Inflation in the News: Numerical Precision, Sensational Framing, and Round-Number Effects*

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Abstract: How do news outlets report inflation, and how does inflation crossing round-number thresholds, such as 5 or 10 percent, affect that coverage? We study a large corpus of inflation-related headlines from 175 mainstream news outlets across 29 European countries, spanning 2017–2024. Beyond the sharp rise in coverage volume during the early 2020s inflation surge, we document novel patterns in headline composition. As inflation rises, the numerical precision of reported inflation figures declines, while sensational framing follows an inverted-U shape, rising initially but declining at particularly high inflation rates. Using a regression discontinuity design, we find that crossings of round-number thresholds induce discrete shifts in headline composition, most notably toward headlines reporting inflation in multiples of five. These findings imply that the media do not merely transmit official inflation statistics but alter how inflation is communicated to the public, in ways that may have economic effects beyond the underlying change in inflation.

Keywords: inflation, left-digit bias, media coverage, numerical precision, sensational framing

JEL classification: D83, E31, L82

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1. Introduction

Inflation in most European economies reached double digits in 2022, the first sustained high-inflation episode in over four decades. Inflation headlines changed with it. In Germany, for instance, the inflation rate crossed 10 percent in September 2022. Before the surge, one German outlet reported *Consumer prices rise by 1.6 percent*. A few years later, with the rate above 10 percent, another led with *Highest rate in 70 years: Inflation rises to 10 percent*.[1] While the first headline reports a decimal figure with neutral framing, the second reports a round number and presents the news as a historical record.

Such changes in media coverage are worth studying because they affect how inflation is communicated to the public. Most households learn about inflation not from statistical releases but from the news. In the Eurozone, survey evidence places mass media well ahead of other sources of inflation information (D'Acunto *et al.*, 2024, Fig. 6). Shifts in media coverage of inflation may therefore alter the inflation signal that reaches the public, potentially affecting household decisions about consumption, saving, and labor supply, as well as the formation of inflation expectations (Lamla and Lein, 2014; Larsen *et al.*, 2021; Binder *et al.*, 2025).

In this paper, we study how inflation coverage changes during an inflation surge. Motivated by anecdotal evidence such as the headlines above, we investigate dimensions that have not been studied in the context of inflation coverage. Specifically, besides coverage volume, we analyze changes in the numerical precision of reported values and in sensational framing through references to historical records and arousing language. Both the opening example and the literature on left-digit bias—the tendency to treat round numbers as reference points and to react disproportionately when one is crossed (e.g., Pope and Simonsohn, 2011; Lacetera *et al.*, 2012; Strulov-Shlain, 2023; List *et al.*, 2023)—suggest that round-number thresholds may matter for how inflation is presented in news coverage along these dimensions. We therefore examine whether changes in inflation coverage occur as discrete shifts at round-number thresholds, for instance, when inflation moves from 9.9 to 10.1 percent. If the amount or composition of coverage shifts discretely at those thresholds, the media do not merely transmit official inflation statistics but alter how inflation is presented, in ways that may have economic effects beyond the underlying change in the inflation rate itself.

Our data cover 277,911 inflation-related headlines from 175 mainstream online news

[1]The first headline is from *Süddeutsche Zeitung*, March 13, 2019. The German original is *Verbraucherpreise steigen um 1,6 Prozent*. The second is from *Der Tagesspiegel*, September 29, 2022, with the German original being *Höchste Rate seit 70 Jahren: Inflation steigt im September auf 10 Prozent*. Both headlines are part of our dataset described in detail in section 2.

outlets across 29 European countries, published between January 2017 and December 2024. We obtain the headlines from the Global Database of Events, Language, and Tone (GDELT; see Leetaru and Schrodt 2013) and use human-coded annotations to fine-tune transformer models that classify each headline along several dimensions. The classifications identify whether a headline is about aggregate consumer-price inflation, whether it cites a numerical figure and in what form (a decimal like "2.1", an integer like "2", or a multiple of five like "10"), and whether it uses sensational framing through references to historical records (e.g., "highest inflation since 1995") or arousing language (e.g., "inflation spirals out of control"). We link headline counts to inflation realizations using Eurostat's release calendar.

We document three descriptive patterns. First, the number of inflation headlines rises sharply with the inflation rate, peaks a few months before inflation itself peaks, and begins to decline even before inflation starts to fall. Second, the numerical precision of the inflation values reported in headlines decreases as inflation rises. Between low-inflation periods and the peak of the surge, the share of headlines citing a decimal figure falls by more than half, while the share citing a multiple of five roughly doubles. Third, sensational framing follows an inverted-U pattern. That is, references to historical records and arousing language increase as inflation rises, peak at moderate-to-high inflation, and decline as inflation climbs further.

These supply-side patterns can partly be explained by the demand-side theory of attention to inflation (Sims, 2003; Maćkowiak and Wiederholt, 2009; Pfäuti, 2026). Paying attention to inflation is costly, and the cost of misforecasting it rises with inflation. Hence, households rationally pay little attention when inflation is low and more when it is high. Our finding that coverage volume rose during the surge is consistent with this theory. Similarly, the coarsening of numerical precision and the rise of sensational framing at low to moderate inflation are consistent with journalists responding to a more attentive audience by either highlighting inflation or exploiting the attention. The observation of a rapid decline in the number of inflation headlines before inflation peaks, and the decline in sensational framing at the highest inflation levels, however, suggests that the relationship between inflation and coverage is not purely level-based but rather depends on changes in inflation or its expected path.

After documenting these patterns, we test for discrete shifts in headline composition at round-number thresholds. We focus on multiples of five in the inflation rate because these are natural anchors in numerical cognition. Human number perception relies on a sub-base-5 structure, and outcomes cluster at multiples of five in settings ranging from age reporting to survey-based inflation expectations (A'Hearn *et al.*, 2009; Houle *et al.*, 2013;

Binder, 2017). To be precise, we compare headline outcomes in months when a country's inflation rate crosses 5, 10, or 15 percent with outcomes in otherwise similar months in which no threshold is crossed. The intuition is to contrast situations in which inflation rises from 9.2 to 9.9 with those in which it rises from 9.4 to 10.1. In both cases, the inflation level and the size of the change are similar, but only in the latter case is the 10 percent threshold crossed. The identifying assumption is that, conditional on smooth changes in the level and change of inflation, such crossings are as good as random with respect to other determinants of headline outcomes. We implement this idea using a regression discontinuity design (RDD) centered on threshold events observed in the sample.

The results show that threshold crossings matter for headline composition rather than for total headline volume. Total headline volume shows no robust jump at the 5, 10, or 15 percent thresholds, so journalists do not cover inflation more when it crosses a round-number threshold. By contrast, the numerical precision of headlines coarsens. Headlines reporting inflation as a multiple of five rise by 45 percent at increasing-inflation crossings and fall by 52 percent at decreasing-inflation crossings,[2] while decimal and integer reporting barely move. This response is not a mechanical labeling effect because our design absorbs the smooth tendency of headlines to use round-number expressions as inflation approaches a multiple of five. The estimated discontinuity therefore isolates the additional jump at the crossing itself rather than the activation of a previously unused label, since "10 percent" is also arithmetically available below the threshold under standard rounding. Arousing language responds asymmetrically, with no robust jump at increasing-inflation crossings but a sharp and significant decline at decreasing-inflation crossings. Sensitivity analyses using integer thresholds other than multiples of five (e.g., 6, 7, 8, etc.) also point to numerical coarsening, but toward headlines reporting inflation with integer precision rather than multiples of five. Overall, these discrete changes in headline composition imply that the media do not simply transmit official inflation statistics but alter the signal that reaches the public.

Related literature. *Media coverage and inflation expectations.* Carroll (2003) proposes an epidemiological model in which households update infrequently in response to news reports of the views of professional forecasters and estimates the implied updating rate using US survey data. A subsequent literature confirms that the volume, tone, and framing of inflation coverage predict household expectations and forecast disagreement across countries (Lamla and Maag, 2012; Pfajfar and Santoro, 2013; Lamla and Lein, 2014; Larsen *et al.*,

[2]These numbers are estimates without time fixed effects. With time fixed effects, the corresponding values are +38 percent and -59 percent.

2021; Kmetz *et al.*, 2022; Macaulay and Song, 2023). Recent contributions identify causal effects of news on expectations (Binder *et al.*, 2025), model editorial selection of inflation events for coverage (Chahrour *et al.*, 2025), and connect salient consumer price signals to expectations formation (D'Acunto *et al.*, 2021). Coibion and Gorodnichenko (2015) provide the broader information-rigidity framework. We complement this work by treating news coverage as the outcome rather than the input. The distinction matters because the literature largely treats media coverage as a transmission channel through which inflation reaches households. Our results show that this channel is not neutral, as headline composition shifts discretely at round-number thresholds, potentially amplifying or distorting the underlying inflation signal. Empirical models of how news affects expectations may therefore understate the role of editorial choices in transmitting the inflation signal that households receive, particularly around round-number thresholds.

Attention to inflation. A recent literature documents that household and firm attention to inflation rises with the inflation environment. Weber *et al.* (2025) pool information-treatment experiments and find that the same exogenous signal teaches agents less when inflation is high, partly because the media supply more inflation content. Korenok and Munro (2024) document an asymmetric pattern in which attention rises quickly with inflation and falls only slowly afterward, remaining elevated even after inflation returns to pre-surge levels. Coibion and Gorodnichenko (2025) formalize a cycle of selective inattention in which households turn attentive only when monetary policy appears to fail, and Pfäuti (2026) models attention as jumping once inflation crosses a threshold. We complement this literature with media-content evidence. The rise in attention with inflation has a parallel in our findings that headline volume rises and numerical precision coarsens with inflation.

Left-digit bias. A large literature in behavioral economics shows that people treat round numbers as reference points and respond disproportionately when one is crossed (Pope and Simonsohn, 2011; Lacetera *et al.*, 2012; List *et al.*, 2023), and that firms exploit this anchoring in pricing (Strulov-Shlain, 2023). In our related work (Garz and Larin, 2026), we document left-digit bias in inflation *expectations*, using the same 29-country European panel. Household expectations jump when realized inflation crosses a multiple of five. The present paper provides a production-side counterpart, showing that headline composition also shifts discretely at those thresholds. Existing evidence of left-digit bias largely concerns individual decision-makers in markets, surveys, and laboratory settings. Our results show that the same threshold pattern appears in the editorial production of inflation news, where the producer is an intermediary between an official statistic and the public. This is a new domain in the round-number literature, with potential consequences for public understanding of macroeconomic conditions.

News coverage of macroeconomic variables. Another related literature studies how media cover macroeconomic variables and uses computational text analysis to measure economic conditions, sentiments, and narratives (e.g., Larcinese *et al.*, 2011; Soroka *et al.*, 2015; Shapiro *et al.*, 2022; Bybee *et al.*, 2024; Gambetti *et al.*, 2025; Garz, 2025; Armona *et al.*, 2026). Existing work has examined coverage volume and tone, asymmetries in how good and bad developments are reported, the role of political context, and the construction of indicators from news text, such as economic policy uncertainty (Baker *et al.*, 2016) or inflation narratives (Andre *et al.*, 2026). These approaches focus largely on the semantic content of coverage, i.e., what is said about the economy and in what tone. We add two dimensions to this literature: the numerical precision with which an economic statistic is reported, and the sensational framing around it through references to historical records and arousing language.[3] Both might shift discretely as inflation crosses a multiple of five, implying that nonlinearities in text-based macroeconomic indicators around round numbers may partly reflect editorial choice rather than the underlying economic change.

Outline. The remainder of the paper is organized as follows. Section 2 describes the inflation and media data. Section 3 presents stylized facts on how inflation coverage shifted during the 2017–2024 period. Section 4 lays out the regression discontinuity framework for the threshold tests. Section 5 presents the results while section 6 concludes.

2. Data

2.1. Inflation data

Our primary inflation measure is the Harmonised Index of Consumer Prices (HICP) provided by Eurostat for 29 European economies over the period January 2017 to December 2024. We use year-on-year rates at a monthly frequency. We work with the data as first published, before any statistical revisions, so the series matches the inflation signal available to the public.[4]

[3]Our measurement of sensational framing draws on journalism studies, which have long examined how news outlets use exaggeration, superlatives, and emotionally arousing language to capture attention (e.g., Tannenbaum and Lynch, 1960; Reinemann *et al.*, 2012). We adapt these concepts to the specific case of macroeconomic reporting, where sensational framing may operate through references to historical records and round-number thresholds rather than through the topical features (crime, celebrity, scandal) that the journalism literature typically studies.

[4]In many countries, the national statistical agency also publishes the consumer price index (CPI), which differs slightly from the HICP. However, CPI data as first published are not consistently available, because

A key decision when working with the HICP concerns which release to use. Flash estimates, published at the end of the reference month, are available for 22 of our 29 sample countries. For the remaining 7 countries, the first publicly available figure is the final estimate, released roughly two weeks into the following month. We therefore use flash estimates where available and the first-published final estimate otherwise. This captures the inflation signal that journalists and households respond to, not the values released after later revisions.

Importantly, we observe the exact publication dates of Eurostat flash and final HICP releases, which we use as a reference point for when new inflation information becomes publicly available across countries.[5] In section 2.3, we document a sharp increase in inflation-related media coverage precisely at the release date, which supports this strategy.

Finally, a potential concern with the analysis that follows is that the numerical formatting of inflation figures in official communication itself varies with the inflation environment, in which case the coarsening we document later could originate with the source rather than with the media. To rule this out, we examine press releases from the national statistical agencies of Croatia, Estonia, France, Germany, Ireland, Italy, the Netherlands, Spain, and Sweden, studying 25 releases for each country, both before and during the surge. We find that statistical agencies consistently report inflation with one decimal place. The format of official communication is hence stable across the sample period and does not shift toward rounded values during the surge.

Multiples of five are natural anchors in numerical cognition. Human number perception relies on a sub-base-5 structure, and outcomes cluster at multiples of five in settings ranging from age reporting to health self-assessments and survey-based inflation expectations (A'Hearn *et al.*, 2009; Houle *et al.*, 2013; Binder, 2017). Since inflation rates rarely exceed 5 or even 10 percent in advanced economies, steps of 5 are more salient than steps of 1 for households interpreting the inflation signal. We therefore center our threshold tests on multiples of five and focus specifically on 5, 10, and 15 percent, the multiples-of-five values crossed often enough in our sample to provide power. Crossings at higher multiples are very rare and are therefore excluded to avoid noisy estimates driven by small cell sizes. We do not consider 0 percent, as crossings at this threshold correspond to transi-

data from Eurostat, national statistical agencies, or third parties such as the OECD are often subject to statistical revisions. As a result, these data do not reliably reflect the information available to the public at the time of the initial release. This constraint motivates our reliance on the HICP. In addition, an inspection of press releases from several national statistical agencies in our sample confirms that the HICP constitutes a central reference measure in public communication across European countries.

[5] While national statistical agencies sometimes release inflation data figures shortly before the corresponding Eurostat publication, a systematic collection of comparable country-specific release dates is not feasible due to incomplete press archives.

tions between inflation and deflation. We also exclude 2 percent. Given the ECB's inflation target, crossings of the 2 percent threshold are routine and expected, and hence conceptually less relevant to media rounding and sensational framing. However, in sensitivity analyses, we also evaluate integer thresholds within the same range that are not multiples of five.

We define an *increasing*-inflation threshold event as the crossing of a threshold from below, whereas a *decreasing*-inflation threshold event occurs when inflation crosses a threshold from above; see Figure B.1 for an illustration. To abstract from short-run fluctuations around thresholds, we require that the same threshold value has not been crossed in the previous 12 months. We also consider 6- and 18-month protection windows as robustness checks. This "protection rule" excludes crossings that are unlikely to be newsworthy (Garz and Martin, 2021). Given these criteria, we observe 66 increasing- and 43 decreasing-inflation threshold events, captured by two binary variables. While these events are clustered during the 2021–2024 inflation surge, they occur across 32 distinct months. They are distributed across all countries in the sample, often during periods when other countries do not experience threshold crossings. Conditional on smooth changes in inflation, this temporal and cross-sectional dispersion suggests that threshold crossings are as good as random with respect to other determinants of media coverage.

2.2. Media data

Online media are now the most-used source of news for households in Europe, ahead of print and at least on par with offline broadcast news (Newman *et al.*, 2023). Accordingly, we measure inflation coverage by analyzing content from online news outlets. We focus on news headlines, which capture the information most likely to be seen and processed by readers, who predominantly scan and scroll rather than click through to full articles (e.g., Meijer and Kormelink, 2015; Searles and Feezell, 2023).

We obtain data on inflation-related headlines from the Global Database of Events, Language, and Tone (GDELT; see Leetaru and Schrodt 2013). GDELT screens over 150,000 news sites worldwide in 15-minute intervals and extracts entities, actors, and themes from reports. The platform collects more than 88 million news reports annually and analyzes their content using advanced natural language processing techniques (Saz-Carranza *et al.*, 2018; Consoli *et al.*, 2020). Its open-source repository allows researchers to analyze large-scale media data over long periods and across countries (Hopp *et al.*, 2019). GDELT has been widely used in economic research, for example, to study business events (Campante and Yanagizawa-Drott, 2018), political mobilization (Manacorda and Tesei, 2020), and ownership structures (Matter and Widmer, 2023).

We access the data through the GDELT 2.0 DOC API and download all headlines and metadata of reports covering the theme ″econ_inflation“. This theme is one of approximately 60,000 themes in GDELT's taxonomy. We also considered alternative themes (e.g., ″macroeconomic_performance“, ″econ_price“, ″price_controls“, and ″commodity_price_shock“) and keyword-based queries (e.g., ″inflation“, ″consumer price index“). These approaches yielded either substantially narrower sets of headlines that omitted clearly relevant content or broader sets that were less closely tied to consumer price developments. Based on these comparisons, we use the ″econ_inflation“ theme as a broad starting point and refine relevance through subsequent content analysis.

We download all 277,911 inflation-related headlines archived in GDELT during our sample period, corresponding to an average of 9,583 headlines per country. Inspection of the downloaded headlines indicates that the platform's classification algorithm captures a wide range of inflation-related reporting. Most headlines directly address inflation-related issues, such as overall price developments and trends in specific price categories (e.g., fuel, electricity, and food), their origins and effects, monetary policy, and perspectives of different actors. Some headlines discuss inflation only indirectly or jointly with other economic news, such as growth, trade, and unemployment, as GDELT's classification algorithm assigns multiple themes to the same news report when applicable. Hence, inflation is not necessarily the only or primary topic addressed in the downloaded headlines. Relying on the ″econ_inflation“ theme substantially reduces the risk of systematically missing content compared to keyword-based queries. Any remaining omissions are unlikely to be systematically related to inflation realizations or their timing, as they stem primarily from limitations of the classification algorithm rather than underlying economic variation.

To obtain proxies of inflation-related news coverage that reaches most households, we restrict the sources to a country's most influential mainstream media outlets. It would be computationally challenging to analyze the universe of inflation-related headlines archived in GDELT, and it could yield poor proxies if we included the long tail of sources that attract little traffic. Hence, we compile a list of the domains of each country's most important news outlets based on the BBC's media country profiles[6], yielding a set of 175 outlets in total, or six news outlets on average per country. See Tables A.1 and A.2 for the complete list.

[6]See, for example, www.bbc.com/news/world-europe-17299010 and https://www.bbc.com/news/world-europe-17551488 for the media profiles of France and North Macedonia, respectively. The BBC provides these profiles for each country in our sample. Under the headline ″press,“ the BBC lists the news outlets with the largest audiences and agenda-setting power.

We measure three dimensions of inflation headlines. *Volume* is the quantity baseline, the most direct production-side proxy for editorial attention. *Numerical precision* tests for left-digit-biased editorial coarsening. If journalists round inflation rates as inflation rises, and especially at multiples-of-five threshold crossings, headlines should shift from reporting the inflation rate with decimal precision toward non-five integers and toward multiples of five. *Sensational framing* captures editorial amplification during an inflation surge. We measure it in two ways. First, references to historical records (e.g., "highest inflation since 1981") frame a current observation as exceptional by emphasizing its novelty and deviation from the ordinary. Such references may also convey substantively useful information, but in headline writing they serve as a salience-enhancing presentational device and thus as one form of sensational framing (Tannenbaum and Lynch, 1960; Reinemann *et al.*, 2012). Second, arousing language (e.g., "spiral", "crisis") functions as a salience-enhancing device by heightening the perceived severity of a development through exaggeration, superlatives, or other attention-grabbing, arousing phrasings.

We focus on these three dimensions because they satisfy four criteria that alternative measures often do not. As detailed in Appendix A.2, they emerge from exploratory qualitative coding of headlines published around threshold crossings and of comparable headlines unrelated to such crossings. They are relevant to how inflation threshold events are communicated, directly observable in headlines alone, can be coded consistently across countries and languages, and can be measured at scale in our data. By contrast, other potentially important characteristics, such as article placement, display duration, visuals, or content marketing, would require proprietary, outlet-specific interface data or audience data that are typically not available to researchers. Generic measures of sentiment or tone are also less tightly linked to left-digit bias.

Three coding criteria capture these dimensions: numerical precision, historical record, and arousing language. Two further criteria narrow what counts as an inflation headline, distinguishing between direct and indirect references to inflation and between aggregate and sector-specific or single-good coverage. In total, the five criteria are:

1. *Inflation reference*: whether the headline refers *directly* to inflation, as opposed to only indirectly (e.g., discussing monetary policy without quoting an inflation figure, or discussing the cost-of-living crisis)
2. *Coverage scope*: whether the headline covers *overall* inflation or focuses on a specific sector (energy, food) or a single good (petrol, electricity).
3. *Numerical precision*: whether the headline contains a numerical value and, if so, in what form. Headlines containing a number are partitioned into three disjoint categories:

a) *decimal*: if the number it reports has a fractional part, for example, "2.3 percent".

b) *integer*: if the number is a whole number not divisible by five, for example, "3 percent".

c) *multiple of five*: if the number is a whole number divisible by five, for example, "15 percent", including verbal phrasings such as "double-digit inflation".

4. *Historical record*: whether the headline references a historical record or anomaly, such as "highest inflation since 1981" or "inflation at a 30-year high".
5. *Arousing language*: whether the headline uses attention-grabbing or arousing language, such as "prices out of control" or "wallets under attack".

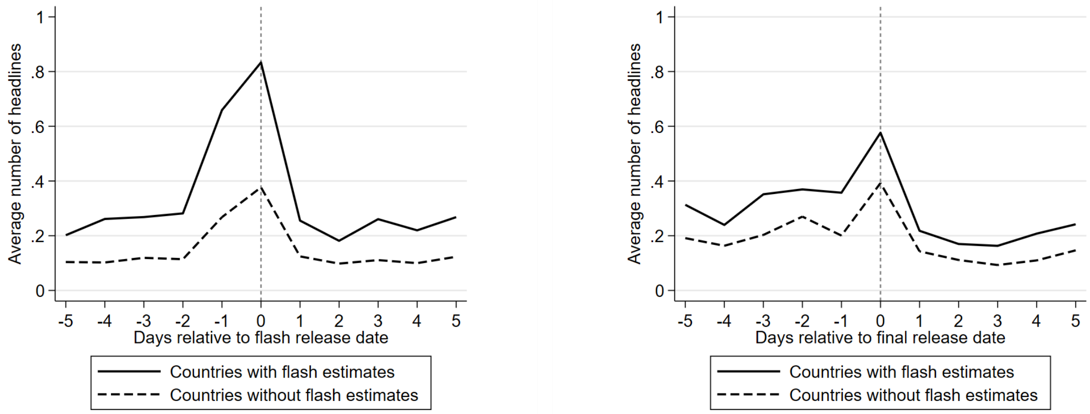
Human coders annotate headlines using content analysis standards (Krippendorff, 2013). They evaluate 25,000 headlines against criterion 1. For the 4,360 headlines coded as directly related to inflation, they evaluate criteria 2-5. Tests for intercoder reliability indicate high to very high rates of agreement (e.g., Cohen's kappa ranging from 0.82 to 1.00). See Table A.3 and Figure A.1 for details and examples.

To scale the classification to the full corpus of 277,911 headlines, we use the human annotations as training data for deep learning classifiers based on state-of-the-art transformer models. For each of the five coding criteria, we fine-tune several candidate classifier models—including BERT, ALBERT, DistilBERT, RoBERTa, and ELECTRA—and select the best-performing model based on held-out predictive performance. The selected classifiers achieve F_1 scores between 0.96 and 0.98 across all five criteria, indicating very high classification accuracy. We use the classifiers to obtain predictions for all headlines not covered by human annotations. Full details of the codebook, intercoder reliability, machine classification, and validation are provided in Appendix A.

In the subsequent analysis, we focus on headlines that are directly related to aggregate consumer price inflation, as identified by criteria 1 and 2, to align the media content with the underlying economic indicator. Within this set of 38,686 headlines, we examine how inflation is communicated by analyzing the presence and precision of numerical information, as well as the use of sensational framing.

2.3. Linking headlines to inflation statistics

Figure 1 plots the average number of inflation headlines per country in the days surrounding the publication of Eurostat's HICP releases. Media attention increases sharply on the release day, consistent with journalists responding to newly published inflation figures. A smaller but noticeable increase also appears one day before the Eurostat re-



(**a**) Flash estimate (**b**) Final estimate

Notes: Counts refer to headlines classified as directly related to aggregate consumer price inflation.

Figure 1: Volume of inflation headlines around inflation statistics release dates

lease. This increase might reflect the advance publication of domestic inflation figures by national statistical agencies or anticipatory reporting on the upcoming release.

To align media coverage with the information available to journalists, we link headline counts to the timing of official inflation releases. As described in section 2.1, we use Eurostat's flash HICP releases or first-published final estimates where flash estimates are unavailable as the reference point for when new inflation data become publicly available. Headlines are therefore linked to the release-month inflation statistic from the release day onward, until the next release becomes available. Even in countries without national flash estimates, inflation information becomes publicly salient at the end of the month through euro-area flash releases, international news coverage, and anticipatory reporting. Consequently, journalists in these countries update their reporting environment at roughly the same time, making the Eurostat release date a consistent anchor for linking headlines to inflation statistics.

Table 1 reports summary statistics of headline counts across content categories. On average, we observe about 14 inflation-related headlines per country-month. Among these, roughly 3 headlines mention any numerical value, of which about 2 report decimals and less than 1 report integers on average. Mentions of multiples of five are relatively rare (0.5 per month), as are references to historical records (1.0) and arousing language (0.7).

	Average number	SD	Min.	Max.
All headlines	13.8	22.1	0	255
Headlines including or mentioning				
numerical value	3.2	5.3	0	53
value with decimal place	2.0	3.4	0	28
integer value	0.7	1.7	0	20
multiple of five	0.5	1.4	0	25
historical record	1.0	2.4	0	28
arousing language	0.7	1.8	0	19

N = 2,729 country–months with up to 29 countries and 95 months. The decimal-place, integer, and multiple-of-five categories are mutually exclusive: each numerical headline is assigned to its coarsest applicable category, so their averages add up to the "numerical value" row.

Table 1: Summary statistics of inflation headlines

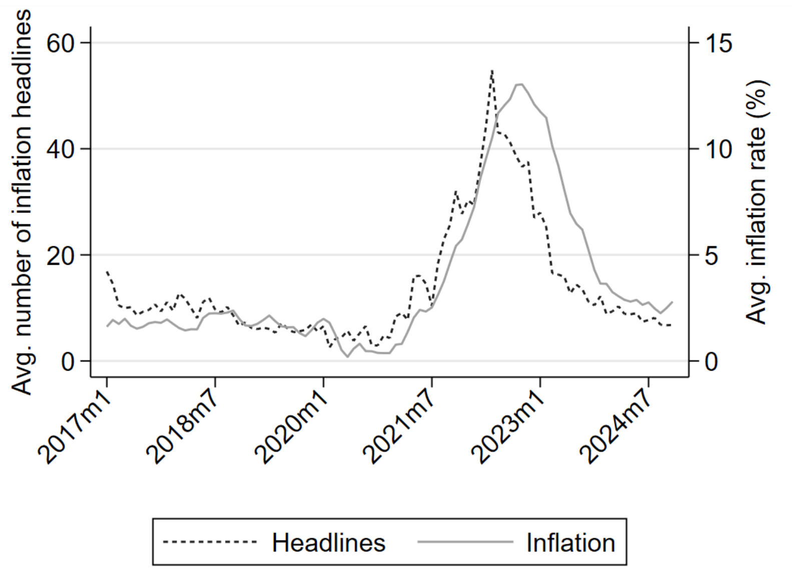
3. Stylized Facts

We document three patterns in how inflation coverage changes during an inflation surge. The first is a volume response, the second a shift in numerical precision, and the third a shift in sensational framing. These are descriptive patterns visible in the cross-country sample over the 2017–2024 period. They establish that coverage shifts substantially with the inflation environment, but they do not distinguish between smooth and discontinuous responses, which section 4 addresses.

Coverage volume rises sharply with the inflation surge and reaches its peak in mid-2022, as Figure 2 shows. The coverage peak precedes the inflation peak by a few months, consistent with journalists responding to inflation's trajectory rather than its contemporaneous level alone. As inflation remains elevated through 2022 and 2023, volume falls back, and by 2024, it has returned close to pre-surge levels even as inflation remains somewhat above the pre-surge baseline. The pattern is consistent with sustained high inflation becoming routine. That is, once double-digit inflation persists, additional months of high inflation carry less news value than the initial crossing into the high-inflation regime.

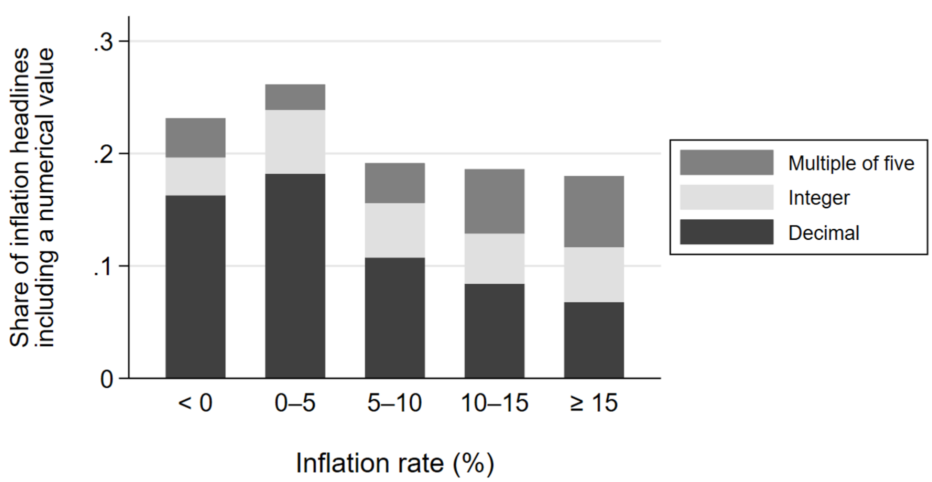
Figure 3 shows that numerical precision in inflation headlines coarsens as inflation rises. The share of headlines containing any number declines somewhat, and the share citing a decimal figure halves between the lowest and highest inflation regimes. Among headlines that do report a number, the composition shifts toward multiples of five. The share citing a multiple of five roughly doubles over the same range, while the share citing a non-five integer rises only modestly. The result is a coarsening of how inflation is represented, not merely a decline in numerical content.

Both dimensions of sensational framing follow an inverted-U pattern across the infla-



Notes: Based on data and methods described in section 2.1. All values are sample means across countries, calculated from counts of headlines classified as directly related to aggregate consumer price inflation. Inflation is measured as the year-on-year change in the Harmonised Index of Consumer Prices (HICP).

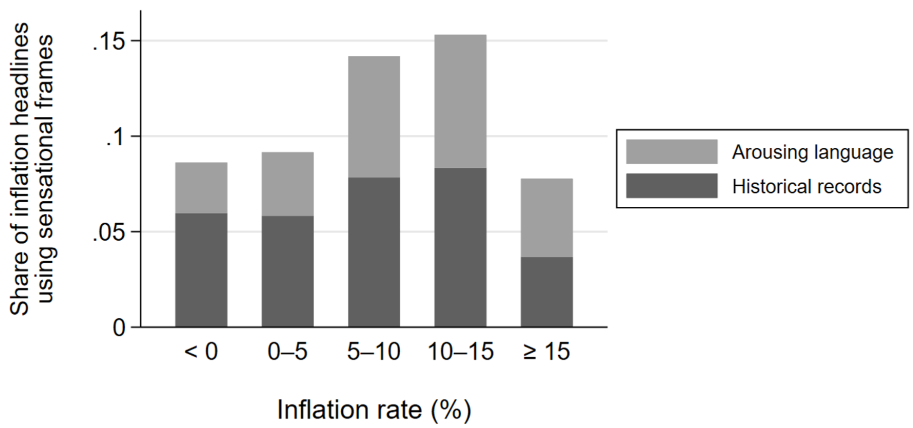
Figure 2: Inflation and volume of inflation headlines over time



Notes: Based on data and methods described in section 2.1. All values are sample means across countries, calculated from counts of headlines classified as directly related to aggregate consumer price inflation. Classification of numerical values includes numerals as well as spelled-out or idiomatic expressions (e.g., "double digit") and accounts for differential formatting across languages (e.g., "5.5" vs. "5,5"). Classification into decimals, integers, and multiples of five is hierarchical, with values assigned to the most coarse applicable category.

Figure 3: Reporting of numerical values across inflation levels

tion level, as Figure 4 shows. Historical-record references and arousing language rise from a low base at low inflation, peak in the moderate-to-high inflation range, and decline again at the highest inflation rates. The share of headlines using arousing language, for instance, more than doubles from the 0–5 percent bin to the 10–15 percent bin, then halves in the highest-inflation bin. One interpretation is that at moderate-to-high inflation levels, headlines can credibly emphasize records or use arousing language because these inflation rates are novel and surprising. At very high inflation levels, by contrast, high inflation becomes less exceptional as it persists, so the scope for framing each new release as a record or a shock diminishes. The cross-sectional pattern is therefore consistent with habituation or attention fatigue, though our descriptive evidence cannot establish this mechanism directly.



Notes: Based on data and methods described in section 2.1. All values are sample means across countries, calculated from counts of headlines classified as directly related to aggregate consumer price inflation. Historical records refer to headlines that highlight long-term comparisons or records (e.g., "inflation at a three-year peak"), while arousing language refers to headlines using arousing wording (e.g., "inflationary spiral").

Figure 4: Sensational framing across inflation levels

These patterns can partly be explained by the demand-side theory of attention to inflation (Sims, 2003; Maćkowiak and Wiederholt, 2009; Pfäuti, 2026). Paying attention to inflation is costly, and the cost of misforecasting it rises with inflation. Hence, households rationally pay little attention when inflation is low and more when it is high. Our finding that volume rises during the inflation surge supports this theory. It aligns well with empirical findings by Bracha and Tang (2023) and Korenok *et al.* (2026), as well as experimental evidence from Cavallo *et al.* (2017) and Weber *et al.* (2025). However, we further find that coverage responds in form, not only in volume. Numerical precision coarsens as decimals give way to multiples of five. Framing turns sensational at moderate inflation and habituates at the highest rates. Both shifts are consistent with supply responding to a more attentive audience, by either drawing attention or exploiting it. Furthermore, we find that volume peaks ahead of inflation and returns to pre-surge levels by 2024, while inflation remains elevated. The timing suggests that attention responds to more than the inflation level. The change in inflation, or its expected path, may also play a role. This observation stands somewhat in contrast to what Korenok and Munro (2024) suggest, namely that demand-side measures of attention recede only slowly, potentially because news supply normalizes faster than demand.

4. Estimation approach

The previous section documents continuous responses of media coverage to the inflation regime. Whether coverage also shifts discretely when inflation crosses a round-number threshold is a separate question, motivated by the left-digit bias in household inflation expectations (Garz and Larin, 2026). We now test for such discontinuities.

We employ a regression discontinuity design centered on inflation threshold events. In contrast to a standard RDD with a single assignment variable and fixed cutoff, treatment assignment in our setting depends on both the level of inflation and its monthly change. That is, whether a threshold is crossed is determined by the distance to the next threshold in the previous month and the size of the current inflation change. As a result, the probability of treatment varies smoothly with inflation dynamics rather than showing a sharp discontinuity in a single running variable. We therefore use a parametric specification that flexibly controls for underlying inflation dynamics.

Figures B.2 and B.3 visualize headline counts around threshold crossings. The figures suggest discrete jumps at the thresholds, but of varying magnitude and with substantial scatter across crossings. We therefore test for threshold effects formally, following Garz and Larin (2026):

$$y_{ct} = \alpha_1 D^+_{ct} + \alpha_2 D^-_{ct} + \alpha_3 \mathbf{Z}_{ct} + \gamma V_{ct} + \theta_c + \rho_t + \epsilon_{ct}$$

where y_{ct} is the headline count for country c in month t, D^+_{ct} and D^-_{ct} are binary indicators for increasing- and decreasing-inflation threshold events, $\mathbf{Z}_{ct}$ flexibly controls for continuous inflation developments, and V_{ct} is total headline volume across all topics (sports, politics, and so on), included so that compositional shifts are not confounded with changes in overall news supply. In the baseline specification, $\mathbf{Z}_{ct}$ includes third-order polynomials in the inflation level and its monthly change. We report variations with second-order and fourth-order polynomials in the robustness checks. Controlling for the inflation level captures the fact that the likelihood of crossing a threshold varies with proximity to that threshold, while controlling for inflation changes accounts for the mechanical relationship between the size of inflation changes and the probability of crossing a threshold. Country fixed effects θ_c account for time-invariant cross-country differences, such as variation in media culture and measurement differences in GDELT.

We optionally add time fixed effects ρ_t. Without them, identification exploits both cross-country and temporal variation in threshold crossings. With them, identification comes from within-month cross-country variation, absorbing all common shocks and time-varying factors shared across countries. The identifying assumption is that, conditional on the polynomials in inflation and its change, threshold crossings are mean-independent of unobserved determinants of headline counts. Under this assumption, α_1 and α_2 recover the causal effect of crossing a round-number threshold on media coverage.

The dependent variables, headline counts, are modeled as count outcomes using Poisson pseudo-maximum likelihood estimation (Correia *et al.*, 2020).[7] The coefficients are reported as incidence rate ratios, which can be interpreted as multiplicative effects on expected headline counts. We report standard errors that are robust to clustering by country (Cameron and Miller, 2015).

5. Results

The main results are presented in Table 2, which exploits cross-country and time variation in threshold events. Increasing-inflation threshold events raise expected total headline counts by 7 percent while decreasing-inflation threshold events reduce them by 9 percent; see Column 1. Neither estimate is statistically significant. Columns (2)–(5) examine numerical reporting. The expected number of headlines containing any numerical value rises by 13 percent at increasing-inflation crossings (significant at the 10 percent level), with no corresponding rise in decimal-value headlines. Headlines containing multiples of five jump by 45 percent at the crossing, statistically significant at the 1 percent level. This is far larger than the rise in headlines reporting any number and also exceeds the change in total headline volume. Hence, at an increasing-inflation crossing, headline composition shifts toward coarser numerical reporting.

[7] An alternative would be to use headline shares as dependent variables. We do not pursue this approach because shares in our data are bounded, highly skewed, and show substantial mass at zero, making linear models inappropriate. Fractional response models are designed for such outcomes but are less well suited to specifications with high-dimensional fixed effects. Poisson pseudo-maximum likelihood is well-suited to count data with many zeros, accommodates high-dimensional fixed effects, and yields coefficients with a straightforward multiplicative interpretation. Using counts also allows us to compare threshold effects on total inflation coverage with the effects on specific headline categories, separating volume and compositional effects.

	All headlines	Headlines including					
	(1)	(2) any number	(3) decimal value	(4) integer value	(5) multiple of five	(6) historical record	(7) arousing language
Incr.-infl. threshold	1.07	1.13*	1.01	1.11	1.45***	1.06	1.15
	(0.06)	(0.08)	(0.08)	(0.14)	(0.19)	(0.10)	(0.13)
Decr.-infl. threshold	0.91	0.86	0.83	1.20	0.48*	0.96	0.33***
	(0.10)	(0.12)	(0.13)	(0.31)	(0.19)	(0.33)	(0.13)
Mean of dep. variable	13.84	3.21	2.03	0.73	0.46	1.03	0.75
SD of dep. variable	22.13	5.33	3.38	1.66	1.44	2.40	1.85
Pseudo R^2	0.66	0.50	0.47	0.31	0.39	0.41	0.43

*Notes: N = 2,729. Poisson pseudo-maximum likelihood estimates (incidence rate ratios) capturing the multiplicative effects on expected headline counts. All models control for third-order polynomials in the inflation level and its change, total headline counts (all topics), and country fixed effects. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, or 15 percent for the first time in the past 12 months. Standard errors (in parentheses) are clustered by country. * p<0.10, ** p<0.05, *** p<0.01*

Table 2: Effects of threshold events on inflation headlines from cross-country and time variation

Conversely, decreasing-inflation threshold events reduce the number of headlines containing any numerical value by 14 percent, again driven by multiples of five, which fall by 52 percent (significant at the 10 percent level).[8]

A mechanical concern is that the labels "5 percent", "10 percent", and "15 percent" are simply unavailable to journalists until inflation actually crosses the corresponding threshold, in which case the jump reflects the appearance of a previously unused label rather than an editorial response. Two features of the results speak against this interpretation. First, the labels are arithmetically available below the threshold. Under standard rounding to the nearest integer, "5 percent" is a valid summary of any true value in $[4.5, 5.5)$, so a journalist observing 4.7 percent can write "5 percent" without distortion. Second, the magnitude of the jump far exceeds what a labeling-availability shift could produce. A 45 percent rise at increasing-inflation crossings and a 52 percent fall at decreasing-inflation crossings imply a substantial reallocation of editorial choices, not the activation of a single previously unused label.

Columns (6) and (7) examine the use of sensational framing. Increasing-inflation threshold events lead to a discrete 6 percent increase in headlines mentioning historical records, while decreasing-inflation threshold events induce a 4 percent decrease, though these effects are not statistically significant. A similar pattern emerges for headlines us-

[8] To assess whether increasing- and decreasing-inflation threshold events have symmetric effects in the multiplicative Poisson pseudo-maximum likelihood model, we test whether the underlying log coefficients are equal in magnitude and opposite in sign, $H_0 : \alpha_1 + \alpha_2 = 0$. We cannot reject symmetry (p-value = 0.419).

ing arousing language, but with larger magnitudes. An increasing-inflation crossing is associated with a 15 percent increase in such headlines, whereas a decreasing-inflation crossing reduces their number by 67 percent. The latter effect is statistically significant at the 1 percent level.

	All headlines	Headlines including					
	(1)	(2) any number	(3) decimal value	(4) integer value	(5) multiple of five	(6) historical record	(7) arousing language
Incr.-infl. threshold	1.00	1.09	0.97	1.08	1.38**	0.97	1.04
	(0.05)	(0.08)	(0.09)	(0.14)	(0.22)	(0.10)	(0.11)
Decr.-infl. threshold	0.93	0.86	0.88	1.14	0.41**	1.35	0.39**
	(0.07)	(0.11)	(0.13)	(0.28)	(0.16)	(0.46)	(0.15)
Mean of dep. variable	13.84	3.21	2.03	0.74	0.52	1.03	0.75
SD of dep. variable	22.13	5.33	3.38	1.66	1.52	2.40	1.85
Pseudo R^2	0.72	0.54	0.49	0.37	0.45	0.53	0.51

Notes: N = 2,729. Poisson pseudo-maximum likelihood estimates (incidence rate ratios) capturing the multiplicative effects on expected headline counts. All models control for third-order polynomials in the inflation level and its change, total headline counts (all topics), and time fixed effects. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, or 15 percent for the first time in the past 12 months. Standard errors (in parentheses) are clustered by country.
** $p<0.10$, ** $p<0.05$, *** $p<0.01$*

Table 3: Effects of threshold events on inflation headlines from within-month cross-country variation

Adding time fixed effects leaves the main patterns intact; see Table 3. The total number of inflation headlines remains insensitive to threshold crossings (Column 1). Headlines containing multiples of five jump by 38 percent at increasing-inflation crossings and fall by 59 percent at decreasing-inflation crossings, both significant at the 5 percent level.[9] Arousing-language headlines again drop sharply at decreasing-inflation crossings, by 61 percent, significant at the 5 percent level.

Comparing the specifications with (Table 3) and without (Table 2) time fixed effects indicates that the main results are largely robust to controlling for common time trends. In particular, the pronounced response in round-number reporting persists when identification is restricted to within-month cross-country variation. This suggests that media responses to threshold crossings are driven by country-specific developments rather than by broader European inflation trends. In other words, journalists respond to threshold events in their domestic inflation environment over and above any common information about inflation.

[9] We cannot reject the null hypothesis of symmetric effects of increasing- vs. decreasing-inflation threshold events (p-value = 0.190).

We assess the robustness of our results using several alternative specifications, focusing on modifications of the model that include time fixed effects, which help rule out confounding by common shocks. First, we consider alternative ways to control for smooth changes in inflation by using second- (Table B.1) and fourth-order (Table B.2) polynomials in the inflation rate level and its change, as well as specifications that include interactions between the level and change polynomials. These modifications yield results very similar to those of the baseline specification. Second, we vary the length of the protection period used to define threshold events, considering windows of 6 months (Table B.4) and 18 months (Table B.5). The results remain largely unchanged. Third, to account for the relatively small number of clusters, we compute p-values using the wild-cluster bootstrap (Table B.6). The resulting inference is consistent with our baseline findings.

The pooled effects mask substantial heterogeneity across the three thresholds (Figure B.4). For increasing-inflation events, the clearest response occurs at the 10 percent threshold. For example, an increasing-inflation crossing of 10 percent raises headlines containing any numerical value by about 25 percent and headlines mentioning multiples of five by about 60 percent. In contrast, crossings at 5 and 15 percent generally yield smaller and statistically insignificant estimates. This pattern suggests that the pooled effect is driven primarily by the crossing into double-digit inflation. For decreasing-inflation events, the pattern is less uniform. In total headline volume, decreasing-inflation crossings below 10 and 15 percent are associated with statistically significant declines of about 20 and 40 percent, respectively. For headlines mentioning multiples of five, the largest decline occurs when inflation falls below 5 percent, corresponding to a reduction of about 65 percent. These threshold-specific estimates should be interpreted with caution, however, because splitting the pooled indicators results in relatively few events at each threshold.

Finally, we re-estimate the baseline specification using threshold events defined by integer values other than multiples of five in the relevant range (Table B.7). The results show small, marginally significant effects of increasing-inflation threshold events on the total number of inflation headlines and on headlines referencing historical records. Most importantly, these threshold events increase the number of headlines reporting inflation with integer precision by 34 percent. This suggests that integer thresholds other than multiples of five can also induce numerical coarsening, though to a weaker extent than multiples-of-five threshold events.

6. Conclusion

We study how news outlets report inflation across 29 European countries between 2017 and 2024, a period that includes the 2021–2024 inflation surge, the first sustained high-inflation episode in Europe in over four decades. We use a large corpus of inflation-related headlines to analyze how coverage volume, numerical precision, and sensational framing shift with the inflation environment. During the surge, the number of inflation headlines rises with the inflation rate and peaks a few months ahead of inflation itself. Numerical precision falls, as decimal reporting drops by more than half between low and high regimes, while multiples-of-five reporting roughly doubles. Sensational framing follows an inverted-U pattern. Headlines using arousing language or mentioning historical records initially increase as inflation rises, but then decrease as inflation reaches particularly high levels.

A regression discontinuity design centered on round-number thresholds identifies discrete production-side responses in addition to these broader patterns. Although we find no evidence that the overall volume of inflation coverage jumps when inflation crosses 5, 10, or 15 percent, several aspects of headline composition do. Specifically, we observe the strongest discontinuous response for headlines reporting the inflation rate in multiples of five. On average, these headlines increase by 45 percent at increasing-inflation crossings and decline by 52 percent at decreasing-inflation crossings.[10]

These discrete changes in headline composition matter because they occur at the same round-number thresholds studied by Garz and Larin (2026). In that paper, we document left-digit bias in household inflation expectations in the same 29-country panel and show that expectations respond disproportionately when realized inflation crosses multiples of five. Experimental evidence further indicates that this bias arises even when participants are exposed to non-rounded inflation figures such as 9.9 versus 10.1 percent. Media rounding is therefore not necessary for left-digit bias to emerge. In the present paper, however, we find that media coverage also changes at these thresholds through discrete shifts in headline composition, most notably toward reporting inflation in multiples of five. These shifts may reinforce left-digit bias in inflation expectations by making round-number representations more prominent precisely when a threshold is crossed.

Our design leaves two questions open. The first concerns mechanisms. Discontinuous changes in numerical precision could arise because journalists and editors themselves process numerical information with left-digit bias, perceiving 10.1 as meaningfully different

[10]These numbers are estimates without time fixed effects. With time fixed effects, the corresponding values are +38 percent and -59 percent.

from 9.9; because editorial norms favor rounding once inflation crosses round-number thresholds to reduce readers' cognitive load; or because profit-maximizing outlets cater to consumer preferences for threshold-related rounding. These explanations are not mutually exclusive, and our data and research design do not allow us to distinguish among them. The second concerns welfare. Rounding and sensational framing may distort perceptions and expectations, or they may simplify complex information and help sustain attention when exact numerical reporting becomes cognitively demanding. Answering both questions requires further work, in particular, individual-level data on news exposure linked to inflation expectations, which would allow future research to identify the dominant mechanism and to determine whether media merely mirror these round-number thresholds, actively reinforce them, or help households process inflation news.

Despite these open questions, the findings have important implications for public-facing communication by central banks and statistical agencies. A given statistical release does not convey the same information regardless of the inflation level: a 0.4-point decline from 10.2 to 9.8 percent will be transmitted differently than the same decline from 8.2 to 7.8 percent, because the former coincides with a discrete shift in headline composition that the latter does not. Communication strategies that treat inflation as a continuous variable risk being miscalibrated at exactly those moments when public attention is highest. Statistical agencies and the media jointly produce the inflation signal reaching households, and anyone communicating inflation to the public may benefit from anticipating how releases will be reframed around round-number thresholds.

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Appendix

A. Data

A.1. Additional information on news outlets and headlines

Country	News outlets	Number of headlines
Austria	diepresse.com, krone.at, kleinezeitung.at, wienerzeitung.at, derstandard.at, kurier.at, news.at	9,602
Belgium	nieuwsblad.be, hln.be, lesoir.be, standaard.be, tijd.be, demorgen.be, lalibre.be, grenzecho.net	6,643
Bulgaria	dnevnik.bg, 24chasa.bg, telegraph.bg, trud.bg, standartnews.com, segabg.com, capital.bg	8,236
Croatia	vecernji.hr, jutarnji.hr, 24sata.hr, slobodnadalmacija.hr, novilist.hr, glasistre.hr, poslovni.hr	11,381
Cyprus	cyprus-mail.com, cyprusweekly.com.cy, philenews.com, politis.com.cy, simerini.sigmalive.com	1,799
Czechia	lidovky.cz, idnes.cz, pravo.cz, blesk.cz, hn.cz, respekt.cz	3,270
Denmark	jyllands-posten.dk, berlingske.dk, politiken.dk, ekstrabladet.dk, information.dk, bt.dk	1,476
Estonia	postimees.ee, ohtuleht.ee, epl.delfi.ee, aripaev.ee, maaleht.delfi.ee, ekspress.delfi.ee	2,532
Finland	hs.fi, is.fi, iltalehti.fi, hbl.fi, kauppalehti.fi, helsinkitimes.fi	6,565
France	lemonde.fr, liberation.fr, lefigaro.fr, ouest-france.fr, lexpress.fr, lepoint.fr	24,028
Germany	faz.net, sueddeutsche.de, welt.de, handelsblatt.com, focus.de, spiegel.de, zeit.de, bild.de, tagesspiegel.de	32,827
Greece	tanea.gr, ethnos.gr, tovima.gr, kathimerini.gr, naftemporiki.gr	17,390
Hungary	magyarhirlap.hu, nepszava.hu, magyarnemzet.hu, blikk.hu, metropol.hu, hvg.hu	7,204
Ireland	irishtimes.com, independent.ie, irishexaminer.com, sundayworld.com, businesspost.ie, thesun.ie, irishmirror.ie	12,471
Italy	corriere.it, repubblica.it, ilmessaggero.it, lastampa.it, ilsole24ore.com	20,035

Table A.1: Sample of news outlets and inflation-related headlines retrieved from GDELT

Country	News outlets	Number of headlines
Latvia	diena.lv, nra.lv, db.lv, la.lv, ves.lv, mklat.lv	2,405
Lithuania	lrytas.lt, kauno.diena.lt, vz.lt, veidas.lt	10,398
Luxembourg	journal.lu, wort.lu, tageblatt.lu	1,892
North Macedonia	novamakedonija.com.mk, vecer.mk, koha.mk, slobodenpecat.mk	2,365
Malta	timesofmalta.com, independent.com.mt, maltatoday.com.mt	4,907
Netherlands	ad.nl, nrc.nl, telegraaf.nl, volkskrant.nl, trouw.nl, fd.nl, vn.nl, parool.nl	4,304
Poland	wyborcza.pl, rp.pl, fakt.pl, se.pl, dziennik.pl, polityka.pl, wprost.pl, newsweek.pl	11,953
Portugal	dn.pt, publico.pt, cmjornal.pt, jn.pt, expresso.pt	1,385
Romania	adevarul.ro, click.ro, libertatea.ro, evz.ro, jurnalul.ro, romanialibera.ro, capital.ro	16,530
Serbia	politika.rs, blic.rs, danas.rs, glas-javnosti.rs, nin.co.rs, vreme.com, novosti.rs	11,512
Slovakia	dennikn.sk, pravda.sk, sme.sk, cas.sk, pluska.sk	5,400
Slovenia	dnevnik.si, delo.si, vecer.com, slovenskenovice.si, finance.si, dnevnik.si, mladina.si, primorske.svet24.si	5,016
Spain	elmundo.es, elpais.com, abc.es, larazon.es, lavanguardia.com, elperiodico.com/es	24,624
Sweden	aftonbladet.se, dn.se, expressen.se, svd.se, gp.se, sydsvenskan.se	9,761
	Total	277,911

Table A.2: Sample of news outlets and inflation-related headlines retrieved from GDELT (continued)

A.2. Qualitative coding

How do news outlets change their coverage of inflation when a threshold event takes place? To tackle this question, we draw a sample of 500 headlines published at the time of a multiples-of-five threshold event and 500 headlines unrelated to threshold events. We carefully read and inductively code the English translations of these headlines, looking for recurring patterns, concepts, and meanings (Saldana, 2015).[11] This exercise results in a taxonomy of attributes that are most relevant when thinking about inflation threshold events, especially what kind of numerical information is included in the headline, and how the news is framed. Specifically, we find that threshold events may induce media outlets to frame inflation news as a historical record (e.g., ”Highest inflation since 1990”) or by using emotion-arousing language (e.g., ”Inflation eats your wallet”), both of which are forms of sensationalism.[12] In contrast, we discard attributes that are unlikely to be relevant for how inflation is communicated in the context of threshold events, such as references to certain actors or geographical units. In addition, we omit attributes that cannot be reliably inferred from headlines, for instance, whether an inflation headline factually reports the current development, provides a forecast, or merely states an opinion (e.g., ”ECB warns of inflation”).

A.3. Content annotation

The qualitative coding allows us to develop instructions for content annotations by human coders (Krippendorff, 2013). Based on the initial attributes and definitions of how to capture them, we iteratively refine the instructions by tentatively applying the codebook and by discussing ambiguous cases among the co-authors. The final codebook is shown in Table A.3 and includes five criteria. We first evaluate whether a headline is directly related to inflation and, if so, whether it refers to aggregate inflation or to prices in individual sectors or of single goods. We also code how inflation is communicated, including whether and what kind of numerical information is reported, whether the headline refers to historical records or comparisons, and whether it uses arousing language. Tests of intercoder reliability on 100 randomly drawn headlines indicate high levels of agreement by

[11] We translate all headlines to English, using the ”M2M100_1.2B” multilingual encoder-decoder model developed by Facebook Research. The model is trained on a corpus of 7.5 billion sentences for 100 languages and provides state-of-the-art machine translations when conducting our investigation (Fan *et al.*, 2021). Comprehensive spot checks of headlines indicate that the translations are reasonably accurate and reliable.

[12] Sensationalism involves news coverage that accentuates a story’s thrilling, shocking, or other emotionally captivating aspects. It favors events and narratives that deviate from the ordinary, especially regarding magnitude or novelty. Sensationalism can be implemented by exaggeration, superlatives, normative statements, all caps, and other techniques that exploit the consumer’s cognitive vulnerabilities (Tannenbaum and Lynch, 1960; Reinemann *et al.*, 2012). In the context of news coverage of the economy, sensationalism may involve references to round numbers or historical rarities (Renton, 2000). We discard options to measure sensationalism by counting the incidence of emotionally loaded terms, for instance, based on the NRC Emotion Lexicon (Mohammad and Turney, 2013). Similarly, we refrain from using language models pre-trained for emotion detection (e.g., Barbieri *et al.*, 2020). Those approaches work well in general-language settings but not in our context, as they do not account for the possibility that using round numbers may arouse emotions and attention.

two co-authors (Cohen's kappa of 0.97 [inflation reference], 1.00 [coverage scope], 0.95 [numerical precision], 0.86 [historical record], and 0.82 [arousing language]).

We annotate 25,000 headlines in terms of criterion 1 [inflation reference]. For those headlines coded as directly related to inflation [inflation reference] = ″1″, we annotate criteria 2 to 5 (N = 4,360).

#	Criterion	Values	Instructions
1	Inflation reference	0: no 1: yes	Is the headline directly related to inflation? Headlines about rising/declining wages, stock prices, gold, and (crypto) currency are coded as "0". In contrast, crude oil may be coded as "1", due to its importance for gasoline and energy price indices. Headlines exclusively talking about the cost-of-living crisis (without referring to prices or inflation) are coded as "0". Examples "0": "DAX hit 8,500 points", "ECB to increase interest rates", "Dollar at all-time high", "Government steps in as cost of living crisis worsens" Examples "1": "Cheap gasoline for 1,66 Euros per litre", "Inflation on the rise", "House price index decreases", "Pasta 200% more expensive", "Rents rise 7% in largest increase since 2019"
2	Coverage scope	0: overall (consumer price) inflation 1: sector-specific inflation or single goods prices	What variable is mentioned? Ambiguous headlines and those referring to both overall and sector-specific inflation are coded as "0". Examples "0": "Price changes bad for savers", "Food prices drive inflation" Examples "1": "Oil price increases", "Energy and housing prices decrease"
3	Numerical precision	0: no num. value 1: decimal place 2: integer 3: multiple of five	Does the headline provide numerical information about the (change of the) inflation rate? Headlines that express numerical values as words are coded in the same way as headlines including numerals. Coding options "1" to "3" are hierarchical, i.e., a headline pointing out an inflation rate of 10% is coded as "3" (multiple of five) even though 10% is also an integer value. Examples "0": "Inflation increases", "Inflation bad for savers" Examples "1": "Inflation increases to 4.1%", "Inflation increases to 10.0%" Examples "2": "Inflation increases to 4%", "Inflation increases by 1%" Examples "3": "Inflation hits single figure", "Inflation hits double-digit figure", "Inflation above 10%", "Inflation below zero"
4	Historical record	0: no 1: yes	Does the headline point out an inflation record, historical anomaly, or make some sort of historical comparison? Comparisons with an implied time horizon of less than one year are coded as "0". Examples "0": "BNR inflation forecast for the end of 2022", "Inflation increases in January", "Used car prices have risen since last month", "Inflation has reached peak" Examples "1": "UK inflation at three-year peak", "Energy price index higher than before the pandemic", "An unprecedented decrease"
5	Arousing language	0: no 1: yes	Does the headline use exaggeration, superlatives, or attention-grabbing, emotion-arousing terms, or sensational framing? Examples "0": "Inflation increases in January", "Inflation passes 10% threshold", "Inflation reaches double digits", "Accelerating inflation reaches milestone" Examples "1": "Inflationary spiral", "How inflation eats your savings", "Energy cost explosion", "Wallets under attack", "Inflation robs you while you sleep", "Inflation tsunami", "CPI nightmare", "Soaring inflation passes 10% threshold", "Shock: double-digit inflation", "Inflation is unstoppable"

Table A.3: Coding scheme for headline classification

Country	Original	Translated	Numerical	Record	Language
Italy	Francia, inflazione confermata in aumento a marzo	French inflation confirmed to rise in March	no	no	no
Cyprus	Στο 2,4 % ο εναρμονισμένος πληθωρισμός τον Νοέμβριο	Harmonised inflation rate in November at 2.4%	decimal	no	no
Greece	Στο 1 % ο ετήσιος πληθωρισμός στην Ελλάδα τον Σεπτέμβριο	Annual inflation rate in Greece at 1% in September	integer	no	no
Hungary	Tíz százalék fölé is lökheti a magyar inflációt az ukrajnai háború	Inflation in Ukraine could rise to 10 percent	multiple of five	no	no
Germany	Inflation: Ob kontrolliert oder explosiv - die Geldentwertung wird kommen	Inflation: controlled or explosive – the devaluation of money will come	no	no	yes
Greece	Πληθωρισμός: Εκτινάχθηκε στο 10,2 % τον Απρίλιο	Inflation: Exploded to 10.2% in April	decimal	no	yes
Bulgaria	Шринкфлация изяде 9 % от шоколада и ядките	Shrinkflation eats 9% of chocolate and nuts	integer	no	yes
Denmark	Forbløffede kunder: Prisen er eksploderet med 195 procent på 10 måneder	Surprising customers: Prices have exploded by 195 percent in 10 months	multiple of five	no	yes
Poland	Kolejny rekordowy odczyt inflacji. GUS podał dane za grudzień	Another record inflation. GUS releases data for December	no	yes	no
Czechia	Inflace v Británii stoupla na téměř šestileté maximum 3,1 pct	Inflation in the UK reached a six-year high of 3.1 percent	decimal	yes	no
Spain	La inflación llega al 2% en la Eurozona por primera vez en cuatro años	Eurozone inflation hits 2% for first time in four years	integer	yes	no
Nether-lands	Inflatie volgens rekenmethode CBS voor het eerst sinds 1975 hoger dan 10%	CBS inflation exceeds 10% for the first time since 1975	multiple of five	yes	no
Malta	ECB unleashes historic rate hike to battle record inflation	ECB unleashes historic rate hike to battle record inflation	no	yes	yes
Spain	La guerra dispara la inflación de la zona euro hasta un récord del 7,5 %	War Shoots Eurozone Inflation to Record 7.5%	decimal	yes	yes
Poland	Rekordowa inflacja wyniosła 11 % ale na tym się nie kończy inflacyjny pożar	Inflation has reached a record level of 11%, but this is not the end of inflation fire	integer	yes	yes
Italy	Inflazione, è allarme: in Spagna, Francia e Belgio mai così alta dal 1980. Per Madrid +10 % in un mese	Inflation is alarming: in Spain, France and Belgium never so high since 1980. For Madrid +10% in a month	multiple of five	yes	yes

Notes: The list shows one randomly selected headline for each value combination of the criteria [numerical precision], [historical record], and [arousing language] from the pool of headlines classified as directly related to inflation [inflation reference] and mentioning overall inflation [coverage scope].

Figure A.1: Machine classification of example headlines

Criterion	Model	Balanced accuracy	Precision	Recall	F_1 score
1 infl_related	DistilBERT	0.97	0.98	0.98	0.98
2 type	ELECTRA	0.94	0.96	0.96	0.96
3 numerical	ELECTRA	0.96	0.97	0.97	0.97
4 record	DistilBERT	0.91	0.98	0.98	0.98
5 language	ELECTRA	0.93	0.96	0.96	0.96

In case of criterion [3 numerical], the metrics refer to the average performance across classes, weighted by the number of true instances of each class.

Table A.4: Evaluation of classifiers

A.3.1. Machine classification

We use the content annotations to fine-tune five deep-learning classifiers (one for each coding criterion) based on transformers (i.e., large language models). For that purpose, we randomly split the annotated samples into training data (70%), validation data (15%), and test data (15%). For each classifier, we select the best performing model (in terms of the F_1 score) from a set of candidate models, including BERT (Devlin *et al.*, 2018), ALBERT (Lan *et al.*, 2020), DistilBERT (Sanh *et al.*, 2019), RoBERTa (Liu *et al.*, 2019), and ELECTRA (Clark *et al.*, 2020).

These transformer models have been pre-trained on large text corpora and are considered state of the art in many natural language processing tasks at the time of conducting our study. The models need to be fine-tuned for the task at hand (i.e., the evaluation of headlines of inflation-related news stories) to competently classify text in a narrow context. For that purpose, we tokenize the translated headlines according to each model's tokenization scheme and obtain vectors of word embeddings with position encodings by applying the weights of the respective model. The human annotations in the training data are then used to update the model weights and create the fine-tuned version of each model. The validation data are used to evaluate the progress of the fine-tuning process and the performance of the updated models. We conclude the fine-tuning once either of two metrics starts to increase—the training loss or the validation loss—to avoid over- and underfitting. We evaluate each model's predictive performance by comparing the human annotations in the test data with the model predictions. Table A.4 summarizes the predictive ability of the best-performing models.

We use the fine-tuned models to classify those headlines in the sample where content annotations by humans are missing and conduct extensive validation spot checks. Due to space constraints, Figure A.1 shows a random sample of headlines, supporting the reliability and accuracy of the machine classifications.

B. Additional tables and figures

	All headlines	Headlines including					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		any number	decimal value	integer value	multiple of five	historical record	arousing language
Incr.-infl. threshold	0.992	1.072	0.948	1.057	1.378**	0.979	1.037
	(0.045)	(0.073)	(0.082)	(0.140)	(0.217)	(0.102)	(0.106)
Decr.-infl. threshold	0.930	0.884	0.909	1.172	0.416**	1.360	0.411**
	(0.063)	(0.103)	(0.128)	(0.288)	(0.158)	(0.459)	(0.160)
Mean of dep. variable	13.844	3.214	2.026	0.735	0.515	1.032	0.745
SD of dep. variable	22.126	5.328	3.377	1.664	1.516	2.403	1.849
Pseudo R^2	0.718	0.534	0.489	0.369	0.445	0.525	0.509

Notes: N = 2,729. Poisson pseudo-maximum likelihood estimates (incidence rate ratios) capturing the multiplicative effects on expected headline counts. All models control for second-order polynomials in the inflation level and its change, total headline counts (all topics), and country and time fixed effects. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, or 15% for the first time in the past 12 months. Standard errors (in parentheses) are clustered by country.
** p<0.10, ** p<0.05, *** p<0.01*

Table B.1: Effects of threshold events on inflation headlines (2nd-order polynomials in inflation levels and changes)

	All headlines	Headlines including					
	(1)	(2) any number	(3) decimal value	(4) integer value	(5) multiple of five	(6) historical record	(7) arousing language
Incr.-infl. threshold	0.990	1.082	0.963	1.085	1.371**	0.971	1.046
	(0.046)	(0.075)	(0.092)	(0.141)	(0.211)	(0.101)	(0.105)
Decr.-infl. threshold	0.899	0.838	0.849	1.101	0.398**	1.343	0.403**
	(0.066)	(0.099)	(0.130)	(0.283)	(0.156)	(0.473)	(0.153)
Mean of dep. variable	13.844	3.214	2.026	0.735	0.515	1.032	0.745
SD of dep. variable	22.126	5.328	3.377	1.664	1.516	2.403	1.849
Pseudo R^2	0.719	0.535	0.490	0.370	0.445	0.525	0.510

Notes: N = 2,729. Poisson pseudo-maximum likelihood estimates (incidence rate ratios) capturing the multiplicative effects on expected headline counts. All models control for fourth-order polynomials in the inflation level and its change, total headline counts (all topics), and country and time fixed effects. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, or 15% for the first time in the past 12 months. Standard errors (in parentheses) are clustered by country.
** p<0.10, ** p<0.05, *** p<0.01*

Table B.2: Effects of threshold events on inflation headlines (4th-order polynomials in inflation levels and changes)

	All headlines	Headlines including					
	(1)	(2) any number	(3) decimal value	(4) integer value	(5) multiple of five	(6) historical record	(7) arousing language
Incr.-infl. threshold	0.987	1.065	0.959	1.045	1.345**	0.961	1.016
	(0.047)	(0.074)	(0.087)	(0.144)	(0.198)	(0.106)	(0.109)
Decr.-infl. threshold	0.837**	0.802	0.845	0.854	0.506*	1.394	0.396***
	(0.073)	(0.111)	(0.143)	(0.292)	(0.202)	(0.491)	(0.138)
Mean of dep. variable	13.844	3.214	2.026	0.735	0.515	1.032	0.745
SD of dep. variable	22.126	5.328	3.377	1.664	1.516	2.403	1.849
Pseudo R^2	0.720	0.536	0.490	0.373	0.447	0.526	0.511

Notes: N = 2,729. Poisson pseudo-maximum likelihood estimates (incidence rate ratios) capturing the multiplicative effects on expected headline counts. All models control for third-order polynomials in the inflation level and its change, as well as all interactions between them, total headline counts (all topics), and country and time fixed effects. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, or 15% for the first time in the past 12 months. Standard errors (in parentheses) are clustered by country.
** p<0.10, ** p<0.05, *** p<0.01*

Table B.3: Effects of threshold events on inflation headlines (3rd-order polynomials in inflation level and change, fully interacted)

	All headlines	Headlines including					
	(1)	(2) any number	(3) decimal value	(4) integer value	(5) multiple of five	(6) historical record	(7) arousing language
Incr.-infl. threshold	0.995	1.084	0.963	1.082	1.380**	0.974	1.037
	(0.046)	(0.075)	(0.090)	(0.144)	(0.216)	(0.101)	(0.106)
Decr.-infl. threshold	0.959	0.902	0.887	1.176	0.545*	1.192	0.652
	(0.069)	(0.113)	(0.143)	(0.256)	(0.194)	(0.380)	(0.238)
Mean of dep. variable	13.844	3.214	2.026	0.735	0.515	1.032	0.745
SD of dep. variable	22.126	5.328	3.377	1.664	1.516	2.403	1.849
Pseudo R^2	0.719	0.535	0.489	0.370	0.444	0.525	0.509

Notes: N = 2,729. Poisson pseudo-maximum likelihood estimates (incidence rate ratios) capturing the multiplicative effects on expected headline counts. All models control for third-order polynomials in the inflation level and its change, total headline counts (all topics), and country and time fixed effects. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, or 15% for the first time in the past 6 months. Standard errors (in parentheses) are clustered by country.
** p<0.10, ** p<0.05, *** p<0.01*

Table B.4: Effects of threshold events on inflation headlines (6-month protection period for threshold events)

	All headlines	Headlines including					
	(1)	(2) any number	(3) decimal value	(4) integer value	(5) multiple of five	(6) historical record	(7) arousing language
Incr.-infl. threshold	0.996	1.090	0.965	1.089	1.382**	0.975	1.040
	(0.045)	(0.075)	(0.088)	(0.145)	(0.216)	(0.101)	(0.106)
Decr.-infl. threshold	1.003	0.842	0.800	1.375	0.259**	2.131**	0.331
	(0.121)	(0.141)	(0.136)	(0.415)	(0.155)	(0.736)	(0.229)
Mean of dep. variable	13.908	3.222	2.031	0.737	0.517	1.036	0.750
SD of dep. variable	22.183	5.342	3.385	1.669	1.520	2.410	1.854
Pseudo R^2	0.719	0.535	0.489	0.371	0.445	0.526	0.509

Notes: N = 2,729. Poisson pseudo-maximum likelihood estimates (incidence rate ratios) capturing the multiplicative effects on expected headline counts. All models control for third-order polynomials in the inflation level and its change, total headline counts (all topics), and country and time fixed effects. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, or 15% for the first time in the past 18 months. Standard errors (in parentheses) are clustered by country.
** p<0.10, ** p<0.05, *** p<0.01*

Table B.5: Effects of threshold events on inflation headlines (18-month protection period for threshold events)

	All headlines	Headlines including					
	(1)	(2) any number	(3) decimal value	(4) integer value	(5) multiple of five	(6) historical record	(7) arousing language
Incr.-infl. threshold	0.996	1.085	0.963	1.081	1.381	0.974	1.037
	[0.630]	[0.386]	[0.576]	[0.666]	[0.074]	[0.781]	[0.556]
Decr.-infl. threshold	0.926	0.860	0.879	1.144	0.408	1.349	0.388
	[0.278]	[0.244]	[0.422]	[0.640]	[0.024]	[0.433]	[0.002]
Mean of dep. variable	13.844	3.214	2.026	0.735	0.515	1.032	0.745
SD of dep. variable	22.126	5.328	3.377	1.664	1.516	2.403	1.849
Pseudo R^2	0.719	0.535	0.489	0.370	0.445	0.525	0.510

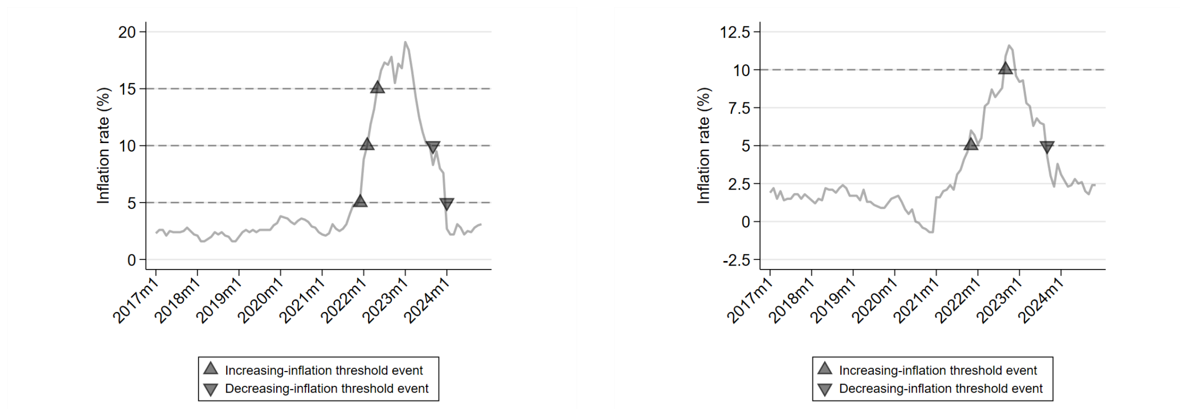
Notes: N = 2,729. Poisson pseudo-maximum likelihood estimates (incidence rate ratios) capturing the multiplicative effects on expected headline counts. All models control for third-order polynomials in the inflation level and its change, total headline counts (all topics), and country and time fixed effects. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, or 15% for the first time in the past 12 months. Values in brackets are p-values based on the wild cluster bootstrap (clustered at the country level).
** p<0.10, ** p<0.05, *** p<0.01*

Table B.6: Effects of threshold events on inflation headlines (wild cluster bootstrap p-values)

	All headlines	Headlines including					
	(1)	(2) any number	(3) decimal value	(4) integer value	(5) multiple of five	(6) historical record	(7) arousing language
Incr.-infl. threshold	1.106**	1.116	1.037	1.341***	1.021	1.135*	0.913
	(0.050)	(0.076)	(0.104)	(0.149)	(0.134)	(0.077)	(0.081)
Decr.-infl. threshold	0.965	0.990	0.931	0.902	1.195	1.168	1.037
	(0.082)	(0.126)	(0.153)	(0.190)	(0.229)	(0.210)	(0.248)
Mean of dep. variable	13.844	3.214	2.026	0.735	0.515	1.032	0.745
SD of dep. variable	22.126	5.328	3.377	1.664	1.516	2.403	1.849
Pseudo R^2	0.719	0.535	0.489	0.371	0.442	0.525	0.509

Notes: N = 2,729. Poisson pseudo-maximum likelihood estimates (incidence rate ratios) capturing the multiplicative effects on expected headline counts. All models control for third-order polynomials in the inflation level and its change, total headline counts (all topics), and country and time fixed effects. A threshold event refers to a situation where a country's inflation rate crosses 6, 7, 8, 9, 11, 12, 13, or 14 percent for the first time in the past 12 months. Standard errors (in parentheses) are clustered by country.
** p<0.10, ** p<0.05, *** p<0.01*

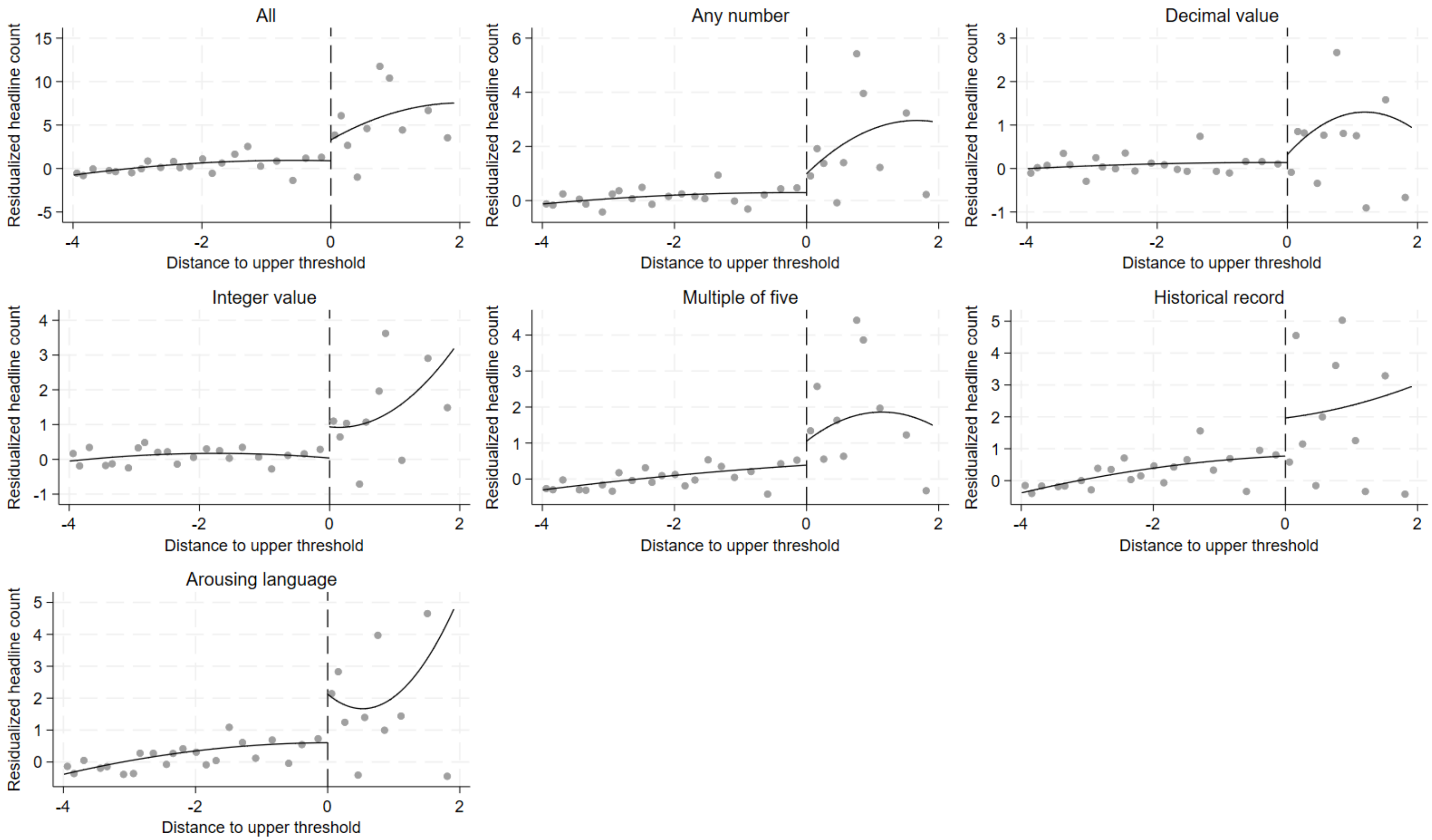
Table B.7: Effects of threshold events on inflation headlines (integer thresholds)



(**a**) Czechia (**b**) Germany

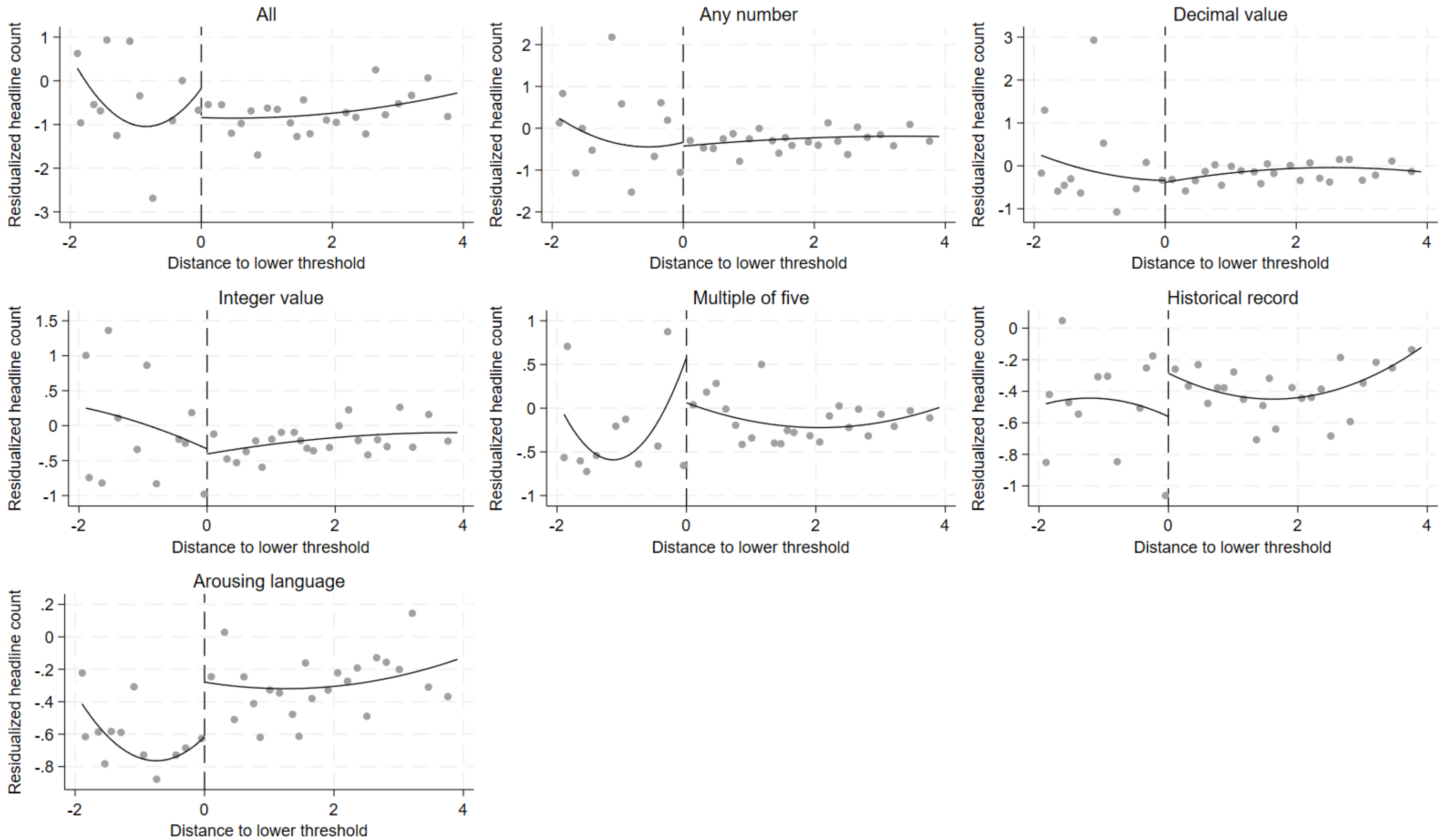
Notes: An increasing-inflation threshold event refers to a situation where a country's inflation rate reaches or exceeds a value of 5, 10, or 15%, compared to the previous month, while not reaching or exceeding that threshold in the past 12 months. A decreasing-inflation threshold event refers to a situation where a country's inflation rate falls below a value of 5, 10, or 15%, compared to the previous month, while not falling below that threshold in the past 12 months.

Figure B.1: Examples of round-number thresholds in the inflation rate



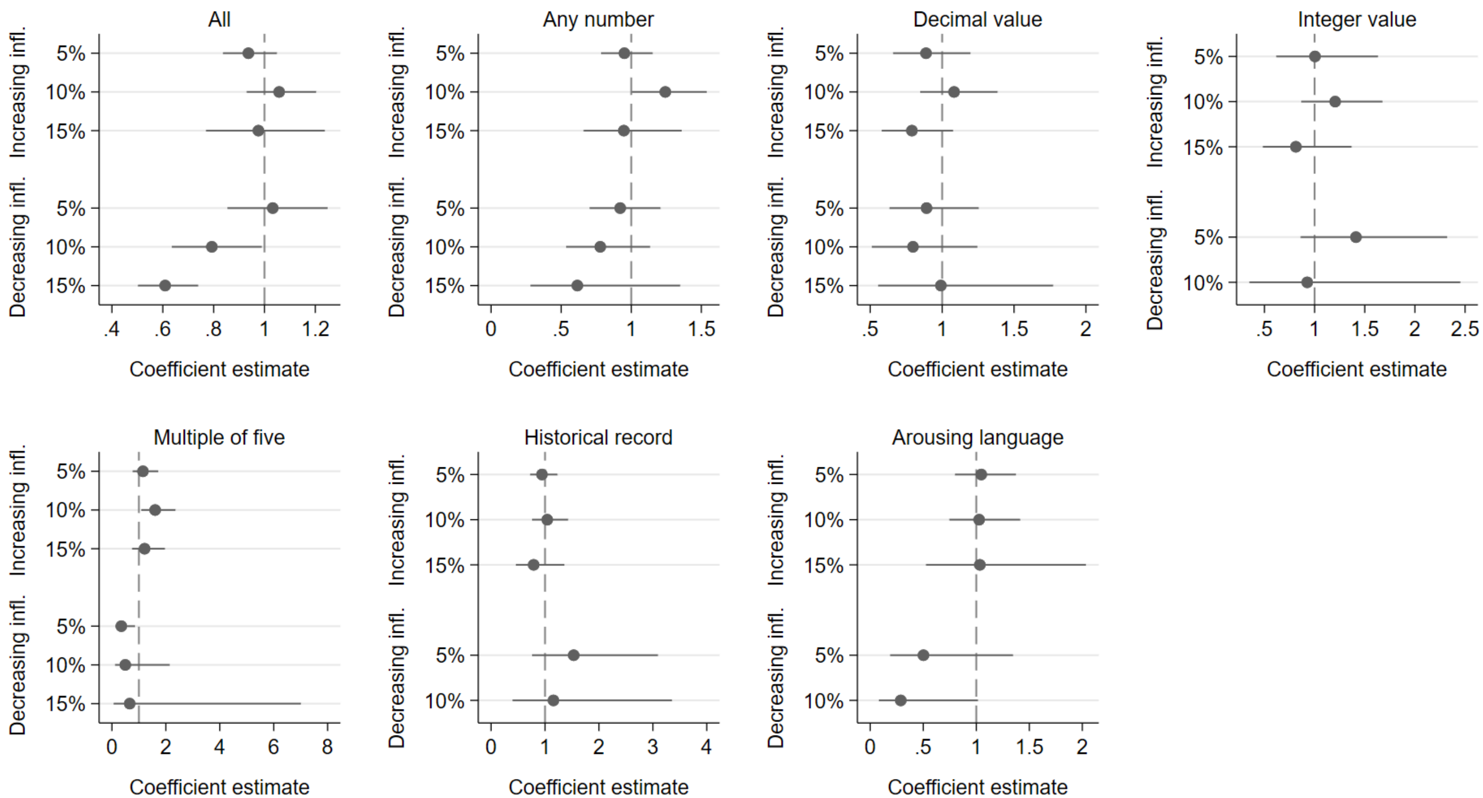
Notes: The figure shows Pearson residuals from Poisson pseudo-maximum-likelihood regressions of headline counts on country fixed effects. The markers denote bin means (quantile-spaced), and lines represent polynomial fits. The x-axis measures a country's distance of inflation in the current month from the next upper threshold (5, 10, or 15 percent) from the past month. Values on the x-axis < 0 *refer to situations without increasing-inflation threshold events, whereas values* ≥ 0 *capture increasing-inflation threshold events. The figure excludes threshold events where the same threshold was reached or exceeded in the past 12 months.*

Figure B.2: Inflation headlines and increasing-inflation threshold events



Notes: The figure shows Pearson residuals from Poisson pseudo-maximum-likelihood regressions of headline counts on country fixed effects. The markers denote bin means (quantile-spaced), and lines represent polynomial fits. The x-axis measures a country's distance of inflation in the current month from the next upper threshold (5, 10, or 15 percent) from the past month. Values on the x-axis < 0 *refer to situations without increasing-inflation threshold events, whereas values* ≥ 0 *capture increasing-inflation threshold events. The figure excludes threshold events where the same threshold was reached or exceeded in the past 12 months.*

Figure B.3: Inflation headlines and decreasing-inflation threshold events



Notes: The figure shows coefficients (incidence-rate ratios) from the baseline Poisson pseudo-maximum likelihood regressions controlling for third-order polynomials in the inflation rate level and its change, total headline count (all topics), and country and time fixed effects. Combined threshold variables are replaced with separate dummies for the 5, 10, and 15% thresholds. The 15% decreasing-inflation threshold dummy is dropped in some models due to perfect collinearity.

Figure B.4: Effects of individual inflation threshold on inflation headlines

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