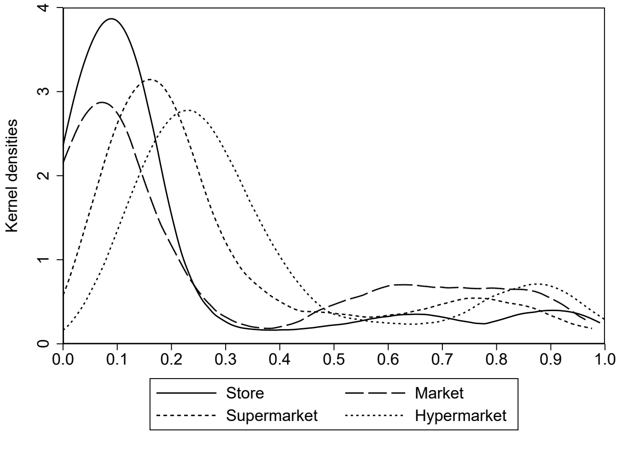
Within the food and non-alcoholic beverages category, on one hand, food and fish and seafood were the industries with the highest share of monthly price changes (64.6% and 51.5%, respectively). Vegetables also presented a high frequency. On the other hand, bread and cereals or sugar, jam, honey, chocolate and confectionery had less frequent price changes (11.2% and 14.8%, respectively).

Our findings also underscore that big outlets adjusted more frequently their prices than the small. In fact, hypermarkets stood out as the type of outlet exhibiting the highest average monthly frequency of price changes, reaching 31.9%. As the size of the outlet decreases, the estimates for each type also decrease:

for the stores and markets, the frequencies are much lower (18.8% and 19.7%, respectively). As a consequence, hyper and supermarkets exhibited relatively shorter spells (4.0 and 5.6 months, respectively), whereas stores and markets demonstrated longer spells (9.6 and 15.3 months, respectively). This suggests that these smaller outlets tend to maintain consistent pricing over an extensive time frame. Such findings may imply differences in pricing strategies, for example, fewer discounts, or unique market dynamics, potentially influencing consumer behaviour and competition. It may also come from higher menu costs for these outlets, which tend to be less efficient in frequently updating their prices.

Figure 5 illustrates the distribution of price change frequencies for each type of outlet and shows that each one exhibits unique distribution patterns. Firstly, hyper and supermarkets demonstrated a higher frequency of significant price fluctuations, as shown by the denser and right-skewed density curves. In contrast, stores and markets displayed a stronger concentration of low frequencies. Additionally, a substantial percentage of products in all outlet types showed no price changes, reflecting the segments of the distribution at zero frequency. This percentage is notably lower in the bigger outlets, consistent with their more volatile pricing behaviour. The long tails in the distributions indicate that extreme price changes, while less common, were present across all types of outlets.

Figure 5: Distribution of the frequency of price changes by type of outlet



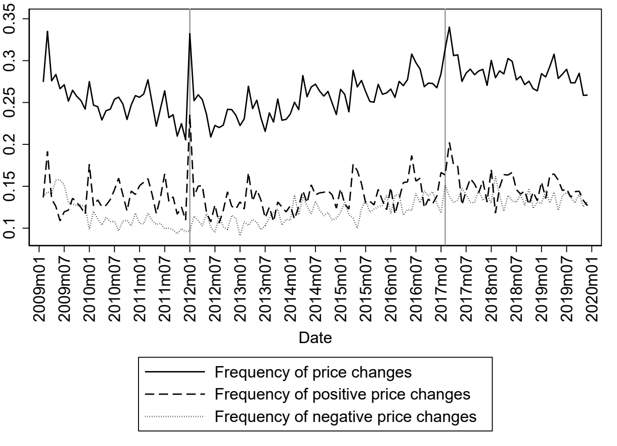
Source: Authors' calculations using CPI monthly data. **Notes:** The estimates correspond to the 2009:2 to 2019:12 period. The distributions were obtained by using kernel weights. No CPI weights were used.

4. Price-Setting Behaviour over Time

Price-setting decisions depend on factors that are specific to the individual firm or to the sector in which it operates (Dedola *et al.* 2024). They may also be subject to aggregate shocks and general macroeconomic conditions that affect all firms. It is thus important to analyse how price adjustments vary over time.

Figure 6 illustrates the evolution of overall, positive, and negative frequencies of price changes between 2009 and 2019. The analysis reveals a notable finding: despite the dynamic nature of market conditions, the frequency of price changes has remained relatively stable. This suggests a degree of equilibrium in the adjustment process, wherein prices respond to changing economic conditions while maintaining a certain level of stability in their overall frequency of changes.

Figure 6: Frequency of price changes over time

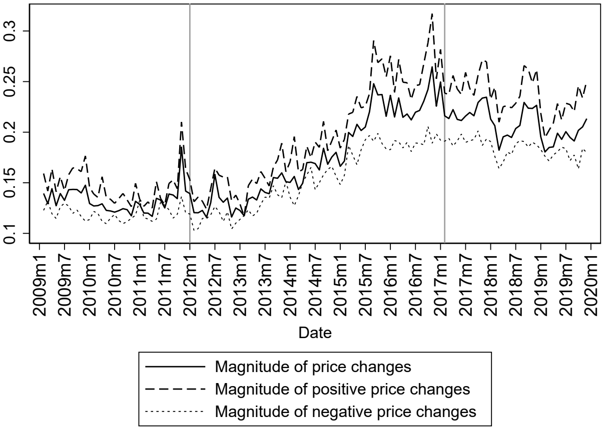


Source: Authors' calculations using CPI monthly data. **Notes:** The estimates correspond to the 2009:2 to 2019:12 period. The vertical line in 2012:01 corresponds to a VAT change and the one in 2017:02 corresponds to the introduction of a tax on sodas. The CPI weights were used at the most detailed level available.

The frequency of price changes shows a noticeable downward trend during the initial period of analysis, from 2009 to 2012. This decline coincides with negative year-on-year rates of change in food and non-alcoholic beverage prices. After this period, the frequency stabilizes, hovering just below 30% in most of the subsequent periods. It is important to note that periods with changes in consumption tax rates — specifically January 2012 and March 2017 — exhibit atypical behaviour and, hence, will be analysed separately. A closer look at the frequency of positive and negative price changes reveals additional insights. As previously observed, the frequency of positive price changes consistently exceeds that of negative price changes. Moreover, positive price changes display a seasonal pattern, particularly from 2009 to 2017, with frequency peaks in the early months of each year. This seasonality likely corresponds to items that undergo annual price adjustments (the so-called "January effect" of price changes).

When examining the magnitude of price adjustments, Figure 7 provides a detailed view of the evolution of overall, positive, and negative price change magnitudes throughout the period. A notable shift occurs at the beginning of 2014, marking a significant change in the pattern of price adjustments. Prior to this shift, the magnitude of price changes was relatively stable, with adjustments averaging around 15%. During this time, positive price changes were consistently larger than the negative. However, starting in 2014, there is a marked increase in magnitudes. By 2016 and 2017, the overall magnitude escalated to approximately 25%, implying a substantial rise in the size of price adjustments.

Figure 7: Magnitude of price changes over time



Source: Authors' calculations using CPI monthly data. **Notes:** The estimates correspond to the 2009:2 to 2019:12 period. The vertical line in 2012:01 corresponds to a VAT change and the one in 2017:02 corresponds to the introduction of a tax on sodas. The CPI weights were used at the most detailed level available.

This upward trend is particularly pronounced in the magnitude of positive price changes, which experienced a much sharper increase compared to negative price changes. Following this peak, the magnitude of price adjustments slightly decreased, settling at around 20% in the subsequent period. This shift suggests that the factors driving price increases, especially the larger positive adjustments, played a significant role in shaping the overall trend during this time.

4.1. Decomposition of Monthly Inflation

A common decomposition for the month-on-month rate of price change is the number of prices that change (frequency) multiplied by the amount by which they change (magnitude). Specifically, denoting monthly inflation at month t with π_t:

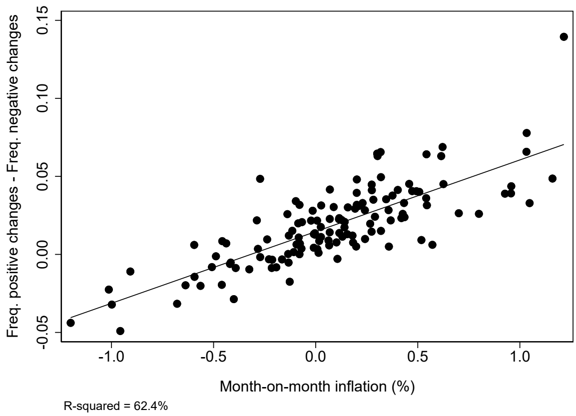
$$\pi_t = f_t \times dp_t, \tag{1}$$

where f_t corresponds to the frequency of price changes and dp_t to the magnitude.

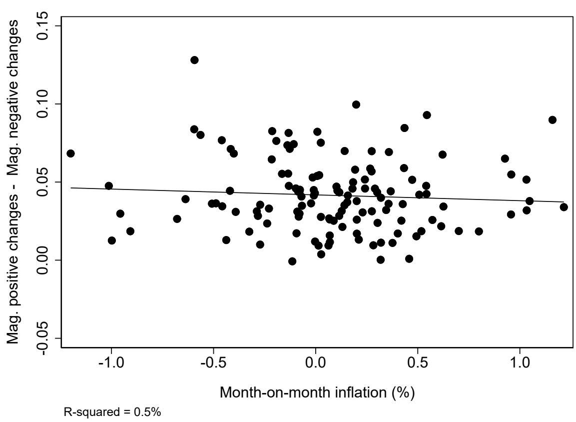
Moreover, we can further decompose the frequency as the sum of the frequency of price increases and price decreases, i.e., $f = f^+ + f^-$. With this frequency decomposition, monthly inflation is obtained as the frequency of prices increases multiplied by the size of average price increases $(f^+ \times dp^+)$ minus the frequency of price decreases multiplied the (absolute) size of average price decreases $(f^- \times dp^-)$.

Next, we explore which component was more relevant for the inflation dynamics. We present the correlation between month-on-month inflation from January 2009 to December 2019 and the two components separately: first, the difference between the frequency of positive and negative price changes in Panel (a) of Figure 8; then, the difference between the size of positive and negative price changes in Panel (b).

Figure 8: Correlation between monthly inflation and frequency and magnitude components



(a) Frequency component (f)



(b) Magnitude component (dp)

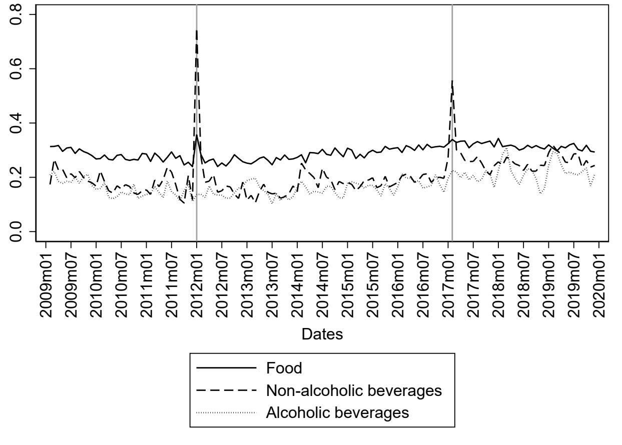
Source: Authors' calculations using CPI monthly data. **Notes:** The estimates correspond to the 2009:2 to 2019:12 period. The CPI weights were used at the most detailed level available.

Panel (a) shows a strong positive correlation between monthly inflation and the frequency component, indicating that variations in the frequency of positive versus negative price changes have a significant impact on monthly inflation. In contrast, Panel (b) reveals a weak correlation between inflation and the magnitude component, suggesting that the size of price adjustments has little impact on the inflation dynamics. These results suggest that inflation during this period was primarily driven by how often food prices were adjusted rather than by how large those adjustments were. Specifically, when the frequency of positive price changes exceeds that of negative changes, inflation tends to rise significantly. However, the magnitude of these changes had minimal influence on overall inflation levels. This highlights the importance of monitoring the frequency of price changes as a key indicator of inflationary trends, rather than focusing solely on their size. Similar results were found in analysis for other countries, e.g. the US (Karadi *et al.* 2023).

4.2. The Case for Consumption Tax Rates

The changes in consumption tax rates can significantly impact on the frequency of price adjustments (Bernardino *et al.* 2024). The period under analysis presents two notable shifts in price-setting behaviour coinciding with two significant changes, as shown in Figure 9. The frequency of price changes over time by type of industry highlights those two events, represented by the vertical dashed lines.

Figure 9: Frequency of price changes over time by type of industry



Source: Authors' calculations using CPI monthly data. **Notes:** The estimates correspond to the 2009:2 to 2019:12 period. The vertical line in 2012:01 corresponds to a VAT change and the vertical line in 2017:02 to the introduction of a tax on sodas. The CPI weights were used at the most detailed level available.

First, in January 2012, most non-alcoholic beverages and some food items had a VAT rate change: from 6% to 23% in the first case and a reduction from 13% to 6% in the case of a restricted group of food items. This translated into a strong spike in the frequency of price changes that reached the 70% in that month for the non-alcoholic beverages category and a smaller one, but surpassing 30%, for the food category. Then, in February 2017, a soda tax was introduced, affecting a fraction of non-alcoholic beverages (Gonçalves and Pereira dos Santos 2020). This time, the increase in the frequency of price changes went from around 20% up to 50% on a single month, returning to the previous levels then after. For the alcoholic beverages, no change in the tax rates happened in this period, which meant that prices were adjusted at a steady rate, without any significant changes. In the Appendix A.2, we present this analysis over time by type of good as well.

5. Price-Setting Behaviour over the Production Value Chain

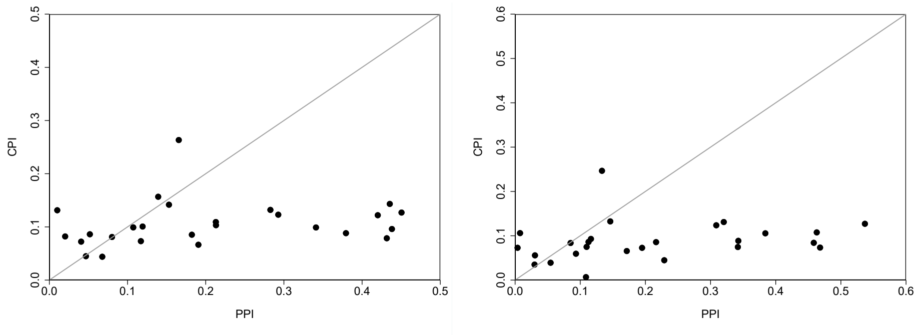
We complement the analysis of consumer prices (CPI) with industrial producer prices (IPPI) to explore how price-setting behaviour changes over the production value chain. To do so, we match the categories from both datasets at the most detailed level possible, yielding a total of 26 categories.[5] The common sample was used for the overlapping period from December 2010 and December 2019.

Figure 10 compares the average frequency of price changes at the consumer and producer levels for each one of the categories matched, controlling for its direction. The 45° line indicates that the frequency is the same for a certain category. If the point lies above (below), then the frequency is lower (higher) at the consumer level. Our findings reveal a higher frequency of price changes at the producer-level than at the consumer level. This result holds true for both positive and negative price changes. In the Appendix A.3, we show this comparison without controlling for the direction. This challenges traditional notions of price transmission mechanisms and underscores the significant role of supply chain dynamics and intermediary processes in influencing price adjustments.

Looking at the median magnitudes of the variation in prices in Figure 11, we find that they are larger at the consumer level. Interestingly, the size of industrial producer price changes tend to be very low and concentrated, both for the positive and the negative ones. There is thus a contrast over the production value chain: producer prices change more frequently but by less than consumer prices.

5. The IPPI categories with a match with a CPI category are the following: Husked rice; Fresh bread; Fresh pastry goods and cakes; Manufacture of prepared meals and dishes; Manufacture of macaroni, noodles, couscous and similar farinaceous products; Manufacture of grain mill products; Processing and preserving of meat; Processing and preserving of poultry meat; Production of meat and poultry meat products; Processing and preserving of fish, crustaceans, and molluscs; Operation of dairies and cheese making; Manufacture of oils; Manufacture of fats; Processing and preserving of potatoes; Manufacture of sugar; Manufacture of cocoa; Manufacture of chocolate and sugar confectionery; Manufacture of condiments and seasonings; Processing of tea and coffee; Other non-alcoholic beverages; Manufacture of soft drinks; production of mineral waters and other bottled waters; Manufacture of fruit and vegetable juice; Distilling, rectifying, and blending of spirits; Manufacture of wine from grape; Manufacture of beer; Manufacture of tobacco products.

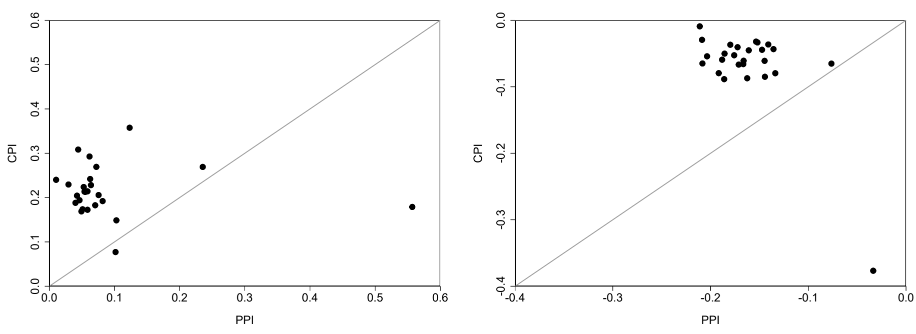
Figure 10: Frequency of price changes at the consumer and producer levels



(a) Positive price changes (b) Negative price changes

Source: Authors' calculations using CPI and IPPI monthly data. **Notes:** The items were matched at the most detailed level possible with the goal of constructing a common sample. No CPI weights were used.

Figure 11: Median magnitudes of price changes at the consumer and producer levels



(a) Positive price changes (b) Negative price changes

Source: Authors' calculations using CPI and IPPI monthly data. **Notes:** The items were matched at the most detailed level possible with the goal of constructing a common sample. No CPI weights were used.

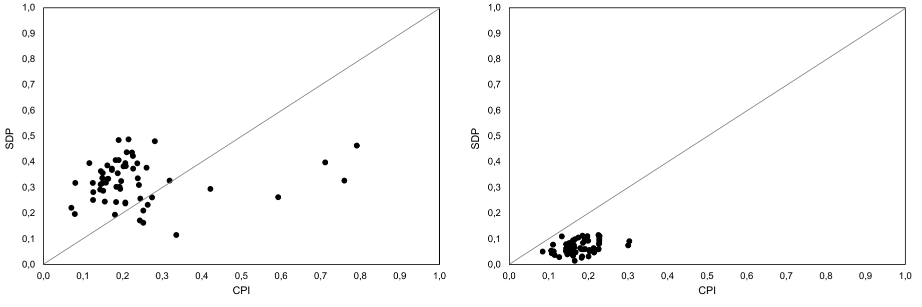
6. Comparison against Daily Prices

In most cases, only one price observation per month for each item is collected. As such, the estimates for the frequency and the magnitude of price changes obtained from the CPI dataset should be interpreted as a lower-bound, since there may be intra-month adjustments that are not captured. In this sense, we end our analysis of the consumer price-setting behaviour with a comparison vis-à-vis the online prices that are collected daily. The goal is to understand whether the frequency and the magnitude of price changes differs significantly between the two datasets: the one collected by INE (CPI) and the one with daily supermarket data (SDP).

One should note, however, that the sample periods of the datasets are not coincident. In fact, INE has only made available data until the end of 2019, while the collection of the SDP has started in 2022. We find that it is important to pursue this analysis to explore how far are the lower-bound estimates from those obtained from daily data. Furthermore, it is also interesting to grasp the intra-month dynamics that may be not captured by the official inflation.

In this analysis, we have 59 categories at the 5-digit COICOP level that are part of the reference consumption basket matched across datasets. For each one, we compute the monthly frequency of price changes and the respective magnitudes, using item-level information and keeping the last day of each month. After doing that, we compare the average values from the SDP dataset with those coming from the CPI. Figure 12 presents this comparison between monthly and daily data.

Figure 12: Frequency and magnitude of price changes on monthly and daily data



(a) Frequency of price changes (b) Magnitude of price changes

Source: Authors' calculations using CPI monthly and SDP daily data. **Notes:** The items were matched at the most detailed level possible with the goal of constructing a common sample. No CPI weights were used.

The findings indicate that the frequency of price changes is generally higher in the daily SDP data across most categories. This discrepancy can be attributed to the higher temporal resolution of the SDP dataset, which captures more granular price movements that the monthly CPI data may miss. For instance, temporary promotions, flash sales, or other intra-month adjustments are likely to be reflected in the SDP data but remain undetected in the CPI data. This confirms that these estimates most certainly under-report the true frequency of price changes, thereby affirming the hypothesis that these estimates should be treated as lower bounds.

In contrast, the magnitude of price changes appears to be higher in the CPI data. This could be due to several reasons. First, the CPI data may capture more substantial, less frequent price adjustments, such as those due to supply chain disruptions, seasonal effects, or policy-driven changes like tax adjustments. Since the CPI reflects a single monthly price, it is more likely to record significant changes when they occur, potentially skewing the magnitude upwards compared to the daily dataset, where smaller but, more frequent adjustments might dilute the average magnitude. Additionally, the methodology used in constructing CPI might attach more weight to larger price shifts, particularly if they coincide with the collection date, further explaining why the magnitude is more pronounced in the CPI data.

7. Conclusion

The importance of price stickiness remains a central question in Economics, with new micro price evidence playing a central role in further deepening its understanding. The microdata helps us to answer questions such as how often and by how much price changes over time. In this sense, this paper leverages a novel dataset with CPI microdata for food items in Portugal between 2009 and 2019, expanding the evidence available on the dynamics of food prices.

First, we corroborate five main features of the consumer price-setting behaviour that had been previously documented in Dias *et al.* (2008). Our analysis reveals that over one-quarter of food prices changed each month during the study period. Notably, there are distinct patterns across food categories and retail formats. Unprocessed goods showed a higher frequency of price changes, with 50% of items adjusting prices monthly, compared to only 17.9% for processed foods. Hypermarkets and supermarkets report the highest frequency, while smaller stores see less frequent changes. Price spells had a median duration of 5.3 months, with positive price changes occurring more often than negative ones. Additionally, price increases tended to be larger than decreases, indicating a pattern of more significant upward adjustments. The magnitude of these changes is generally substantial, often exceeding the average inflation rate for the period, highlighting the importance of price size in adjustment decisions.

The analysis reveals that price-setting behaviour shows a remarkable stability in the frequency of changes over time, with positive price adjustments occurring more frequently and exhibiting seasonal patterns. However, a comparison of producer and consumer price levels highlights that while producer prices change more often, the magnitude of these changes is smaller compared to the larger but less frequent price adjustments observed at the consumer level. Additionally, daily price data indicates a higher frequency of changes than monthly CPI data, suggesting that the CPI is likely to under-report it, though it captures larger price shifts, often tied to significant events like tax changes.

The frequent price changes in food items are a critical consideration because they serve as a rapid conduit for transmitting shocks that impact the production value chain directly to consumers, thereby exerting a significant influence on month-on-month inflation dynamics. These adjustments also play a crucial role in determining how quickly changes in the monetary stance translate into shifts in food inflation. However, price-setting decisions are not uniform; they vary across multiple dimensions. While aggregate shocks and broader macroeconomic conditions affect all firms, other factors — specific to individual firms or particular industries — also play a substantial role in shaping these decisions. This heterogeneity in price-setting behaviour underscores the complexity of managing inflation and economic stability.

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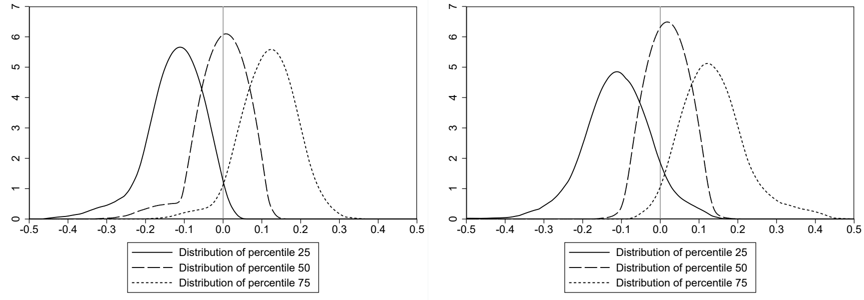
Appendix: Additional Figures

A.1. Distributions of the Magnitude of Price Changes

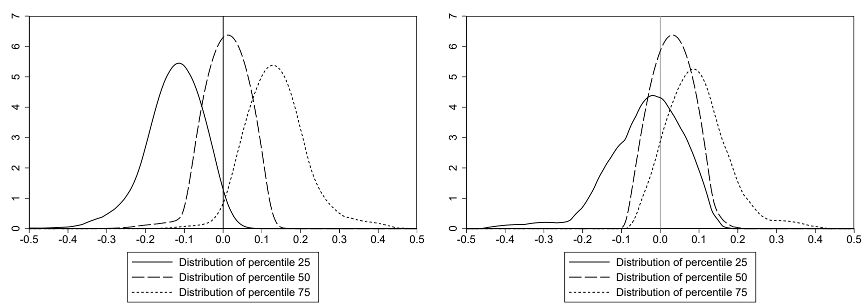
Figure A.1: Distributions of the magnitude of price changes by type of good



(a) Unprocessed (b) Processed (excluding tobacco)

Source: Authors' calculations using CPI monthly data. **Notes:** This Figure shows the distribution of the 25th, 50th and 75th percentiles of the magnitudes of price changes, conditional on a change having occurred, by type of good. Monthly figures were computed using estimates at the outlet $\times$ item level. The estimates correspond to the 2009:2 to 2019:12 period. The distributions were obtained by using kernel weights. No CPI weights were used.

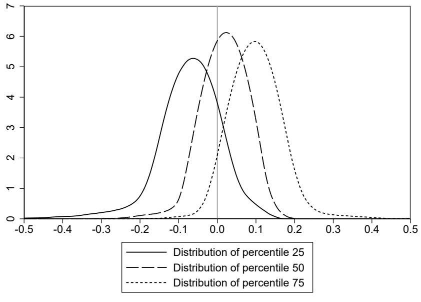
Figure A.2: Distributions of the magnitude of price changes by type of industry



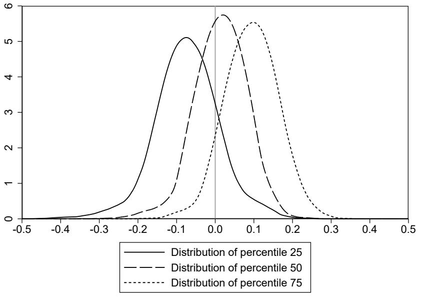
(a) Food and non-alcoholic beverages (b) Alcoholic beverages and tobacco

Source: Authors' calculations using CPI monthly data. **Notes:** This Figure shows the distributions of the 25th, 50th and 75th percentiles of the magnitudes of price changes, conditional on a change having occurred, by type of industry. Monthly figures were computed using estimates at the outlet $\times$ item level. The estimates correspond to the 2009:2 to 2019:12 period. The distributions were obtained by using kernel weights. No CPI weights were used.

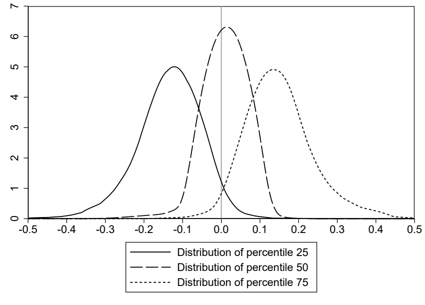
Figure A.3: Distributions of the magnitude of price changes by type of outlet



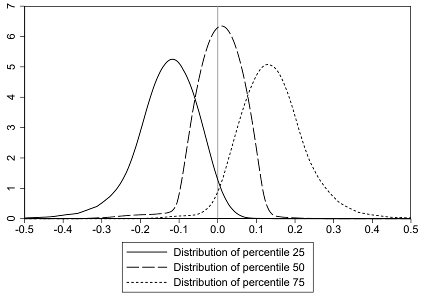
(a) Store



(b) Market



(c) Supermarket

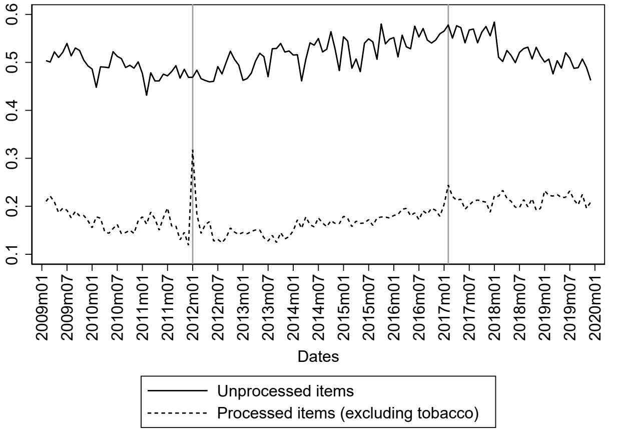


(d) Hypermarket

Source: Authors' calculations using CPI monthly data. **Notes:** This Figure shows the distributions of the 25th, 50th and 75th percentiles of the magnitudes of price changes, conditional on a change having occurred, by type of outlet. Monthly figures were computed using estimates at the outlet $\times$ item level. The estimates correspond to the 2009:2 to 2019:12 period. The distributions were obtained by using kernel weights. No CPI weights were used.

A.2. Price-Setting Behaviour over Time

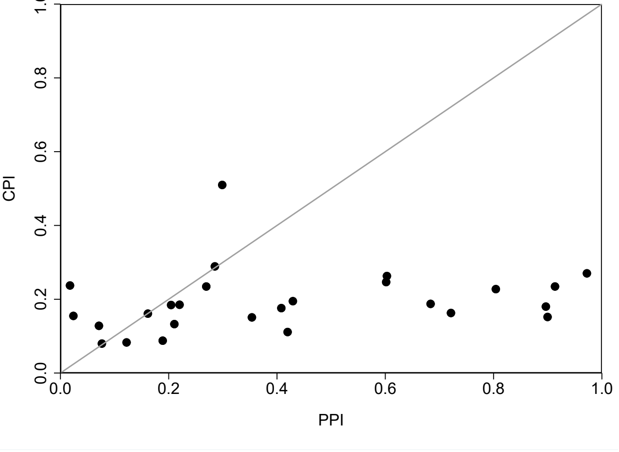
Figure A.4: Frequency of price changes over time by type of good



Source: Authors' calculations using CPI monthly data. **Notes:** The estimates correspond to the 2009:2 to 2019:12 period. The vertical line in 2012:01 corresponds to a VAT change and the vertical line in 2017:02 to the introduction of a tax on sodas. The CPI weights were used at the most detailed level available.

A.3. Price-Setting Behaviour over the Production Value Chain

Figure A.5: Frequency of price changes at the consumer and producer levels



Source: Authors' calculations using CPI monthly data. **Notes:** The items were matched at the most detailed level possible with the goal of constructing a common sample. No CPI weights were used.