Do Firms Adjust Prices through Frequency or Magnitude? Granular High-Frequency Evidence from Peru's Inflationary Episode (2020–2024)

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Abstract

This paper analyzes firm-level price adjustment behavior during Peru's inflationary episode from 2020 to 2024, using high-frequency data from supermarket products. Guided by a simple Rotemberg (1982) model, I distinguish between two margins of adjustment: the frequency and the magnitude of price changes. After filtering out discounts and short-lived price spells, I document a clear upward shift in the distribution of year-on-year price changes—particularly for food items—confirming widespread price adjustment. The price change distribution is skewed toward positive values and bimodal, with few small changes, indicating that firms are more likely to implement sizable price increases than marginal adjustments, in line with the presence of adjustment costs. Hazard rate estimates show that half of prices change within two months, and that the likelihood of price adjustments rose during the inflationary period. Finally, I find that rising inflation was associated with an increase in the frequency of price changes, while the average magnitude remained stable. These results suggest that firms primarily respond to inflation by adjusting prices more often, rather than by raising them more sharply.

Keywords: Web Scraping, Inflation, Retail Prices, Price Duration

JEL classification: E31, C55, L81, L11

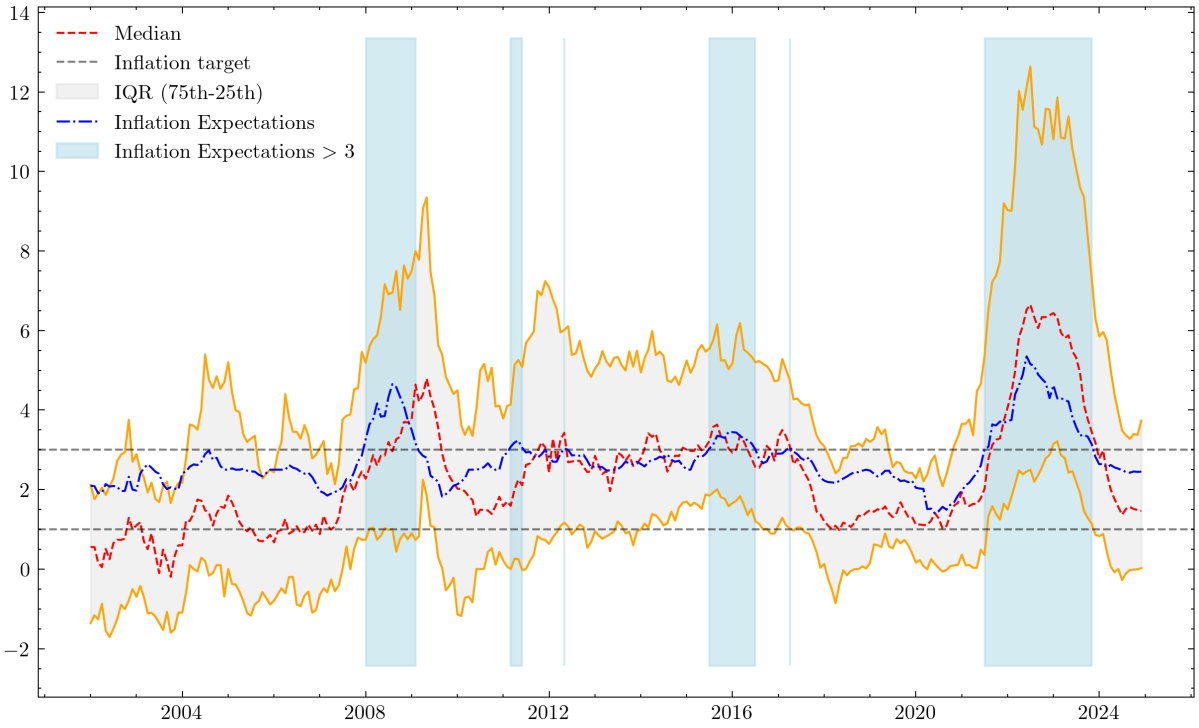
*Email: gonzalo.bueno@bcrp.gob.pe. I would like to thank Marco Vega for his invaluable advice and encouragement. I benefited from discussions with Alan Ledesma and Luis Gonzalo Llosa. I would also like to thank the participants of the 12th biennial IFC Conference (BIS).

1. Introduction

The inflationary process in Peru since the onset of the millennium has been characterized by a stable and low rate, akin to that of developed countries[1]. However, numerous supply shocks have occasionally caused the inflation rate to temporarily rise above its usual low level, since the establishment of inflation targeting. For example, fuel prices affected transportation costs, indirectly raising the price of other goods and food items. On the other hand, a surprise shortage of fertilizers led to a rise in the price of some food items. Additionally, the depreciation of the domestic currency, having a dual role of increasing the cost of final and intermediate imported goods, added further pressure on prices. Finally, a persistent increase in prices directly caused by these shocks led to higher inflation rates as they spread among expectations, intermediate inputs and final goods.

Such inflationary shocks were a major factor in the inflation surge in Peru observed since mid-2021 towards the end of 2023 (See Figure 1). A characteristic of this period is the increase of inflation expectations beyond the upper limit of the inflation target range (3%). At the same time, the distribution of year-on-year variation of the components of the CPI moved towards higher values.

Figure 1: Percentiles of official year-on-year inflation data and inflation expectations



[1] Around 2.7% yearly from January 2000 to December 2019.

This paper is a study of how prices behaved during the last inflationary episode. In particular, I discuss how price-setting behavior changed in response to both growing expectations and realized increases in the price level. Traditional analyses focus on headline measures by examining core inflation dynamics and the impact of supply shocks on food and energy prices. Nonetheless, this offers a partial view as the main source of information consists of monthly variations of indexes. This can be enriched by studying individual prices in high frequency as detailed in Cavallo and Rigobon (2016). The main contribution of this paper is a characterization of price behavior while it pushed official monthly price statistics up.

The Central Reserve Bank of Peru (BCRP) lacked complete high-frequency data on prices of foods and goods. In periods of low inflation, these prices remain relatively stable, making their weekly monitoring less critical for monetary policy. Nevertheless, during a period of high inflation, it is reasonable to assume that firms are behaving differently, becoming more attentive agents. Therefore, to have a better understanding of the effect of inflationary shocks, deeper knowledge about the price formation process is required. A high-frequency price database allows us to observe shock propagation and changes in the duration of prices. Hence, this study fills this statistical information gap by presenting a methodology for the extraction, classification, and processing of high-frequency supermarket price data.

Theoretically, I follow a simple price-setting model as Rotemberg (1982), with quadratic costs of adjustments

$$V_{i,t} = min \sum_{\tau=0}^{\infty} \beta^{\tau} E_t[-(p_{i,t+\tau} - p^*_{i,t+\tau})^2 - c_i(p_{i,t+\tau} - p_{i,t+\tau-1})^2],$$

where firms will have an optimal price $p^*_{i,t}$ which depends on marginal costs. Prices for each firm are a weighted combination of the optimal price, the expectation of future prices, and the last price

$$p_{i,t} = \frac{p^*_{i,t} + c_i[p_{i,t-1} + \beta p^e_{i,t+1}]}{1 + c_i + c_i\beta}.$$

During inflationary episodes, with shocks that lead to high cost pressures, firms have to balance between the costs of updating prices and being out of the optimal. Two arguments can be derived from this. First, higher present optimal and expected prices would generate higher variation magnitudes. Second, the frequency of change should increase, as the difference between the present and the optimal price is much higher than the cost of updating, compared to smaller shocks or movements of the optimal.

The research question is the following: How does a firm achieve its optimal price during inflationary episodes? By frequent increases or by bigger increases? I demonstrate with the data that inflation is related to the first element. I find that during the last inflationary period, the frequency of change increased, but magnitudes remained stable. This leads to the conclusion that under inflationary stress, prices become less sticky in change frequency.

1.1. Related Literature

Research on the use and construction of high-frequency inflation indicators is relatively recent and scarce. Typically, studies have focused on building high-frequency inflation indicators, making monthly inflation predictions from daily or weekly information, and analyzing aspects such as the duration or frequency of price changes to measure the degree of price rigidities.

An initial study on the use of internet data is Lünnemann and Wintr (2006) which compares price rigidities in-store versus online prices. This referred study was even published before the creation of the Billion Prices Project (BPP) in 2008 (see Cavallo and Rigobon (2016)), which involved extracting online prices from stores in up to 50 countries. Although the BPP has been discontinued, it gave rise to PriceStats, a private entity that collects and sells price information and high-frequency inflation indicators for several countries. It is worth noting that there is no price information for Peru in either BPP or PriceStats.

With information from BPP and PriceStats, various analytical studies have been developed. For instance, Cavallo (2013) found that the measure of inflation based on online prices is similar to the official general inflation in Latin America, except in Argentina. Meanwhile, Aparicio and Bertolotto (2020) analyze the utility of data extracted from the web from July 2008 to September 2016 in 10 advanced countries to forecast inflation. Recently, Macias et al. (2022) uses data obtained through web scraping at the National Bank of Poland to conduct inflation nowcasting experiments to show that the use of these data improves the accuracy of inflation projections.

Furthermore, the duration or rigidities of online prices are studied, for example, in Gorodnichenko et al. (2018) or Cavallo (2017). Specifically, Cavallo (2017) finds that online prices in the U.S. for non-food products became more flexible from 2014, reaching levels similar to those of food prices. In the case of Peru, Coronado et al. (2020) conducted a preliminary study on online price rigidities.

A major challenge in using web scraped data in the analysis of high-frequency prices is the classification problem. Given the large volume of unstructured data, the use of specialized machine learning algorithms is inevitable. Consequently, a substantial

body of literature has emerged, primarily from the data science community.

The paper proceeds as follows, Section 2 describes the data extraction method. Section 3 describes the product classification methodology according to the Classification of Individual Consumption According to Purpose (COICOP). Section 4 deals with price filters applied for data analysis. Section 5 presents the results and the analysis of price behavior. Finally, Section 6 concludes the paper.

2. Data Extraction Methodology

Using web scraping techniques, data on prices was collected for all product varieties listed on the websites of two supermarkets since April 2020. The algorithm retrieves basic information from each product listing on the web such as: (i) name, (ii) price, (iii) brand, and (iv) category.

Approximately, 134,000 unique product variety records that have been sold at any time were obtained, regardless of whether they are currently available. The main reasons for a record ceasing to update include the discontinuation of its sale or a change in its presentation. For instance, companies recover costs without altering prices by reducing the weight of their product presentations, which results in a new variety of the product.

On supermarket websites, products can have up to three prices: (i) the regular price, (ii) the "online" price or discounted price, and (iii) the price with a special discount using a specific card. The online price is always available if the product listing is present on the web, whereas the regular price only appears when there is a discount for purchasing the product online. When there is no discount, both prices match. The price used is the discounted one (or the regular one if it is not available), which is the price a consumer would pay.

Each product is differentiated by its name. A change in it generates a new price series. For example, a wine initially registered as "Vino rosé" ("Rosé wine"), with a tilde in its name, and later as "Vino rose" ("Rose wine"), would enter the database as two distinct products. Similarly, if one has "Pack galleta de chocolate" ("Pack chocolate cookie") and "Galleta de chocolate pack" ("Chocolate cookie pack"). To avoid this, each product was assigned an identifier name consisting of its original name with a cleanup of unusual characters (such as tildes or hyphens) and without capital letters. Nonetheless, the latter case cannot be avoided with this cleanup and requires an algorithm that can find similar names in the database.

3. Product Classification Methodology

The downloaded series are associated with a classification according to the supermarkets' criteria. As the goal is to have granular information on inflation, it is necessary to have a grouping according to the CPI categories. These correspond to the COICOP (see Table 1 for an example or the classification hierarchy). Thus, a classification is constructed over a basket of food, beverages, and goods grouped into twelve divisions and disaggregated to the level of specific variety.

Table 1: CPI classification hierarchy example for a rice item

Level	Description
Level 1	**Division:** Food and non-alcoholic beverages
Level 2	**Group:** Food
Level 3	**Class:** Bread and cereals
Level 4	**Subclass:** Rice in all forms
Level 5	**Category:** Rice
Level 6	**Product:** Packaged Rice
Level 7	**Item:** Packaged "Extra variety" Rice
Level 8	**Specific variety:** Paisana rice, orange bag 1kg

The available data from INEI (National Institute of Statistics and Informatics) shows the categories of food and beverages at the category level, and for goods, at the subclass level. To gain a better understanding of the products and varieties that make up the CPI basket, the classifications were reconstructed to the product level with the information available in the National Household Budget Survey (ENAPREF). This survey records household expenditures across the divisions. With the COICOP identification code at hand, the different categories by varieties can be recognized.

Supermarket products were classified using machine learning techniques, with a supervised learning model for text classification (Joulin et al., 2017). In this case, each specific variety name was associated with the corresponding product type. For example, "ABC brand corn oil 1L" is classified as "packaged vegetable oil". This procedure required two stages: (i) cleaning the text identifier name to make it suitable for classification and (ii) creating a training sample.

The first stage involved eliminating units of measure as they do not provide relevant information about the product type. Thus, a product like "ABC brand corn oil 1L" would be changed to "corn oil ABC brand". An outstanding issue is the identification of brands to remove them to improve inputs to the algorithm. For the second stage, out of approximately 22,000 records of food and beverages from one supermarket, 50 percent were manually classified to build a training sample, which was then used to

classify the remaining 50 percent, as well as data from other supermarkets. A similar procedure was done with a sample of 16 thousand goods.

4. Price Series Filters

4.1. Data Imputation

Initially, the extraction code was manually executed at three days a week frequency. However, data was unavailable for some weekends. Since 2022, an automated routine was adopted to address this issue. Given this situation, an algorithm was employed to fill in missing data for some days. We filtered the products that had at least 365 days of observations in the whole sample. This eliminated noisy items that reduced the quality of the sample. Afterwards, the gaps were filled with the last price available.

4.2. 30-day moving average

Price series exhibit volatile behavior due to the presence of short-term price discounts and increases. Graphically, it appears that the price fluctuates around an stable level. To smooth the price series, a thirty-day moving average was calculated with at least 7 days of data. That is, if out of the last 30 days at least 7 days have data, the mean is calculated. The thirty-day moving average filter smooths out the series against jumps; however, it still captures non-trend movements like short-lived discounts.

4.3. Regular Price Extraction

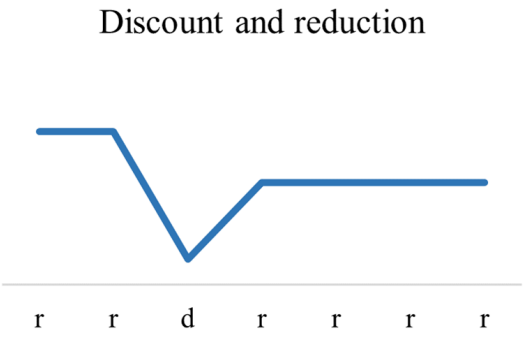
An alternative approach is to use a filter based on Nakamura and Steinsson (2008). This algorithm detects discounts or sales by identifying price patterns in symmetric and asymmetric V shapes. For example, in the first type, a product might have a value of 10 soles in January, then decrease to 8 soles (discount) in February and return to 10 soles in March. The pattern is symmetric because it returns to the value before the discount. In the second type, the rebound can be to higher values. For instance, in March, the price would be 12 instead of 10 (See Figure 2a).

On the other hand, it may happen that discounts persist for a temporal window of such length that it could be assumed that the price level has been reduced. Therefore, it is necessary to establish a limit to that window corresponding to the maximum assumed duration of a discount.

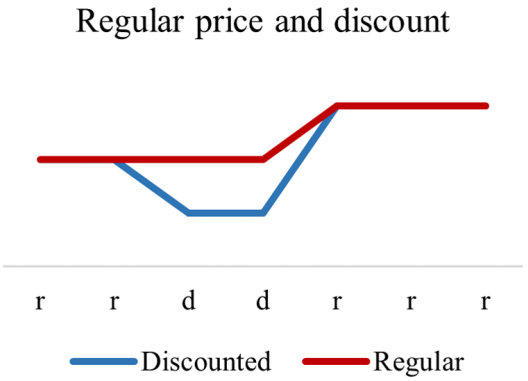
Figure 2: The filter smooths prices to capture trend movements



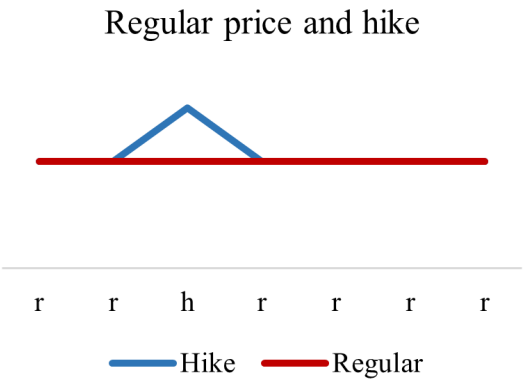
(a) Difference between symmetrical and asymmetrical V shape



(b) B. Discount and reduction



(c) Regular price and discount



(d) Regular price and hike

Symbol	Meaning
r	Day with regular price
d	Day with discounted price
h	Day with hiked price

(e) Legend for date axis

Furthermore, during processing, an additional problem was found: the simultaneous presence of a price discount and a drop in the regular price. For example, a price that drops from 10 soles to 5 soles for a few days, and then remains constant at 6 soles. The middle price should be considered as a discount if it does not exceed a time limit (See Figure 2b).

Since regular and discounted prices are extracted, the duration of discounts can be measured. For food and beverages, the average time is around 30 days, while for goods, it ranges from 30 to 60 days approximately. Therefore, for this article, a maximum discount window of 30 days was established for all products (See Figure 2c).

After filtering discounts, price series with short-lived upward jumps were noticed. The filter was adapted to detect these phenomena, and if they last less than a previously established window, they are not considered as an increase in the regular price. For this article, this value was set to 7 days (See Figure 2d).

As a result, the proposed algorithm requires a vector of three parameters: the first element of these vectors controls how staggering filtered prices will be. The higher this parameter, the filtered price series becomes staggered and monotonically increasing, as more price reductions are filtered out because they are considered as discounts. On the other hand, if this parameter approaches zero, the filtered series becomes similar to or equal to the original series. The second element controls the maximum duration allowed for discounts before price reductions. Finally, the third element captures the minimum duration of a price increase to consider it a trend movement rather than a data mistake or outlier.

5. Results

This section has the following structure. First, I will study the composition of the distribution of year-on-year price changes. This will cover how the proportion of products with positive, negative, and zero changes evolves over time. I show that the prices follow the trend of the recent inflationary episode. Second, the same results will be replicated with filtered prices. I show that the filter captures the inflation episode and is robust to calibrations. Then, I will examine magnitude and frequency of price changes overall the complete sample and show that it follows the logic of the Rotemberg model. Finally, I will explore the relationship between the monthly inflation and the frequency and magnitude of price changes to assess how price stickiness varies during an inflationary period.

5.1. Moving average series

I estimated median values of year-on-year percentage variations using price series produced with the moving average filter (See Figure 3). The increase in inflation intensified during 2022. However, prices of food and beverage items differ from those of other types of goods due to their persistence. Goods prices experienced higher

increases, but since early 2023, they moderated. For the three types of good items in Figure 3, median price changes became anchored at zero at the end of the sample. This evidence points towards a differentiation of low and high inflation periods. In the first one, the median of price changes is equal to zero, and it becomes positive as the regime changes and shocks trigger an increase in the proportion of products that update their prices.

Figure 3: Year-on-year variations median per CPI division

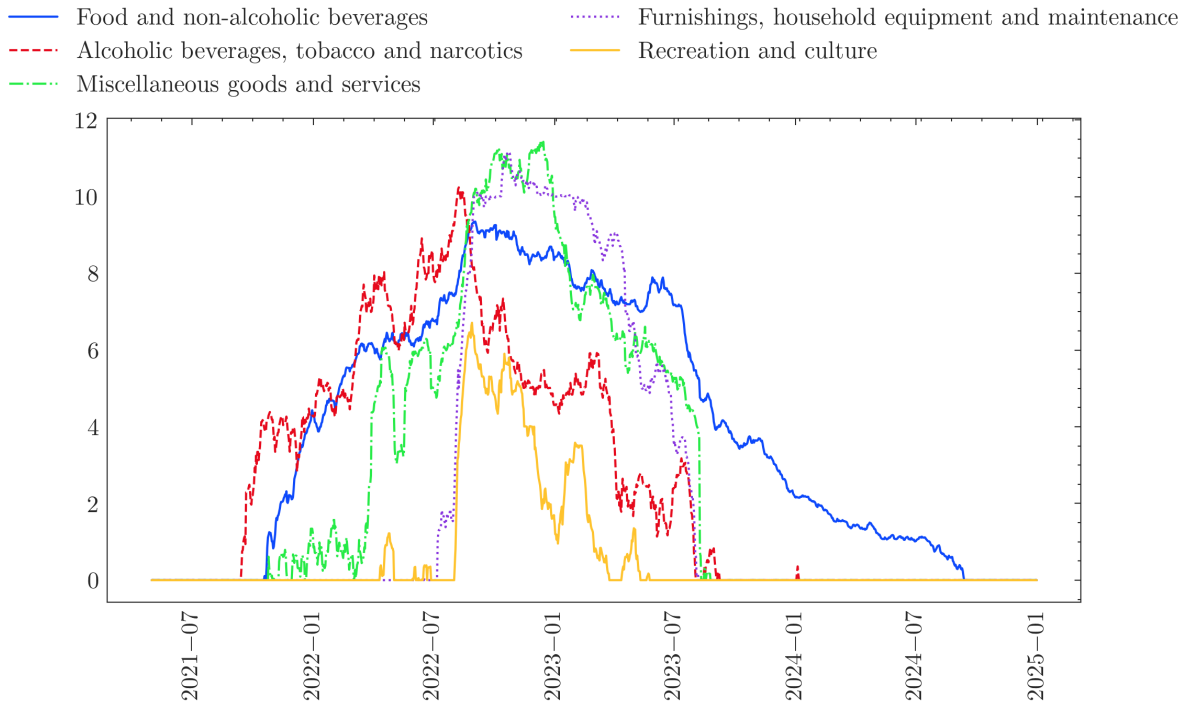
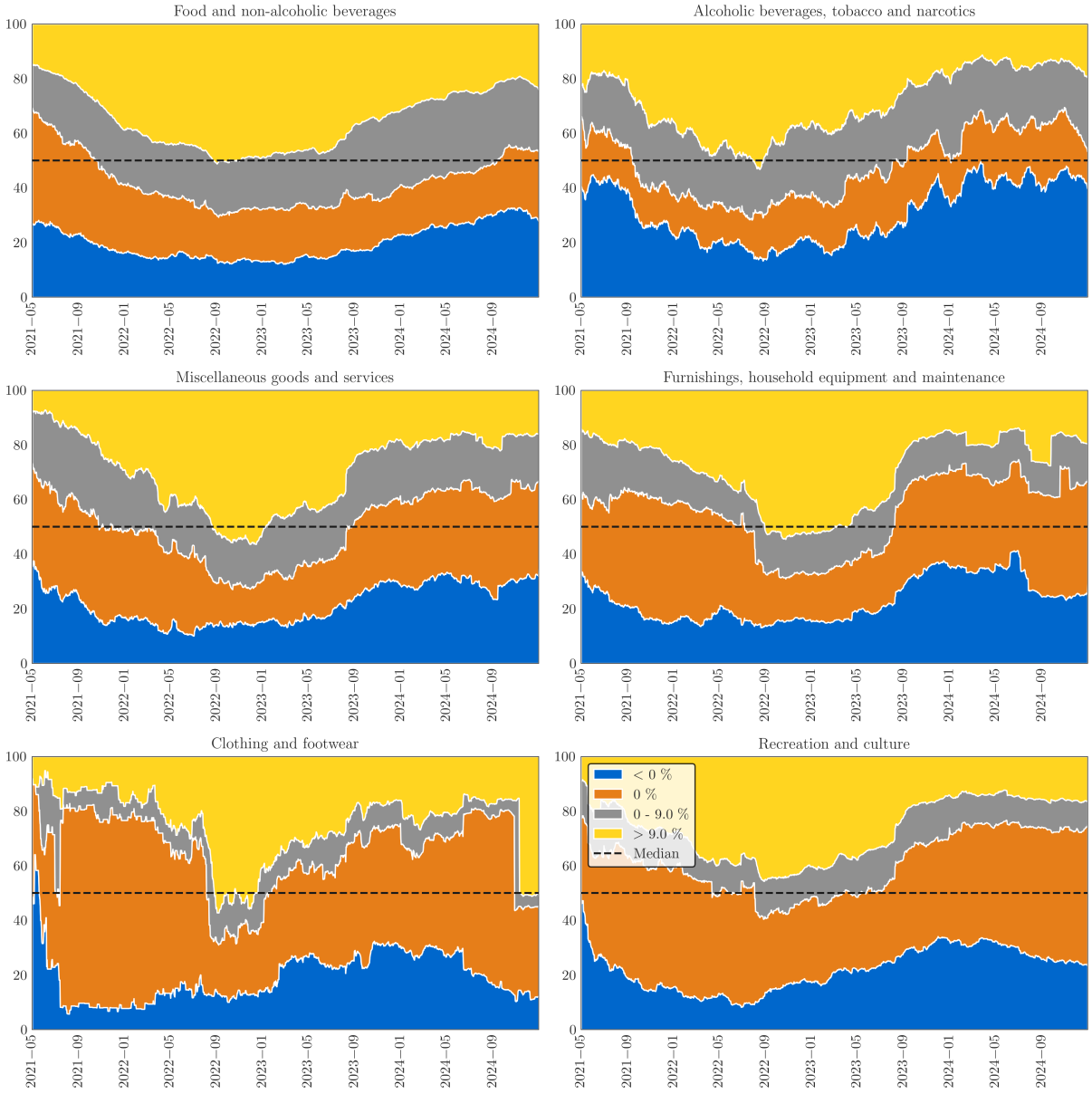


Figure 4 provides a distribution of price changes according to ranges in each of the divisions analyzed. The proportion of food items with price increases above 9 percent year-on-year grows and diminishes slowly barely reaching 50 percent by October 2022. Two good items divisions show a sharper change in the distribution.

Also, the proportion of prices with zero growth increases faster by the end of the sample in the goods category. Since the filter used is a moving average, discounts in prices can generate variations in the series such that the percentage variation is different from zero exactly. Thus, values that are equal to zero coincide with prices that have not varied over a year considering discounts. In the second half of 2022, annual increases in prices peaked, and by the end of 2023, they slowed down. Food and beverages prices moderate smoothly.

Figure 4: Year-on-year percentage change distribution areas

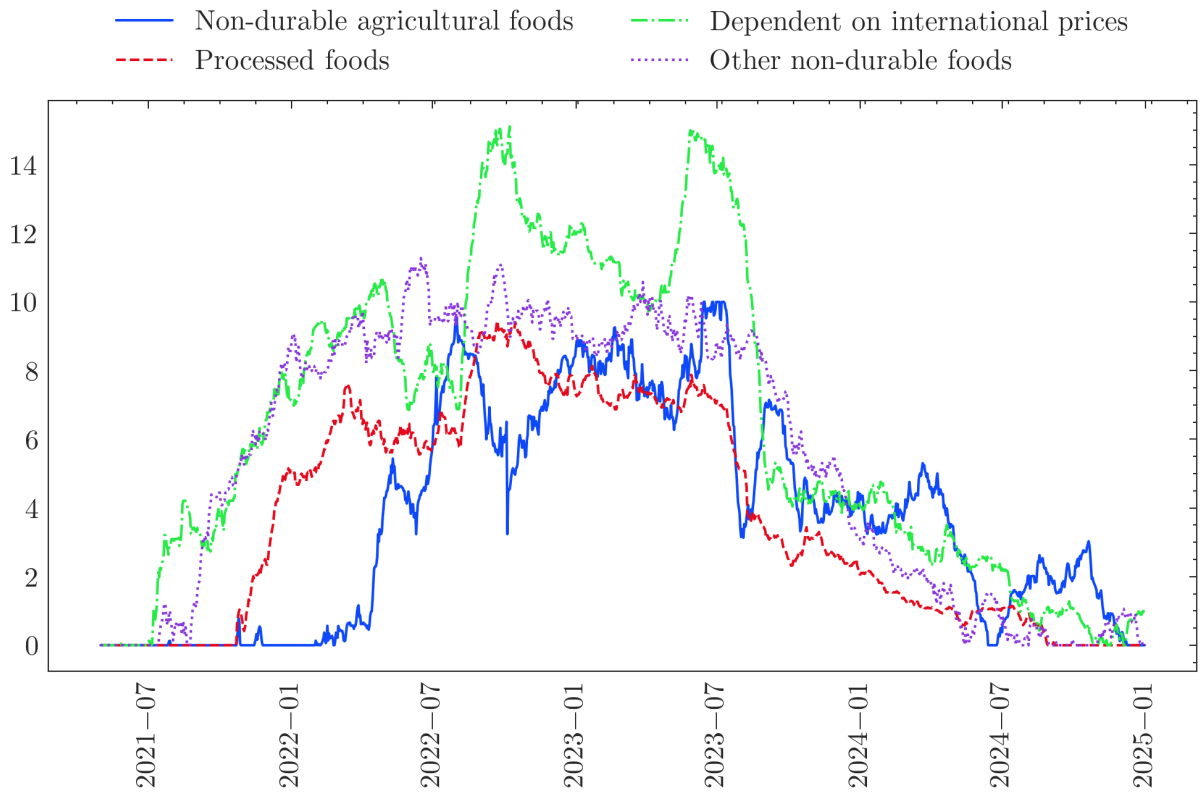


By choosing samples within the food category (see Figure 5), differentiated behaviors and shocks are highlighted. The four groups are Non-Durable Agricultural Foods, Foods Dependent on International Prices, Processed Foods, and Other Non-Durable Foods. Prices of Perishable Agricultural Foods react to changes in the market supplies associated with climate conditions and social turmoil related to blockage of roads that prevent transportation of products. Also, the increase in fertilizer prices affected the productivity of crops.

The sample starts with a decrease in the median in May 2021, that coincides with the reduction in official data due to an increase in market supply. After the normalization of the year-on-year variation, the median is equal to zero. After March 2022 the official

data shows the beginning of an upward trend, caused by an increase in rain and obstruction of roads, that coincides with a positive median for the online data. By the end of 2022, the median becomes stable, as the official year-on-year variation peaks due to the fertilizer shortage . The daily data seem to capture how shocks affect individual prices.

Figure 5: Year-on-year variations median per food sample



Foods Dependent on International Prices faced supply shocks associated with freight costs, commodity prices and the increase in the nominal exchange rate. Official data showed a peak in April 2022 that coincided with the first peak in supermarket data. It seemed that both series captured the increase at the same rate. Nonetheless, the official index change trend decreased by June 2023, while the supermarket prices showed a decline after August 2023. This may be due to a difference in statistical methods but also could be associated with asymmetric price adjustments at the micro level.

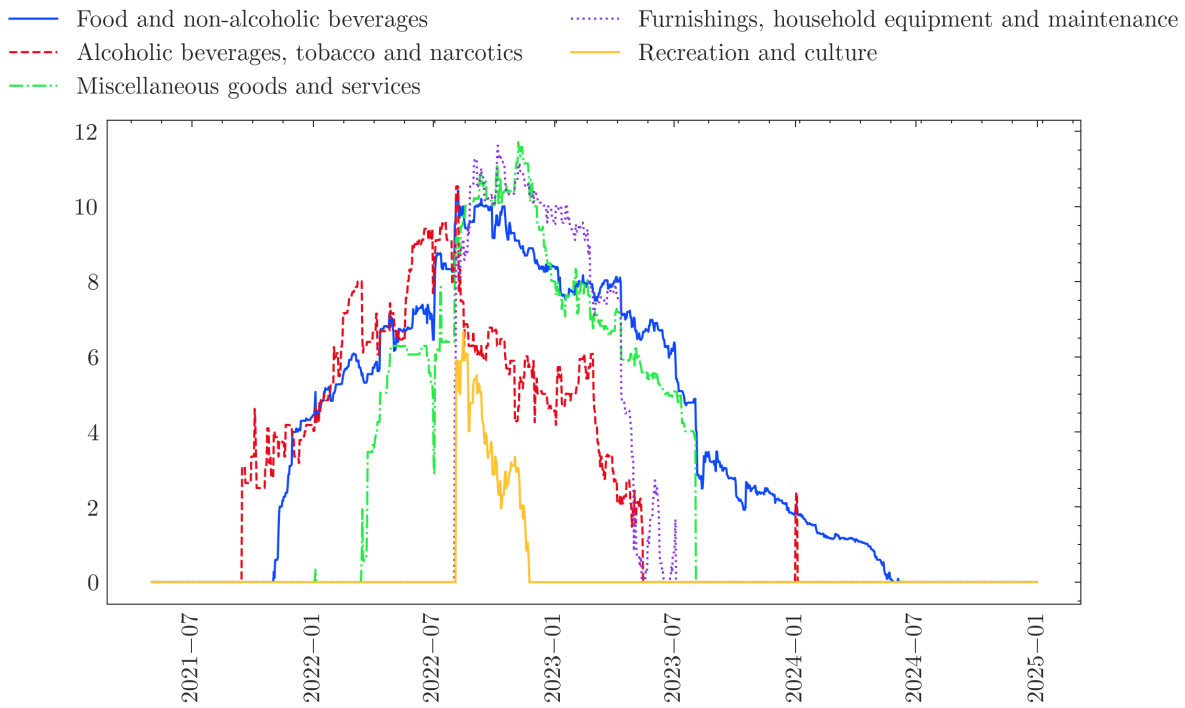
Processed foods are characterized by less volatile prices. From September 2021, the median of the year-on-year percentage changes rose above the zero threshold. It peaked on the first half of 2022 and follows a steady trend with shows less abrupt changes compared to the other samples. It resembles how core inflation behave in

official data. Finally, Other Non-Durable Foods price variations seem to follow a common trend with two samples, but in official data, it is characterized by a volatile and particular path during some periods.

5.2. Series with regular price filter

I replicate the figures of median values and distributions estimated with the regular price series. The results about trends, the price surge of 2022 and subsequent moderation, remain (See Graphs 6, 7 and 8). This implies that the trend of price changes can be captured even with the filter. Additionally, it returns price time series that allow to estimate duration and frequency of change.

Figure 6: Year-on-year variations median per CPI division



The regular price filter captures sharper changes unlike the smoothing of the moving average. As a result, the proportion of products with zero variation is higher. Furthermore, the removal of discounts reduces the proportion of price decreases. Nonetheless, regular prices seem to follow the same evolution in distributions as captured with the moving average, and the swap between the yellow and orange areas points towards two different year-on-year behavior, as more products update and change prices.

Figure 7: Year-on-year percentage change distribution areas

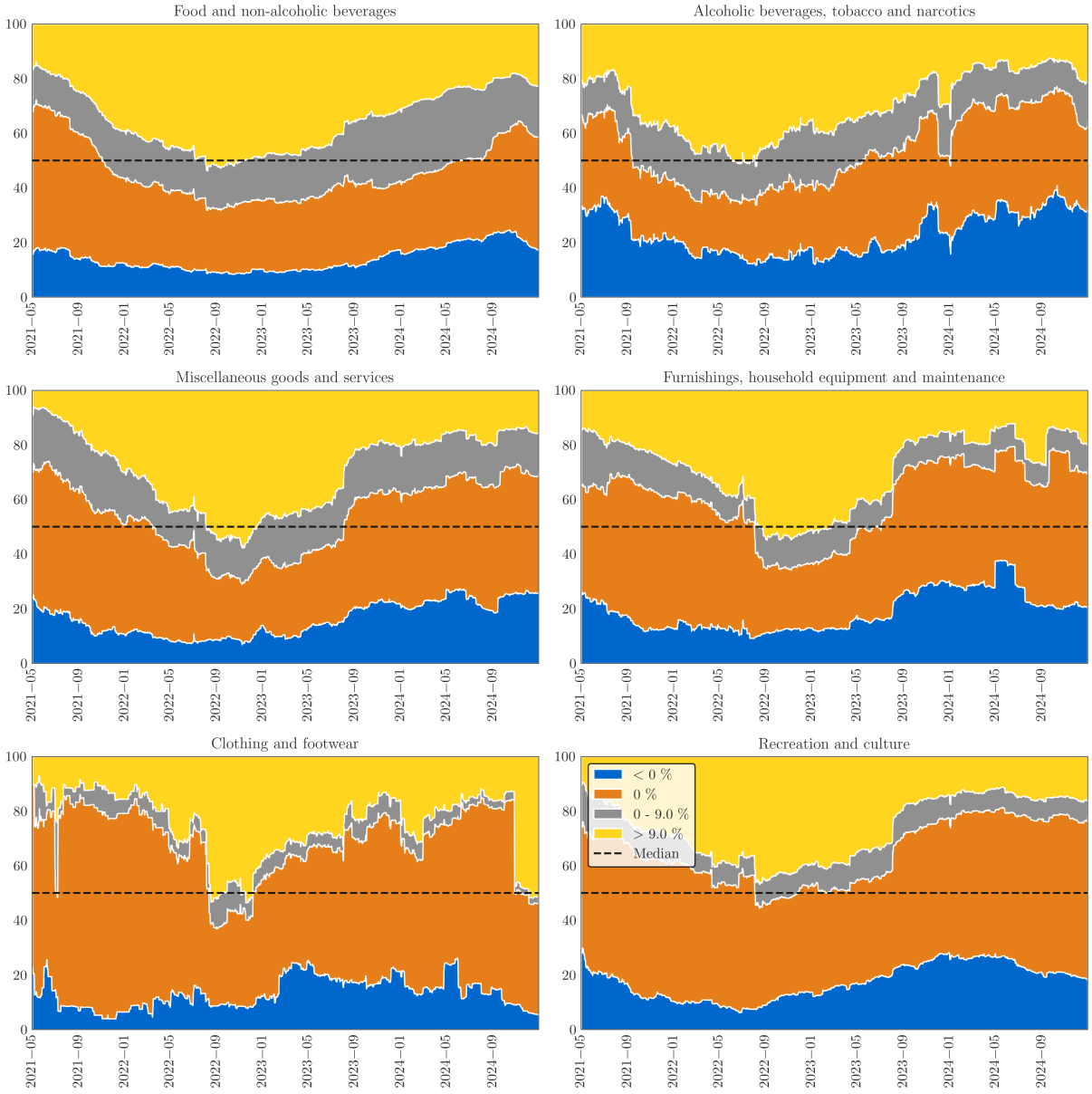
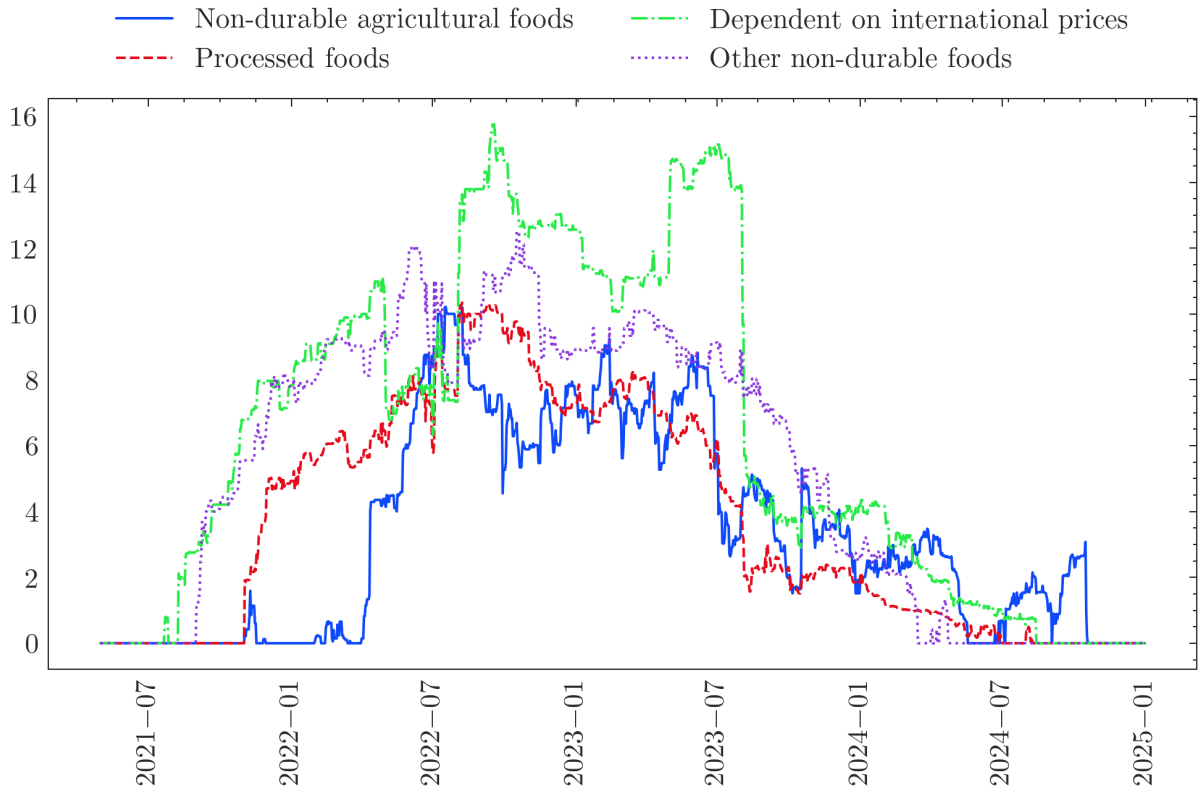


Figure 8: Year-on-year variations median per food sample



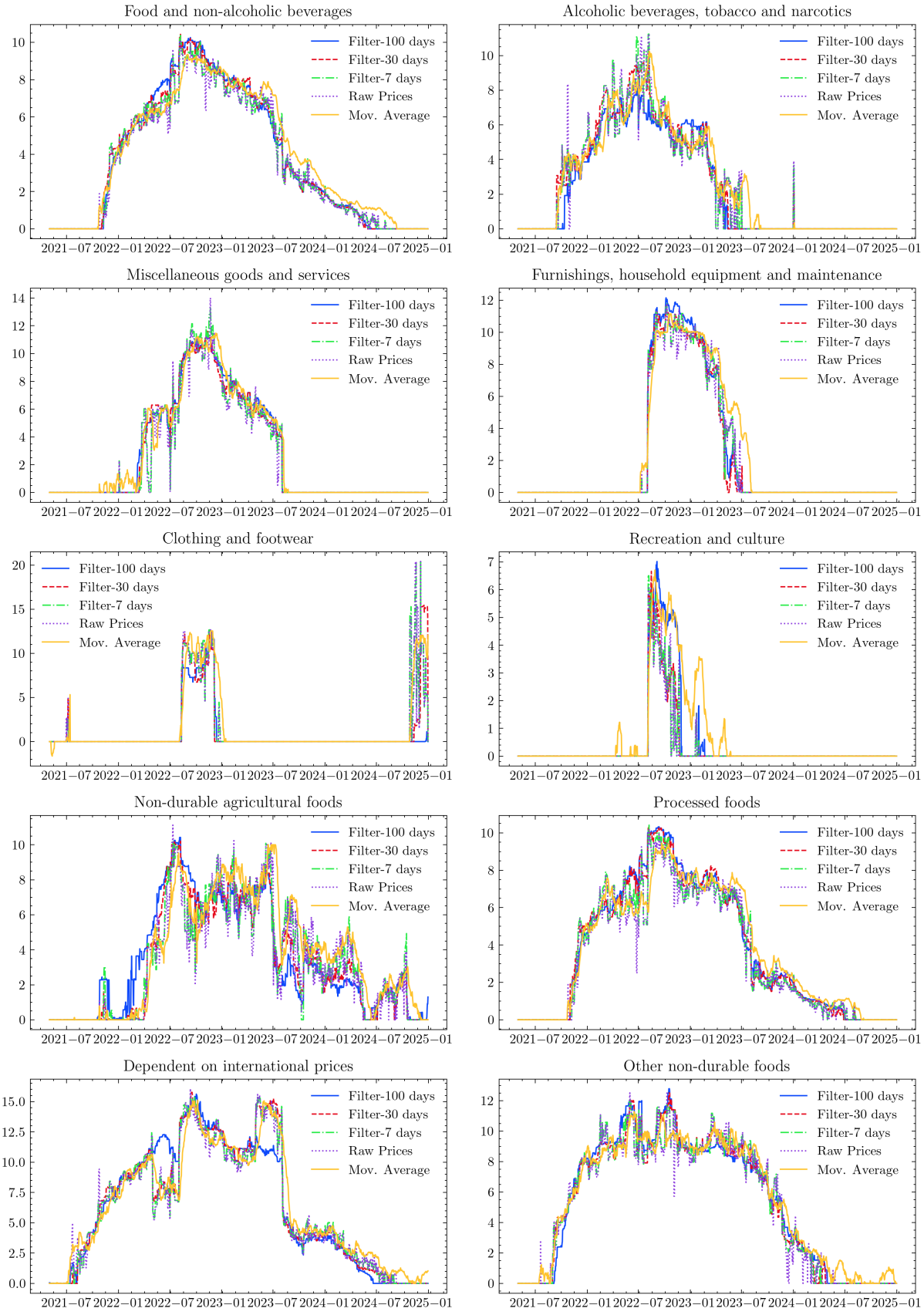
5.3. Comparison of Filters and Robustness Testing

To gauge the robustness of the filters, I assume two additional parameterizations of the filters given by the parameter vectors (100, 30, 30) and (7, 7, 1). They are mainly differentiated by the first parameter, that regulates how long does it allow discount to last. The median series on year-on-year variation do not differ in trend and direction when comparing the moving average to regular price filtered series (see Figure 9). Three results stand out.

The series with the 7-day filter show abrupt increases and reductions. This is because it is the parameterization with less smoothing, and price changes can be noisier. Nonetheless, there are products, such as some foods, whose variation is so frequent that this parameterization could be more convenient for capturing the price direction without losing information on short-term volatility.

For foods dependent on international prices, the 100-day filter stands out for deviating from the common trend in mid-2022 and 2023. For this case, a reduction in prices in 2022 was filtered by the 100-day parameterization. As a result, in that year, prices did not decrease, moderating the median for the same months in 2023.

Figure 9: Comparison of year-on-year variations medians



Finally, in the face of a permanent increase in prices, the moving average takes 30 days to update completely. That is part of its smoothing component. However, the stable price filter does not necessarily have this problem. This can be noted in some sections of the graphs where the moving average curve is slightly shifted to the right.

5.4. Price changes distribution

Available CPI data lacks information on price behavior and how they change and evolve. The constructed databased allows to study the size and number of changes, how frequent they are and how long do price levels last. Table 2 shows that price changes are balanced between positive and negative and homogeneous across product divisions. Eliminating discounts affects this result. Four out of six divisions in the sample are skewed towards increases of prices. This result is stronger for Food and non-Alcoholic Beverages.

Table 2: Positive and negative price changes as proportion of total changes

Division	**Regular Prices**		**30 Days Filter Prices**	
	Positive	**Negative**	**Positive**	**Negative**
Food and non-alcoholic beverages	52.6	47.4	66.1	33.9
Alcoholic beverages, tobacco, and narcotics	47.6	52.4	54.6	45.4
Clothing and footwear	50.9	49.1	58.7	41.3
Furnishings, household equipment and maintenance	45.6	54.4	50.1	49.9
Recreation, sport, and culture	44.0	56.0	49.3	50.7
Miscellaneous goods and services	48.9	51.1	59.4	40.6

Price changes follow a distribution with two peaks (see Figure 10), with a low proportion of variations close to zero. That is, it is more common to have price jumps than small reductions or increases. However, this behavior is less pronounced for goods than foods. In the case of "recreation and culture" and "clothing and footwear," the distribution is more uniform due to the higher presence of changes. Thus, it could be argued that adjustment behavior depends not only on the inflation regime but also on the type of product. Therefore, predictions from macroeconomic models should vary depending on the composition of the basket of goods.

Figure 10: Distribution of price changes for raw prices

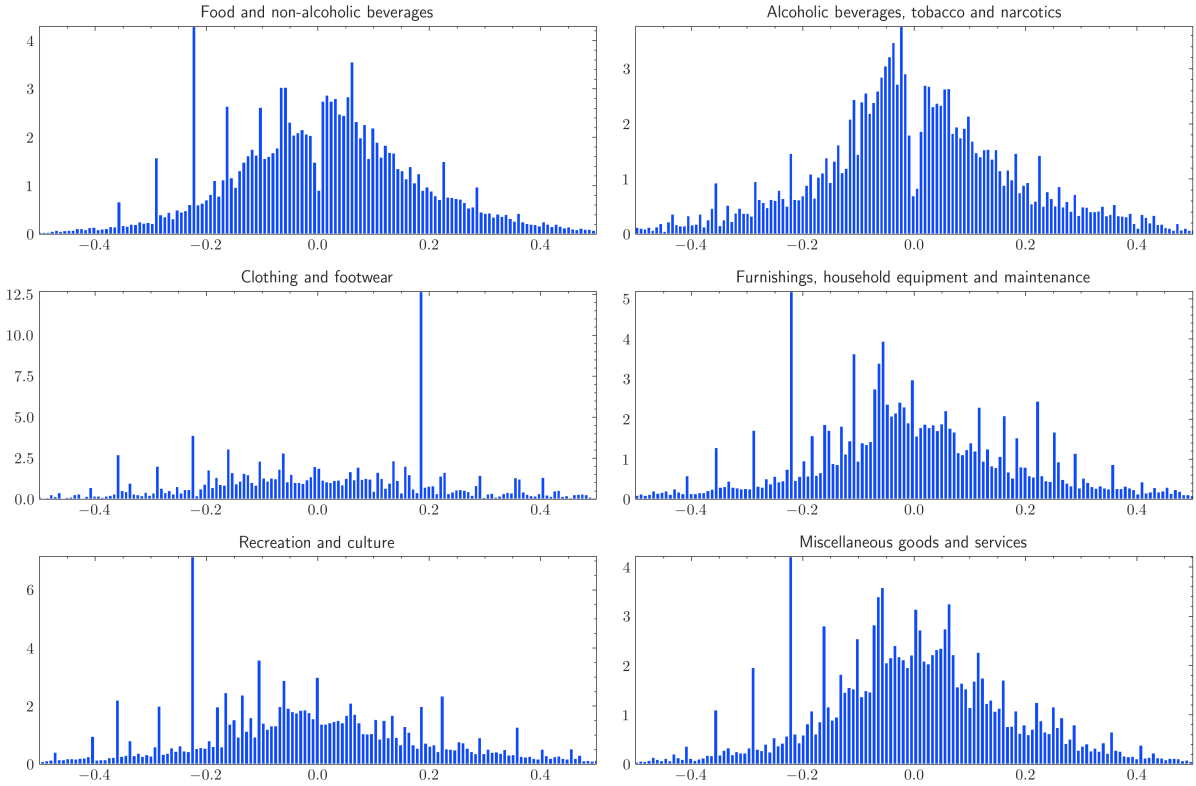
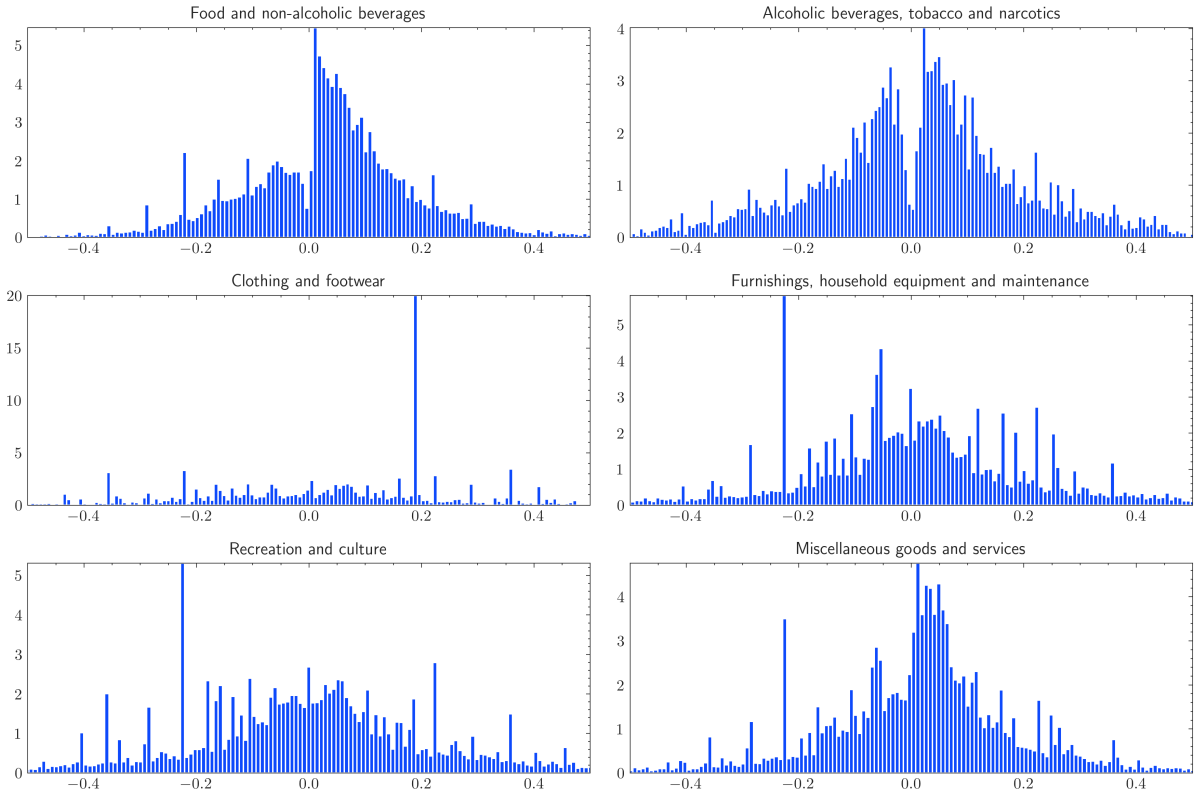


Figure 11: Distribution of price changes for filtered (30,30,7) prices



Data with the 30-day filter show an asymmetric distribution (see Figure 11), with a greater presence of positive values. This may be due to the effect of discount elimination, providing a better perception of the frequency and magnitude of persistent price changes. Nonetheless, due to the sample capturing the inflationary period, it could be assumed that in other episodes the distributions could be different.

These results show that price changes follow the simple Rotemberg (1982) model. Due to the adjustment cost, there is a reduced presence of changes small around zero percent. The distance with the optimal price (and expected path it will have) shapes the distribution as it affects the magnitude. The research question is more evident with these results. Do firms adjust prices by frequent changes around zero or by leaps in higher magnitude. In the following section, I will explore how this pricing behavior changes in time during the inflaionary period and show that the main driver is price frequency.

5.5. Evolution of price change frequency and duration during the inflationary period

Frequency of price changes can be measured as the number of changes within a time period, and it can also be expressed as the fraction or percentage of time during which the product experiences changes. For instance, a product whose price changes 2 times in 90 days would have a frequency of $1/45$, meaning it changes every 45 days, or the daily probability of change is 2.22 percent.

The duration of a price can be implicitly calculated from the frequency of price changes. The probability of a change occurring is subject to a distribution that may depend on time (Kiefer, 1988). Following Nakamura and Steinsson (2008) is assumed that price changes follow an exponential distribution fit $f_{it} = 1 - exp(-\lambda_i t)$ where λ_i is the hazard function or conditional probability of change at $t + 1$ given that the price has survived until t. This distribution has the property of having a constant hazard function over time. Finally, if it is also assumed that the probability is uniform, then $\lambda_i = -ln(1 - f_i)$. The implicit duration is the inverse of this function: $d_i = 1/\lambda_i$. In the previous example, if the monthly probability was 2.22 percent, the value of λ_i would be 44.5 days (a result similar to the duration calculated directly from the update frequency).

Prices without filtering exhibit a rapid update frequency, especially for food and non-alcoholic beverages (see Table 3 and 4). For this group, the implicit duration is around 100 days, while for the rest of the samples, it ranges between 125 and 237 days. Nonetheless, increasing the time limit parameter for discounts reduces the frequency. Assuming that discounts last no more than a week or 30 days, the duration

Table 3: Daily Frequency of Change (probability in percentage)

Division	Median				Mean			
	Raw	7 days	30 days	100 days	Raw	7 days	30 days	100 day
Food and non-alcoholic beverages	0.98	0.73	0.44	0.29	1.03	0.78	0.52	0.38
Alcoholic beverages, tobacco and narcotics	0.80	0.62	0.43	0.26	0.75	0.62	0.44	0.27
Clothing and footwear	0.37	0.33	0.20	0.13	0.50	0.45	0.28	0.17
Furnishings, household equipment and maintenance	0.62	0.58	0.44	0.32	0.56	0.51	0.37	0.28
Recreation, sport and culture	0.42	0.40	0.32	0.24	0.60	0.54	0.39	0.27
Miscellaneous goods and services	0.65	0.57	0.38	0.29	0.63	0.56	0.37	0.28

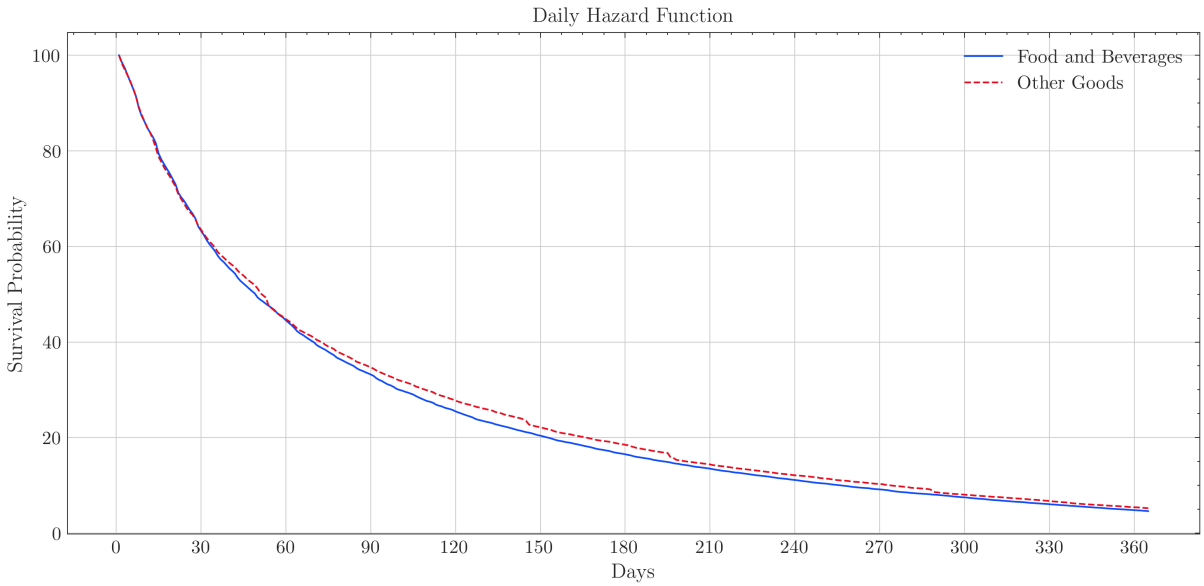
Table 4: Duration of Prices in Days

Division	Median				Mean			
	Raw	7 days	30 days	100 days	Raw	7 days	30 days	100 day
Food and non-alcoholic beverages	101	136	227	344	96	128	192	265
Alcoholic beverages, tobacco and narcotics	125	160	231	387	132	160	228	363
Clothing and footwear	269	301	489	752	200	222	351	595
Furnishings, household equipment and maintenance	160	173	225	308	178	197	271	361
Recreation, sport and culture	237	251	307	422	166	186	253	370
Miscellaneous goods and services	152	174	266	347	158	179	267	355

is increased accordingly. Generating time series with fewer price reductions, taking 100 days yields durations of approximately 12 months for food and beverages, while for goods, it ranges from 10 to 14 months. Another interpretation of this result is as a measure of the upward adjustment frequency, tolerating extended periods of price reduction.

I estimated hazard functions for Food and Beverages and Other Goods. To do this, I calculated the proportion of prices that survived for a number of days[2]. This is an approximation of the probability of a price change at time given that it has survived until that moment. The results are shown in Figure 12. The hazard functions are similar for both groups and, as time progresses, the probability of a price change increases. After two months, more than half of prices have changed.

Figure 12: Hazard Functions for Food and Beverages and Goods



I disaggregated the hazard functions by year to analyze how the inflationary period affected the frequency of price changes. The results are shown in Figure 13 and 14. Due to the data being limited to 2025, the hazard function for 2024 is not shown, as prices set in that year are not yet extinguished. For foods and goods, the hazard function has a displacement down from 2020 to 2023, which indicates that the probability of a price change is higher than the period before the inflationary episode. This is consistent with the idea that prices are less stable in 2023, and were updated more frequently.

[2]This is different than the duration calculation done before.

Figure 13: Hazard Functions for Food and Beverages per year

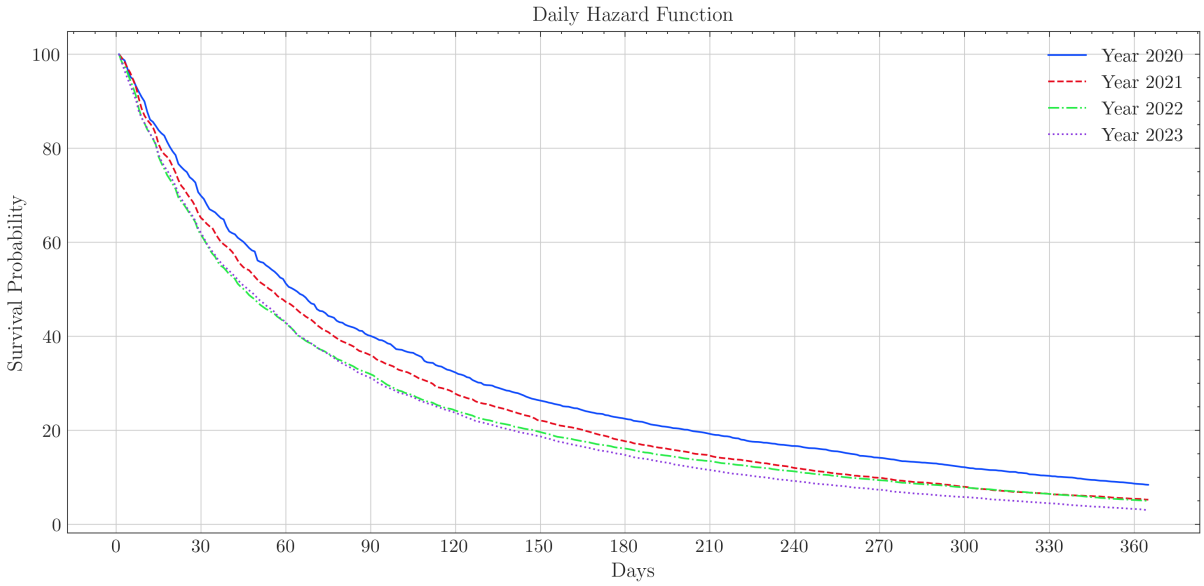
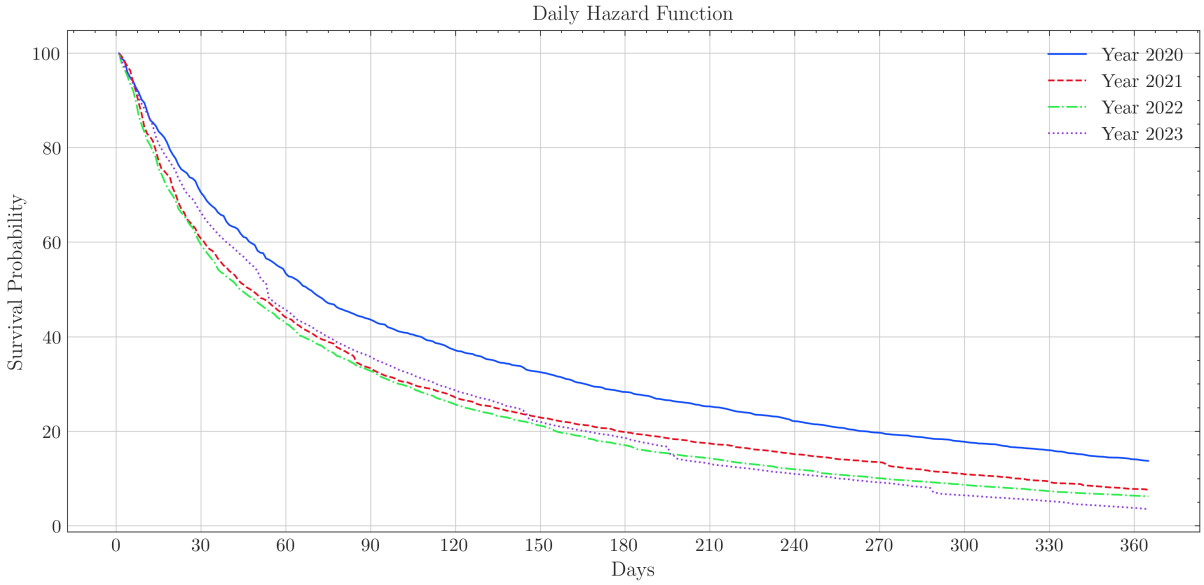


Figure 14: Hazard Functions for Goods per year



I studied the relationship between the frequency of price changes and the monthly inflation rate. To do so, following Martins and Quelhas (2024), I calculated the difference of average positive and negative frequency of change.The results are shown in Figure 15. The correlation is positive and statistically significant for all division except Clothing and Footwear (see Table 5). This indicates that as inflation increases, the frequency of price changes also rises. This is evidence towards frequent price adjustments as a mechanism during inflationary episodes.

Then, in a similar fashion, I studied the relationship between the magnitude of price changes and inflation. The results are shown in Figure 16. The correlation is statistically not significant for any of the divisions studied (see Table 6), indicating that as inflation increases, the magnitude of price changes remains constant. Although firms have to face higher present costs and expected optimal prices, the hike in prices do not seem to be different across the inflationary period.

Figure 15: Correlation between monthly inflation and frequency of change of prices

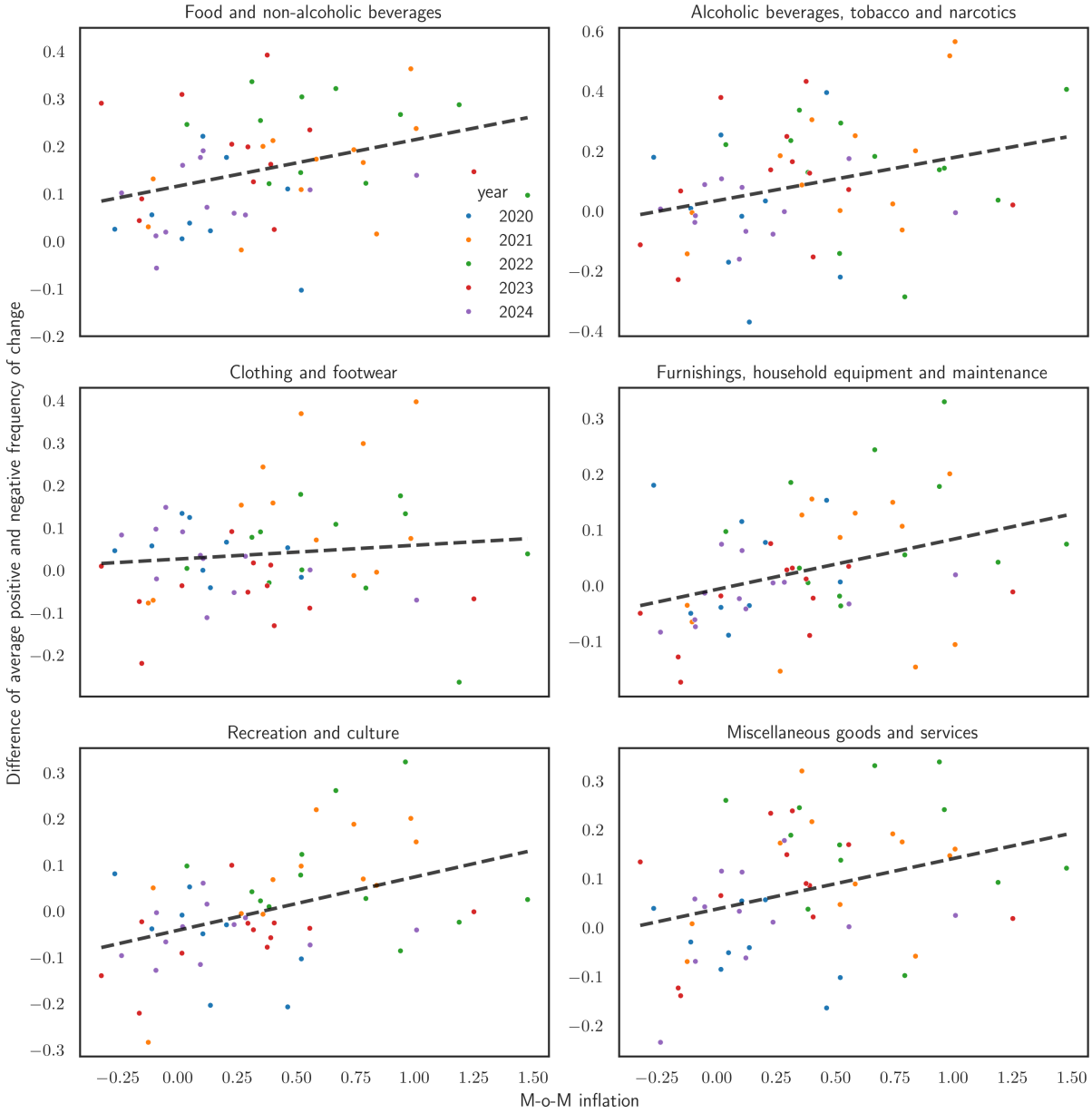


Table 5: Regression Results for Frequency of Change and Inflation

Division	Inflation	Std. Err.	P-value
Food and non-alcoholic beverages	0.0980**	0.0368	0.0102
Alcoholic beverages, tobacco and narcotics	0.1442**	0.0615	0.0227
Clothing and footwear	0.0326	0.0393	0.4099
Furnishings, household equipment and maintenance	0.0904***	0.0315	0.0058
Recreation and culture	0.1160***	0.0338	0.0012
Miscellaneous goods and services	0.1038**	0.0397	0.0116

Figure 16: Correlation between monthly inflation and magnitude of change of prices

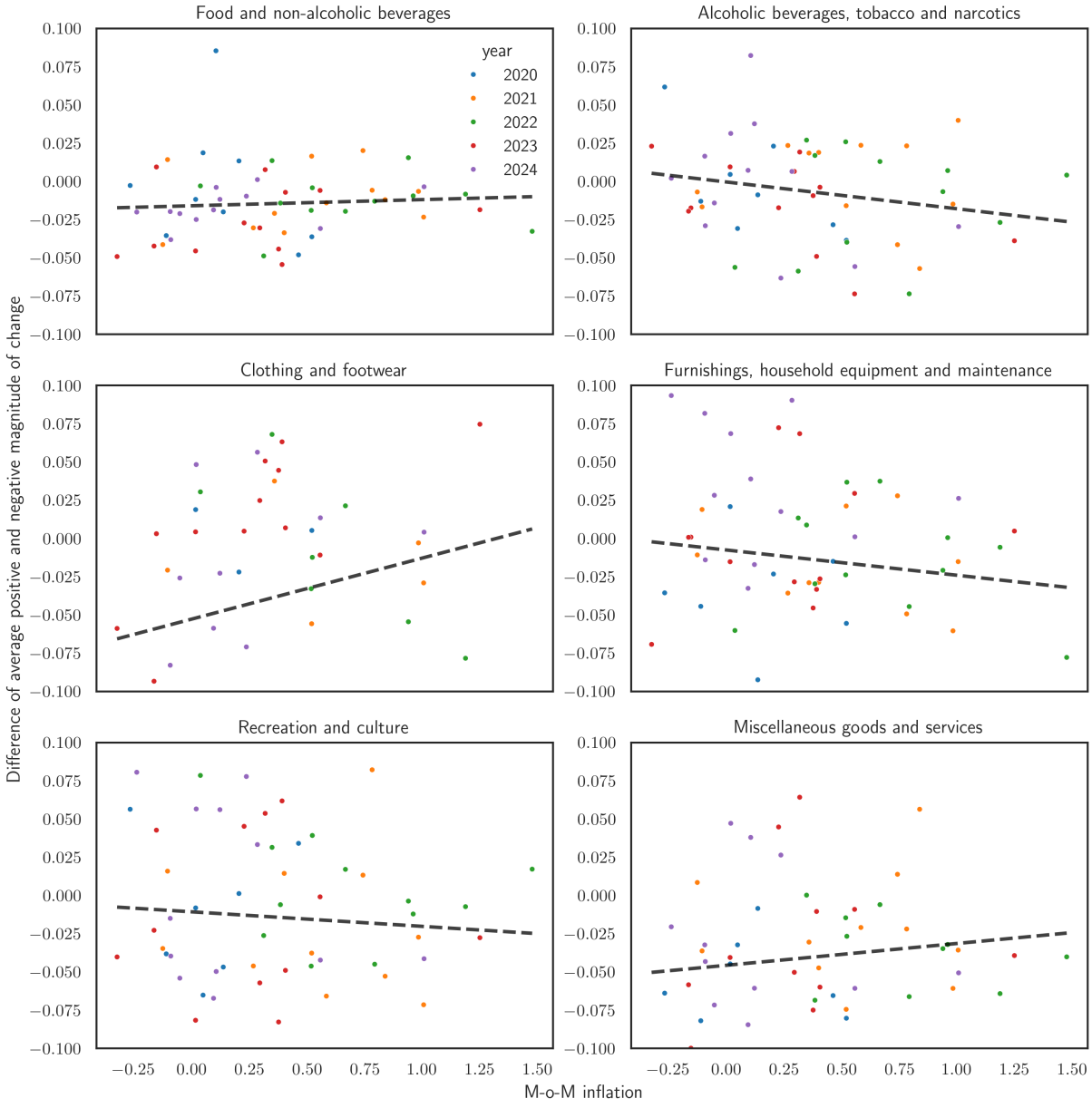


Table 6: Regression Results for Magnitude of Change and Inflation

Division	Inflation	Std. Err.	P-value
Food and non-alcoholic beverages	0.0040	0.0076	0.5982
Alcoholic beverages, tobacco and narcotics	-0.0176	0.0106	0.1042
Clothing and footwear	0.0400	0.0447	0.3743
Furnishings, household equipment and maintenance	-0.0166	0.0175	0.3484
Recreation and culture	-0.0095	0.0177	0.5915
Miscellaneous goods and services	0.0143	0.0180	0.4296

6. Conclusions

In this paper I studied the price dynamics during the inflationary episode in Peru from 2020 to 2024. Based in an adjustment-cost model, I proposed that firms could adjust prices through two mechanisms: (i) the frequency of price changes and (ii) the magnitude of price changes. Using data from supermarkets, I constructed a high-frequency dataset that allowed to study the price dynamics at the micro level. I filtered the data to remove discounts and short-lived price changes, and then analyzed the frequency and magnitude of price changes.

The distribution of year-on-year price changes shifted towards higher values particularly for food items than good. This confirms at the micro-level the adjustment of prices from 2020 to 2024. Afterwards, the distribution of price changes was analyzed. The results show that the its is skewed towards positive values, indicating that firms are more likely to increase prices than to decrease them. Additionally, the distribution of price changes is bimodal, with a low proportion of small changes around zero. This suggests that firms tend to adjust prices in larger increments rather than small adjustments, which is consistent with the Rotemberg model of price adjustment.

Afterwards, I estimated the hazard functions of prices. After two months, half of prices would have changed. When disaggregated per year, the hazard function shows a downward shift from 2020 to 2023, indicating that the probability of a price change is higher during the inflationary period. This is consistent with the idea that prices adjusted more frequently.

Finally, I studied the relationship between the frequency and magnitude of price changes and inflation. The results show that as inflation increases, the frequency of price changes also increases, while the magnitude of price changes remains constant. This suggest that inflation captured in monthly statistics is caused by increments in frequency of changes rather than hikes in prices.

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