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# Consumer Prices Trends in Colombia: Detecting Breaks and Forecasting Inflation

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# Consumer Prices Trends in Colombia: Detecting Breaks and Forecasting Inflation *

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**Abstract**

Colombia's annual inflation reached 13.3% in March of 2023, the highest rate since the start of the inflation-targeting regime for monetary policy in 2000. However, some groups in the basket show signs of lower inflation, while others show higher inflation. The persistence of this trend is a matter of active debate that involves analyzing the trend component of both year-to-year and month-to-month changes in the price indices. This paper employs time series models to identify inflation shift levels based on the 188 price indices in the basket. We categorize trend breaks as positive or negative and further classify them into tradable versus non-tradable, core versus regulated, and other CPI categories. Using trend models that incorporate these breaks, we forecast total and group inflation. Our results show that including trend breaks enhances prediction accuracy for monthly annual inflation across all time horizons.

**keywords:** Consumer Price Indexes, Linear Trend Models, Structural Breaks, Forecasting, Forecasting Evaluation.

**JEL Codes:** C22, C43, E31, E37.

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# Tendencia de los precios al consumidor en Colombia: detección de quiebres y pronósticos de la inflación

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## Resumen

En marzo de 2023, la inflación anual en Colombia alcanzó el 13,3%, la tasa más alta desde que se implementó el régimen de inflación objetivo en el año 2000. Sin embargo, mientras algunos grupos de la canasta básica muestran signos de menor inflación, otros experimentan un aumento. La persistencia de esta tendencia es objeto de un debate activo, que ha utilizado las variaciones anuales y mensuales en los índices de precios para detectar posibles cambios en la tendencia.

En este documento, empleamos modelos de series de tiempo para identificar cambios en los niveles de inflación, basándonos en los 188 índices de precios que conforman la canasta. Clasificamos las rupturas de tendencia como positivas o negativas y las agrupamos según diversas categorías, tales como transables y no transables, básicos y regulados, entre otros grupos del IPC.

Adicionalmente, utilizamos estos modelos de tendencia, con posibles quiebres, para pronosticar la inflación total y la inflación por grupos. Nuestros resultados indican que incorporar los quiebres en las tendencias mejora la precisión de los pronósticos de acuerdo con las medidas de evaluación tradicionales.

**Palabras clave**: Índices de Precios al Consumidor, Modelos de Tendencia Lineal, Quiebres Estructurales, Pronósticos, Evaluación de pronósticos.

**Códigos JEL:** C22, C43, E31, E37.

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# 1 Introduction

Price stability in empirical applications is associated with a moderate inflation rate, linking the understanding of long-term trend inflation to the monetary policy framework. Estimating trend prices aids in predicting future inflation and identifying trend breaks. In Colombia, inflation peaked at 13.34% in march 2023. While some sectors have recently shown decline, others indicate stable or rising inflation trends.

Estimating the trend of a price index has been a focus of recent literature. Perron (2020) suggests that most macroeconomic time series can be modeled as stationary fluctuations around a deterministic trend function. The year-on-year inflation rate is often used to measure changes in this trend, but it relies on current and past prices, which can be influenced by the base effect, complicating the analysis. Alternatively, some use monthly price index rates compared to the previous month, requiring smoothing or the moving average techniques to extract the trend; This method can lead to problematic interpretations due to the arbitrary choice of smoothing parameters or moving average degrees. Consequently, variations based on current and reference periods may result in imprecision in identifying structural changes and trend direction.

The base effect can distort current inflation figures due to unusually high or low inflation rates in the previous period. For instance, if inflation was low a year ago, even a small increase in the price index could lead to a high inflation rate. Conversely, if inflation was high a year ago, a similar increase will cause a lower inflation rate. This effect complicates the accurate assessment of inflation levels over time but diminishes when price changes remain stable without extreme fluctuations.

Our main contribution is to shed light on the role of the goods and services groups and items as sources of aggregate inflation levels for the Colombian economy. Our key finding is that the variation in aggregate trend prices can be decomposed into trend items and sectors.

In this study, we are focusing on measuring and forecasting. We are using the official consumer price indices as our main input for a simple empirical alternative based on linear regression. This will help us to detect changes in the trends of both the subgroups and individual indices, which are used to calculate Colombian inflation. In this preliminary analysis, we are using econometric techniques to automatically identify negative, neutral, and positive structural changes in the price indices. To model the trend component, we are relying on the linear-trend specification, where the slopes of the price indices in the time-series regressions provide the location of the trend-breaks as well as their direction and magnitude. See Yang (2017) and Yuingo et al. (2023).

The specific goals are:

1. To identify the dates of structural breaks in the price indices' trends using automatic statistical techniques based on time-series linear regression slope, and assess the recent trend direction—whether increasing, neutral, or decreasing—for each item and group in the CPI basket.

2. To summarize the trend behavior by groups and subgroups based on inflation classifications using the weight structure of the CPI. The Central Bank's preferred classifications include core inflation, tradable and non-tradable goods, unregulated food items, and total inflation.

3. To set a forecasting exercise to accurately predict each item's trend for up to twelve months and group them accordingly based on classification.

This paper consists of six sections beyond the introduction. Section 2 offers a survey of relevant studies. Section 3 describes the Colombian data, followed by the break-point methodology in Section 4 and the break-date results in Section 5. Section 6 presents the results of the forecasting exercise, while Section 7 concludes and suggests future research directions. Technical details and intermediate results are included in the appendices.

# 2 Related literature

Price trend estimation has been studied in the time series literature by both academics and practitioners, using two main approaches: deterministic and stochastic models. Deterministic models approximate trend segments with lower-order polynomials, while stochastic models operate as a non-stationary process that requires a unit-root, with the inherent increase in the forecast uncertainty (reflected in wider forecast intervals).

From the perspective of trend inflation in economic models, Ascari and Sbordoni (2014) review empirical research on the dynamics of U.S. trend inflation and methods for evaluating the volatility and persistence of trend-based inflation gaps. They develop a *New Keynesian* model incorporating positive trend inflation, finding that an increase in trend inflation leads to greater economic volatility and can destabilize inflation expectations. Additionally, Coibion and Gorodnichenko (2011) offers an empirical analysis linking trend inflation to expectations via Taylor rules.

Well-known time series models include the unobserved components model by Stock and Watson (2007) and Stock and Watson (2016), which demonstrate that inflation dynamics are primarily driven by a trend component estimated through a univariate time-varying trend-cycle model with stochastic volatility. Additionally, the multivariate framework utilizes the trend component of a Bayesian VAR model to elucidate the fluctuations in inflation, as noted by Cogley and Sbordone (2007).

Kumber and Wong (2020) develop an empirical model to analyze how global factors influence trend inflation and the inflation gap through trend-cycle decomposition of annualized inflation.

This paper predominantly draws on the empirical approach outlined in Casini and Perron (2018), which summarizes methodological concerns regarding estimation, testing, and computation for models with structural changes. It addresses testing for multiple breaks and models with endogenous regressors, among other aspects, and offers practical methods rather than focusing solely on theoretical issues.

Recent empirical applications have utilized high-frequency price data. For instance, Cavallo and Kryvtsov (2022) employed a detailed micro-dataset on product availability and stockouts to create a direct, high-frequency measure of consumer product shortages during the 2020-2022 pandemic. We also drew insights from Cavallo and Evans (2022), which examines the occurrence of trend breaks to reduce inflation by directly analyzing price indices based on high-frequency online prices across various countries.

# 3 Data

This section outlines the original dataset, and the classifications of frequent inflation metrics monitored by the central bank. The primary data for estimating breakpoints is the Colombian monthly time series, specifically the price index for 188 items and the weight structure published by DANE (National Statistics Department) since December 2018 up to August 2024.

We completed the series from December 2008 to November 2018 by combining the price indices of the 188 items in the December 2018 basket with the 183 items from December 2008. To achieve this, we extrapolated the annual variations of the corresponding indices for subcategories that contain items in the 2018 basket but not in the earlier one[1].

Figure 3 in the main text and Figure 13 in the Appendix display the 188-time series of logarithmic price indices categorized into twelve groups by DANE. The food group, with the highest number of items at 59, is divided into three subgraphs. The observed step patterns in various items arise because these goods change at specific times each year, show minimal variation within a year, or change by a predefined proportion monthly. For instance, panels (d) and (e) of Figure 3 illustrate the differing price dynamics among items within the same category, supporting the idea of modeling each time series separately.

Figure 2 shows the scheme of the twelve divisions recommended by the OECD, an organization of which Colombia has been part since 2020. According to its weights, the division 'Accommodation, Services, and other Fuels' holds the most weight in the basket, accounting for almost a third of the total weight. It is followed, distantly, by 'Food and non-alcoholic beverages', which contributes 15%. The number of items per division is also very dissimilar varying from 2 in 'information and communication' to 59 in 'food and nonalcoholic beverages'.

[1] At the end, we need to complete only four series, because we have available data for *Aguardiente* and whisky separately since December 2008.

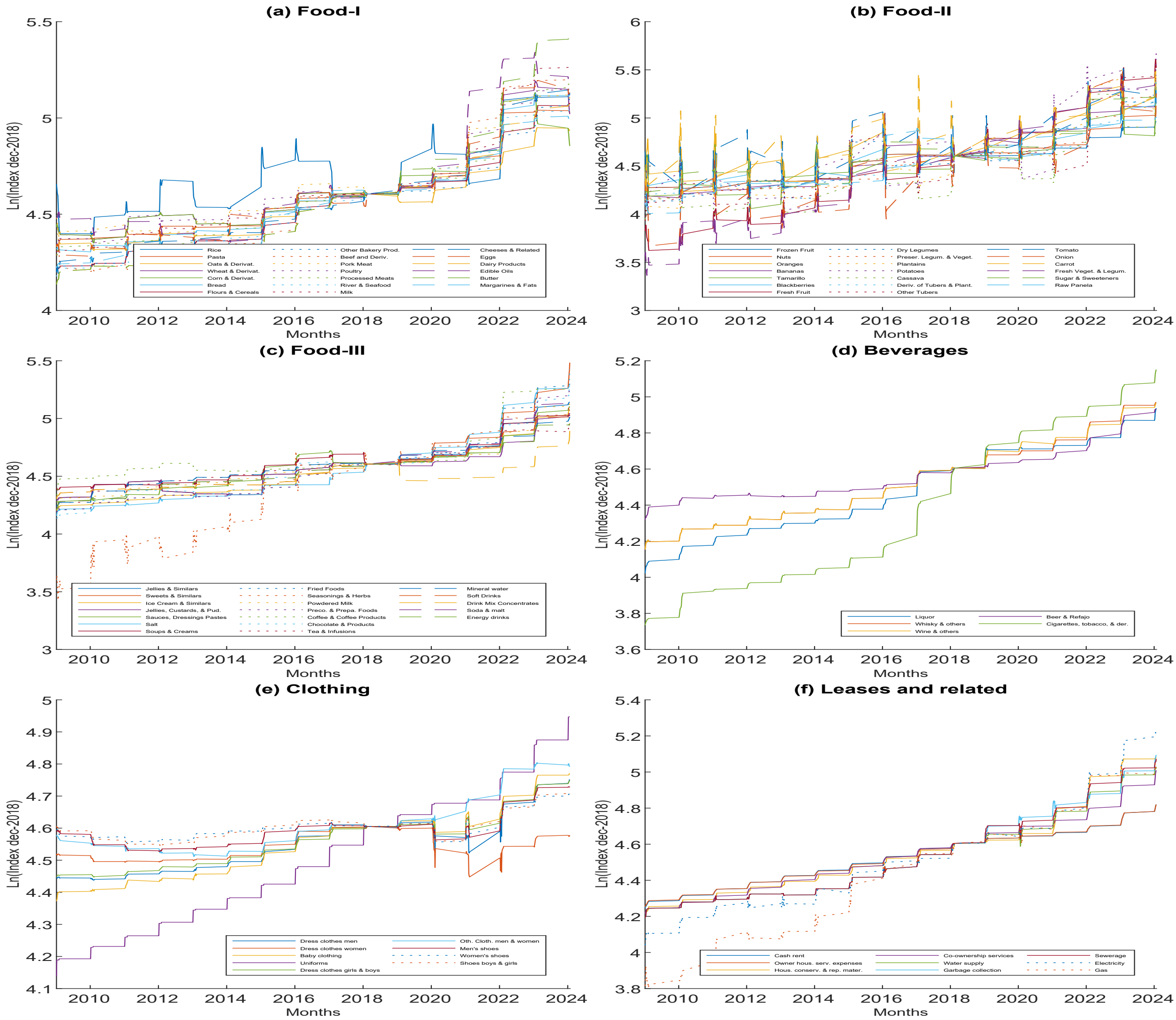


Figure 1: Logarithms of CPI by groups-I. Source: DANE

# 4 Methodology

This section describes the fundamental concepts for detecting trend-breaks in Colombian CPI items and the common classifications used by analysts. We employ a trend-break model based on linear specifications to estimate breakpoints and trends, with the regression slopes changes indicating the breakpoints. For a detailed methodology, refer to Casini and Perron (2018) and Perron (2020). (and Appendix 8.3).

For each *CPI* item, the general setup can be expressed as:

$$y_{it} = x_{it}^{'} \beta_i + z_{it}^{'} \delta_{ij} + u_{it} \tag{1}$$

where $y_{it}$ is the consumer price index at time $t$ for item $i$ belonging to the *CPI* basket, with $t = T_{j-1}^{i} + 1, \cdots, T_j^i, T_0^i = 1, T_{m_i+1}^{i} = T$; $i = 1, \cdots, 188$; and $j = 1, \cdots, m_i$, $m_i$ is the number of times where the item $i$ trend breaks.

The vectors $z_{it}$ are $p$ available independent or deterministic variables (like intercepts and linear

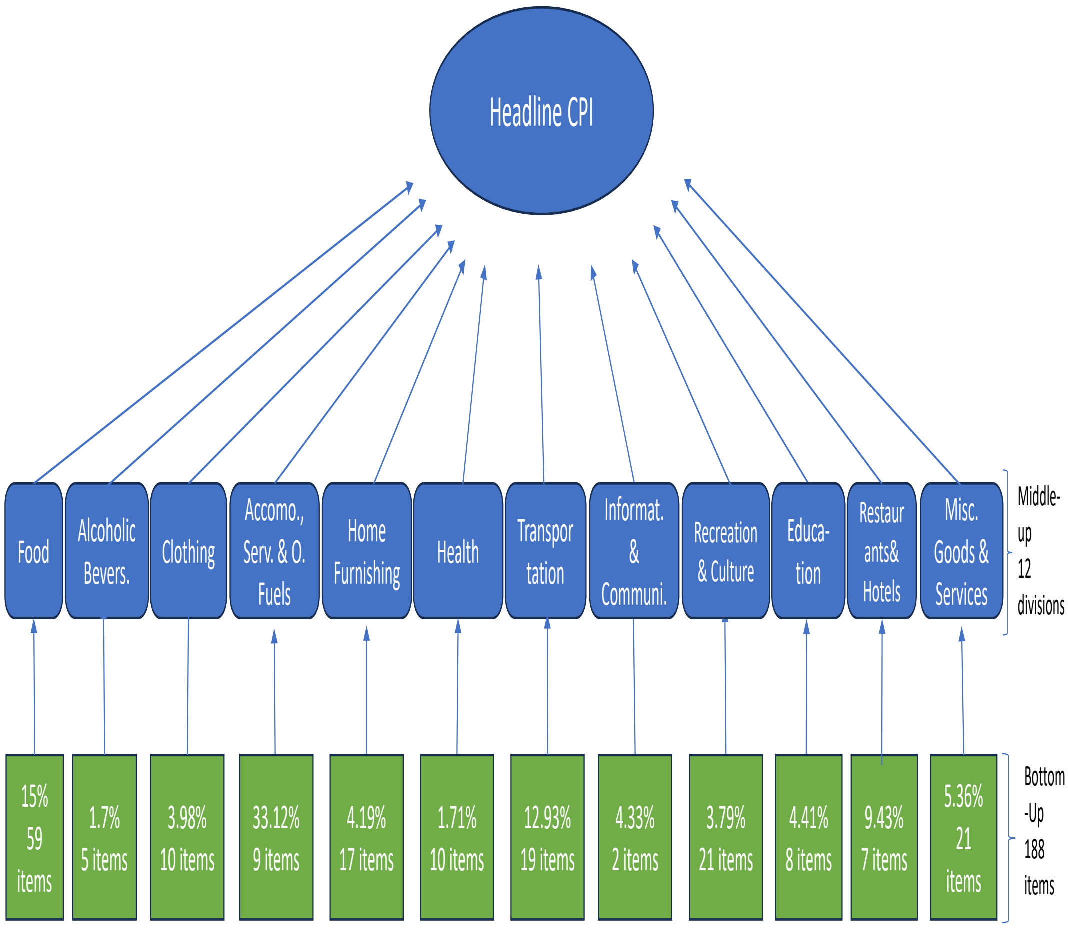


Figure 2: Structure of CPI by Divisions. Source: DANE

trends); $x_{it}$ are $q_i$ variables that could contains lags of $y_{it}$. $\beta_i$ and $\delta_{ij}$ are their respective vector of coefficients, where the $\delta_{ij}$ are potentially different per segment, and the break dates for each *CPI* item $(T_1^i, \cdots, T_{m_i}^i)$ are unknown and must be estimated. The Case of a *pure structural* change model results when $p = 0$. (see Appendix 8.3 for a short explanation of the methodology for estimating breakpoints).

According to standard *OLS* regression, to get the estimated $m_i$ breakpoints $(\hat{T}_1^i, \cdots, \hat{T}_{m_i}^i)$, the optimization problem is posed as:

$$argmin_{T_1^i, \cdots, T_{m_i}^i} \sum_{j=1}^{m_i+1} \sum_{t=T_{j-1}^i+1}^{T_j^i} [y_{it} - x_{it}^{'}\beta_i - z_{it}^{'}\delta_{ij}]^2 \tag{2}$$

where for convenience $T_0^i = 1$ and $T_{m_i+1}^i = T$. Furthermore, estimates for $\beta_i$, $\hat{\beta}(T_j^i)$, and for $\delta_{ij}$, $\hat{\delta}(T_j^i)$, are based on the partition $(T_1^i, \cdots, T_{m_i}^i)$.

Figure 2 illustrates the identification of the break-trend methodology. This indicates the break-points and the slope coefficients of the linear regression in each of the five segments.

Even though the presence of jumps in the *CPI* affects the level of the index but not the trend; a first-difference transformation is employed, for consistency reasons, as pointed by Yang (2017). Worth to clarify that this is an intermediate or artificial step to easy the break-date

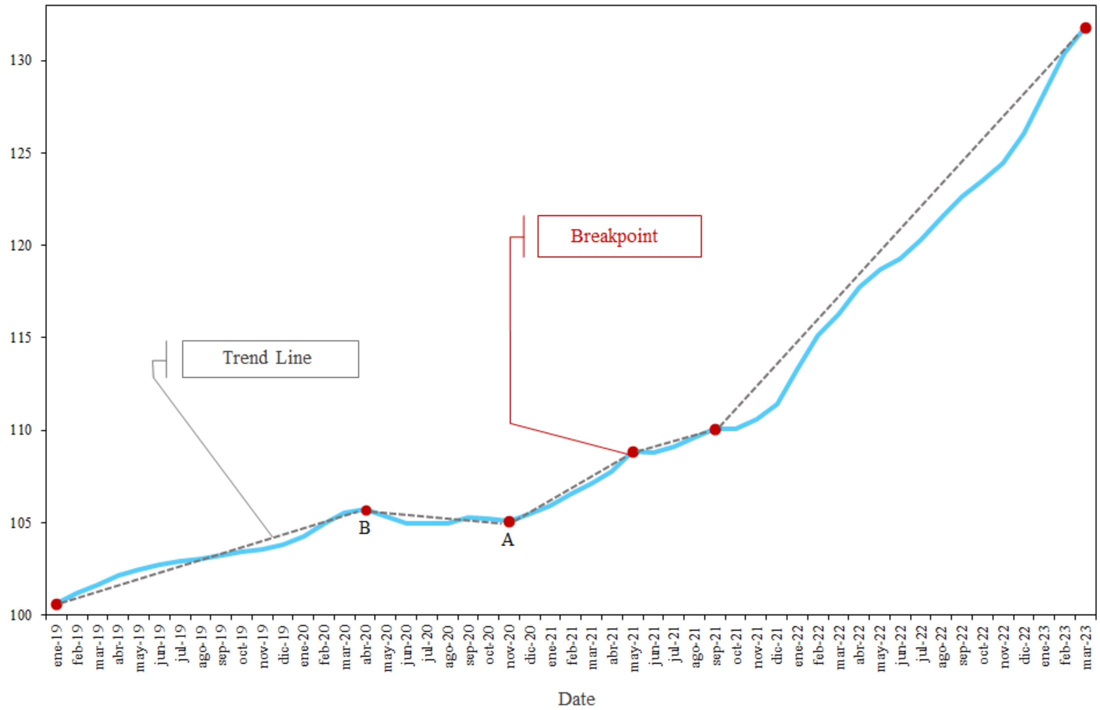


Figure 3: The breakpoints methodology fits lines for every regime according to the estimated breakpoints, where the slope is known as the *trend force*. While pointing signals, the trend shifts down. Point A indicates the trend is rising, while point B indicates it is decreasing.

detection not to model the prices series; the conclusion so extracted are about log-levels of the series.

A consistent estimator of the location of $m$ breakpoints, or equivalently $m + 1$ regimes, is implemented by sequential least squares, $SLS$; see Perron (2020).

The pure structural change model could specify the trend-break model, for example in a model with just one break:

$$y_t = \beta_0 + \beta_1 t + \delta_1 \mathbb{1}[T > T_b] + \delta_2 t \mathbb{1}[T > T_b] + \epsilon_t \; t = 1, \cdots T_b, \cdots T \tag{3}$$

taking first difference, we obtain,

$$y_t - y_{t-1} = \beta_1 + \delta_2 \mathbb{1}[T = T_b] + \Delta\epsilon_t \qquad t = 1, 2, \cdots T \tag{4}$$

The steps required are summarized below:

1. Estimating a single break-date in the presence of multiple breaks, the estimator converges to the true break fraction $T_b^*$ that produces the maximum reduction in the $SSR$ compared to the model without breaks.

2. Estimating a second break-date, the estimator converges to the true break fraction $T_b^{**}$ that produces the second-highest decrease in the $SSR$.

3. If the $SSR$ of the model with two breaks at $T_b^*$ and $T_b^{**}$ is smaller than the one of the model with a single break at $T_b^*$, two breaks at $[T_b^*, T_b^{**}]$ are chosen.

A dynamic programming approach can be efficiently used to evaluate which partition achieves a global minimization of the overall sum of squared residuals. In the statistical hypothesis framework, we test for the presence of one break via the $supF(0,1)$ and move forward to test for the presence of $l+1$ breaks, via the $F(l+1|l)$ ratio. The procedure continues to locate up $l$ breakpoints; with $l \leq l_{max}$, a predefined maximum number of breaks allowed.

# 5 Breaks results

This section analyzes structural breaks in the items and groups of the CPI from December 2008 to August 2024. We chose exogenous variables, $z_{it}$, to implement our methodology. The model employed is a linear trend plus two lags of $y_{it}$, which offers flexibility compared to an AR(1) and requires fewer parameters than other alternatives. For robustness, we validated our findings using 4 and 6 lags, which yielded the same results.

Table 1 presents the dates and instances of breaks for certain CPI items. Analyzing the Colombian CPI aggregate revealed two significant trend breaks. The first, a negative break identified in October 2021, indicated rising inflation. Conversely, the second break, signaling a positive trend shift, occurred in March 2023, when inflation was declining. Similar break trends were observed in the accommodation, services, and home furnishing sectors. Figure 5 illustrates the break dates for CPI items, with detailed break locations provided in Appendix 8.3. The histogram of break dates for the entire period shows a notable concentration of breaks post-pandemic (2021 Q4).

Table 1: Estimated trend breaks dates for some *CPI* items

| Name | # breaks | Date 1 | Date 2 | Date 3 |
|---|---|---|---|---|
| Rice | 0 | | | |
| Beer & Refajo | 2 | Aug-2022 | Oct-2023 | |
| Small electrical devices | 0 | | | |
| Pasta | 0 | | | |
| Oats & Derivat. | 0 | | | |
| Toiletries | 0 | | | |
| Baby clothing | 2 | Dec-2021 | Aug-2023 | |
| Beauty Products | 4 | Jun-2010 | Feb-2015 | Jul-2017 |
| Corn & Derivat. | 0 | | | |
| Bread | 1 | Aug-21 | | |
| Domestic service | 0 | | | |
| Flours & Cereals | 1 | Mar-21 | | |
| Pharm. & derm. products | 2 | May-04 | Dec-21 | |
| Medical devices | 0 | | | |
| Beef and Deriv. | 0 | | | |
| Therapeutic equipment | 2 | Mar-15 | Apr-22 | |
| Pork Meat | 1 | May-20 | | |
| Party decor. & garments | 4 | Jun-2010 | Sep-2013 | Jan-2022 |

To identify the sectors that were driving the speed-up of the aggregate inflation rate, Figure 5 displays the estimated date-breaks, grouped by quarters, for a classification that is of particular interest for macro-economist and central banks staff: Food and Beverages, Goods or tradable, Services or non-tradable and Regulated groups. In this figure, positive values indicate upward movements, while negative values indicate downward movements in trends. The 'Services' group shows the most breakpoints compared to the others, with significant fluctuations both up and down, particularly noted at the end of 2021, reflecting the global circumstances at that time.

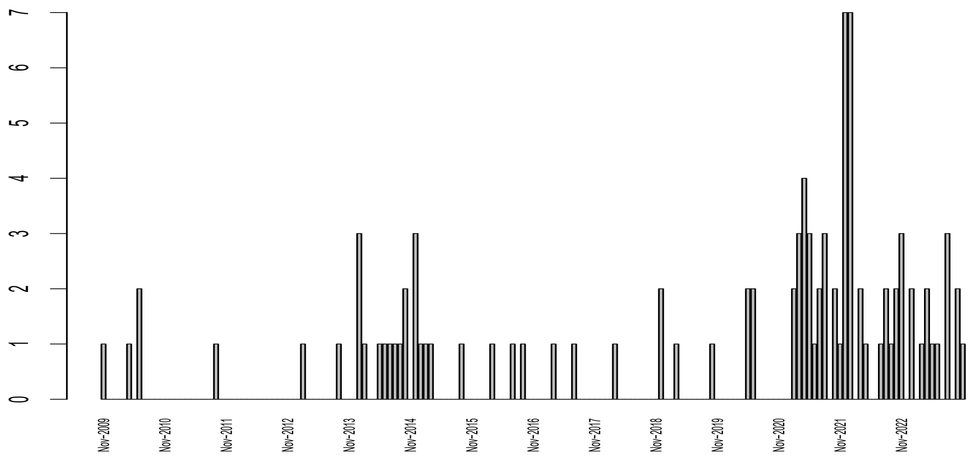


Figure 4: Breaks dates items histogram. Source: Authors' calculations.

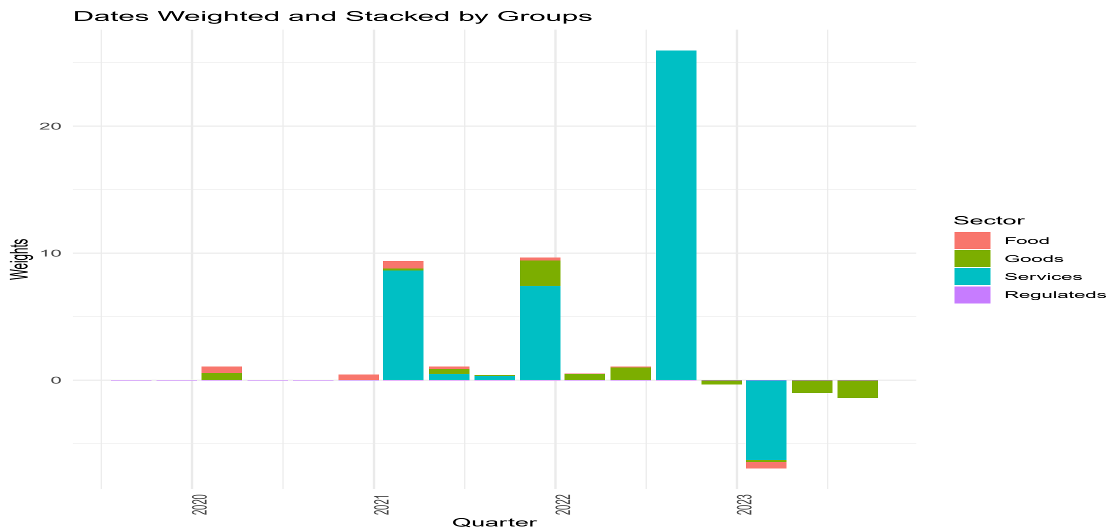


Figure 5: Breaks dates items histogram by group and quarterly. Source: Authors' calculations.

Figure 6 presents a smoothed version of the diffusion index for a given month. Such an index measures how the changes in inflation regimes have impacted inflation by using the official weights of the *CPI* to aggregate the groups according to whether they have negative breaks (0), no breaks (0.5), or positive breaks (1).

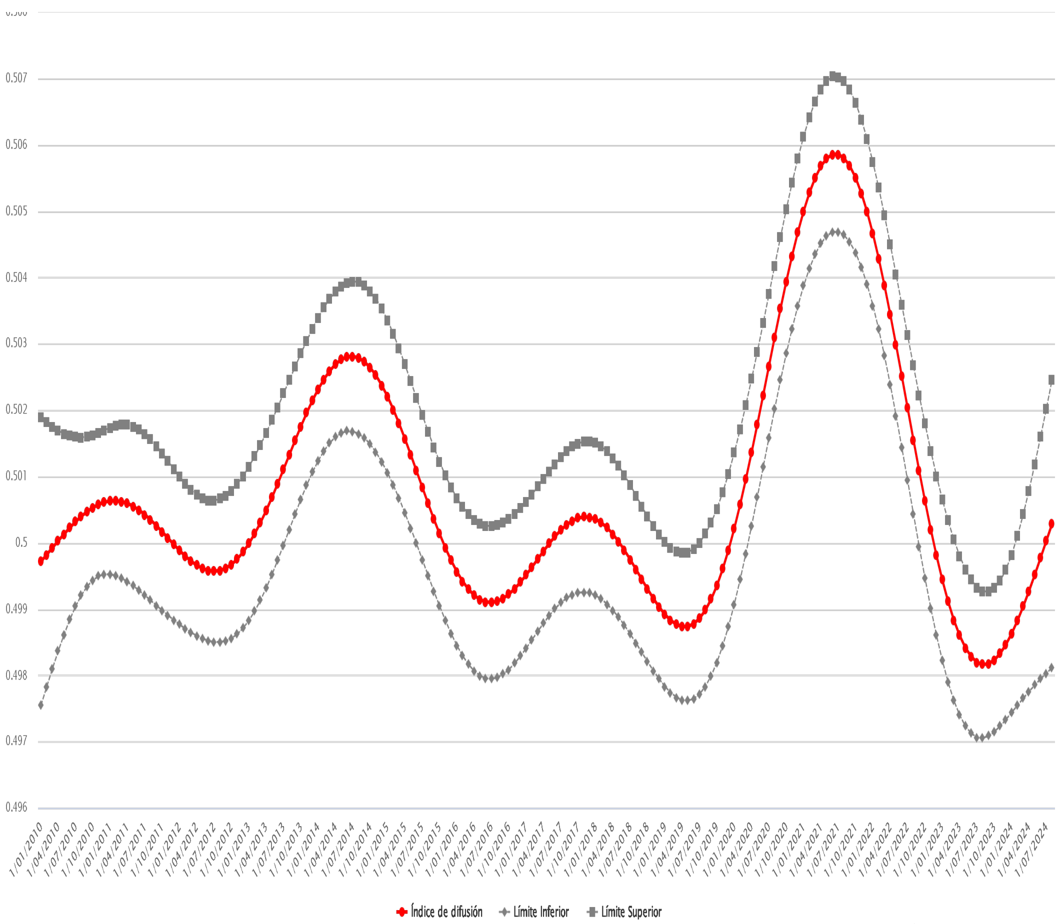


Figure 6: Smoothed diffusion index of the structural breaks for *CPI* items up to August 2024. Source: DANE, and authors' calculations.

The Consumer Price Index weights, categorized by their structural changes, are summarized in Table 2 and illustrated in Figure 7. Of these weights, 51% experienced a positive change, while 1.1% had a negative change, and 48.3% showed no detectable structural alteration in the inflation trend. Categories that experienced lower inflation rates include recreation and culture as well as furniture, which has a smaller weight in the index. In contrast, categories with higher inflation include 'restaurants and hotels,' 'accommodation, water supply, other combustibles, and electricity,' 'miscellaneous goods and services,' and 'food and non-alcoholic beverages.'

| CPI groups | Less inflation | | No break | | More inflation | |
|---|---|---|---|---|---|---|
| | Weight | % | Weight | % | Weight | % |
| Food and non-alcoholic beverages | 0.48 | 3.2 | 11.35 | 75.67 | 3.17 | 21.13 |
| Alcoholic beverages and tobacco | | | 0.57 | 33.53 | 1.13 | 66.47 |
| Clothing and footwear | | | 1.86 | 46.62 | 2.13 | 53.38 |
| Accommodation, water, electricity, gas and other fuels | | | 2.69 | 8.12 | 30.43 | 91.88 |
| Furniture, household items and ordinary maintenance of the home | 0.13 | 3.10 | 3.32 | 79.05 | 0.75 | 17.86 |
| Health | | | 1.51 | 87.79 | 0.21 | 12.21 |
| Transport | | | 11.75 | 90.87 | 1.18 | 9.13 |
| Information and communication | | | 4.33 | 100 | | |
| Recreation and culture | 0.40 | 10.53 | 2.75 | 72.37 | 0.65 | 17.11 |
| Education | | | 4.42 | 100 | | |
| Restaurants and hotels | | | 0.49 | 5.20 | 8.93 | 94.80 |
| Miscellaneous goods and services | 0.03 | 0.56 | 3.29 | 61.50 | 2.03 | 37.94 |

Table 2: Share (%) of CPI weights with structural breaks, August 2024. The estimated break can be classified as negative which generates less inflation, positive with more inflation, or no break detected. Source: DANE, and authors' calculations.

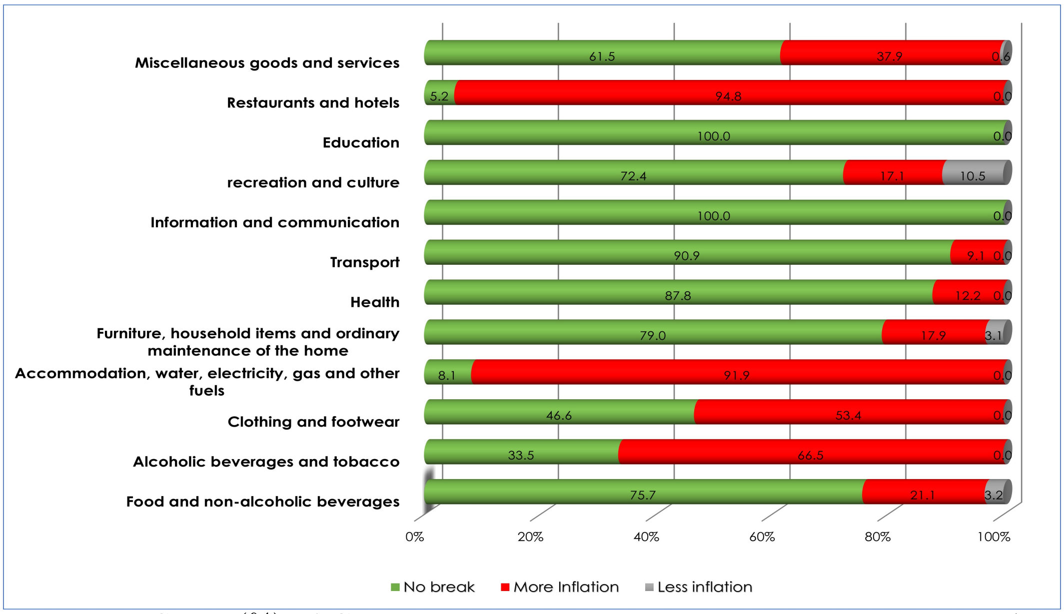


Figure 7: Figure 7: Share (%) of CPI weights with structural breaks split by groups, August 2024. The green area denotes no extra inflation, the red area identifies more inflation, and the grey area represents less inflation. Source: DANE, and authors' calculations.

Figure 8 shows the results according to CPI classifications frequently analyzed by the users. The 68.2% of the weight of the food group and the 62.8% of the weight of the non-tradable group have contributed to more inflation. The tradable and regulated groups have experienced more inflation with 57% and 39%, of their weights.

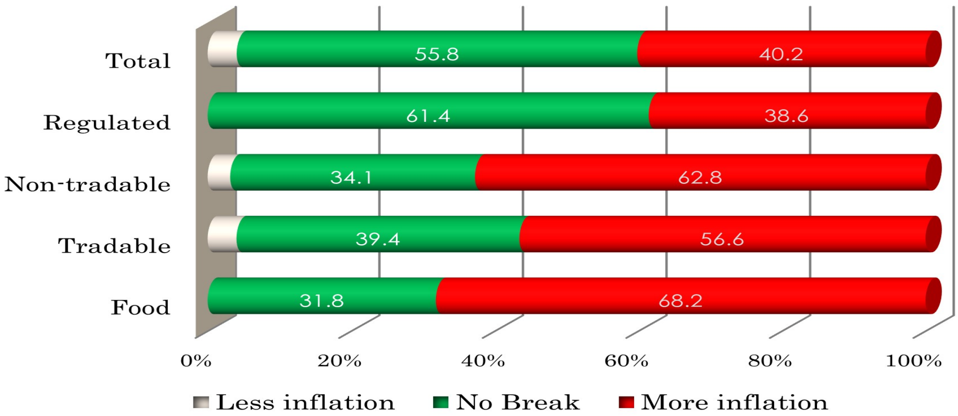


Figure 8: Share (%) of CPI weights with structural breaks split by central bank classifications, August 2024. The light-gray areas identify less inflation, the red areas identify more inflation, and the green color has no extra inflation. Source: DANE, and authors' calculations.

# 6 Forecasting

Figure 9 presents the aggregated monthly forecast plot for the annual inflation rate from August 2024 to February 2026 for each group within the Consumer Price Index (CPI) basket. This analysis includes observed data up to August 2024, with each forecast adjusted to correct for bias introduced by logarithm transformations. In this case, the AR(2) model previously used for break tests has been expanded to select from $ARMA(p*, q*)$ models, where $p*$ and $q*$ are chosen based on the in-sample Bayesian Information Criterion (BIC).

These forecasts are generated using an adaptation of the optimal reconciliation approach, which allows us to predict the evolution of every item in each group. Reconciled forecasts are calculated for the entire group by applying the weights of the CPI basket. This method is known as the *bottom-up* approach. Its primary advantage is its simplicity, as it models and forecasts the basket at the most detailed level, thereby minimizing information loss due to aggregation and reducing bias. A further discussion on this topic can be found in Wickramasuriya et al. (2019) and Rossi (2021). Another possible approach to consider is forecasting the breakpoints within the prediction horizon, with one option being discussed in Pesaran et al. (2006).

The forecasting results indicate that, while the predicted annual inflation decreases or remains stable for most *CPI* groups during the remaining months of 2024 and the beginning of 2025, there are exceptions: Lease, Restaurants, Beverages, and Recreation are expected to see increases. Furthermore, the rate of change varies among different groups; for instance, inflation for hotels, clothing, and footwear is projected to rise slowly compared to home furnishings or information and communication groups. However, an upward trend in inflation is anticipated by mid-2025, partly driven by increases in Accommodation, Restaurants, and Services(lease).

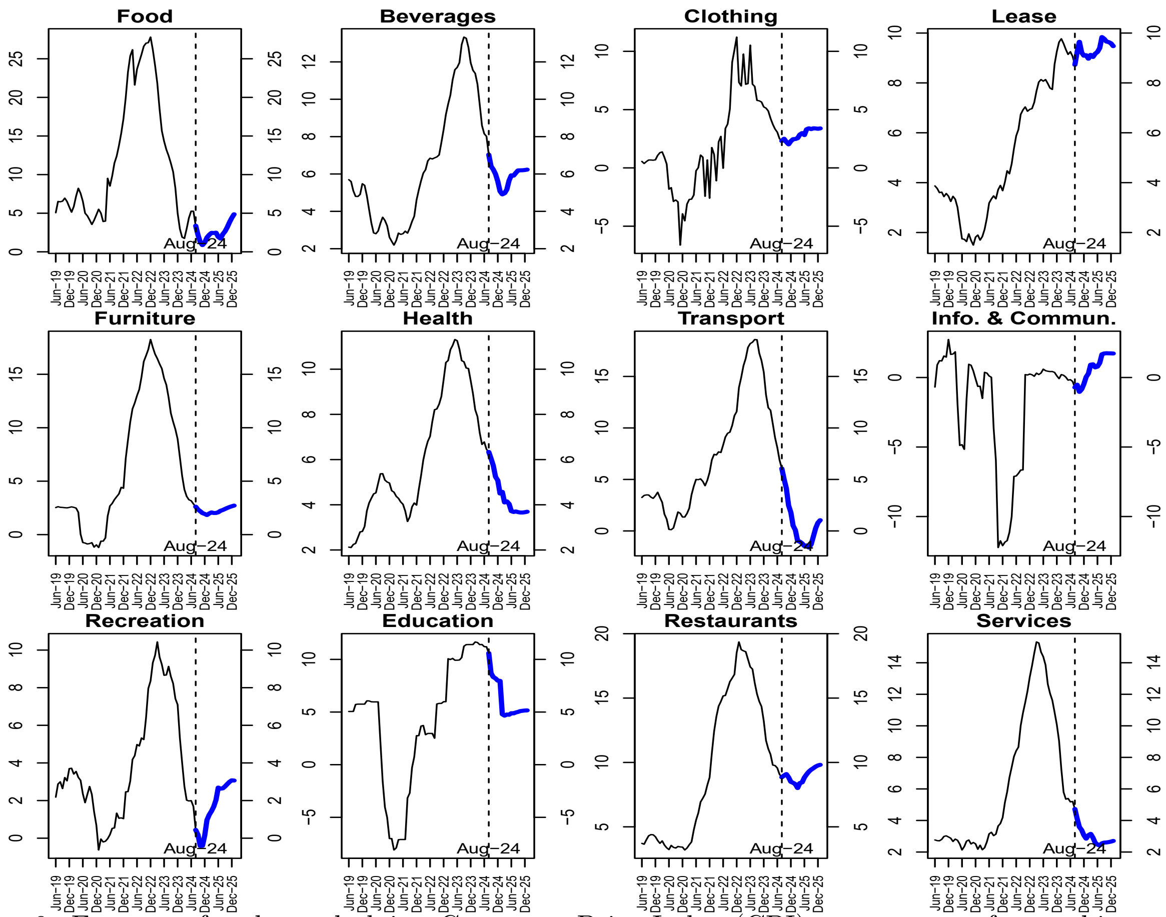


Figure 9: Forecasts for the underlying Consumer Price Index (CPI) groups come from a hierarchical aggregation method known as the bottom-up approach. First, we generate independent forecasts for every item at the lowest level of the hierarchy. Then, we combine these forecasts to develop projections for upper subgroups.

Tracking the relative prices of food, tradable goods, and non-tradable goods is crucial and can be easily accessed, as depicted in Figure ??. Current data indicates that by the end of this year, we can expect the relative prices for both tradable goods and food to stay low, while non-tradable goods will probably remain at high prices. This information is valuable for making informed decisions moving forward.

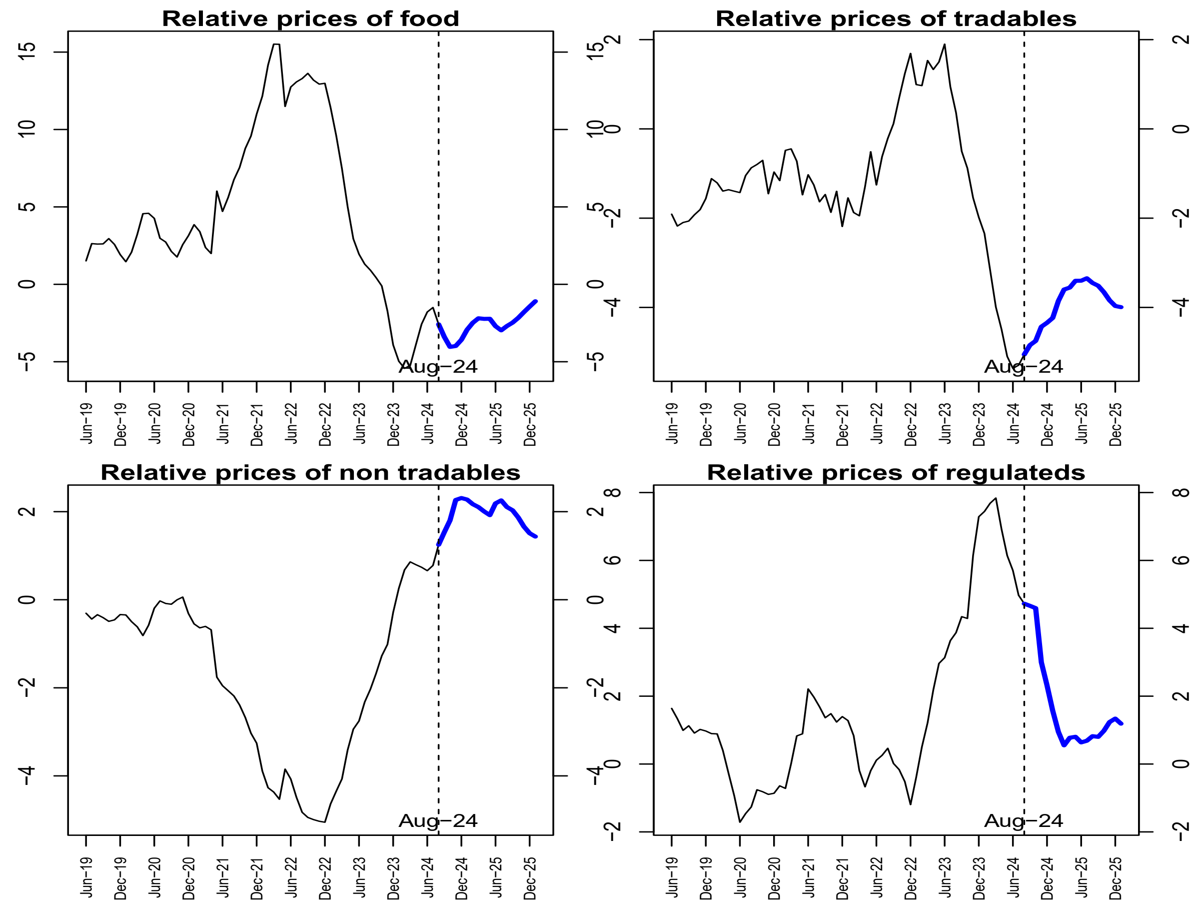


Figure 10: *Bottom-up* forecasts for the group relative prices.

The forecast for total annual inflation, based on data available up to August 2024 and using a bottom-up strategy, is shown in Figure 11. It predicts an inflation rate of 5.8% for September 2024, 4.97% for December 2024, and a minimum of 4.75% in March 2025. In the next section, we will assess the forecasting accuracy of the aggregation strategies (bottom-up and middle-up). To achieve this, we implemented a rolling window evaluation, which is illustrated in Figure 12. This figure depicts the rolling forecasts using breakpoints and ARMA models that were automatically selected for each item in the basket.

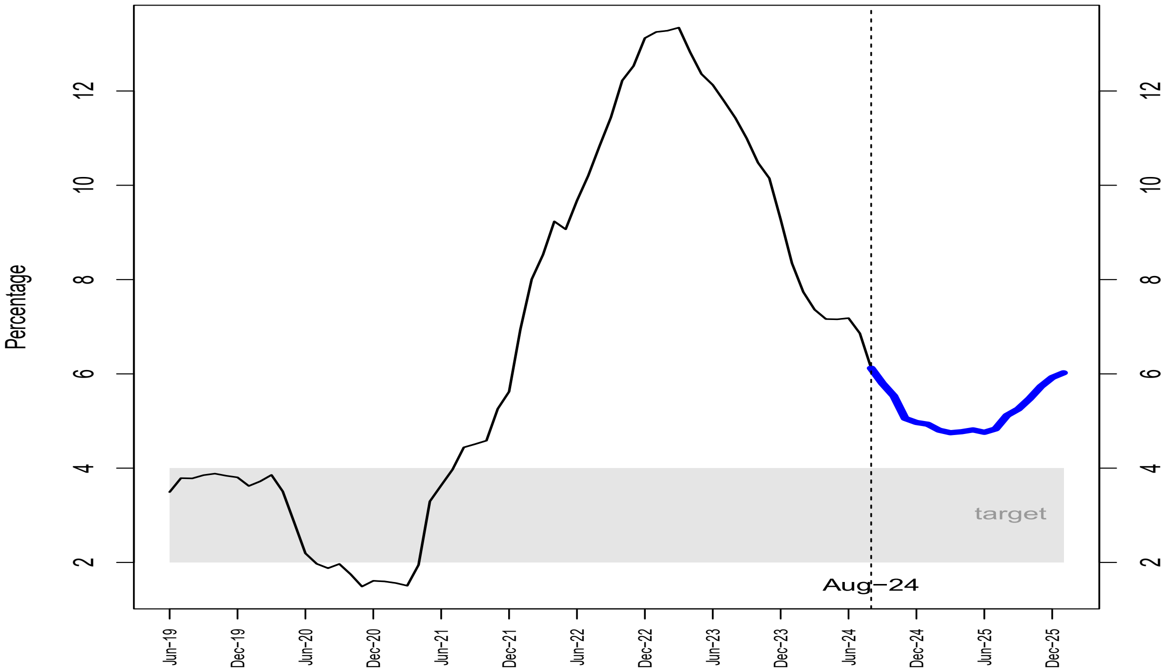


Figure 11: Total annual inflation forecast based on the *bottom-up* reconciliation method.


Figure 12: Rolling window forecasts for *CPI* annual inflation by items.

Table 3: Forecast Evaluation Statistics for Headline *Inflation*
(expanding windows) Period: Jan-2020 - Aug-2024

| Horizon | Model | # Obs. | MFE | MAPFE | RMSFE | U-Theil |
|---|---|---|---|---|---|---|
| 1 | ARIMA | 56 | 0.083 | 6.44 | 0.37 | 0.087 |
| 1 | Middle up-ARIMA | 56 | 0.114 | 6.99 | 0.40 | 0.095 |
| 1 | Bottom up-ARIMA | 56 | 0.149 | 6.37 | 0.41 | 0.095 |
| 1 | ARMA+Breaks | 56 | 0.011 | 5.16 | 0.28 | 0.065 |
| 1 | Middle up-ARMA+Breaks | 56 | 0.006 | 5.40 | 0.31 | 0.073 |
| 1 | Bottom up-ARMA+Breaks | 55 | 0.061 | 4.87 | 0.30 | 0.070 |
| 2 | ARIMA | 55 | 0.242 | 12.37 | 0.82 | 0.181 |
| 2 | Middle up-ARIMA | 55 | 0.291 | 13.82 | 0.87 | 0.192 |
| 2 | Bottom up-ARIMA | 55 | 0.347 | 12.75 | 0.84 | 0.187 |
| 2 | ARMA+Breaks | 55 | 0.042 | 9.04 | 0.54 | 0.119 |
| 2 | Middle up-ARMA+Breaks | 55 | 0.047 | 10.14 | 0.65 | 0.144 |
| 2 | Bottom up-ARMA+Breaks | 55 | 0.147 | 8.83 | 0.56 | 0.125 |
| 3 | ARIMA | 54 | 0.447 | 19.69 | 1.29 | 0.272 |
| 3 | Middle up-ARIMA | 54 | 0.499 | 19.89 | 1.32 | 0.279 |
| 3 | Bottom up-ARIMA | 54 | 0.572 | 18.41 | 1.26 | 0.266 |
| 3 | ARMA+Breaks | 54 | 0.089 | 12.51 | 0.80 | 0.168 |
| 3 | Middle up-ARMA+Breaks | 54 | 0.093 | 14.63 | 0.98 | 0.205 |
| 3 | Bottom up-ARMA+Breaks | 54 | 0.255 | 12.50 | 0.83 | 0.175 |
| 6 | ARIMA | 51 | 1.259 | 37.03 | 2.60 | 0.484 |
| 6 | Middle up-ARIMA | 51 | 1.297 | 33.40 | 2.60 | 0.484 |
| 6 | Bottom up-ARIMA | 51 | 1.308 | 33.11 | 2.45 | 0.456 |
| 6 | ARMA+Breaks | 51 | 0.296 | 25.13 | 1.73 | 0.323 |
| 6 | Middle up-ARMA+Breaks | 51 | 0.186 | 28.28 | 1.94 | 0.361 |
| 6 | Bottom up-ARMA+Breaks | 51 | 0.576 | 26.22 | 1.72 | 0.321 |
| 9 | ARIMA | 48 | 2.233 | 47.86 | 3.89 | 0.668 |
| 9 | Middle up-ARIMA | 48 | 2.321 | 44.91 | 3.83 | 0.657 |
| 9 | Bottom up-ARIMA | 48 | 2.223 | 44.38 | 3.58 | 0.614 |
| 9 | ARMA+Breaks | 48 | 0.691 | 36.10 | 2.94 | 0.505 |
| 9 | Middle up-ARMA+Breaks | 48 | 0.381 | 42.79 | 3.21 | 0.551 |
| 9 | Bottom up-ARMA+Breaks | 48 | 1.054 | 36.26 | 2.76 | 0.473 |
| 12 | ARIMA | 45 | 3.328 | 55.43 | 5.16 | 0.833 |
| 12 | Middle up-ARIMA | 45 | 3.470 | 51.60 | 5.12 | 0.825 |
| 12 | Bottom up-ARIMA | 45 | 3.263 | 48.79 | 4.77 | 0.769 |
| 12 | ARMA+Breaks | 45 | 1.307 | 50.39 | 4.41 | 0.712 |
| 12 | Middle up-ARMA+Breaks | 45 | 1.058 | 54.87 | 4.55 | 0.734 |
| 12 | Bottom up-ARMA+Breaks | 45 | 1.672 | 47.74 | 3.91 | 0.631 |

Table 3 presents the results of six strategies for forecasting headline annual inflation. First, Auto-ARIMA models on the total CPI series; second, the aggregation of Auto-ARIMA models for the twelve Divisions (middle-up aggregation, 12 ARIMA models); third, Auto-ARIMA on each of the 188 items; fourth, stationary Auto-ARMA model around (possibly-) breaking linear trend with breaks on the aggregated series, fifth, the weighted aggregation of the twelve division each with breaking linear trends; sixth, the weighted aggregation of 188 forecast on items considering breaks. Besides the amount of data used for the evaluation, with rolling exercises as displayed in Figure 12, the usual statistics are presented: Mean Forecast Error (MFE), Mean Absolute Percentage Forecast Error (MAPFE), the Root Mean Squared Forecast Error (RMSFE) and the U-Theil statistic.

The results presented in Table 3 show that the bottom-up approach with breaks consistently outperforms the other methods across all forecasting horizons, based on the Mean Absolute Percentage Forecast Error (MAPFE). Additionally, the U-Theil statistics for all methods are below one, suggesting that the random walk forecast is never superior to any of the six forecasting options evaluated.

In Appendix 8.4, we present similar results for month-to-month inflation over the same period (January 2020 to August 2024). Our findings indicate that, both in the short run and even in the mid-term, the aggregated forecast, which accounts for potential breaks, is the most effective forecasting option, as indicated by the MAPFE. All these measures are provided and can be compared with other methodologies beyond those discussed here.

# 7 Conclusions

In this paper, we identify the dates and direction of the trend breaks for the Colombian price indices based on the disaggregated basket of the Consumer Price Index *(CPI)*. Additionally, based on these results two hierarchical forecasting exercises for the annual inflation rate were performed.

To identify the sources of trend-breaking inflation, we rely on measuring at the item level. Our analysis reveals positive structural breaks in prices trends for about 51 percent of the weight of the *CPI* conforming the basket. The most recent inflection date for a negative change in total inflation was detected around October 2023. The groups identified to exert more inflation are related to household services, restaurants and hotels. According to different classifications, non-tradable and tradable items contributed to accelerate the 2022 inflation rate and to decelerate by 2023. However, the regulated inflation classifications experienced reduced pressure, where 61 percent of the *CPI* share were identified with no trend breaks.

To forecast the inflation rate, we use a hierarchical forecasting approach where the aggregation exercise considers the weighting structure in the *CPI* methodology by implementing the *bottom-up* reconciliation forecasts, which shows to better forecast than the nonaggregating and even better than the middle-up alternative. The results suggest a pattern of reduction of inflation for most *CPI* groups in 2024 at different velocities. However, an upward trend is predicted for key groups in 2025.

The results suggest that tests for structural breaks could be an essential tool for detecting changes in inflation trends and improving forecasting. The implications of these results for the inflation targeting framework rely on the identification of trend breaks associated with the systematic behavior of monetary policy or changes in the persistence of shocks.

We developed a web-based application to replicate the results in this paper, and it is available for internal use under administrative authorization. Future developments for real-time analysis rely on the combination of official *CPI* with high-frequency price data and exogenous information. We are also exploring the construction of prediction intervals for the reconciled forecasts based on bootstrapping techniques.

Another front of work could be multivariate models, as suggested by Bai et al. (2020) by using and modeling the cross-correlation, which would help detect breakpoints close to the sample ending and improve the aggregated forecasts.

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# 8 Appendix

## 8.1 CPI by groups

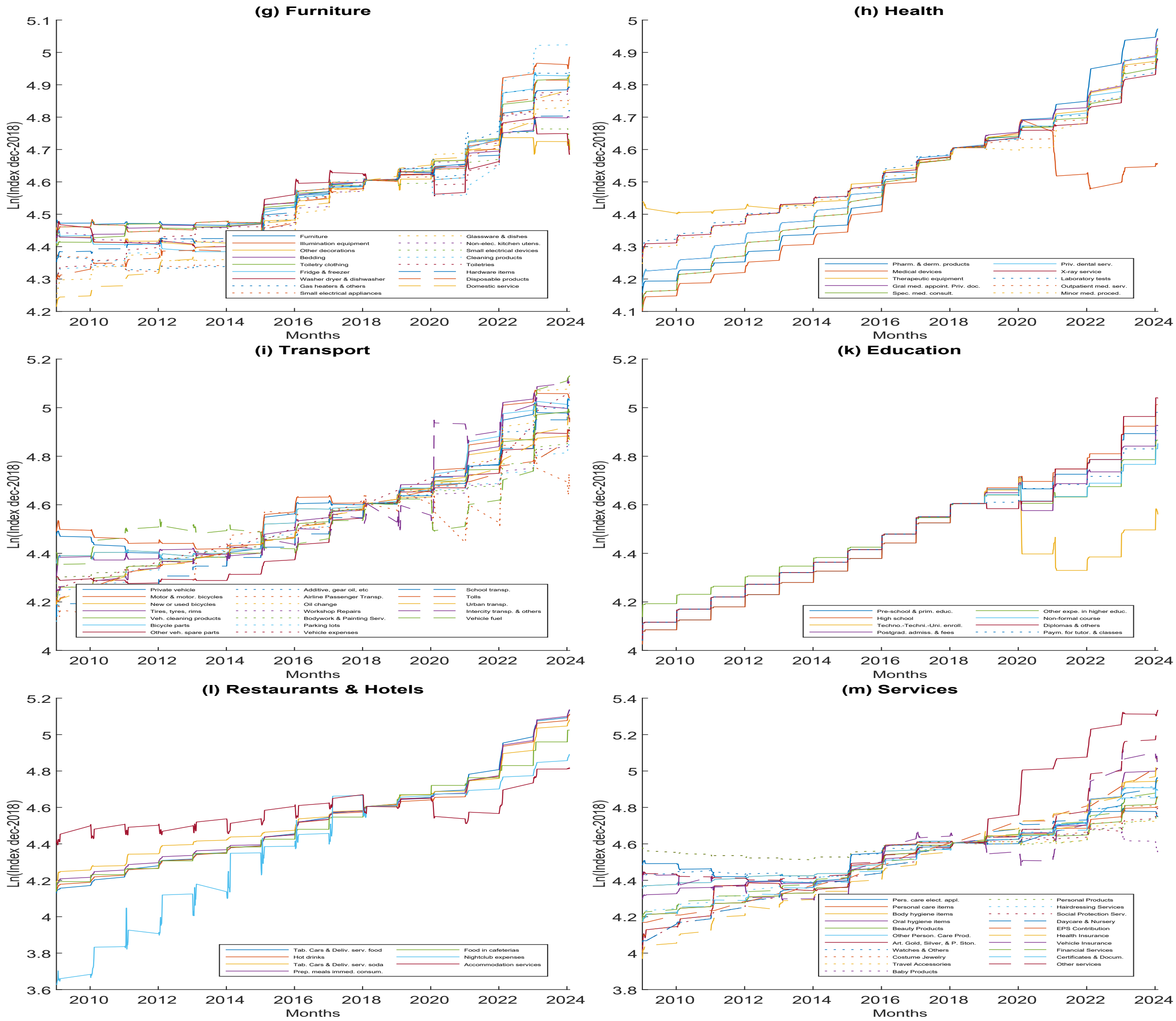


Figure 13: Logarithms of CPI by groups-II. Source: DANE

## 8.2 Structural breakpoints for selected *CPI* items

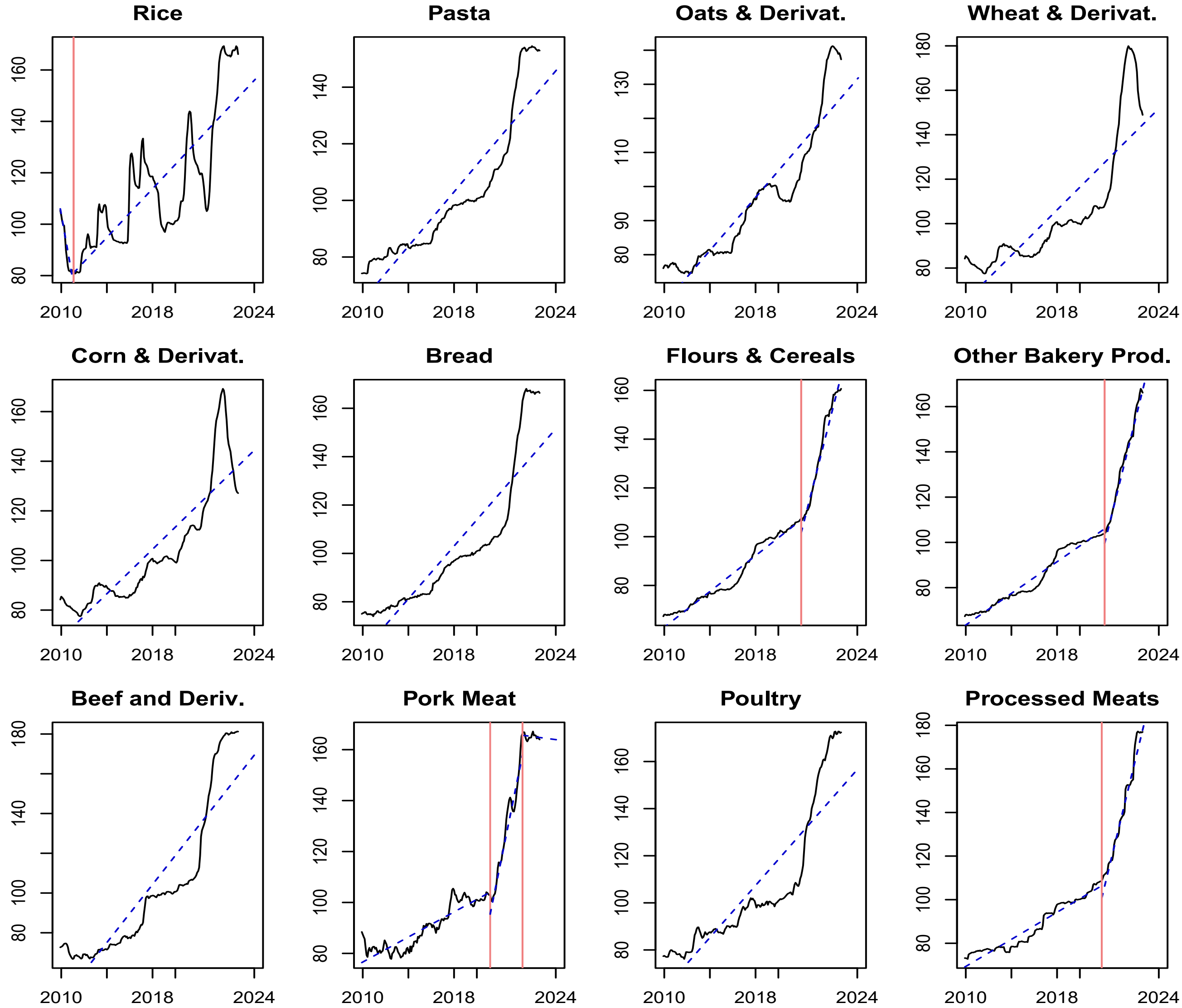


Figure 14: Structural breakpoints for the food and beverages group. Source: DANE

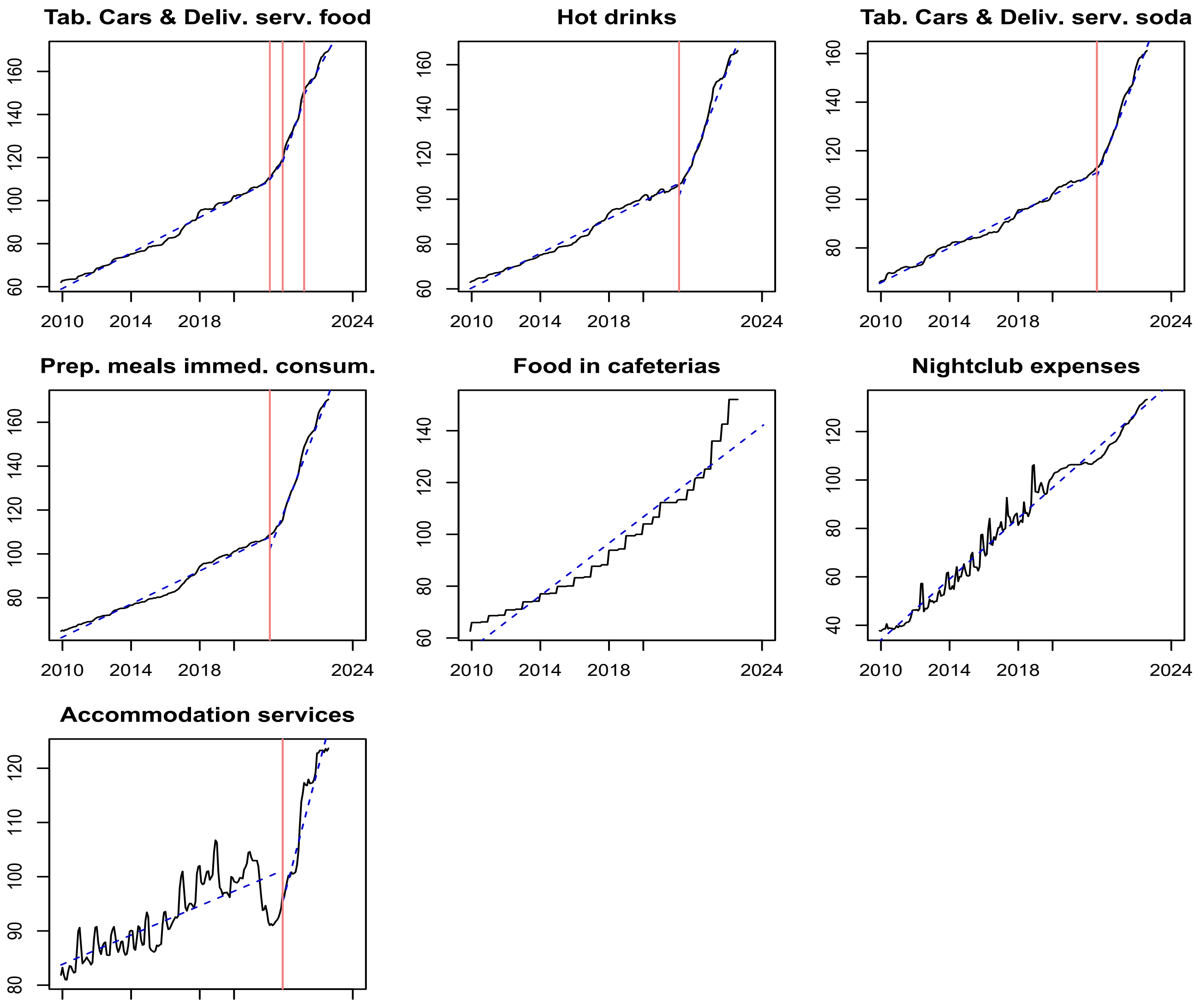


Figure 15: Structural breaks points for the restaurant and hotels group. Source: DANE

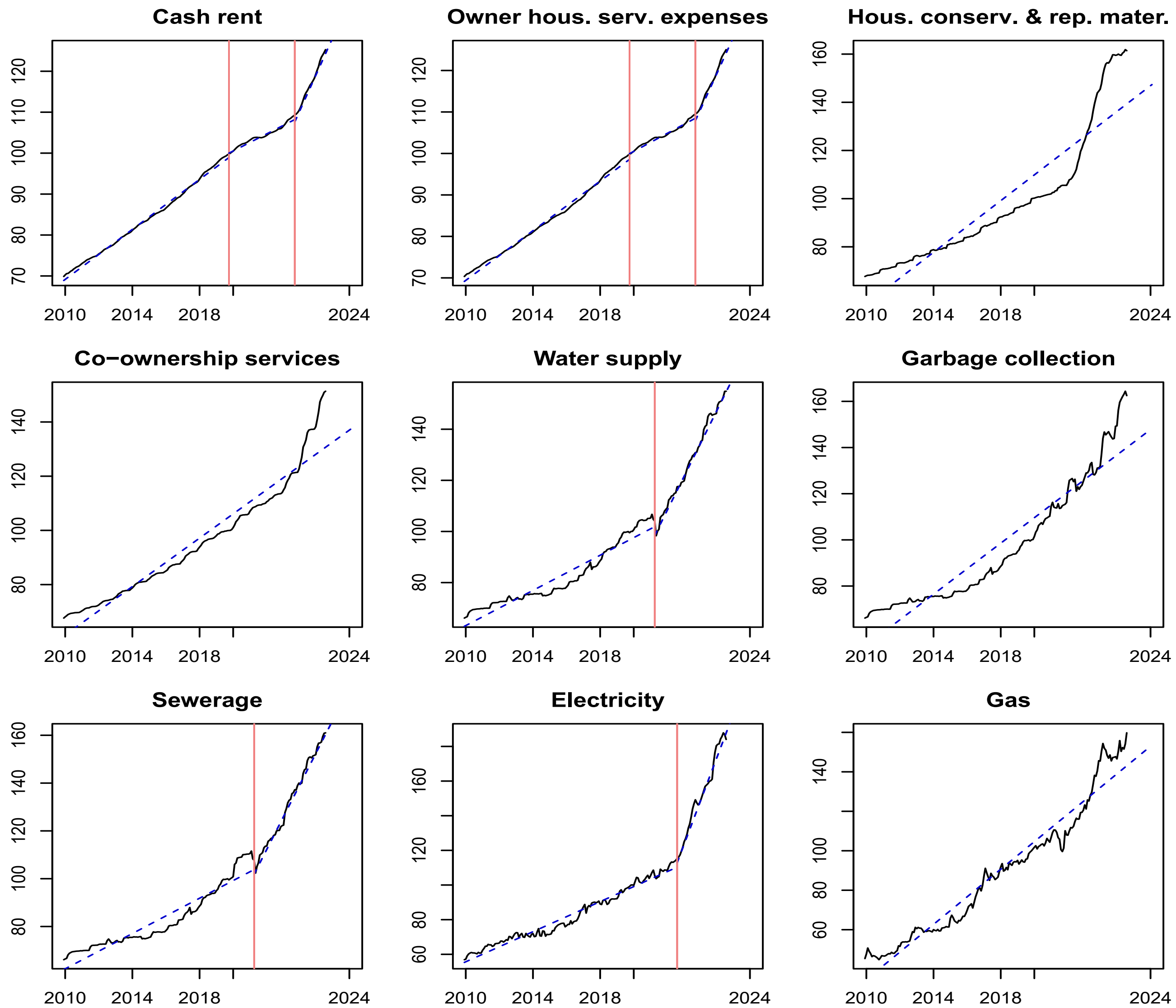


Figure 16: Structural breaks points for the accommodation and services group. Source: DANE

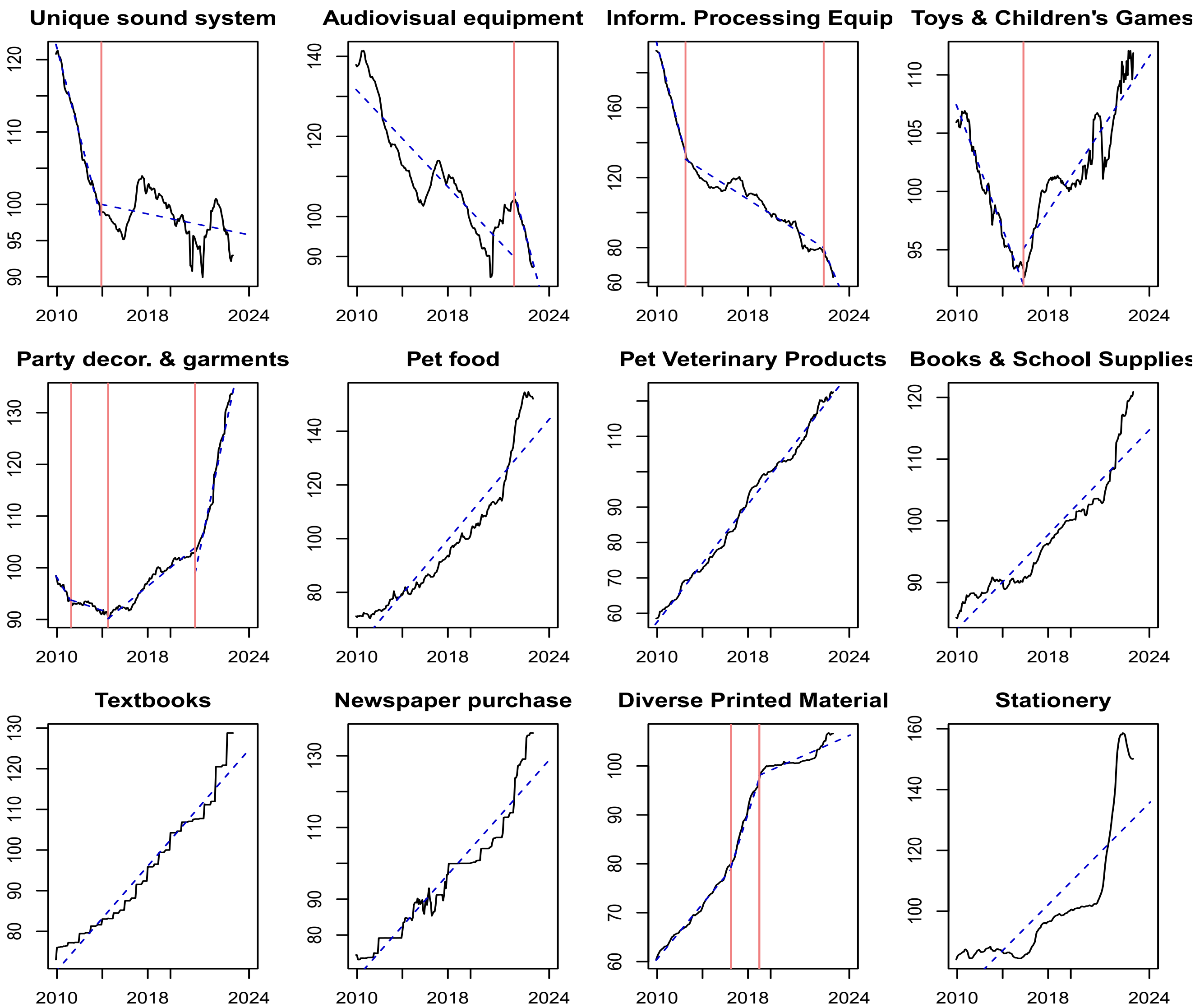

Figure 17: Structural breaks points for the recreation and culture group. Source: DANE

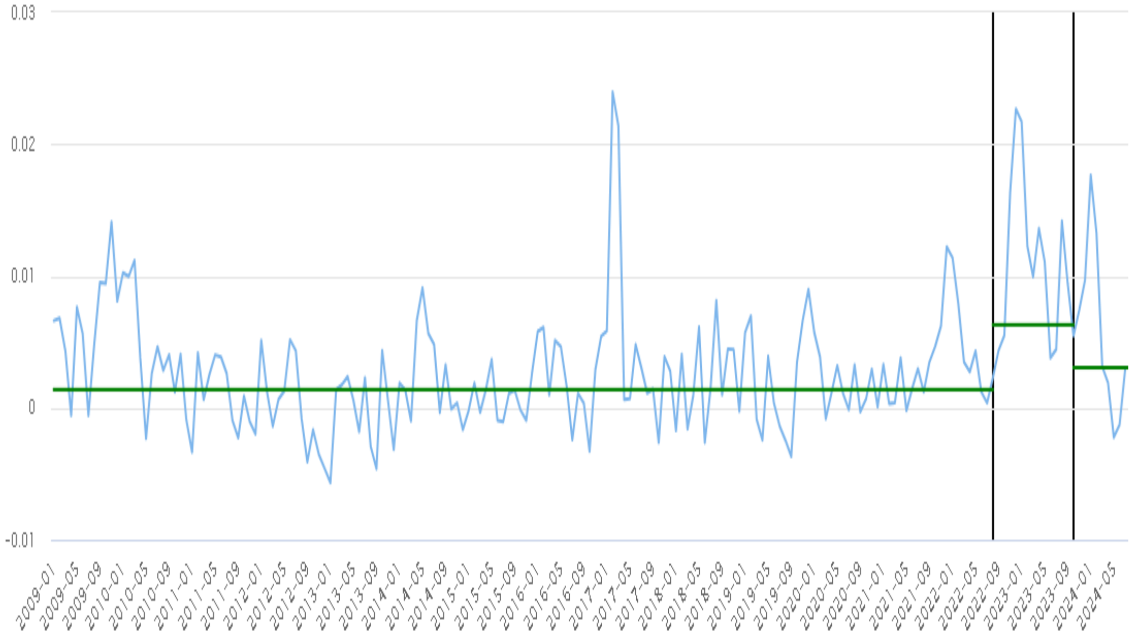


Figure 18: Breaks dates for Beer.
Source: Authors' calculations.

## 8.3 Methodology for break-points estimation

The Bai and Perron methodology (BP) is an efficient algorithm for finding the least squares break points based on a linear regression model for the time series of the form in equation (4). The basic steps would include testing for the presence of one (additional) break, via the $supF(0,1)$, and moving forward to test for the presence of $l+1$ breaks via the $F(l+1|l)$ ratio, stopping when the null is not rejected.

The strategy starts by supposing just one break point and trying all suitable points, choosing the one that produces the supF statistic for the hypothesis of no change against change at that selected time point. It is worth saying that intercept terms are considered a column in $z_{it}$; the method used is based on the non-parametric supF test.

To avoid a break near the beginning or the end of the series, we set the minimum trimming at 5% ($\approx 10$ data points for the whole sample). This limitation avoids the detection of breakpoints happening at the end of sample. Hidalgo and Seo (2013) propose a strategy to detect this kind of points but is still spending to be implemented on our data set. Bai et al (2020) presents a methodology to detect multiple breakpoints in a multivariate setup; it is to be expected that this kind of VAR detects breaks closer to the sample end.

The variance-covariance of $\delta$ embedded in this test is robust to heteroskedasticity and autocorrelation. Thus, the BP approach accounts for these features, unlike the information-criterion-based approaches. Other alternatives for testing structural changes are the Chow test, the Quandt Likelihood Ratio test, the CUSUM test, and the Hansen and Nyblom tests; but are not tried in this work.

The procedure sequentially increases the number of breaks from 1 to m until the sequential tests reject and estimate the structural change model with the corresponding estimated breaks. For that purpose, we use the *dosequa* function from the R package *mbreaks*. In this case, we apply the procedure to each series taken in first differences of logarithms (as **?**, suggests), one by one, and it returns a vector containing the dates when the structural changes occurred. With these results, a linear regression model is estimated for each segment generated by the employed structural breaks of each series, and the respective trend of the model is plotted. Alternatives to structural break models, like the one we used here, are time-varying parameter models, threshold AR models, Smooth transitions, and Markov-switching models.

Table 4: Breaks dates for every CPI item

| Name | # breaks | Date 1 | Date 2 | Date 3 | Name | # Breaks | Date 1 | Date 2 | Date 3 |
|---|---|---|---|---|---|---|---|---|---|
| Rice | 1 | Apr-2010 | | | Small electrical devices | 0 | | | |
| Pasta | 0 | | | | Cleaning products | 0 | | | |
| Oats & Derivat. | 0 | | | | Toiletries | 0 | | | |
| Wheat & Derivat. | 0 | | | | Hardware items | 0 | | | |
| Corn & Derivat. | 0 | | | | Disposable products | 0 | | | |
| Bread | 0 | | | | Domestic service | 0 | | | |
| Flours & Cereals | 1 | Mar-2021 | | | Pharm. & derm. products | 0 | | | |
| Other Bakery Prod. | 1 | May-2021 | | | Medical devices | 0 | | | |
| Beef and Deriv. | 0 | | | | Therapeutic equipment | 2 | Mar-2015 | Apr-2022 | |
| Pork Meat | 1 | May-2020 | | | Gral med. appoint. Priv. doc. | 0 | | | |
| Poultry | 0 | | | | Spec. med. consult. | 0 | | | |
| Processed Meats | 1 | Feb-2021 | | | Priv. dental serv. | 0 | | | |
| River & Seafood | 0 | | | | X-ray service | 1 | Jan-2022 | | |
| Milk | 0 | | | | Laboratory tests | 1 | Nov-2022 | | |
| Cheeses & Related | 0 | | | | Outpatient med. serv. | 0 | | | |
| Eggs | 0 | | | | Minor med. proced. | 1 | Mar-2021 | | |
| Dairy Products | 0 | | | | Private vehicle | 0 | | | |
| Edible Oils | 0 | | | | Motor & motor. bicycles | 0 | | | |
| Butter | 0 | | | | New or used bicycles | 0 | | | |
| Margarines & Fats | 0 | | | | Tires, tyres, rims | 0 | | | |
| Frozen Fruit | 1 | Aug-2021 | | | Veh. cleaning products | 0 | | | |
| Nuts | 1 | Jan-2022 | | | Bicycle parts | 1 | Dec-2014 | | |
| Oranges | 0 | | | | Other veh. spare parts | 1 | May-2014 | | |
| Bananas | 0 | | | | Additive, gear oil, etc | 0 | | | |
| Tamarillo | 0 | | | | Airline Passenger Transp. | 0 | | | |
| Blackberries | 0 | | | | Oil change | 1 | Mar-2021 | | |
| Fresh Fruit | 1 | Nov-2009 | | | Workshop Repairs | 1 | Nov-2022 | | |
| Dry Legumes | 0 | | | | Bodywork & Painting Serv. | 2 | Oct-2019 | Mar-2022 | |
| Preser. Legum. & Veget. | 0 | | | | Parking lots | 0 | | | |
| Plantains | 0 | | | | Vehicle expenses | 0 | | | |
| Potatoes | 0 | | | | School transp. | 1 | Aug-2021 | | |
| Cassava | 0 | | | | Tolls | 0 | | | |
| Deriv. of Tubers & Plant. | 0 | | | | Urban transp. | 0 | | | |
| Other Tubers | 0 | | | | Intercity transp. & others | 0 | | | |
| Tomato | 0 | | | | Vehicle fuel | 0 | | | |
| Onion | 0 | | | | Mobile phones | 0 | | | |
| Carrot | 0 | | | | Com. & Internet Serv. | 0 | | | |
| Fresh Veget. & Legum. | 0 | | | | Unique sound system | 1 | Feb-2013 | | |
| Sugar & Sweeteners | 0 | | | | Audiovisual equipment | 1 | Jan-2023 | | |
| Raw Panela | 0 | | | | Inform. Processing Equip. | 2 | Sep-2011 | Aug-2023 | |
| Jellies & Similars | 1 | Dec-2021 | | | Toys & Children's Games | 1 | Jan-2015 | | |
| Sweets & Similars | 1 | Aug-2022 | | | Party decor. & garments | 4 | Jun-2010 | Sep-2013 | Jan-2022 |
| Ice Cream & Similars | 1 | Dec-2021 | | | Pet food | 0 | | | |
| Jellies, Custards, & Pud. | 1 | Jun-2022 | | | Pet Veterinary Products | 0 | | | |
| Sauces, Dressings Pastes | 1 | Jan-2022 | | | Books & School Supplies | 0 | | | |
| Salt | 1 | May-2021 | | | Textbooks | 0 | | | |
| Soups & Creams | 2 | Jun-2021 | May-2023 | | Newspaper purchase | 0 | | | |
| Fried Foods | 0 | | | | Diverse Printed Material | 2 | Sep-2015 | Mar-2018 | |
| Seasonings & Herbs | 0 | | | | Stationery | 0 | | | |
| Powdered Milk | 0 | | | | Writing Supplies | 0 | | | |
| Preco. & Prepa. Foods | 1 | Dec-2021 | | | Pain. & Draw. Supplies | 0 | | | |
| Coffee & Coffee Products | 0 | | | | Natural Plants | 0 | | | |
| Chocolate & Products | 0 | | | | Veterinary Serv. and others | 1 | Jul-2021 | | |
| Tea & Infusions | 0 | | | | Recreative services | 0 | | | |
| Mineral water | 1 | Jan-2022 | | | Services in Sports Venues | 0 | | | |
| Name | # breaks | Date 1 | Date 2 | Date 3 | Name | # breaks | Date 1 | Date 2 | Date 3 |

| | | | | |
|---|---|---|---|---|
| Soft Drinks | 1 | Aug-2021 | | |
| Drink Mix Concentrates | 1 | Aug-2022 | | |
| Soda & malt | 0 | | | |
| Energy drinks | 0 | | | |
| Liquor | 0 | | | |
| Whisky & others | 0 | | | |
| Wine & others | 0 | | | |
| Beer & Refajo | 2 | Aug-2022 | Oct-2023 | |
| Cigarettes, tobacco, & der. | 1 | Sep-2016 | | |
| Dress clothes men | 1 | Dec-2021 | | |
| Dress clothes women | 0 | | | |
| Baby clothing | 2 | Dec-2021 | Aug-2023 | |
| Uniforms | 0 | | | |
| Dress clothes girls & boys | 2 | Dec-2021 | Aug-2023 | |
| Oth. Cloth. men & women | 3 | Jan-2014 | Nov-2020 | Dec-2022 |
| Men's shoes | 2 | Dec-2021 | Aug-2023 | |
| Women's shoes | 0 | | | |
| Shoes boys & girls | 0 | | | |
| Laundry & ironing clothes | 1 | Jan-2022 | | |
| Cash rent | 2 | Dec-2018 | Nov-2022 | |
| Owner hous. serv. expenses | 2 | Dec-2018 | Nov-2022 | |
| Hous. conserv. & rep. mater. | 1 | Dec-2020 | | |
| Co-ownership services | 1 | Dec-2022 | | |
| Water supply | 1 | Jun-2020 | | |
| Garbage collection | 0 | | | |
| Sewerage | 1 | Jun-2020 | | |
| Electricity | 1 | Oct-2021 | | |
| Gas | 0 | | | |
| Furniture | 0 | | | |
| Illumination equipment | 0 | | | |
| Other decorations | 0 | | | |
| Bedding | 0 | | | |
| Toiletry clothing | 1 | Aug-2020 | | |
| Fridge & freezer | 0 | | | |
| Washer dryer & dishwasher | 1 | Jan-2023 | | |
| Gas heaters & others | 1 | Oct-2014 | | |
| Small electrical appliances | 2 | Sep-2014 | Jul-2016 | |
| Glassware & dishes | 0 | | | |
| Non-elec. kitchen utens. | 1 | Dec-2014 | | |
| Cinemas & Theatres | 1 | Oct-2014 | | |
| TV Network & Cable | 0 | | | |
| All-inclusive packages | 0 | | | |
| Pre-school & prim. educ. | 0 | | | |
| High school | 0 | | | |
| Techno.-Techni.-Uni. enroll. | 0 | | | |
| Postgrad. admiss. & fees | 0 | | | |
| Other expe. in higher educ. | 0 | | | |
| Non-formal course | 0 | | | |
| Diplomas & others | 0 | | | |
| Paym. for tutor. & classes | 0 | | | |
| Tab. Cars & Deliv. serv. food | 3 | Apr-2021 | Jan-2022 | Apr-2023 |
| Hot drinks | 1 | Apr-2021 | | |
| Tab. Cars & Deliv. serv. soda | 1 | Oct-2021 | | |
| Prep. meals immed. consum. | 1 | Apr-2021 | | |
| Food in cafeterias | 0 | | | |
| Nightclub expenses | 0 | | | |
| Accommodation services | 1 | Jan-2022 | | |
| Pers. care elect. appl. | 2 | Aug-2014 | Dec-2015 | |
| Personal care items | 0 | | | |
| Body hygiene items | 0 | | | |
| Oral hygiene items | 1 | Sep-2021 | | |
| Beauty Products | 4 | Jun-2010 | Feb-2015 | Jul-2017 |
| Other Person. Care Prod. | 0 | | | |
| Art. Gold, Silver, & P. Ston. | 0 | | | |
| Watches & Others | 3 | Dec-2014 | Mar-2016 | Mar-2019 |
| Costume Jewelry | 0 | | | |
| Travel Accessories | 2 | Jan-2014 | Nov-2021 | |
| Baby Products | 2 | Jan-2014 | Oct-2022 | |
| Personal Products | 1 | Dec-2021 | | |
| Hairdressing Services | 1 | Jan-2022 | | |
| Social Protection Serv. | 0 | | | |
| Daycare & Nursery | 1 | Oct-2022 | | |
| EPS Contribution | 0 | | | |
| Health Insurance | 0 | | | |
| Vehicle Insurance | 0 | | | |
| Financial Services | 0 | | | |
| Certificates & Docum. | 0 | | | |
| Other services | 2 | Jun-2014 | Jul-2021 | |

## 8.4 Forecast Evaluation for alternative Periods

Table 5: Forecast Evaluation for Monthly *Inflation* (expanding windows)
Period: Jan-2020 - Aug-2024

| Horizon | Model | # Obs. | MFE | MAPFE | RMSFE | U-Theil |
|---|---|---|---|---|---|---|
| 1 | ARIMA | 56 | 0.077 | 624.19 | 0.35 | 0.71 |
| 1 | Middle up-ARIMA | 56 | 0.105 | 669.47 | 0.38 | 0.77 |
| 1 | Buttom up-ARIMA | 56 | 0.136 | 839.05 | 0.38 | 0.78 |
| 1 | ARMA+Breaks | 56 | 0.011 | 739.00 | 0.26 | 0.53 |
| 1 | Middle up-ARMA+Breaks | 56 | 0.007 | 547.68 | 0.29 | 0.60 |
| 1 | Bottom up-ARMA+Breaks | 56 | 0.055 | 585.58 | 0.28 | 0.57 |
| 2 | ARIMA | 55 | 0.142 | 553.43 | 0.48 | 0.86 |
| 2 | Middle up-ARIMA | 55 | 0.154 | 1003.58 | 0.49 | 0.87 |
| 2 | Bottom up-ARIMA | 55 | 0.172 | 1098.20 | 0.47 | 0.83 |
| 2 | ARMA+Breaks | 55 | 0.025 | 749.19 | 0.32 | 0.56 |
| 2 | Middle up-ARMA+Breaks | 55 | 0.033 | 533.15 | 0.37 | 0.66 |
| 2 | Bottom up-ARMA+Breaks | 55 | 0.071 | 669.72 | 0.32 | 0.57 |
| 3 | ARIMA | 54 | 0.181 | 946.57 | 0.53 | 0.82 |
| 3 | Middle up-ARIMA | 54 | 0.174 | 1205.59 | 0.52 | 0.81 |
| 3 | Bottom up-ARIMA | 54 | 0.187 | 1150.56 | 0.49 | 0.75 |
| 3 | ARMA+Breaks | 54 | 0.034 | 538.67 | 0.34 | 0.52 |
| 3 | Middle up-ARMA+Breaks | 54 | 0.035 | 664.03 | 0.38 | 0.59 |
| 3 | Bottom up-ARMA+Breaks | 54 | 0.086 | 837.81 | 0.35 | 0.54 |
| 6 | ARIMA | 51 | 0.246 | 830.50 | 0.55 | 0.72 |
| 6 | Middle up-ARIMA | 51 | 0.231 | 1316.53 | 0.55 | 0.72 |
| 6 | Bottom up-ARIMA | 51 | 0.210 | 1289.73 | 0.52 | 0.68 |
| 6 | ARMA+Breaks | 51 | 0.067 | 696.76 | 0.40 | 0.53 |
| 6 | Middle up-ARMA+Breaks | 51 | 0.029 | 658.56 | 0.42 | 0.56 |
| 6 | Bottom up-ARMA+Breaks | 51 | 0.089 | 927.71 | 0.39 | 0.50 |
| 9 | ARIMA | 48 | 0.291 | 602.03 | 0.57 | 0.75 |
| 9 | Middle up-ARIMA | 48 | 0.295 | 703.34 | 0.56 | 0.74 |
| 9 | Bottom up-ARIMA | 48 | 0.266 | 684.40 | 0.53 | 0.69 |
| 9 | ARMA+Breaks | 48 | 0.110 | 613.70 | 0.47 | 0.62 |
| 9 | Middle up-ARMA+Breaks | 48 | 0.069 | 995.28 | 0.49 | 0.65 |
| 9 | Bottom up-ARMA+Breaks | 48 | 0.119 | 833.47 | 0.44 | 0.58 |
| 12 | ARIMA | 45 | 0.340 | 709.33 | 0.56 | 0.85 |
| 12 | Middle up-ARIMA | 45 | 0.342 | 844.50 | 0.58 | 0.88 |
| 12 | Bottom up-ARIMA | 45 | 0.326 | 715.50 | 0.55 | 0.84 |
| 12 | ARMA+Breaks | 45 | 0.153 | 1065.46 | 0.53 | 0.80 |
| 12 | Middle up-ARMA+Breaks | 45 | 0.125 | 1140.95 | 0.54 | 0.82 |
| 12 | Bottom up-ARMA+Breaks | 45 | 0.141 | 881.68 | 0.47 | 0.71 |

## 8.5 A view of the Application for series handling and forecast

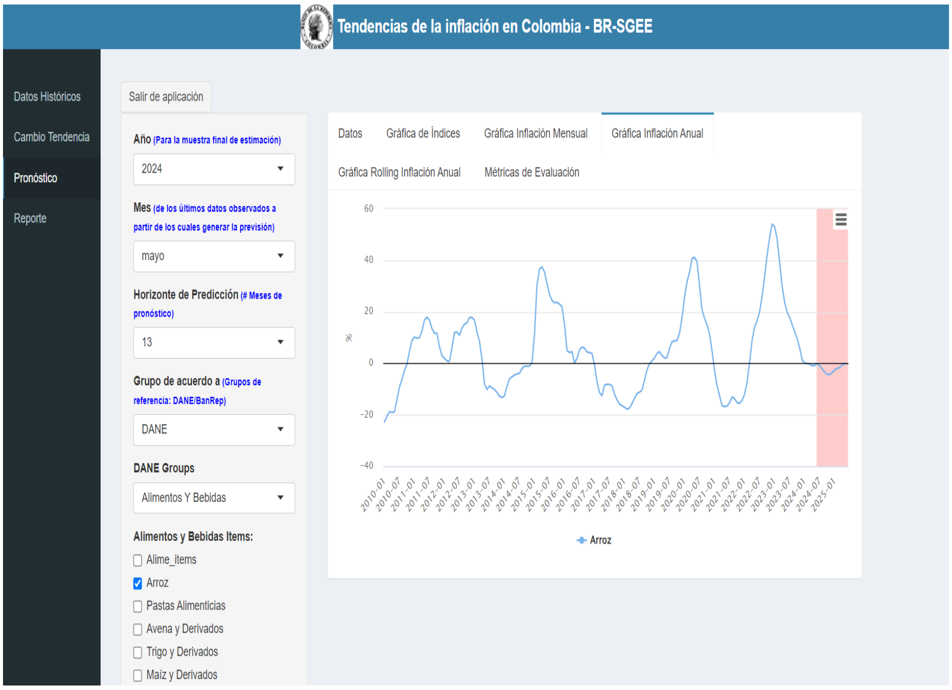


Figure 19: App Forecast for "rice".