Turning Points in Inflation: A Structural Breaks Approach with Micro Data*

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PRELIMINARY DRAFT

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Abstract

We introduce a novel methodology for detecting inflation turning points that combines high-frequency, disaggregated price data with standard structural break techniques to provide policymakers with more precise and timely signals of inflation dynamics. The methodology consists of three key components: measuring inflation as the slope of the log price index rather than using conventional inflation rates, employing structural break techniques to detect shifts in this slope, and leveraging highly disaggregated price indexes to identify trend breaks at a granular level. We apply this approach to study two critical recent episodes: Argentina's 2024–2025 disinflation and the inflationary impact of U.S. tariff adjustments in 2025. For Argentina, we detect a broad-based disinflationary turning point in mid-2024. For the U.S., we find significant sectoral inflation accelerations in early 2025, notably in food and furnishings, despite stable aggregate inflation measures. These applications demonstrate the utility of our approach for enhancing real-time inflation monitoring and policy decision-making.

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1 Introduction

Identifying turning points in inflation dynamics is critical for policymakers operating in a context of data uncertainty and lagged policy impact. This was particularly evident during the 2021–2024 global inflation surge, as central banks debated the timing and magnitude of interest-rate adjustments. In most countries, monetary authorities were surprised by the speed and magnitude of inflation in 2021 and early 2022, as well as by the uneven disinflation that followed in 2023 and 2024. Inflation concerns resurfaced in early 2025 when the United States threatened to impose broad tariffs on many countries. These episodes of uncertainty underscore the limitations of standard inflation measures—such as annual or monthly price changes—which are often distorted by base effects and short-term volatility, making it difficult to identify turning points in inflation dynamics.

Over the past few decades, the econometrics literature has made significant methodological improvements for detecting structural breaks in macroeconomic time series, including shifts in inflation trends (see Casini & Perron, 2018 for a comprehensive survey). However, the low frequency and publication lags of official Consumer Price Index (CPI) data have largely confined these methods to historical analyses of long-run aggregate trends, limiting their utility for real-time policy decisions. This paper bridges that gap by introducing a novel methodology that combines high-frequency, disaggregated price data with standard structural break techniques to detect inflation turning points with greater precision and timeliness.

Our approach can be summarized in three key elements. First, rather than using conventional inflation rates, we measure inflation trends using the slope of the log price index. This measure provides a stable estimate of the price level's growth rate and avoids common problems associated with inflation rates, such as *base effects* and short term volatility. Second, we use standard structural break techniques to detect significant shifts in the slope of the log price index. Third, we leverage highly disaggregated price indexes constructed from online price data to detect these breaks at a granular level and define a *turning point* as a date when the majority of the sectors of the CPI basket have experienced a significant shift in the same direction (either slowdown or acceleration).

We first demonstrate how our approach can be used to detect broad-based inflation turning points by applying it to the 2022–2023 U.S. inflation slowdown. While some standard indicators showed softening price pressures by early 2023, uncertainty remained about whether this marked a genuine turning point. Using data available through April 2023, our methodology detects a significant inflation shift as early as September 2022. By April 2023, almost 80% of the CPI basket—weighted by expenditure shares—had experienced a statistically significant negative break in the slope of the log price index. In contrast to traditional metrics, which offered only tentative signals, our framework provides early and robust evidence of the specific timing of a broad-based disinflationary turning point.

We then apply our methodology to two recent events: Argentina's 2024 disinflation and the inflationary effects of U.S. tariff adjustments in 2025. First, in the case of Argentina, we show that the disinflation process began in early 2024. Despite significant volatility in monthly inflation rates—and considerable debate in the press—the underlying trend remained relatively stable through April 2025. Shortly after the government eased certain foreign exchange capital controls, we observe renewed evidence of a further deceleration. Second, using recent U.S. microdata, we find that while the impact of tariffs is not yet visible in aggregate indices, disaggregated price data reveal a clear and significant acceleration in underlying pricing pressures.

The remainder of this paper proceeds as follows. Section 2 details our methodology, including the structural break framework and the PriceStats dataset, and shows how our approach can be used to detect broad-based inflation turning points, using the 2022–2023 U.S. inflation slowdown as an illustrative case study. Section 3 extends the analysis to two more recent applications: the Argentina's 2024 disinflation and the effect of the tariffs in the U.S. in early 2025. Lastly, section 4 concludes.

2 Methodology and Data

Our methodology to identify broad-based inflation turning points consists of three key components: i) we measure inflation as the slope of the log price index rather than using conventional inflation rates; ii) we employ standard structural break techniques to detect shifts in the slope of the log price index; iii) we leverage highly disaggregated price indexes constructed from microdata to identify trend breaks at a granular level and define a *turning point* as a date when the majority of the sectors of the CPI basket have experienced a significant shift in the slope of the log price index in the same direction (slowdown or acceleration).

This section proceeds as follows. Firstly, we introduce the PriceStats dataset. Then, we justify our focus on the slope of the log price index over traditional inflation rates and present the trend-break detection methodology. Next, we show how our approach can be used to detect broad-based inflation turning points, using the 2022–2023 U.S. inflation slowdown as an illustrative case study. Finally, while high-frequency data offer advantages in terms of timing and precision, we demonstrate that our methodology can also be effectively applied to conventional monthly CPI data.

2.1 High-Frequency Price Indices

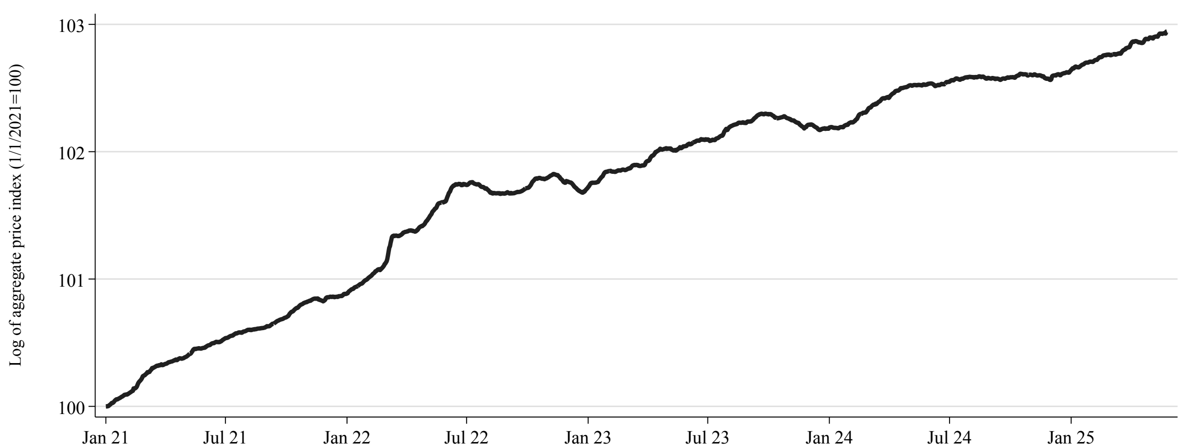
We use daily price indices produced by PriceStats, a private firm that tracks inflation in over 25 countries using data collected from the websites of large multi-channel retailers. These indices—and the underlying microdata—have been widely used in academic research by members of the Billion Prices Project, the HBS Pricing Lab, and other scholars for a variety of purposes.

Most relevant to this paper, they have been shown to closely mirror official CPI statistics in many countries and frequently anticipate shifts in aggregate inflation trends (see Cavallo, 2013 and Cavallo & Rigobon, 2016).[1]

In this paper, we analyze daily price indices for the United States and Argentina covering the period from January 1, 2021, through May 26, 2025. These indices provide high-frequency information on consumer prices across a broad range of goods and services. Specifically, the dataset includes six major CPI sectors classified at the 1-digit COICOP level, along with 76 subsectors at the 3-digit level. On average, the indices capture approximately 60% of the expenditure weights used in the official CPI calculations for each country. While coverage is nearly comprehensive for goods within the CPI basket, representation of services is more limited. In particular, the indices do not include any measures of shelter costs, such as actual rents or owners' equivalent rents, which are typically a substantial component of official inflation statistics.

A striking feature of these indices is that, despite their high frequency, they tend to display stable inflation trends that often persist for weeks or months, making it easier to detect trend changes. Figure 1 illustrates this by showing the U.S. aggregate log-price index over the full sample period.[2] A simple visual inspection of the index's slope reveals several turning points, most notably the slowdown in mid-2022. The structural-breaks methodology introduced in Section 2.3 provides a systematic way to identify such shifts across all levels of aggregation.

Figure 1: US Aggregate Daily Price Index



Notes: This figure shows the log of the daily US aggregate price index computed from all the sectors covered in the PriceStats dataset. We normalize the index to 100 on Jauary 1st, 2021.

[1]For comparisons between online and brick-and-mortar price levels, see Cavallo (2017). For a comparison of online and traditional retail pricing behaviors, see Goolsbee and Klenow (2018).

[2]As shown in Figure A-1, despite a level difference due to coverage gaps, the PriceStats aggregate index captures trend changes similar to those observed in the official CPI—often with less delay.

2.2 Slope of the Price Index

Analyzing the slope of the price indices offers several advantages over conventional inflation rates. First, the slope of the log price index provides a stable estimate of the price level's growth rate, which we refer to as the *inflation trend*.[3] This measure proves particularly useful for detecting turning points and informing real-time policy decisions, as it captures an underlying *trend* that can persist for weeks, months, or even years—without requiring a pre-specified window of analysis, as is typically the case with conventional monthly or annual inflation rates.

Second, using the price index avoids common problems associated with inflation *rates*, which are calculated by comparing the price level at two discrete points in time. In the case of annual rates, this comparison is made relative to prices twelve months earlier. As a result, these measures are highly sensitive to *base effects*—that is, changes in the inflation rate driven not by current price movements, but by what happened a year ago. This can mislead observers into interpreting inflation as accelerating or decelerating, even when the underlying trend remains stable. For instance, as shown in Appendix Figure A-2, between January and October 2023 the US annual inflation rate was falling, despite the fact that the price index trend showed no significant change over that period. In addition, month-to-month inflation rates tend to be highly volatile, making it difficult to discern meaningful shifts in underlying inflation dynamics. As shown in Appendix Figure A-3, the monthly inflation rate for the US fluctuates considerably over the full period, introducing noise that can obscure genuine turning points. In contrast, the log price index in Figure 1 shows persistent trends are more readily visible, allowing for a clearer identification of shifts in inflation momentum.

Furthermore, annual and monthly inflation rates are sensitive to abrupt price-level shifts that may not correspond to changes in the inflation trend. Such distortions can occur, for instance, due to tax adjustments, currency devaluations, or regulatory price changes, which can trigger sudden jumps in price levels without affecting the overall trend. This phenomenon is illustrated in Appendix Figure A-4, which presents the effect of changes in the U.K. energy price cap on the aggregate log price index, monthly inflation, and annual inflation. While Panel A shows a discrete level shift in the log price index with an unchanged trend, both the monthly and annual inflation rates exhibit significant spikes in response to the shock, with the annual rate remaining elevated for several months.

2.3 Detecting Structural Breaks

The first step to finding a turning point in inflation is to identify trend breaks in individual price series. To achieve this, we rely on structural-break test methodologies that are standard

[3] Note that this definition differs from the long-term average rate of inflation—or "trend inflation"—often estimated using time-series models to isolate cyclical fluctuations (Stock & Watson, 2016). In our approach, the inflation trend is defined as the slope of the index between structural breaks.

in the literature (see Casini & Perron, 2018 for a comprehensive survey). In this section, we describe the single-break methodology, which allows us to detect the single date $\hat{T}_b^*$ with the most significant break in the slope of the log price index within a given period. This methodology is particularly suitable for short periods, in which the likelihood of multiple breaks is small. For longer time series, we later extend this methodology to allow for multiple breaks.

Consider, for each price series, the following model:

$$p_t = \delta_1 + \beta_1 DT_t + \delta_2 I[t > T_b] + \beta_2\, DT_t \times I[t > T_b] + \mu_t, \quad t = t_1, ..., T_b, ..., T \tag{1}$$

where p_t is the log price level at time t, DT_t is a deterministic trend, and μ_t is the disturbance. This model allows for a single break at $t = T_b$. Since we are interested in trend breaks (and not in level breaks), we focus on β_2. If $\beta_2 = 0$, there is no trend break. If $\beta_2 \neq 0$, there is a trend break at $t = T_b$. Since the breakpoint T_b is unknown, we need to determine its location before testing the significance of β_2.

Bai (1997) and Bai and Perron (1998) show that one can consistently estimate the location of these breaks using Ordinary Least Squares (OLS), even when the number of breaks is underspecified. But although the consistency of the OLS estimator has been well documented for level shifts models, the simulations and asymptotic analysis in Yang (2017) show that this strategy fails to hold in trend models. When the number of breaks is underspecified, the trend break estimator does not converge to one of the true break dates. A simple solution to the inconsistency problem, as proposed by Yang (2010), is to take first differences and look for level shifts in the first-differences model. Yang (2012) provides a detailed comparison between the level and first-differences estimators and shows that, when the breaks are sufficiently large, the first-difference estimator has much higher peaks in the density at the true breaks than the levels break point estimator. For this reason, we estimate the following first-differences model for each price series:

$$p_t - p_{t-1} = \alpha_1 + \alpha_2\, I[t > T_b] + \mu_t, \quad t = t_1, ..., T_b, ..., T \tag{2}$$

where $p_t - p_{t-1}$ is the first difference of the observed price level at time t, and μ_t is the disturbance. Let $\hat{\alpha}_1(T_j)$ and $\hat{\alpha}_2(T_j)$ be the OLS estimates when the break is assumed to occur at some point $t = T_j$. For each $T_j \in (t_1, T)$, the sum of squared residuals (SSR) is given by:

$$SSR(T_j) = \sum_{t=t_1}^{T_j} \left[(p_t - p_{t-1}) - \hat{\alpha}_1(T_j)\right]^2 + \sum_{t=T_j+1}^{T} \left[(p_t - p_{t-1}) - \hat{\alpha}_1(T_j) - \hat{\alpha}_2(T_j)\right]^2 \tag{3}$$

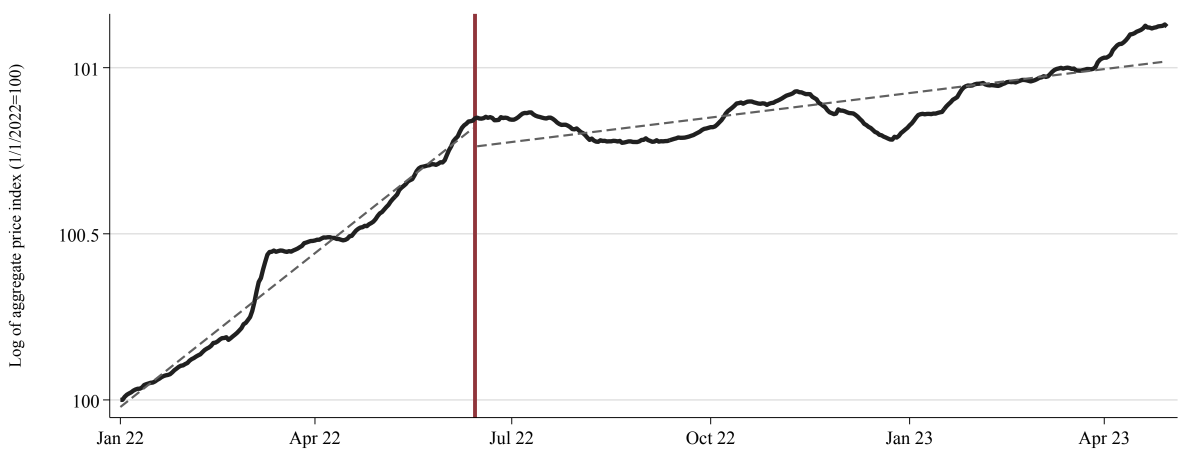
The estimated break point $\hat{T}_b^*$, with the associated parameter estimates $\{\hat{\alpha_1}(\hat{T}_b^*), \hat{\alpha_2}(\hat{T}_b^*)\}$, is the one that produces the minimum SSR. Since $\hat{T}_b^*$ can take a finite number of values in the discrete interval (t_1, T), we can find it by a grid search. To avoid the possibility of estimating a break near the beginning or the end of the series, we set a trimming of 10%. To increase the efficiency of the search process, we use the algorithm developed by Bai and Perron (2003a) based on the principle of dynamic programming.

Once we find the breakpoint $\hat{T}_b^*$ that produces the minimum SSR, we can test its significance by using a Supreme F-Test:

$$H_0 : \alpha_2(\hat{T}_b^*) = 0 \quad vs \quad H_A : \alpha_2(\hat{T}_b^*) \neq 0$$

We reject the null if the SSR from the model with a break at $\hat{T}_b^*$ is *sufficiently* smaller than the SSR of the model with no breaks according to a standard F-Test. Since $\hat{T}_b^*$ is the breakpoint that minimizes the SSR, it is also the breakpoint that produces the maximum F-Statistic. The asymptotic critical values for a 10% trimming rate are provided in Bai and Perron (2003b). We adopt a heteroskedasticity and autocorrelation-consistent (HAC) estimator for the covariance matrix of the disturbance. Since $\hat{T}_b^*$ is the breakpoint that produces the minimum SSR, under the null we conclude that there is no break at $t = \hat{T}_b^*$ nor at any other date. Under the alternative, we conclude that there is a break at $t = \hat{T}_b^*$.

Figure 2: US Aggregate Price Index - Single Break Methodology



Notes: This figure shows the log of the daily US aggregate price index computed from all the sectors covered in the PriceStats dataset. We normalize the index to 100 on Jauary 1st, 2022. The red vertical line indicates the trend break identified using the methodology described in Section 2.3. The grey dashed lines represent the estimated linear trend before and after the break.

To illustrate the single-break methodology, in Figure 2, we apply it to the U.S. aggregate price index from January to April 2023. We identify a significant negative trend break on June

14th.

While the single-break methodology is well suited for short time spans, it may fail to capture the full complexity of inflation dynamics in longer time series, where multiple structural changes are more likely. In such cases, the approach can be extended to allow for multiple breaks, enabling a more comprehensive identification of trend shifts over time. This extension involves estimating a sequence of breakpoints that partition the series into multiple regimes, each characterized by a distinct trend. The procedure, detailed in Appendix B, builds on the work of Bai (1997) and Bai and Perron (1998), and can be further enhanced using a double maximum test as suggested by Bai and Perron (2006).

2.4 Broad-Based Turning Points

While applying the structural break methodology to a single aggregate price index can yield useful insights—as illustrated in Figure 2—it may also produce misleading or inconclusive results when the detected break is driven by just one or a few prominent sectors.

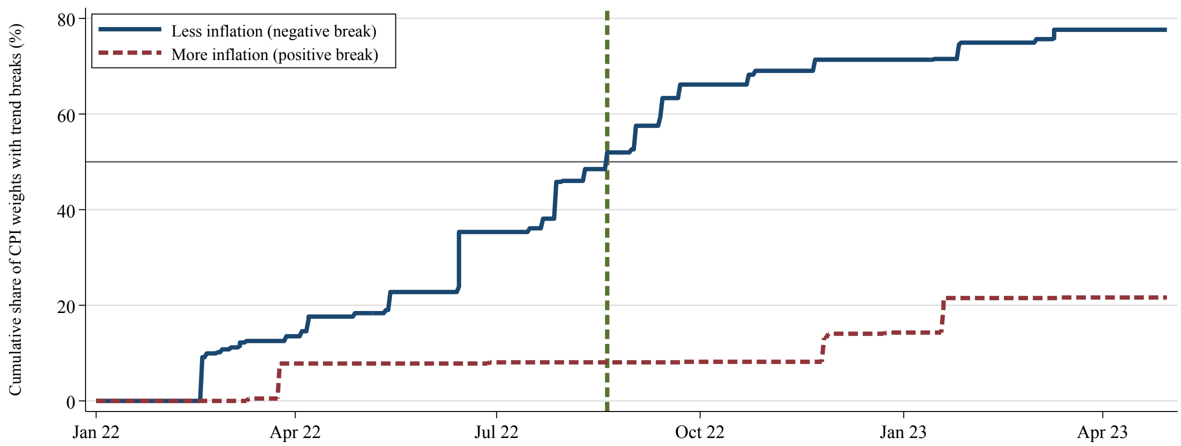
For example, the trend break identified in June 2022 coincides with a sharp change in fuel prices. In this case, not only was the magnitude of the fuel price change substantial, but the sector's weight in the overall CPI basket is also significant. When looking at this data in real-time, the key uncertainty is whether such a break reflects a broad-based shift in inflation dynamics or simply the outsized influence of a specific category.

To illustrate this, Figure A-5 shows the estimated breaks for some relevant 1-digit sectors around the time of the aggregate break. Panels A and B depict the estimated breaks for two of the most volatile headline sectors in the US: *transportation* and *food and beverages*. The transportation sector, which is considerably driven by fuel, experienced a large negative structural break on June 15th, 2022. Food also experienced a negative break, but it happened on September 14th and was of a much smaller magnitude (hard to detect by just looking at the graph). There are also significant differences if we focus on some core goods sectors, as shown in panels C and D. The sector *household and furnishings* experienced a small but early break on April 7th, 2022, shortly after the Federal Reserve started to increase interest rates. This might be expected because this sector includes many durable goods, which are presumably more sensitive. By contrast, the *recreation and electronics* sector experienced no structural break at all, despite a notable seasonal decline in the price level around the holidays.

A more comprehensive understanding of the underlying inflation trends can be obtained by looking at the price indices computed at the more disaggregated level available. Specifically, we apply the single-break methodology to each level-3 COICOP category and compute, by date, the cumulative share of sectors in the CPI basket —weighted by expenditure weights— with positive and negative trendbreaks. We then define an *inflation turning point* as a date when more than 50% of the CPI basket shows a statistically significant shift in the slope of the log price index in the same direction, either an acceleration or deceleration.

Figure 3 shows the results. The cumulative share of weights with negative trend breaks (blue solid line) rises steadily throughout 2022, surpassing the 50% threshold in September (dashed vertical line). These results therefore suggests that the true turning point in inflation occurred around September 2022, when the majority of the CPI basket—by expenditure weight—had already shifted to a new disinflationary trajectory.

Figure 3: Cumulative Share of US CPI Weights with Trend Breaks

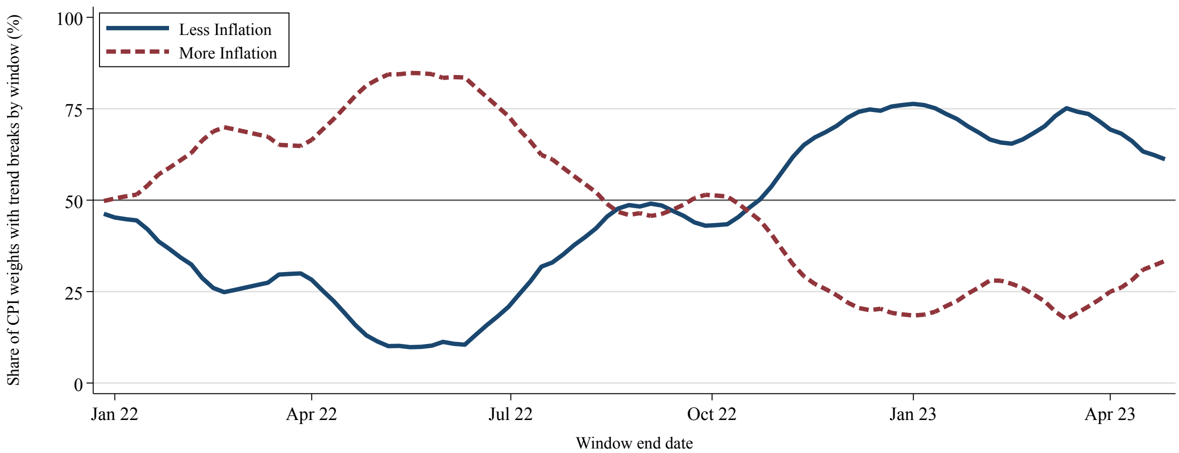


Notes: This figure shows the cumulative share of CPI weights with positive (more inflation) and negative (less inflation) breaks between January and April 2023. To identify the breaks in each COICOP level-3 sector we use the single-break methodology described in Section 2.3.

So far, we have started our analysis from a fixed point in time—January 2022— which is appropriate for studying inflation dynamics after a large shock or policy response episode. However, as the sample expands over time, this approach becomes less reflective of current conditions and may obscure more recent shifts in inflation trends. An alternative is to rely a rolling-window version of the single-break methodology, which allows us to continuously update the analysis and detect turning points as new data become available, making it particularly suitable for real-time applications.

To illustrate this method, we define 12-month rolling windows from January 2022 to April 2023 and apply the single-break test to each 3-digit COICOP category within each window. We then aggregate the results by calculating the share of CPI weights that exhibit either negative or positive trend breaks in each window. The key intuition behind this design is that while price series in high-volatility environments may experience multiple breaks over long horizons, they are less likely to do so within shorter, 12-month windows—making the single-break approach more robust and informative for detecting timely shifts in inflation trends.

Figure 4: Share of Weights with Breaks - 12-Month Rolling Windows



Notes: This figure shows the share of CPI weights with negative (blue solid line) and positive (red dashed line) in each 12-month rolling windows. The x-axis indicates the end of the window. To estimate the breaks within each window, we use the single-break methodology described in Section 2.3

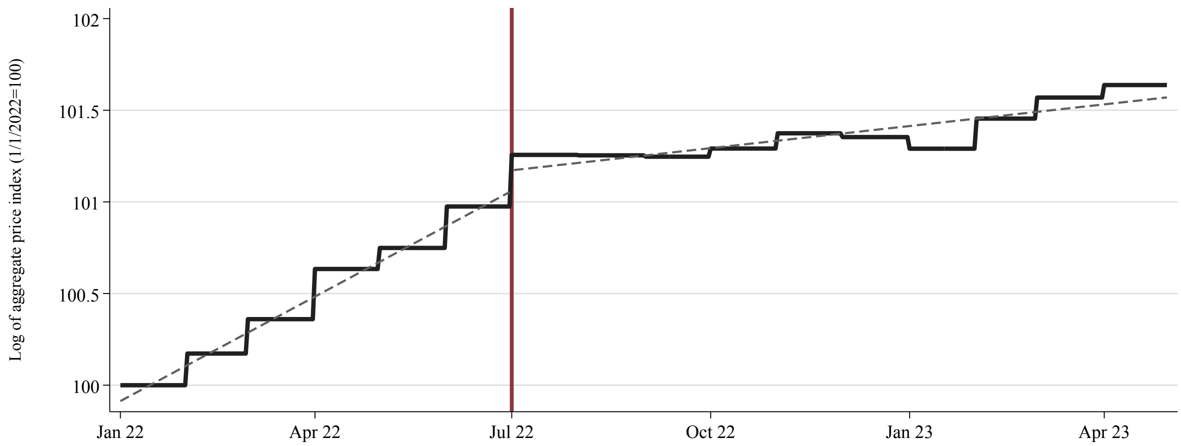
Figure 4 presents the results, revealing two clearly defined periods. From January to June 2022, the share of CPI weights exhibiting positive trend breaks—indicating rising inflation—increased steadily. This trajectory reversed sharply in mid-2022, and the share of weights with negative breaks accelerated rapidly. Between September and November 2022, this share surpassed 50% and continued rising into early 2023. By later 2022, the majority of basket weights were already on a disinflationary trajectory compared to 12 months before.

Interestingly, however, this shift was not yet apparent to policymakers relying on conventional monthly or annual inflation rates. For example, in a speech on November 30, 2022, Federal Reserve Chair Jerome Powell remarked that ”while October inflation data received so far showed a welcome surprise to the downside, these are a single month's data, which followed upside surprises over the previous two months... down months in the data have often been followed by renewed increases. It will take substantially more evidence to give comfort that inflation is actually declining.”[4] A month later, in December, he reiterated after an FOMC meeting that "it will take substantially more evidence to give confidence that inflation is on a sustained downward path"[5]. In contrast, the methodology proposed in this paper would have provided clear and timely evidence by September 2022 that the disinflationary path was already well established at that time.

The real-time usefulness of the rolling-window approach is further illustrated in Section 3.2, where we extend the analysis through 2025 and study the inflationary impact of the U.S. tariff adjustments.

[4] (Powell, 2022)
[5] (Committee, 2022)

Figure 5: Single Break Methodology - Monthly CPI Data



Notes: This figure shows the log of the daily US aggregate price index computed from all the sectors covered in the PriceStats dataset. We normalize the index to 100 on Jauary 1st, 2022. The red vertical line indicates the trend break identified using the methodology described in Section 2.3. The grey dashed lines represent the estimated linear trend before and after the break.

2.5 Application to CPI Data

The PriceStats data described in Section 2.1 offers the advantage of high-frequency coverage, enabling more timely detection of trend shifts. However, our structural-break methodology remains applicable to lower-frequency CPI data and continues to outperform traditional monthly or annual inflation measures in many respects, as discussed in Section 2.2. This is especially true when the underlying shocks or breaks in the series are large, as such shifts can still be reliably identified even with less frequent observations.

To illustrate this, we apply the single-break methodology to the U.S. CPI aggregate index from January to December 2022 (Figure 5). A negative structural break is identified on July 1—approximately two weeks after the break detected using the high-frequency PriceStats data (Figure 2). Despite this modest detection lag, the results based on CPI data closely mirror those obtained from higher-frequency series. Appendix Figure A-6 further supports this consistency: replicating the disaggregated analysis using CPI data produces results that are nearly identical to those in Figure 3. Similarly, Appendix Figure A-7 replicates the rolling-windows analysis from Figure 4 using CPI data, producing results that are closely aligned with those derived from the daily price series.

3 More Recent Applications

In this section, we apply our approach to study two more recent events: Argentina's 2024 disinflation and the inflationary effects of U.S. tariff adjustments in 2025.

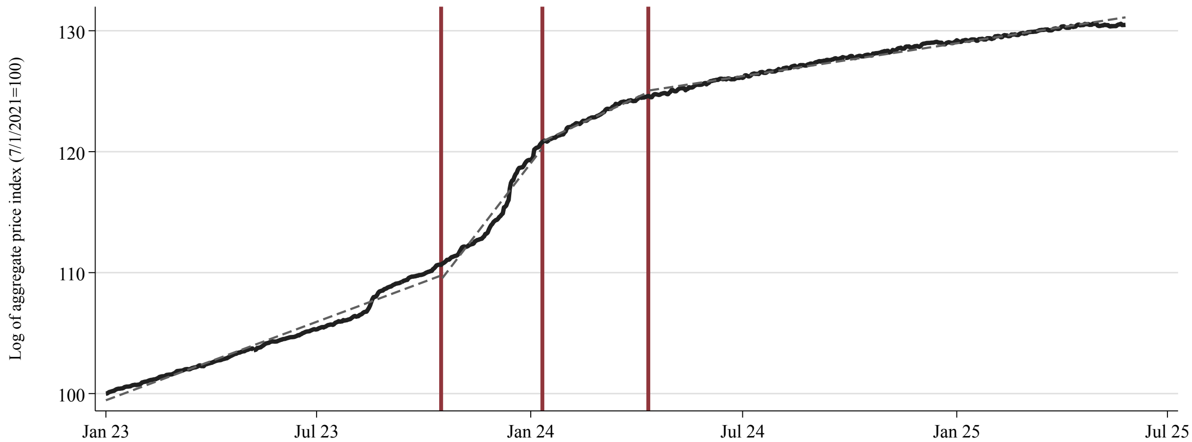
3.1 The Argentinian Disinflation in 2024-2025

Over the past few decades, Argentina experienced an increasingly high inflation. Since 2024, however, inflationary pressures have shown signs of easing driven by a strong fiscal adjustment. This section analyzes Argentina's 2024 disinflation to demonstrate how our methodology can provide policymakers in volatile economies with timely signals of inflation accelerations or slowdowns.

Figure 6 displays the aggregate log price index for Argentina, constructed using all sectors available in the PriceStats dataset. We apply the multiple-break methodology outlined in Appendix B and identify three structural breaks: one positive break (indicating inflationary accelerations) in October 2023, and two disinflationary breaks (the first in January 2024 and the second one in April 2024).

These breaks coincide with significant shifts in Argentina's economic policy. In late 2023, the country experienced a surge in inflation following a currency devaluation and the expansionary monetary and fiscal measures implemented before the general elections. After December 2023, the new government launched an aggressive fiscal austerity policy, deregulation, and currency stabilization measures to combat inflation, achieving a budget surplus that resulted in a structural break in the price trend in January, and another significant slowdown in April 2024. Notably, despite considerable public attention on monthly inflation volatility, the overall inflation trend remained remarkably stable through the end of the sample in April 2025.

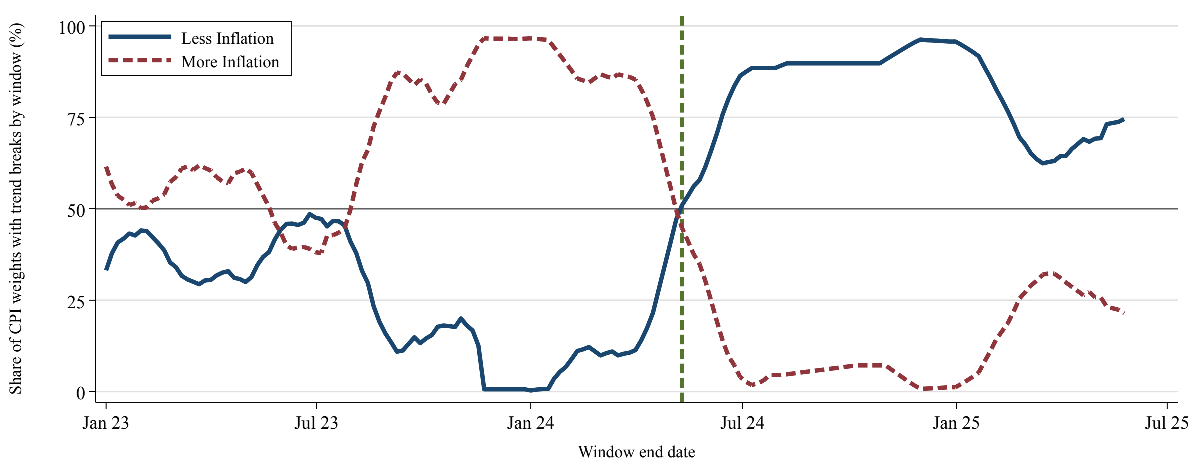
Figure 6: Argentina Aggregate Price Index - Multiple Breaks Methodology



Notes: This figure shows the log of the daily aggregate price index for Argentina computed from all the sectors covered in the PriceStats dataset. We normalize the index to 100 on Jauary 1st, 2021. The red vertical lines indicate the trend breaks identified using the methodology described in Section 4. The grey dashed lines represent the estimated linear trends within two breaks.

To further disentangle the scope of these aggregate breaks, we analyze level-3 COICOP sectors individually and apply the rolling-window version of the single-break methodology described in Section 2.4 to estimate the timing of the turning point in inflation.

Figure 7: Argentina - Rolling Windows Analysis



Notes: This figure shows the share of CPI weights with negative (blue solid line) and positive (red dashed line) in each 12-month rolling windows. The x-axis indicates the end of the window. For instance, the green vertical line corresponds to the window that starts on May 10th, 2023 and finishes on May 10th, 2024. To estimate the breaks within each window, we use the single-break methodology described in Section 2.3.

Figure 7 presents the results. The share of sectors with positive breaks (more inflation) increases steadily after a major devaluation of the Peso in August 2024. By the beginning of

2024, nearly all sectors were on a higher inflationary trajectory than a year before. In April the share of sectors with negative breaks (less inflation) started to increase, and we can identify a disinflationary turning point on May 10, 2024. Shortly after, the share of sectors with negative breaks exceeds 90%, underscoring the rapid and broad-based nature of the disinflation.

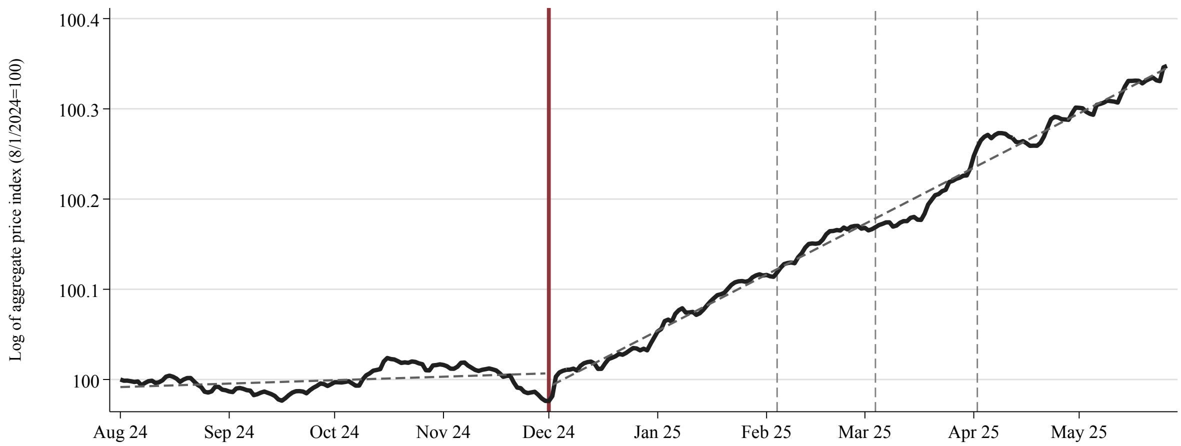
A noteworthy feature of Figure 7 is the renewed increase in the share of sectors experiencing disinflation around mid-April 2025. While this episode does not meet our formal definition of a turning point, it marks a clear deepening of the disinflationary trend. It also highlights the value of disaggregated data: although no break is yet evident in the aggregate price index at this time—at least not one comparable in size to earlier shifts—the sector-level results indicate a renewed momentum in disinflation. The timing coincides with policy announcements by the Argentine government to ease foreign exchange controls (the so-called *cepo*), suggesting that this move may have significantly influenced inflation expectations and pricing behavior among retailers in the sample.

3.2 USA 2025 - The Effect of the Tariffs

In early 2025, the U.S. government announced broad tariffs on imports from several countries. This policy move raised concerns among policymakers and economists about a resurgence of inflationary pressures. In this section, we use our structural breaks approach to assess the short-run impact of the U.S. tariffs on inflation.

First, examining the U.S. aggregate price index, we find no clear evidence of a significant positive break that coincides with the announcement and implementation of the tariffs. As shown in Figure 8, applying the single-break methodology to the aggregate index from August 2024 to May 2025 does not reveal a statistically significant acceleration of inflation in early 2025. Instead, we identify an inflationary break in December 2024, as shown in Figure 1, primarily driven by an upward shift in the price trends of transportation and energy, detailed in Appendix Figure A-8. This break also aligns with a recurring seasonal pattern observed in the aggregate index over a longer time horizon. However, following this break, the aggregate index remained relatively stable through May 2025, with no additional significant trend shifts that could be clearly linked to the timing of the new tariff announcements and implementation dates, indicated by the dashed vertical lines in the figure.

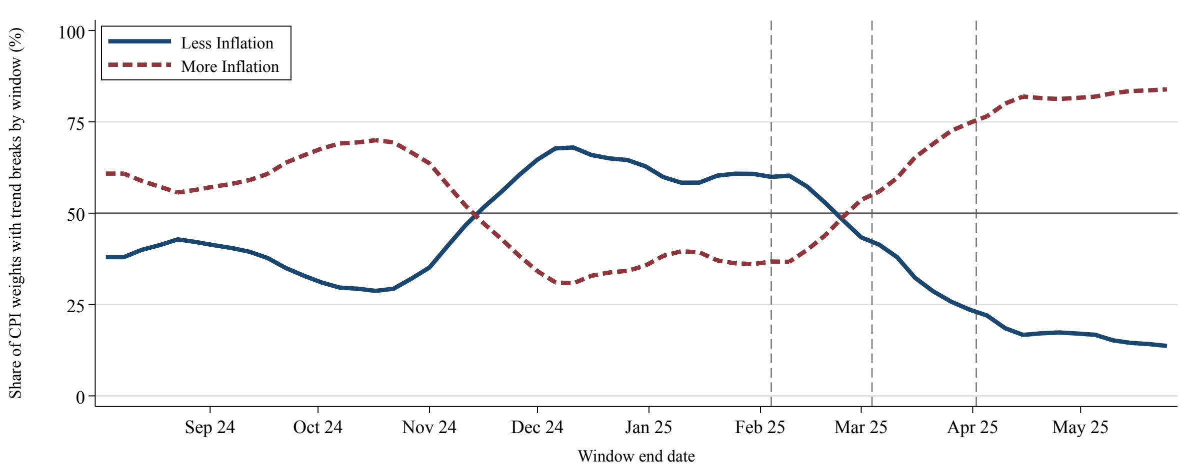
Figure 8: US Aggregate Price Index - Single Break Methodology



Notes: This figure shows the log of the daily US aggregate price index computed from all the sectors covered in the PriceStats dataset. We normalize the index to 100 on Jauary 1st, 2022. The red vertical line indicates the trend break identified using the methodology described in Section 2.3. The grey dashed lines represent the estimated linear trend before and after the break.

However, aggregate measures can mask emerging inflationary pressures at the sector level. A more granular analysis reveals a different story. Extending the rolling-window analysis from Section 2.4 through May 2025, Figure 9 shows a notable increase in the share of CPI weights experiencing positive trend breaks immediately after the first additional tariffs on China were implemented on February 4th.

Figure 9: United States - Rolling Windows Analysis



Notes: This figure shows the share of CPI weights with negative (blue solid line) and positive (red dashed line) in each 12-month rolling windows. The x-axis indicates the end of the window. To estimate the breaks within each window, we use the single-break methodology described in Section 2.3.

These results point to a broad-based rise in sectoral inflation trends, even as the aggregate index remained relatively stable. This highlights the importance of disaggregated analysis for real-time monitoring of inflation dynamics, particularly when inflationary pressures are driven by targeted policy interventions. To identify which sectors were most affected by the tariffs, we apply the single-break methodology to each level-1 COICOP category. As shown in Figure A-8, the sectors experiencing significant inflationary breaks around the time of the tariff implementation include *food and beverages*, *household furnishings*, and *electronics*—suggesting these categories were particularly sensitive to the trade measures.

4 Conclusion

This paper introduces a novel approach to detect inflation turning points that combines high-frequency, disaggregated price data with standard structural break techniques. Our methodology addresses the limitations of conventional inflation measures, such as annual or monthly inflation rates, which often fail to capture underlying trends due to base effects and short-term volatility.

Applying our methodology to recent inflation episodes, we demonstrated its effectiveness in providing early and precise signals of inflation turning points. The 2022-2023 U.S. inflation slowdown served as a key case study, where our approach identified a significant disinflationary shift as early as September 2022, ahead of traditional metrics which provided only tentative indications. Furthermore, the application to Argentina's 2024 disinflation revealed that significant negative inflation trends could be detected in real-time even in highly volatile economies. Similarly, our analysis of the 2025 U.S. tariffs highlighted the importance of sector-level data in understanding inflationary impacts. Despite the absence of a positive break in the aggregate index, key sectors such as household furnishings, clothing, and electronics show signs of renewed inflationary pressures coinciding with the timing of the policy announcements and implementations.

By offering a more precise and timely identification of inflation turning points, our aim is to support more informed and agile policy responses—especially in environments marked by data uncertainty and delayed policy transmission, where early recognition of trend shifts is crucial for effective decision-making. While our findings demonstrate the practical value of this approach, further research is needed to adapt the methodology to seasonally adjusted data, to refine how we distinguish between statistically significant and economically meaningful breaks, and to explore extensions that allow its effective application to lower-frequency data.

References

Bai, J. (1997). Estimating multiple breaks one at a time. *Econometric theory*, *13*(3), 315–352. (Publisher: Cambridge University Press)

Bai, J., & Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica : journal of the Econometric Society*, 47–78. (Publisher: JSTOR)

Bai, J., & Perron, P. (2003a). Computation and analysis of multiple structural change models. *Journal of applied econometrics*, *18*(1), 1–22. (Publisher: Wiley Online Library)

Bai, J., & Perron, P. (2003b). Critical values for multiple structural change tests. *The Econometrics Journal*, *6*(1), 72–78. (Publisher: Oxford University Press Oxford, UK)

Bai, J., & Perron, P. (2006). Multiple Structural Change Models: A Simulation Analysis. In B. E. Hansen, D. Corbae, & S. N. Durlauf (Eds.), *Econometric Theory and Practice: Frontiers of Analysis and Applied Research* (pp. 212–238). Cambridge: Cambridge University Press. Retrieved 2023-06-13, from https://www.cambridge.org/core/books/econometric-theory-and-practice/multiple-structural-change-models-a-simulation-analysis/E0DFD2531E66B2B1A4516EB8B99C6E36 doi: 10.1017/CBO9781139164863.010

Casini, A., & Perron, P. (2018). Structural breaks in time series. *arXiv preprint arXiv:1805.03807*.

Cavallo, A. (2013). Online and Official Price Indexes: Measuring Argentina's Inflation. *Journal of Monetary Economics*, *60*(2), 152–165.

Cavallo, A. (2017). Are Online and Offline Prices Similar? Evidence from Large Multi-Channel Retailers. *American Economic Review*, *107*(1).

Cavallo, A., & Rigobon, R. (2016). The Billion Prices Project: Using Online Data for Measurement and Research. *Journal of Economic Perspectives*, *30*(2), 151–78.

Committee, F. O. M. (2022, December 14). *Transcript of chair powell's press conference.* Retrieved from https://www.federalreserve.gov/mediacenter/files/FOMCpresconf20221214.pdf (Board of Governors of the Federal Reserve System)

Goolsbee, A. D., & Klenow, P. J. (2018). Internet Rising, Prices Falling: Measuring Inflation in a World of E-Commerce. *AEA Papers and Proceedings*, *108*, 488–492. Retrieved 2018-07-25, from https://www.aeaweb.org/articles?id=10.1257/pandp.20181038 doi: 10.1257/pandp.20181038

Powell, J. H. (2022, November 30). *Speech by chair powell on the economic outlook, inflation, and the labor market.* Retrieved from https://www.federalreserve.gov/newsevents/speech/powell20221130a.htm (Board of Governors of the Federal Reserve System)

Stock, J. H., & Watson, M. W. (2016). Core inflation and trend inflation. *Review of Economics and Statistics*, *98*(4), 770–784. Retrieved 2025-05-29, from https://direct.mit.edu/rest/article-abstract/98/4/770/58346 (Publisher: The MIT Press)

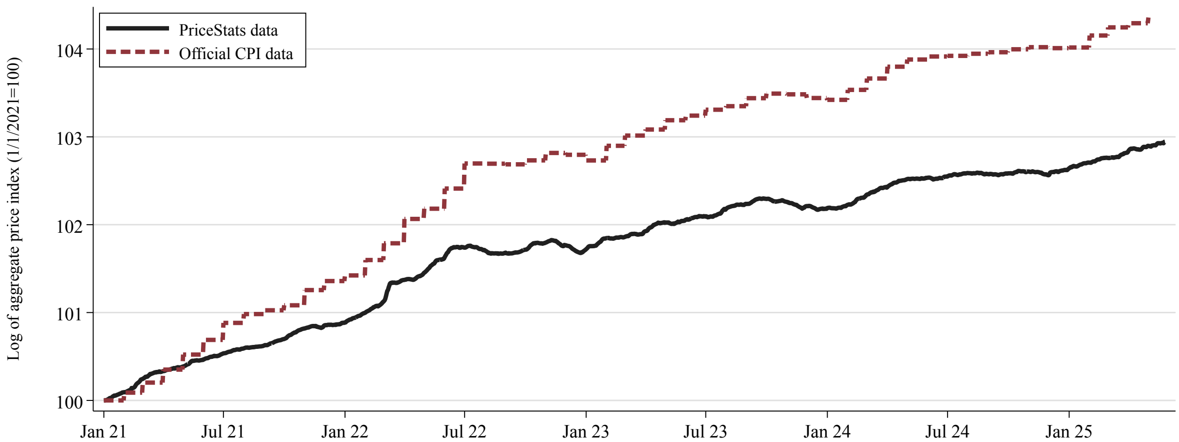
Yang, J. (2010). *Essays on estimation and inference in models with deterministic trends with and without structural change*. Michigan State University. Economics.

Yang, J. (2012). Break point estimators for a slope shift: levels versus first differences. *The Econometrics Journal*, *15*(1), 154–169. Retrieved 2023-09-23, from https://academic.oup.com/ectj/article-abstract/15/1/154/5060279 (Publisher: Oxford University Press Oxford, UK)

Yang, J. (2017). Consistency of trend break point estimator with underspecified break number. *Econometrics*, *5*(1), 4. (Publisher: MDPI)

Appendix A

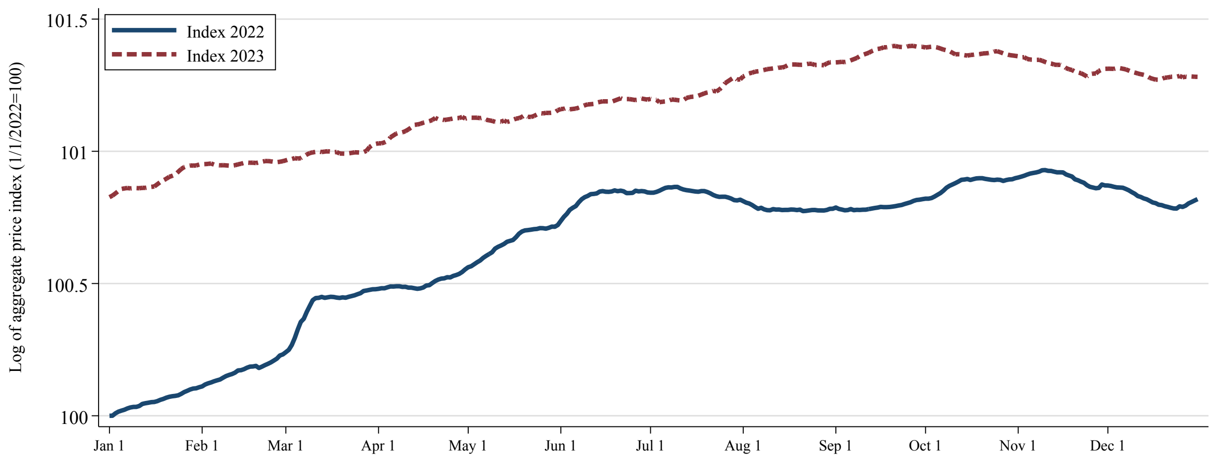
Figure A-1: US Aggregate Daily Price Index - Official CPI vs PriceStats Data



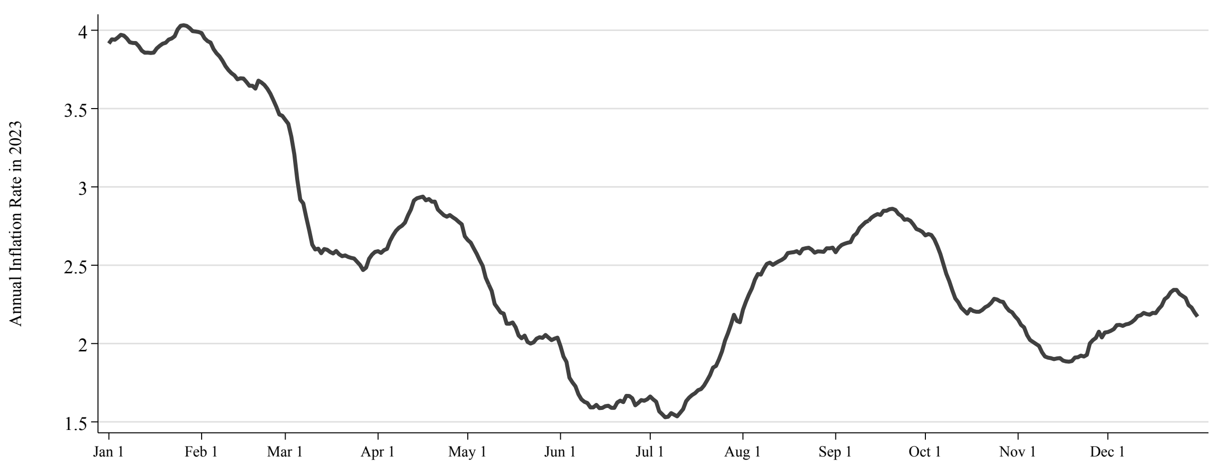
Notes: This figure shows the US aggregate log price index using PriceStats data (black solid line) and official CPI data (red dashed line). We normalize the indices to 100 on January 1st, 2021.

Figure A-2: Base Efffects in Annual Inflation Rates

A. U.S. Price Index in 2022 and 2023

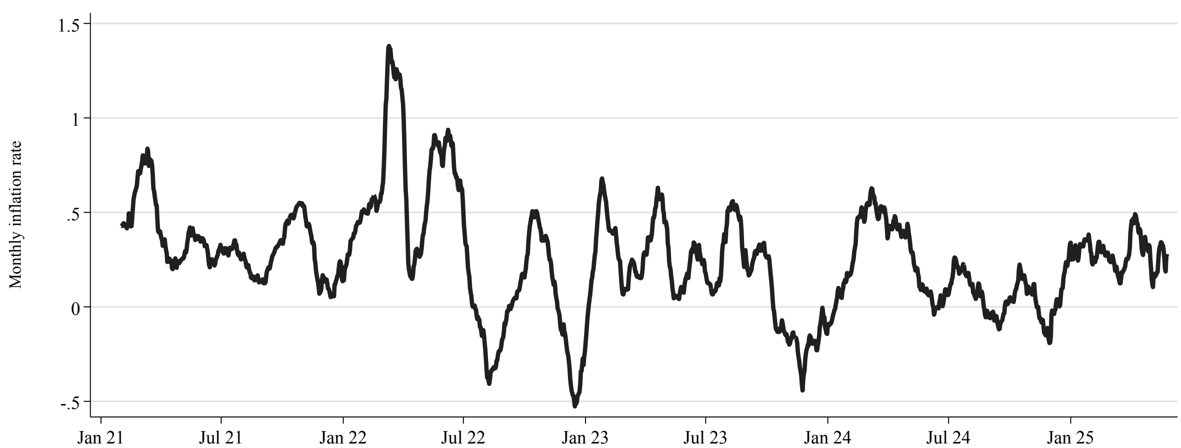


B. U.S. Annual Inflation Rate in 2023



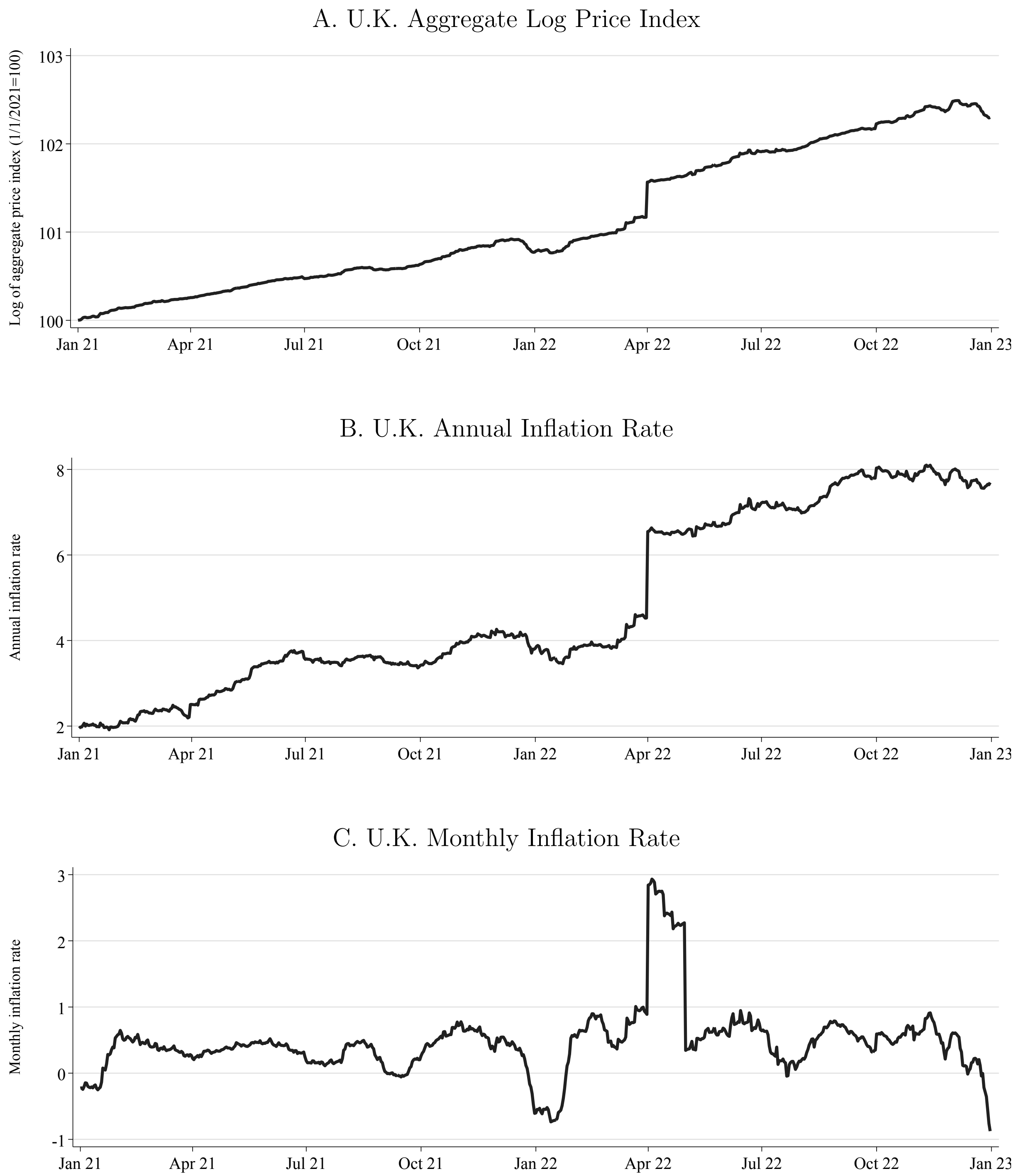
Notes: Panel A shows the US aggregate index for 2022 (blue solid line) and 2023 (red dashed line) normalized to 100 on January 1st, 2022. Panel B shows the annual inflation rate during 2023. We use the daily data from PriceStats described in Section 2.1.

Figure A-3: US Aggregate Monthly Inflation Rate



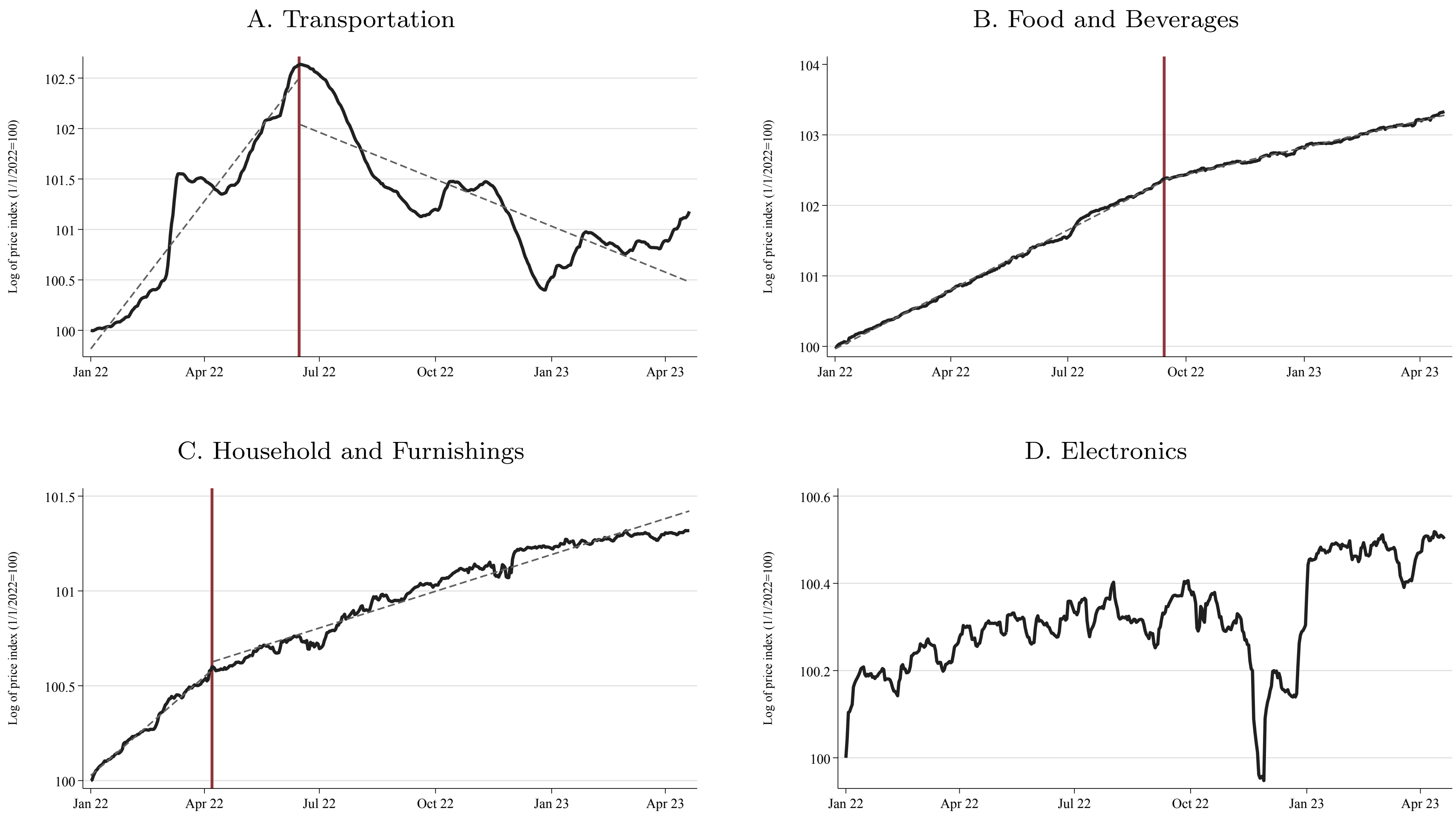
Notes: This figure shows the monthly inflation rate based on the daily US aggregate price index computed from all the sectors covered in the PriceStats dataset.

Figure A-4: U.K. Aggregate Index and Inflation Rates



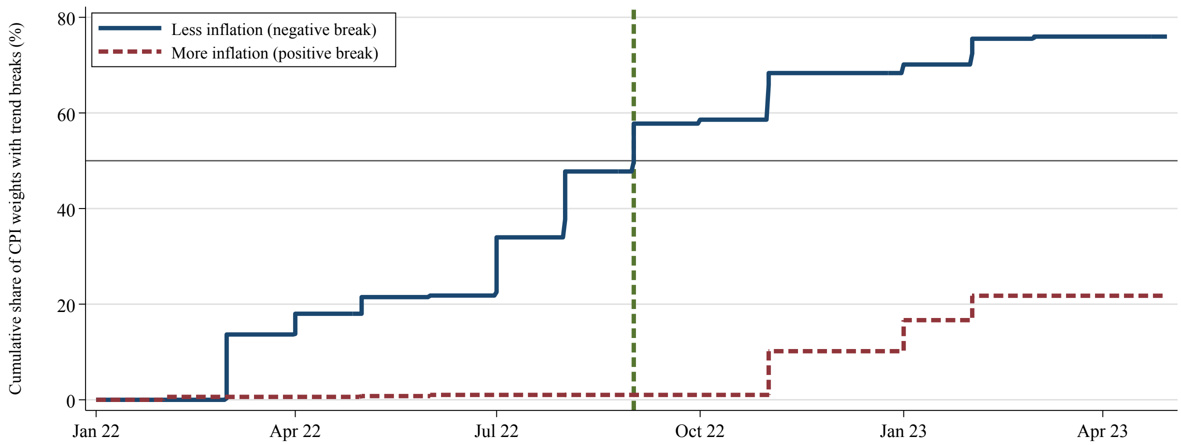
Notes: Panel A shows the shows the log of the daily U.K. aggregate price index computed from all the sectors covered in the PriceStats dataset. Panels B and C show the annual and monthly inflation rates computed from this daily index, respectively.

Figure A-5: US Level 1 Sectors - Single Break



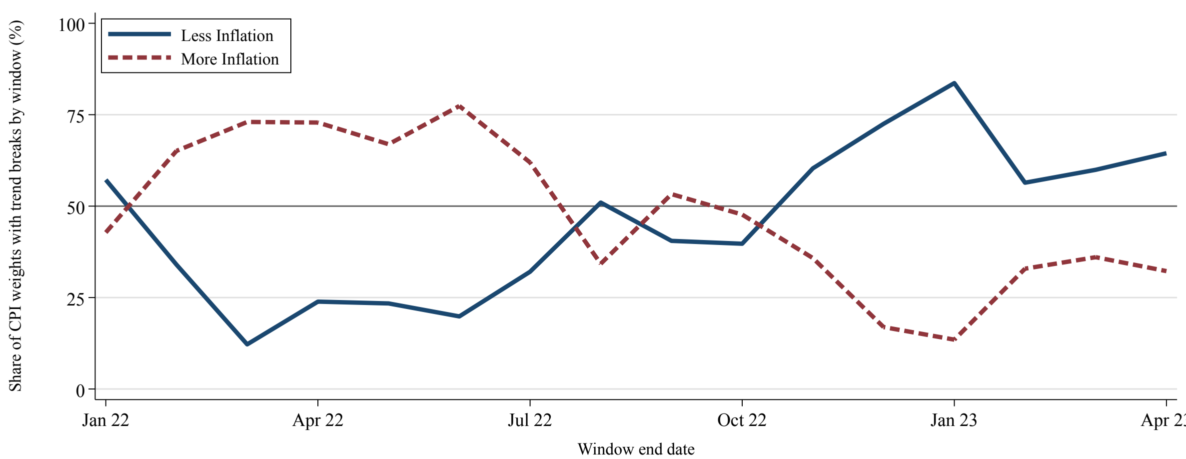
Notes: This figure shows the log of the daily US price index for four different level-1 sectors. We normalize the indexes to 100 on Jauary 1st, 2022. The red vertical lines indicate the trend break identified using the methodology described in Section 2.3. The grey dashed lines represent the estimated linear trend before and after the break.

Figure A-6: Cumulative Share of US CPI Weights with Trend Breaks - CPI Data



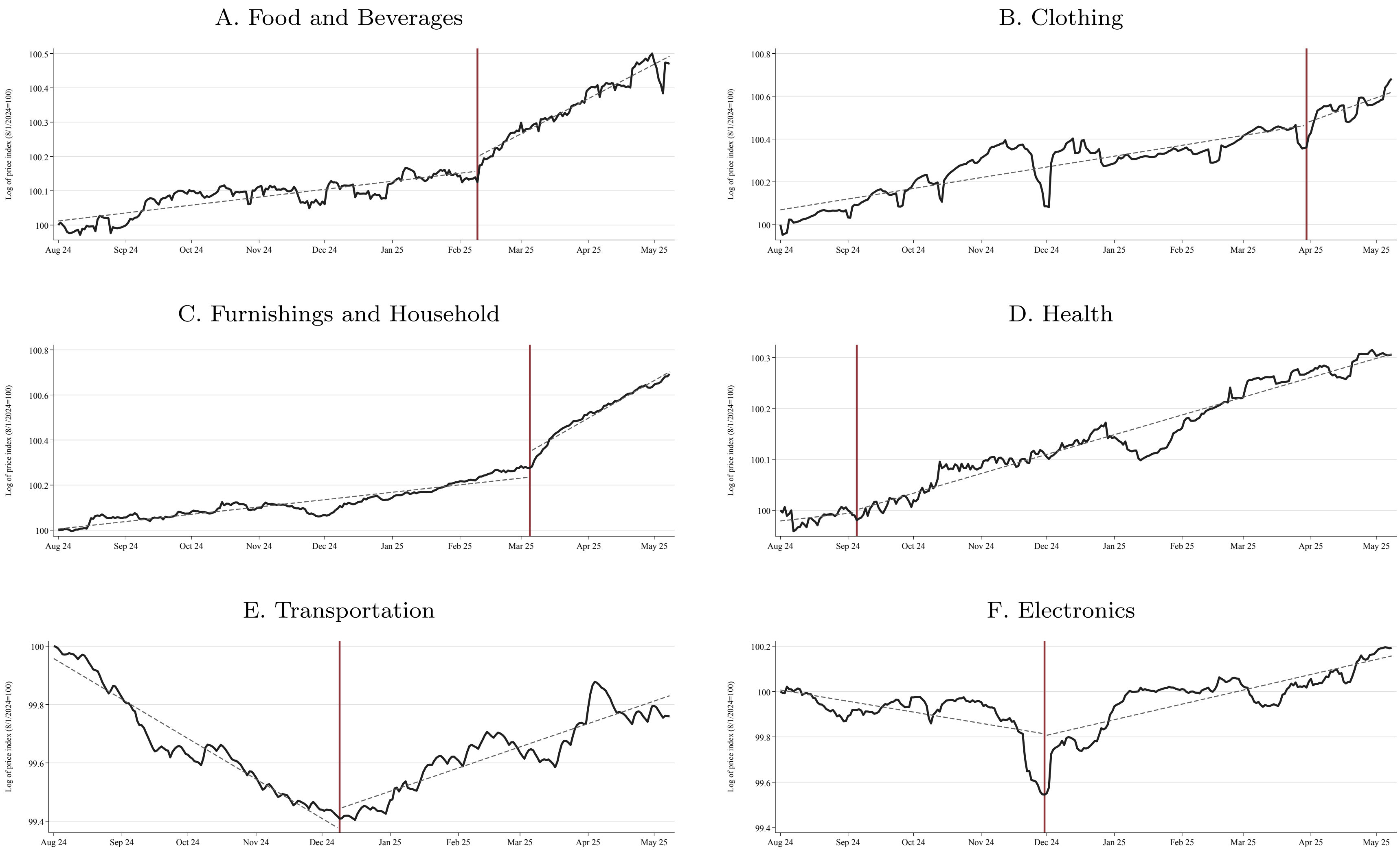
Notes: This figure shows the cumulative share of CPI weights with positive (more inflation) and negative (less inflation) breaks between January and December 2022. To identift the breaks in each COICOP level-3 sector we use the single-break methodology described in Section 2.3.

Figure A-7: Share of Weights with Breaks - 12-Month Rolling Windows - CPI Data



Notes: This figure shows the share of CPI weights with negative (blue solid line) and positive (red dashed line) in each 12-month rolling windows. The x-axis indicates the end of the window. To estimate the breaks within each window, we use the single-break methodology described in Section 2.3.

Figure A-8: The Effect of Tarrifs on US Level 1 Sectors - Single Break Analysis



Notes: This figure shows the log of the daily US price index for four different level-1 sectors. We normalize the indexes to 100 on Jauary 1st, 2022. The red vertical lines indicate the trend break identified using the methodology described in Section 2.3. The grey dashed lines represent the estimated linear trend before and after the break.

Appendix B: Multiple Breaks Methodology

While the single-break methodology is effective for short time spans, it may fail to capture important shifts when applied to longer time series, where multiple structural changes are more likely. In such cases, the approach can be naturally extended to accommodate multiple breaks.

Consider the following model for each price series:

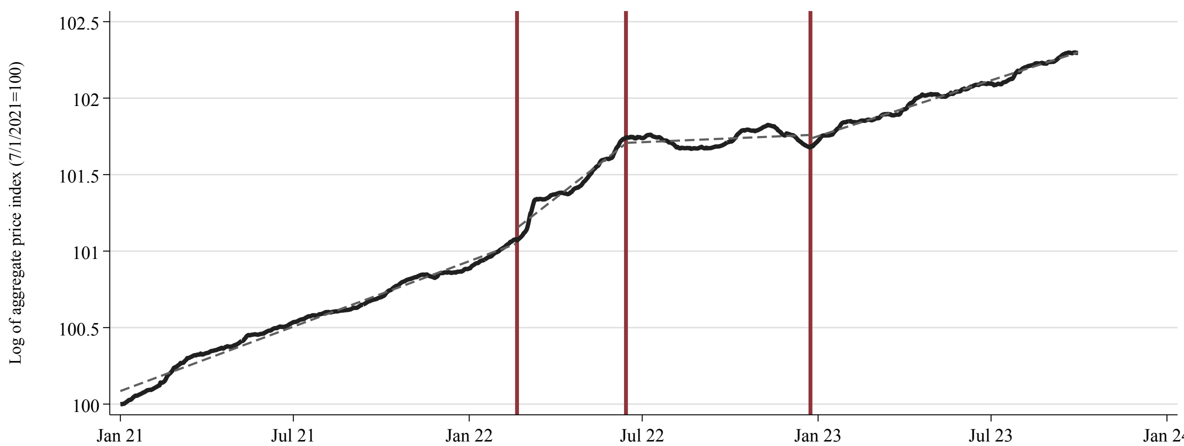
$$p_t - p_{t-1} = \alpha_j + \mu_t, \quad t = T_{j-1} + 1, ..., T_j, \tag{4}$$

for $j = 1, ..., m + 1$. This model allows for m breaks (or $m + 1$ regimes). The breakpoints $(T_1, ..., T_m)$ are unknown. Following Bai (1997) and Bai and Perron (1998), we estimate all the breakpoints sequentially using Ordinary Least Squares. The sequential procedure works as follows. Start by testing for a single break using the Supreme F-Test described in Section 2.3. If a break is detected at some date T_b^*, then test the null of one break against the alternative of two breaks. To do so, perform a Supreme F-Test inside each of the two subsamples obtained by cutting off at T_b^*. If a new break T_b^{**} is found, then repeat the process inside each of the new subsamples obtained by cutting off at T_b^{**}. By repeating this procedure until the null of s breaks is not rejected in favor of the alternative of $s + 1$ breaks, we can consistently estimate the location of all the breaks.

Bai and Perron (2006) show via simulations that there are instances where the performance of the sequential procedure described above can be improved using a double maximum test for the null of no breaks against the alternative of $1 \leq m \leq M$ breaks. The procedure is the following: 1) compute the Supreme F-Statistic for each $m = 1, ..., M$; 2) keep the highest F-Statistic among the ones computed in step 1; 3) perform a standard F-Test using the statistic chosen in step 2. If the null of no breaks is rejected, then perform the sequential procedure to determine the exact number of breaks. Starting with a double maximum test is particularly useful for cases where more than one break is present, but it is hard to distinguish between no breaks and one break.

To illustrate the multiple-breaks methodology, in Figure B-1 we apply it to the U.S. aggregate price index from January 2021 to October 2023. We identify three significant trend breaks: there is an inflation speed-up on February 20, 2022, a marked slowdown on June 14, 2022, and a new acceleration on December 24, 2022.

Figure B-1: US Aggregate Price Index - Multiple Breaks Methodology



Notes: This figure shows the log of the daily US aggregate price index computed from all the sectors covered in the PriceStats dataset. We normalize the index to 100 on Jauary 1st, 2021. The red vertical lines indicate the trend breaks identified using the methodology described in Section 4. The grey dashed lines represent the estimated linear trends within two breaks.